

**VOLTAGE CONTROL OF ACTIVE DISTRIBUTION
NETWORKS WITH EV CHARGING STATIONS USING
MULTI-TIME SCALE MODEL PREDICTIVE CONTROL**



Mudasar Rahman Dar



VOLTAGE CONTROL OF ACTIVE DISTRIBUTION NETWORKS WITH EV CHARGING STATIONS USING MULTI-TIME SCALE MODEL PREDICTIVE CONTROL

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by

**Mudasar Rahman Dar
(206102102)**

under the guidance of

Dr. Sanjib Ganguly



**DEPARTMENT OF ELECTRONICS AND ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY GUWAHATI
GUWAHATI - 781039, INDIA**

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Certificate

This is to certify that the thesis entitled “**Voltage control of active distribution networks with EV charging stations using multi-time scale model predictive control**” submitted by **Mudaser Rahman Dar** (206102102), to the Indian Institute of Technology Guwahati for the award of the degree of Doctor of Philosophy is a bona fide record of the research work done by him under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Date:

Place: Guwahati

Dr. Sanjib Ganguly

Associate Professor

Dept. of Electronics and Electrical Engg.,

Indian Institute of Technology Guwahati,

Guwahati - 781039, Assam, India.



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This Thesis is dedicated to the

Loving Memory of my Grandfather

Noor Mohammad Dar





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Date:

Place: Guwahati

Mudaser Rahman Dar

Abstract

The rapid proliferation of photovoltaic (PV) units and controllable loads, notably electric vehicles (EVs), has significantly altered the operational dynamics of active distribution networks (ADNs), causing various issues. Their large-scale integration and uncertain behavior induce frequent and severe voltage violations, thereby challenging traditional voltage regulation mechanisms, which involve localized control of on-load tap changers (OLTCs), static voltage regulators (SVRs), etc. For this purpose, coordinated voltage control (CVC) schemes have been developed, wherein the control capabilities of fast-acting devices, such as PV inverters and EV charger inverters, storage devices, and other power electronic interfaced devices, are utilized for voltage regulation and loss minimization. A multi-time scale model predictive control (MPC) based real-time receding horizon control mechanism, enabling coordination of diverse resources including OLTC, PV, and EV charging station (EVCS) inverters, and distribution static synchronous compensators (DSTATCOMs), lies at the core of this thesis. The multi-time scale design allows OLTC operation on a slower time scale, and coordinated operation of inverter-driven control devices (IDCDs) on a faster time scale.

Taking into consideration the need for extensive measurement infrastructure and communication overhead, in centralized control frameworks, an MPC-based centralized control framework has been developed. To avoid the need for a fully observable network, a reduced-order control framework has been developed, with reduced measurement and communication infrastructure requirements, mitigating cost and computational complexity, while enhancing scalability. Based on a novel ranking index, a minimum set of available control resources is identified and employed for voltage regulation and energy loss minimization. The performance of the reduced model framework is comparable to that of the full-order model, with a mean and standard deviation in the difference between the voltage profiles at the critical bus of 0.0036 p.u. and 0.0029 p.u., respectively.

To effectively address the uncertainties associated with nodal power injections, due to PVs, EVs, and conventional loads, a chance-constrained model predictive control (CC-MPC) based centralized control framework has been developed to contain uncertainties with known probability distributions. A scenario-based solution approach has been developed to solve the chance-constrained (CC) problem, ensuring predefined solution accuracy within the network security constraints, while enhancing computational efficiency using the backward scenario reduction technique. The CC-MPC framework eliminates all the violations as compared to the deterministic MPC, with an increase in energy loss and reactive power exchange by around 20% and 3%, respectively. In addition, a distributionally robust chance-constrained formulation is introduced to consider the uncertainties in nodal power injections and real-time measurements with unknown distributions, but with partially available information. Unlike the scenario-based approach to the CC problem, a tractable solution approach has been utilized by modifying the upper and lower limits of CCs with a dynamically adjusted safety margin, based on available information about uncertainties. A local rapid-response control mechanism is also integrated to mitigate fast voltage violations and act as a backup layer for the central controller.

To enhance scalability and preserve data privacy, a centralized-distributed hybrid hierarchical control architecture has been developed for large networks, while considering the demerits of centralized control. The IDCDs are controlled using MPC with distributed coordination among network clusters, and OLTC employs centralized control requiring sparse communication. An improved modularity metric is introduced, incorporating cluster diameter, in addition to voltage sensitivities and device regulation capacities, for optimal partitioning of the network, for distributed coordination. Within these partitions, distributed coordination among IDCDs is achieved using the alternating direction method of multipliers (ADMM), which enables local decision-making with limited communication overhead. Furthermore, a scenario-based chance-constrained MPC framework has been developed to incorporate the nodal power uncertainties in the centralized-distributed hybrid control paradigm. It is seen that the distributed coordination of IDCDs provides a near-optimal solution, with 0.0024 p.u. mean deviation in the voltage profile at the critical bus as compared to centralized optimal coordination.

The proposed control strategies are extensively validated on standard test networks, such as the 33-bus distribution network and the modified IEEE 123-bus distribution network, under high PV and EV penetration levels. All the time domain simulations in this thesis have been carried out using the Power System Analysis (PSAT) toolbox in MATLAB, and the optimizations are carried out using IBM ILOG CPLEX with the MATLAB interface.



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List of Acronyms



ADN	Active distribution network
ADMM	Alternating direction method of multipliers
ANM	Active network management
ANN	Artificial neural network
APC	Active power curtailment
AVR	Automatic voltage regulator
BESS	Battery energy storage system
BEV	Battery electric vehicle
CB	Capacitor bank
CC	Chance constraint
CC-MPC	Chance-constrained model predictive control
CVC	Coordinated voltage control
CVR	Conservation voltage reduction
DER	Distributed energy resource
DG	Distributed generation
D-MPC	Deterministic model predictive control

DNO	Distribution network operator
DRCC-MPC	Distributionally robust chance-constrained model predictive control
DSO	Distribution system operator
DSTATCOM	Distribution static synchronous compensator
ESS	Energy storage system
EV	Electric vehicle
EVCS	Electric vehicle charging station
FC	Fixed capacitor
FTS	Fast time scale
G2V	Grid-to-vehicle
IDCD	Inverter driven control device
LSTM	Long short-term memory
LV	Low voltage
LVR	Line voltage regulator
MILP	Mixed integer linear programming
MINLP	Mixed integer non-linear programming
MIQP	Mixed integer quadratic programming
MISOCP	Mixed integer second order cone programming
ML	Machine learning
MPC	Model predictive control

MV	Medium voltage
NOP	Normally open point
NR	Newton-Raphson
OLTC	On-load tap changer
OPF	Optimal power flow
PCC	Point of common coupling
PDF	Probability Density Function
PDN	Power distribution network
PEV	Plug-in electric vehicle
PHEV	Plug-in hybrid electric vehicle
PSAT	Power system analysis toolbox
PV	Photo-voltaic
QP	Quadratic programming
REX-PEV	Range extended plug-in electric vehicle
RES	Renewable energy source
RTU	Remote terminal unit
SC	Switched capacitor
STS	Slow time scale
SVR	Step voltage regulator
SOP	Soft-open-point
TSO	Transmission system operator

VSC	Voltage sources converter
V2G	Vehicle-to-grid
VAC	Voltage adaptive control
VVC	Volt/var control
VVO	Volt/var optimization





List of Symbols

α_{ij}	Voltage sensitivity of node i with respect to node j
$\bar{V}_P/\bar{V}_S$	Primary side/secondary side voltage of an OLTC transformer
$\bar{P}_{mn}$	Active power flow in the line (m,n)
$\bar{Q}_{mn}$	Reactive power flow in the line (m,n)
$\bar{s}_n$	Net complex power injection at node n
$\bar{S}_{mn}$	Complex power flow in the line (m,n)
$\bar{V}_n$	Complex voltage at node n
$\bar{V}_{DG}$	Voltage of DG connected bus in the network
$\bar{z}_{mn}$	Impedance of line $\mathcal{L}_{mn}$
χ	Output prediction matrix
ψ	Matrix linking control input changes to predicted outputs
Λ_c	Voltage sensitivity coefficient matrix of boundary nodes with respect to control inputs in cluster c
λ_c	Vector of dual variables (Lagrange multipliers) in cluster c
μ_m	Mean vector of measurement uncertainties
μ_p	Mean vector of uncertainties in nodal power injections

ω	Vector of measurement errors
σ	Slack variable vector
Σ_m	Covariance matrix of measurement uncertainties
Σ_p	Covariance matrix of uncertainties in nodal power injections
Θ	Worst-case cumulative distribution function (CDF) from ambiguity set
ζ	Vector of uncertainties in nodal power injections
$\Delta\Omega$	Uncertainty vector over the whole prediction horizon
Δp	Vector of change in active power injection
Δq	Vector of change in reactive power injection
ΔU	Control input vector over the whole control horizon
Δu_c	Vector of change in control inputs in cluster c
ΔV	Vector of change in the bus voltages
ΔV_0	Change in substation voltage
Δv_c^b	Vector of voltage deviations at the boundary nodes of cluster c
$\Delta \mathcal{U}_c$	Feasible set of admissible control deviations for cluster c
Δd_s^r	Change in relative diameter between two clustering stages
ΔQ_{PV}^l	Change in reactive power exchange due to local control layer
ΔV_{tap}	Change in OLTC reference voltage
ℓ_{mn}	Square of the current magnitude flowing in branch (m, n)
$\frac{\partial \mathbf{V}}{\partial \zeta}$	Sensitivity of bus voltages to nodal power uncertainties
γ	Confidence parameter

$\hat{\mathbf{A}}$	System matrix for linear MPC
$\hat{\mathbf{B}}$	Input matrix for linear MPC
$\hat{\mathbf{C}}$	Output matrix for linear MPC
$\hat{\mathbf{D}}$	Disturbance matrix for linear MPC
$\hat{\mathbf{G}}$	Matrix mapping previous input to the current input sequence
$\hat{\mathbf{y}}_p$	Desired or reference output vector
κ	Discrete time step index
Λ_i	Variance-based safety margin used in voltage bounds under uncertainty
$\mathbf{A}$	Square invertible sub-matrix of the incidence matrix $\tilde{\mathbf{A}}$
$\mathbb{D}_r$	Voltage sensitivity matrix corresponding to the nodal active powers
$\mathbb{D}_x$	Voltage sensitivity matrix corresponding to the nodal reactive powers
$\mathbb{E}(\cdot)$	Expected value
$\mathbb{P}$	Probability
$\mathbf{y}_1$	Output vector corresponding to the bus voltages
$\mathbf{y}_2$	Output vector corresponding to the line currents
$\mathbf{y}_3$	Output vector corresponding to the power losses
$\mathbf{1}$	Vector of ones
$\mathbf{a}_0$	First row of incidence matrix $\tilde{\mathbf{A}}$ (corresponding to the substation bus)
$\mathbf{a}_c, \mathbf{a}_d$	Auxiliary variable vectors corresponding to the boundary nodes of clusters c and d
$\mathbf{D}_m$	Sensitivity matrix with respect to measurement errors

$\mathbf{D_p}$	Sensitivity matrix with respect to nodal power uncertainties
$\mathbf{e}_i$	i^{th} canonical basis vector
$\mathbf{g}_c$	Vector of global consensus variables for cluster c
$\mathbf{I}$	Vector of distribution line currents
$\mathbf{P}$	Vector of active power flows in lines
$\mathbf{p}$	Vector of net active power injections
$\mathbf{p}_l$	Active power loss of the network
$\mathbf{Q}$	Vector of reactive power flows in lines
$\mathbf{q}$	Vector of net reactive power injections
$\mathbf{r}$	Vector of line resistances
$\mathbf{R}_l$	Diagonal matrix of line resistances
$\mathbf{r}_c$	Primal residual vector for cluster c defined as $(\mathbf{a}_c - \mathbf{g}_c)$
$\mathbf{S}_v^{\text{tap}}$	Voltage sensitivity matrix corresponding to the OLTC tap position
$\mathbf{S}_i^p$	Current sensitivity matrix corresponding to the active power injections
$\mathbf{S}_i^q$	Current sensitivity matrix corresponding to the reactive power injections
$\mathbf{S}_l^p$	Loss sensitivity matrix corresponding to the active power injections
$\mathbf{S}_l^q$	Loss sensitivity matrix corresponding to the reactive power injections
$\mathbf{S}_v^p$	Voltage sensitivity matrix corresponding to the active power injections
$\mathbf{S}_v^q$	Voltage sensitivity matrix corresponding to the reactive power injections
$\mathbf{u}_c$	Control input vector of cluster c
$\mathbf{V}$	Vector of network bus voltages excluding that of substation node

$\mathbf{w}_i$	Objective weight matrix associated with the line currents
$\mathbf{w}_l$	Objective weight matrix associated with the power losses
$\mathbf{w}_s$	Objective weight matrix associated with the slack variables
$\mathbf{w}_u$	Objective weight matrices associated with the control inputs
$\mathbf{w}_v$	Objective weight matrix associated with output voltages
$\mathbf{x}$	Vector of line reactances
$\mathbf{X}_l$	Diagonal matrix of line reactances
$\mathbf{Y}_p$	Output vector over prediction horizon (N_p)
$\mathbf{Y}$	Admittance matrix
$\mathbf{y}_p(\kappa)$	Predicted output vector at time-step κ
$\mathbf{w}_y$	Objective weight matrix for output voltage deviations
ℓ_{mn}	Square of the current magnitude of line (m, n)
$\mathcal{B}_{cd}$	Set of boundary nodes between neighboring clusters c and d
$\mathcal{C}^*$	Set of clusters in optimal network partitioning
$\mathcal{C}_i$	Cluster i in the hierarchical clustering process
$\mathcal{D}$	Number of disturbance parameters in the MPC model
$\mathcal{D}_a$	Ambiguity set defined by known moments of uncertainties
$\mathcal{E}$	Set of all lines in the network
$\mathcal{I}$	Number of input variables in the MPC model
$\mathcal{L}$	Set of all branches or lines in the network
$\mathcal{L}_a$	Augmented Lagrangian function of the overall decomposition problem

$\mathcal{L}_c$	Augmented Lagrangian of the subproblem associated with cluster c
$\mathcal{L}_{mn}$	Line connecting node m with node n
$\mathcal{N}$	Set of all network buses excluding the slack bus
$\mathcal{N}^{EV}$	Set of network nodes with EVCSs
$\mathcal{N}^{PV}$	Set of network nodes with PVs
$\mathcal{N}_k$	Set of downstream nodes from a given node
$\mathcal{N}_{cont}$	Optimal set of controllable PV resources
$\mathcal{N}_c$	Set of the control resources
$\mathcal{N}_{meas}$	Set of nodes equipped with measurement devices
$\mathcal{N}_{obsv}$	Set of observation nodes
$\mathcal{O}$	Number of output variables in the MPC model
$\mathcal{S}$	Number of state variables in the MPC model
$\mathcal{U}_c$	Feasible region of change in control inputs for cluster c
N/B	Normal/beta distribution
$\text{Var}(\cdot)$	Variance operator
$\text{Var}(V_i)$	Variance of the i^{th} node voltage
$\overline{\overline{\Delta n_{tap}}}$	Maximum tap change of an OLTC
$\overline{\overline{\Delta \mathbf{u}}}$	Maximum change in control input
$\overline{\overline{\mathbf{I}}}$	Vector of thermal limits of distribution lines
$\overline{\overline{\mathbf{u}}}$	Vector of maximum limits of the control inputs
$\overline{\overline{\mathbf{V}}}$	Vector of maximum limit of the bus voltages

$\overline{\overline{n_{cap}}}$	Maximum number of units in a capacitor bank
$\overline{\overline{n_{tap}}}$	Maximum limit of the OLTC tap positions
$\overline{\overline{Q_{DG}}}$	Rated reactive power injection capacity of a DG inverter
$\Re$	Real number
ρ	Penalty parameter of the augmented Lagrangian in ADMM
σ_1, σ_2	Slack variables for lower and upper bound of voltage violations
σ_3	Slack variable for thermal limit violations
$\tilde{\mathbf{A}}$	Bus incidence matrix
$\underline{\underline{(.)}} / \overline{\overline{(.)}}$	Minimum/ maximum value of a quantity
$\underline{\underline{\Delta \mathbf{u}}}$	Vector of minimum changes in control inputs
$\underline{\underline{\mathbf{u}}}$	Vector of minimum limits of the control inputs
$\underline{\underline{\mathbf{V}}}$	Vector of minimum limits of the bus voltages
$\underline{\underline{n_{tap}}}$	Minimum limit of OLTC tap positions
$\zeta_n^{ev}(t)$	Uncertainty in EV power at node n and time t
$\zeta_n^l(t)$	Uncertainty in load power at node n and time t
$\zeta_n^{pv}(t)$	Uncertainty in PV power at node n and time t
a_c, a_d	Auxiliary scalar variables at the boundary nodes of clusters c and d
D_{ij}^c	Inter-cluster electrical distance between cluster $\mathcal{C}_i$ and $\mathcal{C}_j$
d_s^r	Relative diameter of the network at clustering stage s
D_{ij}	Electrical distance between node i and node j
d_i^c	Diameter of cluster $\mathcal{C}_i$

$f_c(\cdot)$	Local objective function of cluster c
g_c, g_d	Consensus (global) variable associated with clusters c, d
$h(\cdot)$	Function mapping control deviations to residuals
H_{tap}	Integral deviation parameter of OLTC controller
I_{mn}	Magnitude of current flowing in branch (m, n)
J_{rated}	Rated capacity of a battery
K_{tap}	Inverse time constant of OLTC controller
L_i	Proximity index of node i within a network cluster
L_{mn}	Inductance of line connecting buses m, n
n_{cap}	Number of units in a capacitor bank
N_c	Control horizon
N_p	Prediction horizon
n_{tap}	Number of tap steps of an OLTC
p_n	Net active power injection at node n
p_n^g	Active power generation at node n
p_n^l	Active power load demand at node n
P_b	Battery charging/discharging power
P_b^{rated}	Rated power of a battery
$P_{EV}(\kappa)$	EV charging load at time step κ
P_{mn}	Active power flow in branch (m, n)
$P_{PV}(\kappa)$	Active power generation of PV at time step κ

$P_{t,m}^{sop,loss} / P_{t,n}^{sop,loss}$	SOP active power loss at node m/n , at time t
$P_{t,m}^{sop} / Q_{t,m}^{sop}$	SOP active/reactive power injection at node m , at time t
q_n	Net reactive power injection at node n
q_n^g	Reactive power generation at node n
q_n^l	Reactive power load demand at node n
q_{cap}	Reactive power capacity of each unit in a capacitor bank
Q_{DG}	Reactive power injection by a DG source
Q_{EV}	Reactive power exchange by EV charging inverter
Q_{mn}	Reactive power flow in branch (m, n)
q_{stat}	Reactive power exchanged by DSTATCOM
r_l/x_l	Resistance/reactance of a distribution line
r_{mn}	Resistance of line connecting buses m, n
RI_i	Ranking index of i^{th} control resource
S_{DG}	Rated power of a DG inverter
S_{EV}	Rated capacity of an EV charging inverter
S_{PV}	Rated capacity of PV inverter
SOC	State of charge of a battery
T_{stat} / K_{stat}	STATCOM time constant/ controller gain
V^0	Reference voltage (1 p.u.)
V_n	Voltage magnitude at node n
V_g	Grid voltage

V_{low1}/V_{up1}	Lower/ upper limit of normal operation range of voltages
V_{low2}/V_{up2}	Lower/ upper limit of the unacceptable range of voltages
v_n	Square of the voltage magnitude at node n
V_{oP}	Nominal value of transformer voltage on primary side
V_{oS}	Nominal value of transformer voltage on secondary side
v_{stat}/i_{stat}	DSTATCOM voltage/ injected current
V_{tap}	Voltage at which OLTC is controlled
w_p	Scalar weight for the active power control input
w_q	Scalar weight for the reactive power control input
w_s	Scalar weight for the slack variables
w_y	Scalar weight for the system output
w_{tap}	Scalar weight for the OLTC tap operation
x_{mn}	Reactance of line connecting buses m, n
$\Delta\omega$	Nodal power uncertainty vector at time step κ
V_0	Magnitude of bus voltage at the substation
x_t	State variable representing OLTC tap position



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Chapter 1

Introduction

The significant integration of distributed energy resources (DERs), notably the renewable energy sources and electric vehicles (EVs) in recent years has remarkably transformed the electric distribution networks. The proliferation of these DERs, particularly photovoltaic (PV) systems, has transitioned conventionally passive networks into dynamic active distribution networks (ADNs). DERs play a crucial role in ADN management by facilitating a more reliable, economical, secure, and environmentally sustainable energy supply, while also supporting the growing energy demand [1]. Nevertheless, the large integration of distributed generation (DG) units, accompanied by their temporal uncertainties, may cause frequent and severe voltage variations, which may lead to over-voltage and under-voltage events, reverse power flow, line congestion, thermal limit violations, stability issues, and altered fault levels [2]. The reverse power flow may compromise the system reliability due to the conventional unidirectional configuration of protection schemes. These insecure and unforeseen incidents complicate the real-time network operation, thereby increasing the operational challenges for distribution network operators (DNOs) [3]. These emerging complexities necessitate the adoption of advanced control setups and communication infrastructures to ensure the reliable, secure, and efficient operation of these evolved distribution networks [4, 5]. The frequent and uncertain voltage violations form one of the main issues in ADNs, thus restricting the wide integration of DERs. These frequent violations also interfere with the operation of conventional slow-acting devices, such as on-load tap

changers (OLTCs) and step voltage regulators (SVRs), leading to their frequent operation, thus increasing wear and tear. The regulation of these devices is further deteriorated by the simultaneous over/under voltage occurrences, due to the simultaneous renewable generation and EV demands, thus restraining the use of only traditional devices and control strategies. Moreover, the existing networks lack the infrastructure for topological changes brought about by the expansive integration of DERs and EV charging stations (EVCSs), forcing steps towards active network management (ANM) [6]. ANM involves the deployment of advanced control and communication, utilizing the fast-acting capabilities of advanced control devices, such as power electronic-based devices, for optimal control and operation.

Future power distribution networks (PDNs) seem to have an immense rise in plug-in electric vehicles (PEVs) due to efforts to reduce carbon footprints. The uncertainty in their charging/discharging patterns, state-of-charge, and randomness in their driving patterns pose issues, such as voltage violations, increased power losses, and localized system overloading, if uncoordinated [7]. PEVs are integrated either in grid-to-vehicle (G2V) mode or in both grid-to-vehicle (G2V) and vehicle-to-grid (V2G) modes, wherein EVs can be employed for grid services. Participation EVs using V2G technology as auxiliary services, and their smart charging schemes can be utilized for grid support functions, such as voltage control. With the concept of active distribution network (ADN), things like smart meters, control equipment, bidirectional communication links forming a complex communication network, and adjustable loads increase the computation burden, as well as communication burden, to a large extent. Furthermore, data acquisition and metering become essential components in ADNs, with increased demand for data collection, which may raise concerns among the users regarding data privacy [8].

1.1 The Problem of Voltage Fluctuation in ADNs and its Control

The frequent voltage fluctuation in distribution networks is largely attributed to the integration of PVs and PEVs. PVs raise voltages, particularly at feeder ends under the situation of lower load demand and high PV generation, affecting the voltage profile of nodes that are relatively more sensitive to the power variations. Similarly, EV charging adds to the power demand, leading

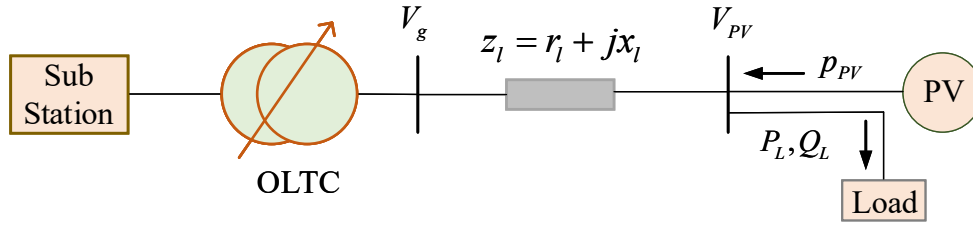


Fig. 1.1: Grid-connected PV system.

to localized voltage dips. In certain scenarios, simultaneous over-voltage and under-voltage can aggravate the voltage profile, wherein large dips may lead to instability in weak networks. If these issues remain unaddressed, the instability may lead to voltage collapse. A typical PV source-induced voltage rise problem in an ADN can be understood using Fig. 1.1. If the PV generation is greater than local load demand, the reverse power flow occurs from the PV source back to the utility grid, elevating the voltage at the PV node. If $\Delta V = \Delta V_r + j\Delta V_x = \bar{V}_{PV} - \bar{V}_g$ is the voltage difference between the PV bus and the bus connected to the utility grid, linked through a line with impedance $\bar{z}_l = r_l + jx_l$, then,

$$\Delta V = \frac{(P - jQ)}{\bar{V}_g^*} \cdot (r_l + jx_l) = \frac{(r_l P + x_l Q)}{\bar{v}_g^*} + j \frac{(x_l P - r_l Q)}{\bar{V}_g^*} \quad (1.1)$$

where, $P = P_{PV} - P_L - P_{loss}$ and $Q = Q_{PV} - Q_L - Q_{loss}$ are the active and reactive powers flowing to the grid, respectively, and P_{PV} , P_L and P_{loss} are the PV injected power, local load power demand, and line power loss, respectively. In low voltage (LV) distribution networks, R/X is high compared to the transmission networks. Thus, assuming $\bar{V}_g = 1\angle 0^\circ$, ΔV can be approximated to real component ΔV_r . Neglecting the reactive component of voltage deviation (ΔV_x), voltage deviation reduces to the equation,

$$\Delta V \simeq r_l P + x_l Q \quad (1.2)$$

It is noteworthy that voltages in LV distribution networks exhibit more sensitivity to active power variations due to inherently higher line resistance to reactance ratio ($r_l > x_l$). Consequently, active power control utilizing battery storage, heat pumps, and controllable load (such as V2G functionalities of EVs) provides alternatives in voltage regulation under reactive power insufficiency.

Additionally, to alleviate over-voltage conditions in ADNs, active power curtailment (APC) of

PV units presents a feasible solution. However, it is generally avoided and kept as a last resort to avoid the loss of renewable energy.

In active network management (ANM), the distribution network operator (DNO) pre-defines a voltage reference for each bus within a network. The selection of these target voltages is generally guided by operational requirements to ensure secure or economical operation. However, attaining these precise voltage setpoints is not practically feasible, due to the dynamic and stochastic nature of ADNs. Consequently, the bus voltages are regulated within permissible limits around the reference setpoint known as the normal operation limits. The control mechanism ensures that the network voltages remain confined within these pre-defined acceptable operation limits. The deviations beyond the normal operation limits are undesirable (undesirable range) up to a critical emergency threshold (emergency limit). However, if the voltage violations are beyond the emergency limits, the controller employs its full regulatory capabilities to re-establish the system voltages within the defined normal operation limits.

The permissible voltage deviation (normal operation range) in a distribution network is governed by the corresponding national standards. For instance, in accordance with the definition of range A in ANSI standard C84.1-2016, the medium voltage (MV) deviations are restricted to the upper bound and lower bound of +5% and -2.5%, respectively, while LV network voltage bounds are limited to $\pm 5\%$ [9]. Similarly, in Germany, the grid voltage is required to stay within $\pm 10\%$ of the RMS voltage averaged over 10 minutes, as per European standard EN50160 [10]. The voltages should remain in this range for greater than 95% of all 10-minute time steps of a week, and for less than 5% of all 10-minute intervals in a week, the voltages can go below 90% of the nominal value but should stay above 85% of the nominal voltage. In power networks with high PV penetration, more stringent requirements are demanded during peak generation hours. For example, in Hawaii (USA), it is demanded by the grid authority that the voltages during peak generation hours must stay inside 0.975 p.u. and 1.025 p.u. [11]. These requirements are relaxed to a maximum deviation of $\pm 5\%$ in off-peak hours. The service voltage variation ranges of some of the countries are provided in Table 1.1 [12]. Conventional voltage regulation in distribution networks relies on devices such as OLTCs, line voltage regulators (LVRs), switched capacitors (SCs), and feeder capacitors (FCs). However, the emergence of bidirectional power flows undermines the

effectiveness of OLTCs and LVRs, which were originally designed under the assumption of unidirectional power flow. Moreover, the significant voltage rise at DER-connected buses can exceed the compensating range of LVRs due to limited tap operations. Traditional distribution networks engage manual tap settings or automatic tap changing by employing OLTC to limit the voltage within pre-specified limits. The OLTC changes its tap setting by measuring the feeder current and thus the voltage drop of the feeder, assuming unidirectional flow. Bi-directional power flow due to active generation makes the operation of OLTC unforeseeable and uncontrollable [13]. Moreover, OLTC is not able to regulate voltage for fast fluctuations of renewable sources due to its comparatively slow operation. The switched capacitors (SCs) can be deployed to improve voltage at the point of common coupling (PCC). However, uncoordinated DER offset currents in the feeder steer bidirectional currents in the network, thus interacting with capacitor switching operations. It is noteworthy that in conventional control of OLTC and SCs, there is no communication or use of a remote-control facility [14].

Incorporation of DERs for fast voltage control is a promising solution under such cases [15]. The complexity of coordinated regulation requires the utilities to adopt stringent requirements for the grid connection of DERs. Previously, DG units were not permitted to actively regulate the voltage in PDNs and were operated at unity power factor to prevent interference with existing voltage control schemes and overloading of equipment (due to additional reactive current) [16]. The revised standards (IEEE 1547 of 2018) permit the DER owners to control voltage by active/reactive power management [17]. DG units can provide regulated active and reactive power

Table 1.1: Standard of service voltage variation ranges in different countries [12].

Country	Nominal voltage	Mandatory regulation limits (min./max.)
Japan	100 V	-6% / +6%
U.S.	120 V	-5% / +5%
Germany	230 V	-10% / +10%
Australia	230 V	-6.1% / +10%
Korea	220 V	-5.9% / +5.9%
U.K.	230 V	-6% / +10%
Canada	230 V	-8.3% / +4.2%

as per IEEE Standard 1547-2018 [17], with active power adjustments mandated for supporting the proper voltage regulation. To address the voltage control issue, various control devices and strategies are suggested by the researchers which comprise of (a) VAr compensation (b) DG active power curtailment (c) reactive power control by DG inverters (d) area-based voltage control operation of OLTC (e) distributed energy storage systems (f) load control (g) reactive power control by EVCS inverters (h) V2G services of PEVs. The detailed operation of these devices and strategies is discussed in section 1.2 below.

1.2 Voltage Control Devices Employed in ADNs

In this section, the voltage control devices used for control in ADNs, their models, and operation constraints are presented, which include conventional slow-acting devices and power electronic-based fast-acting devices.

1.2.1 Distributed Energy Resources (DERs)

The integration of DERs provides a promising way to avoid or put off the expenditure for the installation of large power plants [18]. Apart from supporting the increasing active power demand, DERs have numerous capabilities in dealing with power quality issues like voltage regulation.

1.2.1.1 Distributed Generation (DG)

The active and reactive power control capability of smart inverters equipped with DG units like solar PVs can be utilized for voltage control, subject to the capacity of interfacing inverters [19]. DER inverters mostly operate below their rated power capabilities, which establish provisions for active/reactive power exchange, utilizing the reserve capacity [20]. DG units can be operated in constant power factor mode, in which the reactive power injection from the inverter changes dynamically according to the active power generation. The other way around is voltage adaptive control (VAC), which employs droop in voltages with active power and reactive power [21]. Utilities may pre-define operational conditions for DG owners. For example, as per standard VDE-AR-N 4105 power grid in Germany requires DG units of capacity between 3.68

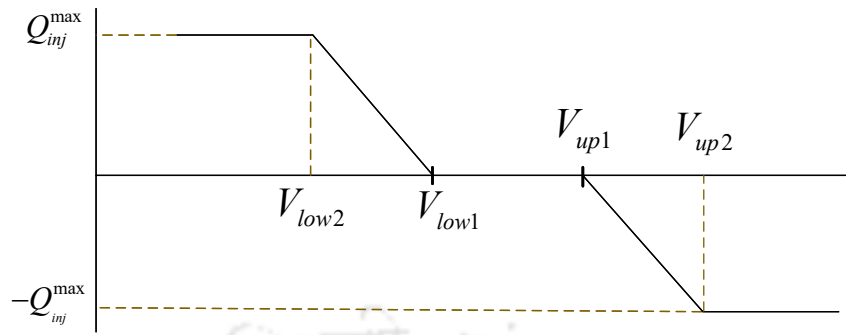


Fig. 1.2: $Q(V)$ curve of DG inverters for local control.

kVA and 13.8 kVA to maintain a power factor of 0.95 (lagging or leading) at the medium voltage (MV) level (for voltages between 1 kV and 35 kV). For low voltage (LV) networks (voltage levels < 1 kV) with DG units of capacity above 13.8 kVA, the power factor is demanded to remain within 0.90 leading or lagging [22]. Under changes in active power, the reactive power support may be through active power/power factor characteristic or voltage/reactive power characteristic, or through power factor/reactive power set points [23]. The latest PV smart inverters are able to participate in volt/var control, in which the operating power factor is determined by a communication-based centralized control algorithm, utilizing reactive Q/V characteristic. As per revised IEEE standard 1547 (2018) [17], DERs are required to provide the following mutually exclusive modes for reactive power support functions: (i) constant reactive power mode, (ii) active power-reactive power mode, (iii) constant power factor mode, (iv) voltage-reactive power mode. DERs shall be able to supply reactive power when the active power generation is 5% or above of the rated output. Under maximum power generation, DERs are required to be able to exchange reactive power of at least 44% of the apparent power rating. When the active power generation is within 5%–20%, the DERs should be able to supply reactive power equal to 44% of the rated value multiplied by the fraction of active power output to 20% of the rated value. Renewable DG units (PVs) operate under maximum power point tracking; thus, DG inverters need to be slightly over-rated by around 10%, to be able to keep up the reactive power supply of 44% under maximum power generation. The inverter-interfaced DG units are generally used to provide the reactive power injection/absorption instantly according to the piece-wise linear $Q(V)$ curves shown in Fig. 1.2. In the constant power factor mode, the inverter adjusts its reactive power dy-

namically based on real-time active power output. Alternatively, voltage-adaptive control (VAC) employs droop-based strategies such as P/V and Q/V characteristics to regulate voltage locally. The reactive power injection of the DG inverter from the QV curve in Fig. 1.2 can be written as,

$$Q_{DG} = \begin{cases} 0 & V_{low1} \leq V \leq V_{up1} \\ \overline{\overline{Q_{DG}}} & V \leq V_{low2} \\ -\overline{\overline{Q_{DG}}} & V \geq V_{up2} \\ \frac{V-V_{low1}}{V_{low2}-V_{low1}} \cdot \overline{\overline{Q_{DG}}} & V_{up2} < V < V_{up1} \\ -\frac{V-V_{up1}}{V_{up2}-V_{up1}} \cdot \overline{\overline{Q_{DG}}} & V_{up1} < V < V_{up2} \end{cases} \quad (1.3)$$

The operational constraints of DG inverters can be expressed as

$$\underline{\underline{Q_{DG}}}(t) \leq Q_{DG}(t) \leq \overline{\overline{Q_{DG}}}(t) \quad (1.4)$$

$$\overline{\overline{Q_{DG}}}(t) = \sqrt{S_{DG}^2 - P_{DG}^2(t)} \quad (1.5)$$

$$\underline{\underline{Q_{DG}}}(t) = -\sqrt{S_{DG}^2 - P_{DG}^2(t)} \quad (1.6)$$

Where, $\underline{\underline{Q_{DG}}}(t)$ and $\overline{\overline{Q_{DG}}}(t)$ are the reactive power limits available at a given time, corresponding to the active power generation $[P_{DG}(t)]$, and DG inverter rating S_{DG} .

A substantial amount of research is devoted to the studies of coordination of distributed PV sources, such as in [24,25], to provide reactive power support both from the grid operator, as well as from the customer end. Voltage regulation of radial LV networks is studied in [24] to utilize the reactive power capabilities of PV inverters, leveraging voltage sensitivities. A consensus-based distributed control mechanism is provided in [26] considering unbalanced phase powers. The PV inverters are centrally coordinated in [27] to dispatch reactive power and provide droop functions for local control. Authors in [28] have proposed a two-stage model for optimal dispatching of PV inverters to maximize the PV power surplus, and to determine the optimal subset of PV units for reactive power support under the uncertainties. It is noteworthy to mention that in conventional volt/var control using PV inverters, the required reactive power is dispatched based

on the VA ratings of the inverters. The full utilization in real practice depends on rated current, and thus limits the full capability utilization, available as per apparent power rating. Furthermore, most of the techniques do not provide efficacy during transient voltage overshoots due to sudden generation change. A decentralized volt/var control scheme, using a voltage-oriented control technique, is provided in [29] to effectively eliminate transient overshoots in voltage. Furthermore, the VVC control methods utilizing the reactive power capabilities of the inverters widely ignore the reliability of the inverters. Utilizing inverters for reactive power support significantly reduces their life-span, which is usually less than other components in the distribution network [30]. Since the existing reliability assessment measures are difficult to implement in conjunction with VVC, authors in [25] have attempted to bring forth and consider detailed reliability modeling in VVC optimization, considering the reliability constraints to enhance the life of inverters.

1.2.1.1.1 Generation Curtailment: Voltage rise in ADN can also be alleviated by bringing down or curtailing the output active power of DG units. The reactive power compensation and active power curtailment (APC) of the smart inverter-interfaced PVs are the major techniques used for ADN voltage control [31]. The active power output can be curtailed easily by disconnecting the specific DG or group of DG units. If the control for mitigating the DG output is available, like the pitch control of wind turbines, then the complete detachment of DG is not necessary. Renewable generation curtailment leads to the loss of green energy. Further, being uneconomical, DG owners discourage the active power curtailment. Therefore, this control strategy is reserved as a last resort or for emergency conditions, when all other control resources are exhausted.

1.2.1.2 Distributed Storage

As far as distributed energy storage is considered, the battery energy storage systems (BESS) and plug-in electric vehicles (PEVs) are mainly employed for voltage regulation, owing to their operation at lagging or leading power factors. Due to recent advancements in lithium-ion battery technology and their high energy density and low self-discharging tendencies, they are affordably employed in the PEV applications [32,33]. The effective response of battery storage to transients, ability to meet peak demand, application in energy management, and ability for voltage regulation

(using its DC/AC bidirectional converter) have paved the way for the wide integration of BESS in the LV distribution networks [34,35]. A simple battery model considering the power flowing in and out is given by the equations:

$$\frac{d}{dt}(SOC) = -\frac{\eta \cdot P_b}{J_{rated}} \quad (1.7)$$

$$-P_b^{rated} \leq P_b \leq P_b^{rated} \quad (1.8)$$

$$0 \leq SOC \leq 1 \quad (1.9)$$

where, SOC means the state-of-charge of the battery; J_{rated} is the energy capacity; P_b is instantaneous power flowing in or out of the battery; η is the efficiency, where $\eta = \eta_{out}$ while discharging ($P_b > 0$), and $\eta = \eta_{in}$ while charging ($P_b < 0$). Furthermore, BESS are suitable storage devices for high energy and long duration applications as compared to the non-battery type storage systems, which are applicable for short durations [33]. In a similar fashion, the PEVs can be employed for voltage control during high demand using V2G technology. The batteries used in PEV can be used to provide V2G services by proper management of charging periods and discharging services needed under heavy demands. Even though the PEV integration leads to the additional demand in the power distribution network, by the use of advanced communication technologies and metering devices, they can be effectively utilized to provide services for grid stability [36,37]. The charging strategy can be centralized in which the utility controls the charging scheme, and in decentralized way in which users have control based on the incentives in price.

1.2.2 OLTC and Capacitor Banks (CBs)

The OLTC uses the local current and voltage measurements to regulate its tapping operation based on unidirectional power flow, to maintain voltage locally and does not require any communication network [38]. The OLTC operation can be integrated in the centralized control scheme where the set points of all the control equipment are coordinated in a centralized manner [32]. A simple model of an OLTC transformer connected at the substation with tap-changing operation on the secondary coil is shown in Fig. 1.3. If the primary side and secondary side voltages are

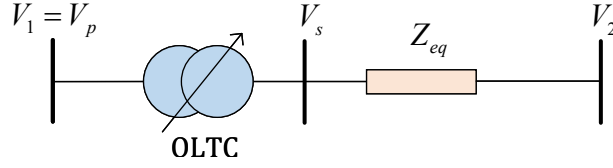


Fig. 1.3: Equivalent circuit of an OLTC transformer.

V_p and V_s respectively, the relation of the secondary voltage corresponding to the different tap positions and operational constraints can be expressed as [39],

$$\frac{V_s}{V_p} = (1 + n_{tap} \cdot \Delta V_{tap}) \frac{V_{oP}}{V_{oS}} \quad (1.10)$$

$$\underline{\underline{n_{tap}}} \leq n_{tap}(k) \leq \overline{\overline{n_{tap}}} \quad (1.11)$$

$$\underline{\underline{\Delta n_{tap}}} \leq \Delta n_{tap}(k) \leq \overline{\overline{\Delta n_{tap}}} \quad (1.12)$$

where n_{tap} and ΔV_{tap} are the tap position, and the discrete change in voltage per step, respectively.

V_{oP} and V_{oS} are the nominal values of transformer voltages on primary and secondary sides.

The reactive power injection of capacitor banks changes in discrete steps, which can be expressed as,

$$Q_{cap}(t) = n_{cap}(k) \cdot q_{cap} \quad (1.13)$$

n_{cap} and q_{cap} are the number of CB units in use and the maximum reactive power limit of each unit, respectively. The reactive power injection of CBs is restricted by the number of units and the maximum change in reactive power in a certain time interval, which can be expressed using the constraints:

$$0 \leq n_{cap}(k) \leq \overline{\overline{n_{cap}}} \quad (1.14)$$

$$\underline{\underline{\Delta n_{cap}}} \leq \Delta n_{cap}(k) \leq \overline{\overline{\Delta n_{cap}}} \quad (1.15)$$

1.2.3 Electric Vehicles (EVs)

The widespread incorporation of Electric Vehicles (EVs) in the last decade has added significantly to the emerging distribution systems as controllable loads, thus necessitating the study of advanced techniques and mechanisms for EV integration and its impacts. The large-scale deploy-

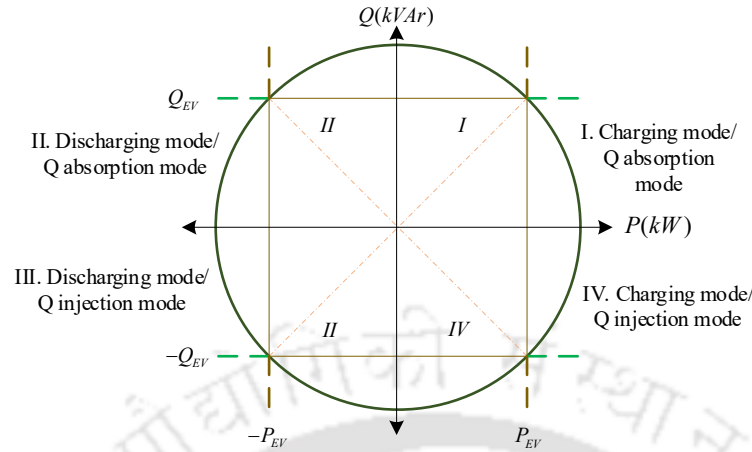


Fig. 1.4: EV inverter capability for active/reactive power exchange.

ment of EVs (variable load) poses different challenges, like randomness in charging/discharging patterns due to the stochasticity associated with their frequency in visiting parking lots, charging capacities, and charging demand. However, EV integration potentially has numerous advantages for the distribution networks. Different from conventional loads, EVs can at times be deployed in the distribution network for backing reliable, efficient, stable, and resilient operation [34]. Using V2G operation, active and reactive power from EVCS is used for grid services. EVs can be considered as energy storage systems, which possess the capability to provide energy to the grid or customers under needed circumstances, employing V2G technology. EV integration to the ADN and their contributions in inertia and frequency regulation are studied in [35]. Moreover, EV charging is made possible by a power electronic interface, by which the reactive power capability of EV chargers (inverters) is used for energy control and voltage regulation. Different operation modes depend upon the active/reactive power exchange from the grid to the EV charger or EV charger to the utility grid. The possible operational modes of smart inverter-interfaced EVs, as discussed in ref. [40], are depicted in Fig. 1.4. Mode I: $P > 0$ and $Q = 0$, Mode II: $P > 0$ and $Q > 0$, Mode III: $P = 0$ and $Q > 0$, Mode IV: $P < 0$ and $Q > 0$, Mode V: $P < 0$ and $Q = 0$, Mode VI: $P < 0$ and $Q < 0$, Mode VII: $P = 0$ and $Q < 0$, Mode VIII: $P > 0$ and $Q < 0$.

Generally, EV operates in Mode I (power factor=1), for battery charging only. Modes II and VIII enable the reactive power injection/absorption capability in addition to battery charging.

Modes IV and VI enable the V2G operation for active power support as well, in addition to the

reactive power support. An operation scenario is created by modes III and VII in which the EVCS can exchange reactive power when no battery is connected. If the EV interfacing inverter rating is S_{EV} , the operational constraints of EV charging inverters for VVC are,

$$\underline{\underline{Q_{EV}}}(t) \leq Q_{EV}(t) \leq \overline{\overline{Q_{EV}}}(t) \quad (1.16)$$

$$\overline{\overline{Q_{EV}}}(t) = \sqrt{S_{EV}^2 - P_{EV}^2(t)} \quad (1.17)$$

$$\underline{\underline{Q_{EV}}}(t) = -\sqrt{S_{EV}^2 - P_{EV}^2(t)} \quad (1.18)$$

Where $P_{EV}(t)$ is the power absorbed for charging at instant t or the discharging power if V2G provision is enabled. $Q_{EV}(t)$ is the reactive power exchange at instant t , and $\underline{\underline{Q_{EV}}}(t)$ and $\overline{\overline{Q_{EV}}}(t)$ are the minimum and maximum available power at time instant t , respectively.

A hybrid distributed and local control is provided in [24] for low voltage (LV) distribution networks using sparse communication, wherein, distributed control at a higher level determines the voltage regulation inputs. At a lower level, the local control determines the active/reactive power exchange of EV chargers based on the operational requirements. Uncertainty in EVs is considered in [41] in studying the impacts of EVs on energy and voltage regulation in LV networks. An effective EV integration demands customer satisfaction in terms of charging and discharging, when V2G services are needed. A transactive energy-based control frame is provided in [42] to simultaneously consider the economics and voltage control based on coordinated charging/discharging of EVs while preferring customer needs. Authors in [27] provide a model-free and multi-agent deep reinforcement learning-based active and reactive power control of DG units together with coordination of EVs for voltage control. The distributed coordination for EVs is based on a partially observable Markov process, and the proposed strategy well encompasses the uncertainties in DG units, EVs, and market prices.

1.2.4 Soft Open Point (SOP)

Soft open point (SOP) is deployed to connect two nodes in a distribution network, where a normally open point (NOP) exists. It is a power electronic-based device generally using two back-

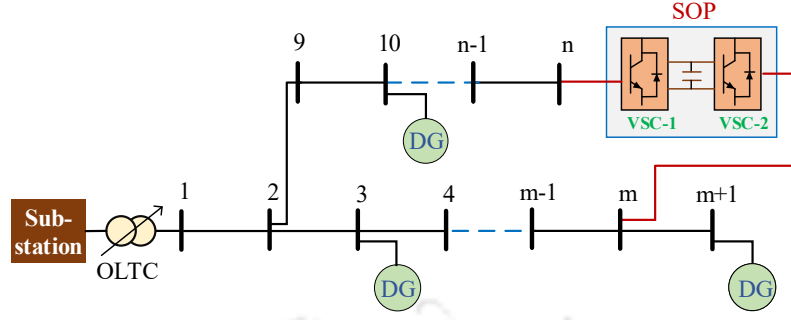


Fig. 1.5: Schematic of the SOP placement in distribution network.

to-back connected voltage source converters (VSCs) to control the flow of active and reactive power between two branches or feeders. A schematic of using SOP is depicted in Fig. 1.5. SOP model generally includes active power transmission constraints and reactive compensation capability constraints [43]. The operational constraints for SOP, shown in Fig. 1.5, can be expressed as follows:

$$P_{t,m}^{sop} + P_{t,n}^{sop} + P_{t,m}^{sop,loss} + P_{t,n}^{sop,loss} = 0 \quad (1.19)$$

$$P_{t,m}^{sop,loss} = C_m \sqrt{(P_{t,m}^{sop})^2 + (Q_{t,m}^{sop})^2} \quad (1.20)$$

$$P_{t,n}^{sop,loss} = C_n \sqrt{(P_{t,n}^{sop})^2 + (Q_{t,n}^{sop})^2} \quad (1.21)$$

Similarly, the constraints corresponding to the reactive power exchange can be expressed as,

$$Q_{m,min}^{sop} \leq Q_{t,m}^{sop} \leq Q_{m,max}^{sop} \quad (1.22)$$

$$Q_{n,min}^{sop} \leq Q_{t,n}^{sop} \leq Q_{n,max}^{sop} \quad (1.23)$$

and the SOP capacity constraints can be expressed as,

$$\sqrt{(P_{t,m}^{sop})^2 + (Q_{t,m}^{sop})^2} \leq S_m^{sop} \quad (1.24)$$

$$\sqrt{(P_{t,n}^{sop})^2 + (Q_{t,n}^{sop})^2} \leq S_n^{sop} \quad (1.25)$$

Where, $P_{t,m}^{sop}$ and $Q_{t,m}^{sop}$ are active and reactive power injected by SOP at node m at time t . $P_{t,n}^{sop}$ and $Q_{t,n}^{sop}$ are active and reactive power injection at node n at time instant t ; $P_{t,m}^{sop,loss}$ and $P_{t,n}^{sop,loss}$

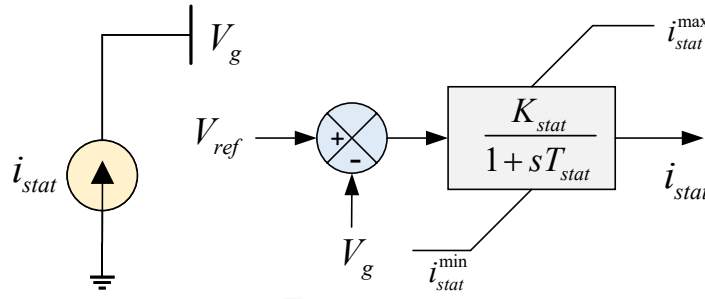


Fig. 1.6: Current injection model of a STATCOM.

are active power losses at node m and node n , respectively. C_m and C_n are SOP power loss coefficients. The capacity limit of SOP at node m and node n are S_m^{sop} and S_n^{sop} , respectively. SOP operation in ADNs has been carried out for real-time and cost-effective voltage control in [43]. SOPs are generally coordinated in a centralized manner. However, authors in refs. [44, 45] have used SOP for voltage control in a decentralized manner. To address voltage issues due to frequent DG power variation, a data-driven adaptive voltage control is carried out in ref. [46] utilizing the capabilities of multi-terminal soft open points.

1.2.5 Distribution Static Synchronous Compensator (DSTATCOM)

DSTATCOM, a shunt-connected power electronic-based custom power device of various topologies, has been used for controlling voltages in active distribution networks. DSTATCOM has the capability for injection and absorption of reactive power by current injection in quadrature with the bus voltage at the connected point, thus capable of providing dynamic voltage support [47]. In addition to the reactive power compensation for voltage support, DSTATCOM has harmonic elimination and load balancing capabilities as well. During reactive power exchange with the grid, current stays in quadrature with the grid voltage to avoid active power exchange. A current injection model for DSTATCOM operation for voltage control is used in ref. [48]. The differential equation for the dynamic model shown in Fig. 1.6 is represented by,

$$\dot{i}_{stat} = [K_{stat}(V_{stat} - V_g) - i_{stat}]/T_{stat} \quad (1.26)$$

where T_{stat} and K_{stat} are the time constant and controller gain of DSTATCOM. V_{stat} and V_g are the DSTATCOM voltage and voltages of the bus at which DSTATCOM is connected, respectively. The reactive power exchange with the grid is represented by the equation:

$$Q_{stat} = V_g i_{stat} \quad (1.27)$$

Direction of current flow (i_{stat}) determines whether reactive power is injected or absorbed. Authors in [47] have carried out a study on the influence of PV penetration on on-load tap changer in LV networks, and developed a mitigation approach to overcome the consequences using the capabilities of DSTATCOM. The interaction of DSTATCOM with OLTC is studied to enable the determination of technical provisions and the optimal size of DSTATCOM for voltage regulation. A coordinated control strategy for voltage balancing in active distribution networks is carried out in ref. [48] using the model predictive control (MPC) approach. The MPC approach is based on dual-stage coordination of control resources of varying temporal characteristics, wherein the control capabilities of DSTATCOM for dynamic fast voltage control are studied in coordination with PVs and EVs.

1.3 Voltage Control Methods in ADNs Based on Recent Literature

Over the years, voltage control technologies have significantly advanced for the reliable operation of power networks. The advent of improved technologies has been utilized in voltage control with network side management as well as demand side management [49]. From the network end, the distribution system operators (DSOs) use devices like switched capacitors, OLTCs, PV inverters, etc., to control grid voltages, and from the demand side, consumers mainly in the industrial and commercial sectors actively participate in network management by utilizing roof-top PVs, smart inverters, conservation voltage reduction, and other measures for demand response. Voltage control strategies for ANM in current distribution networks have been studied broadly in three categories, which are: (i) local voltage control, (ii) centralized voltage control, (iii) dis-

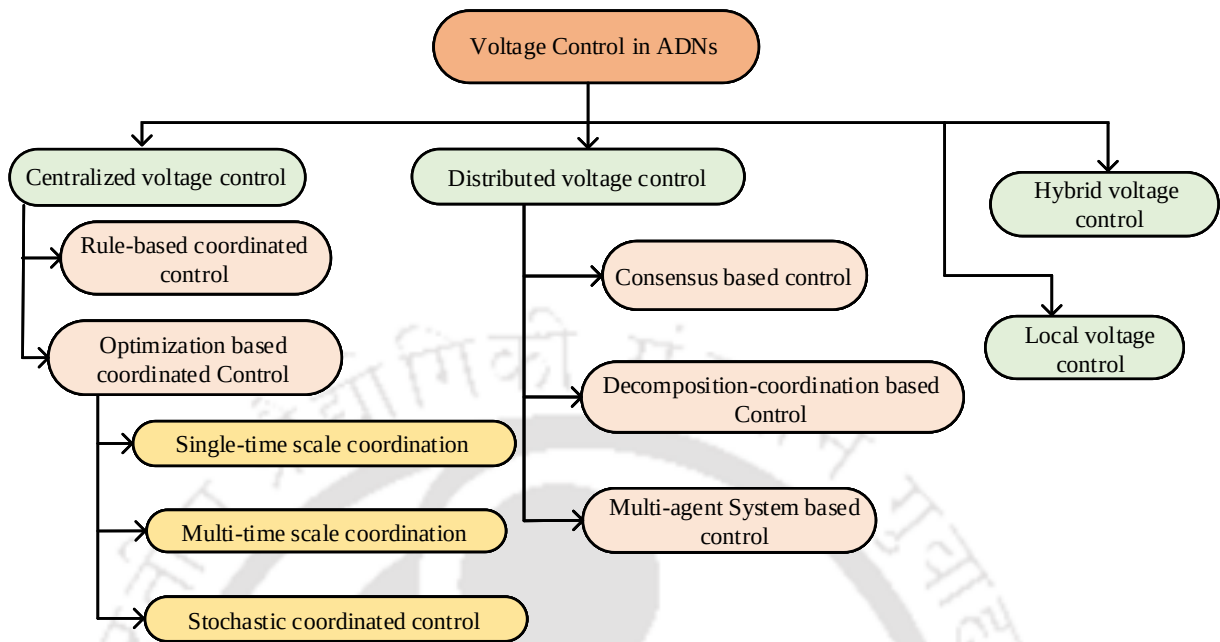


Fig. 1.7: Classification of the voltage control schemes in ADNs.

tributed voltage control, and (iv) hybrid voltage control. A detailed classification of different control schemes is shown in Fig. 1.7. Local control is the simplest communication-less control mechanism, while centralized and distributed control strategies employ a communication setup in the network for coordination.

1.3.1 Local Voltage Control

The simplest voltage regulation method in active distribution networks can be thought of as local control. The fast control actions are achieved, wherein the control actions are taken based on local measurements. Control resources in the local control approach are mainly steered through, based on pre-specified rules. Since the communication facility is not availed, the control resources are dispatched based on local measurements, without any coordination among the control resources [50]. A local voltage control strategy is studied in [51] to demonstrate the voltage regulation capabilities of EVs using droop control. The applied droop controller is designed based on voltage limit thresholds. The intelligent charging strategy can effectively regulate voltage even without the use of V2G services. A coordinated, decentralized, and MPC-based voltage control

approach is proposed in [52] based on local tuning of DG-QV curves. The ADN is partitioned using a dynamic network partition to relieve the computation and communication burden. DG units react fast locally to correct any voltage violation, while a decentralized coordination is performed based on the alternating direction method of multipliers (ADMM), for optimal operation, by tuning the local DG curves, thus forming a two-level control strategy. Local voltage control techniques with capacitor banks, in addition to other devices such as OLTCs, BESSs, and DG units, and network reconfiguration, have been provided in various studies. For example, authors in ref. [53] simultaneously allocate storage devices and CBs for voltage drop mitigation. Authors in ref. [54] use DG units, OLTC, and CBs to minimize voltage violations and energy loss. Network reconfiguration is incorporated in [55] for voltage regulation and network power loss reduction to enhance network security.

Local control is resilient and economical, but the control resources may be unnecessarily over-utilized, which leads to sub-optimal operation. The over-utilization of resources may lead to insufficient reactive power, due to which the network may demand active power curtailment from DG units frequently. BESSs and EV charging can be employed in integration with DG units for local voltage control, to mitigate the need for APC wherein reactive power control is rendered insufficient.

1.3.2 Centralized Voltage Control

Centralized voltage control strategies are widely studied in literature owing to their coordination capabilities in small or medium-sized networks, and relatively ease in implementation as compared to distributed control methods. The control resources are coordinated using a wide range of communication networks with a central controller generally at the substation. A simple schematic of the centralized control scheme is shown in Fig. 1.8. In literature, the centralized voltage control in active distribution networks with multiple control variables is achieved by coordinating the control inputs in two ways: (i) rule-based coordination of control resources, (ii) optimization-based coordination of control resources. A brief taxonomy of voltage control in ADNs is provided in Table 1.2.

Table 1.2: Brief taxonomy of voltage control in ADNs

Ref.	Control strategy	Control methodology	Optimization formulation	Control Devices	Objective
[16]	Centralized	MPC	Quadratic programming	OLTC, PV inverters	Minimization of voltage control actions
[3]	Hybrid (centralized + Local)	MPC	Quadratic programming	DG units	Minimization of voltage control actions
[26]	Distributed	Branch flow model/ Consensus algorithm	Rule-based coordination	PV inverters	Inter-phase coordination/ Over-voltage mitigation
[2]	Centralized	MPC	Quadratic programming	OLTC, DG units	Minimization of losses, OLTC operation, active power curtailment
[43]	Centralized	Dist. load-flow (BFS)	MINLP reduced to MISOCP	SOP, OLTC, CBs	Minimization of losses (network losses, switching losses, SOP losses)
[53]	Local	Optimal placement of CBs & BESSs (Loadflow)	—	CBs and BESSs	Mitigation of losses and voltage drop
[40]	Hybrid (centralized +Local)	MPC	NL stochastic optimization	OLTC, CBs, EVs, PV inverters	Minimization of cost of (CVR, losses, control actions)
[56]	Centralized	CI (correction index) based VVC	—	CBs, VRs, DG units	Minimization of voltage deviations
[57]	Centralized	MPC	Linear Programming	OLTC, DG units	Minimization of losses and control actions
[55]	Local	Loadflow approach	Non-linear programming	CBs and reconfiguration switches	Voltage violation reduction and minimization of power loss
[58]	Centralized	Robust constrained MPC (RC-MPC)	Mixed integer QP	OLTC, controllable PVs , Uncontrollable PVs	Minimization of control actions, APC and voltage deviations
[31]	Distributed	Sensitivity analysis	MILP	PV-DG units (active/ reactive power)	Minimization of control actions and APC
[52]	Hybrid (decentralized +local)	MPC	MINLP reduced to MISOCP	DGs (PVs and WTs)	Minimization of cost and voltage deviation
[59]	Centralized	OPF/Sensitivity analysis	Non-linear programming	DG units (active power only)	Minimization of active power curtailment
[60]	Distributed	MPC	Quadratic programming	EVs (reactive power)	Minimization of voltage deviations
[61]	Centralized	Power flow based	NLP	OLTC, SVCs, DG units	Minimization of losses, imported power, loss of sensitive loads, cost of DG operation
[39]	Hybrid (distributed +local)	Consensus algorithm	—	EVCs in LV networks	Minimization of voltage deviations
[39]	Centralized	MPC	MIQP	OLTC, SVR, CBs (STS) ; DG units (FTS)	Minimization of voltage deviations and control actions
[62]	Distributed	Distributed MPC	MIQP	CBs, DG units (active/reactive power)	Minimization of operation cost, voltage deviation and APC
[63]	Centralized	Stochastic MPC /linear distflow	MIQP	OLTC, CBs, DG units (active/ reactive power)	Minimization of control actions, APC, network losses
[64]	Decentralized	Multi-agent deep reinforcement learning	MILP	OLTC, DG units (PVs, WTs) and EVs	Minimization of cost of active/reactive power of DG units
[65]	Centralized	Sensitivity analysis	MILP	OLTC, DG units (active/ reactive power)	Maximization of utility cost function
[41]	Coordinated	Loadflow approach	Nonlinear stochastic programming	OLTC, CBs, controllable loads and EVs	Minimization of operation cost of control devices, energy and voltage violations
[66]	Hybrid (centralized +distributed)	MPC	MINLP	OLTC, CBs, BESS, DG units (active/reactive power)	Minimization of voltage deviation, losses, APC and control actions
[49]	Distributed	Distflow approach	Non-linear programming	DG units (WT,PV), ESS	Minimization of losses and voltage deviations
[67]	Distributed	Distflow approach	—	EV chargers (EVCs)	Minimum power exchange from EVCs
[68]	Centralized	MPC	Quadratic programming	OLTC, DG units, BESSs	Minimization of voltage deviations and control actions
[8]	Distributed	Distflow approach	MINLP	OLTCS, DERs (reactive power)	Minimization of cost of control actions
[69]	Centralized	MPC	Quadratic programming	OLTC, DSTATCOM, DG units	Minimization of control actions, voltage deviations and energy demand
[69]	Hybrid (centralized +distributed)	OPF, (PAC) proximal atomic coordination algorithm	—	PVs, CBs	Minimization of voltage deviations and power loss
[70]	Centralized	MPC	Quadratic programming	OLTC, EVs, DG units (active/reactive)	Minimization of control actions, voltage deviations and APC
[48]	Centralized	MPC	Quadratic programming	OLTC, DSTATCOMs, EVs, DG units	Minimization of control actions, voltage deviations and APC
[71]	Centralized	MPC	MIQP	OLTC,CBs, and DG units	Minimization of control actions, and power loss

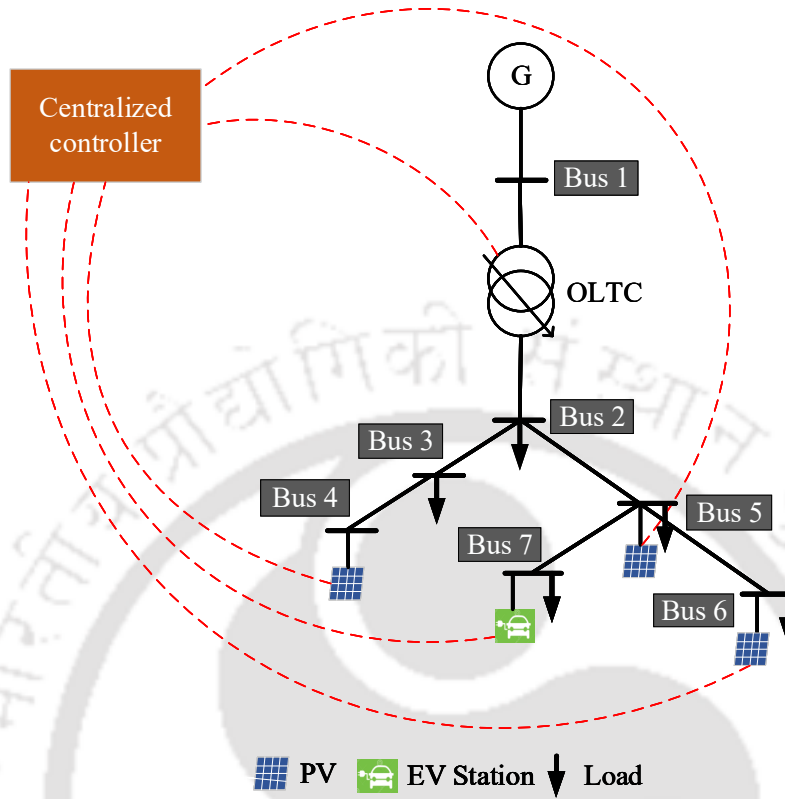


Fig. 1.8: A simple schematic of the centralized control scheme in ADNs.

1.3.2.1 Rule-based Coordinated Voltage Control

Rule-based coordinated voltage control strategies are suitable for networks that possess only a handful of control possibilities. Defining rules for a large number of control possibilities becomes a significantly complex task in networks in which a large number of control devices are present. A novel coordinated voltage control is proposed in [36] to maintain the voltage within specified limits by centrally controlling the tap positions of OLTC. It is established that the estimation of minimum and maximum voltages in the network is sufficient to maintain the voltages within specified bounds. However, this can be true only for controlling voltages with the inability to carry out optimal operation. The remote terminal units (RTUs) are employed at DG locations for estimation so that the extreme voltage violations are eliminated with proper control. A rule-based voltage control approach utilizing OLTC and a DER is carried out in [37]. The control mechanism is further improved in [38] to facilitate the control of several DERs coupled with voltage control at the substation. A rule-based distributed voltage regulation using a consensus

algorithm is provided in [26] to effectively coordinate the unbalanced phases in LV distribution networks.

1.3.2.2 Optimization-based Coordinated Voltage Control (CVC)

Unlike traditional power distribution networks, ADNs have numerous control possibilities. It becomes suitable to employ optimization-based coordinated control to coordinate all resources with single or multiple objectives. It is evident that the control resources operate on different time scales. OLTC operation is slow and discrete, while PV inverters act swiftly and provide a continuous range of controllable reactive power. Coordination of control resources with varying temporal characteristics becomes a complex task, thus necessitating the coordination of device groups with the same temporal characteristics. To deal with this, centralized control is studied using single-time-scale coordination or multi-time-scale coordination in the literature.

1.3.2.2.1 Single-time Scale CVC: Based on single-time scale coordination, real-time centralized voltage is carried out in refs. [2, 3, 40, 43, 59, 72]. A centralized voltage control based on SOP is proposed in [43] for real-time voltage control of ADN. The mixed integer non-linear programming (MINLP) optimization problem developed for loss minimization is converted to mixed integer second order cone programming (MISOCP) by model linearization and cone relaxation, so as to remove the convexity of the objective formulation, for proper real-time implementation. Authors in ref. [59] have proposed a control strategy for LV networks by carrying out uniform active power curtailment (APC) in a centralized and optimal way. The set points of the droop curves are determined by optimization using the interior point method. In ref. [56], a coordinated voltage control strategy is developed by identifying the global set of effective and low-cost control variables based on correction index (CI), which in turn is developed using the notion of electrical distances. The method is resilient and works under network structural changes. The proposed technique uses neither rule-based voltage control nor optimization-based voltage control. However, in [56], the algorithm based on the correction indices with respect to control variables identifies the effective and economical control devices to be put in use during voltage violations. Different from the existing MPC-based centralized control techniques, authors in ref. [57] have

proposed an MPC-based centralized voltage control in ADNs, in integration with a PI controller, to address the need of reactive power demand by the transmission system operator (TSO), at the point of common coupling (PCC). The reactive power demand by transmission system operator (TSO) is uniformly distributed among all the control devices in the network. Furthermore, the sensitivities of losses are calculated by an artificial neural network (ANN). Since the centralized control schemes solely rely on efficient communication with the central controller, researchers have made attempts to combine the application of centralized and local control to provide resilient and reliable control under the circumstances of any failures or mishaps in the communication setup. Furthermore, the incorporation of local control mechanisms results in fast control signals as compared to the centrally allocated control signals, thus enhancing the control efficiency [40]. An MPC-based coordinated two-level voltage control is proposed in [3] to control voltage by optimal operations of DG units. The control scheme developed comprises a central controller and local controllers. The local controllers act continuously for any voltage violations, based on piece-wise linear reactive power curves of DG units. The local control scheme acts as a backup in case of communication failures of the central controller.

1.3.2.2.2 Multi-time Scale CVC: The spatial-temporal features of control devices can be addressed by decomposition of the control problem on a multi-time scale basis, so as to avoid inefficient operation and over-utilization of the control resources. Various research articles, such as [39, 48, 63, 70] provide multi-time scale cooperation of volt/var control devices, both in centralized as well as distributed control strategies. Authors in ref. [39, 48, 63, 69] have carried out the coordination by decomposing the coordinated VVC optimization into a slow time scale (STS) coordination problem, and a fast time scale (FTS) problem, with optimization at both stages. A third stage is added in ref. [70] to consider the optimal EV charging as well. A coordinated dual-stage deterministic MPC-based voltage control framework is developed in [48] and [69], considering different time-based characteristics of control equipment used in ADNs. Furthermore, demand response (DR) and conservation voltage reduction (CVR) techniques have been integrated into the said control framework to enhance energy efficiency. Considering different temporal characteristics of control devices, double-time scale (FTS and STS) MPC-based voltage control is

proposed in [39]. Alternating direction method of multipliers (ADMM) based fast QP solver is used in FTS, and branch and bound (B&B) based tailored exact solution is provided at slow time scale (STS). A detailed MPC-based coordinated voltage control strategy utilizing PV inverters and BESSs for voltage regulation of ADNs is proposed in [68], employing two operational modes (preventive and corrective). Furthermore, the hierarchical clustering method (based on electrical distances) is used for zoning of the network, so that limited critical buses are selected for measurements. The authors in [63] have proposed a coordinated voltage control framework combining the advantages of stochastic programming and MPC, wherein the control strategy is carried out in two layers based on time scale decomposition corresponding to the device response speeds. To study the coordinated control of EVs together with the DER-based voltage control devices, a three-stage deterministic MPC-based centralized voltage regulation framework is proposed in [70]. The discrete and slow operating devices like OLTC are coordinated after every 1 hour, while the fast response devices (DG units and EVs) are regulated after every minute, considering the temporal characteristics of VVO devices. Furthermore, EVs are dispatched after every 30 minutes in the third stage to account for customer satisfaction and operating cost, based on the real-time electricity price. In [48, 57, 69, 72], the active/reactive power exchange leveraging smart inverters is used along with an on-load tap changer (OLTC); however, the measurements are assumed to be available from every node, so that the controller apprehends the system state for real-time control. The network-wide measurement and communication infrastructure increases the cost and complexity of the system. Moreover, all control resources are utilized, increasing the communication burden. In [68], a real-time MPC-based voltage control scheme for ADNs is proposed, mitigating the reliance on extensive measurement infrastructure. However, the centralized control entails the deployment of all available control assets, in addition to being a single-stage MPC framework, coordinating fast-responsive resources, such as DG units and energy storage systems (ESSs).

1.3.2.2.3 Stochastic/Robust CVC: Most of the research conducted on real-time control in ADNs rely on the anticipation of the active power output from PVs, and do not take into account the unavoidable inaccuracies or uncertainties in such predictions. Stochastic programming is a commonly employed technique for studying the randomness or unpredictability in power gen-

eration and load demand [73]. A detailed study of the EV impacts on energy and voltage control on the distribution system is studied in [41], considering fast and slow charging of EVs. The stochasticity in charging and discharging of EVs is assumed to be randomly distributed. A robust optimization technique is introduced in [74], designed to encompass uncertainties related to system demand and EV behavior. The optimization framework addresses EV-related uncertainties via deterministic sets; however, the absence of real-time control may result in over-utilization of control resources. Additionally, the control approach does not utilize the coordination with other control assets, such as PV inverters, and conventional legacy devices like OLTC. The optimization corresponding to the optimal cost of operation of control devices is carried out using improved mixed real and binary vector-based swarm optimization (IMVBSO). A two-stage optimal coordination framework is proposed in [75], employing a scenario-based chance-constrained VVC. Nodal power uncertainties are addressed through a multi-scenario methodology, generating scenarios based on predetermined probability distributions. The exactness of the solution obtained using the proposed scenario-based approach is maintained by a pre-defined confidence parameter. Nonetheless, this method overlooks the integration of EVs and their control capabilities. Moreover, it relies on day-ahead optimization, thus neglecting the advantages of real-time control facilitated by advanced measurement infrastructure. A stochastic MPC framework is proposed in [76] to consider uncertainties in renewable power, by formulating the voltage constraints as chance constraints. The uncertainties in renewable generation are contained using the affine-disturbance feedback control policy; however, the EV penetration and the associated uncertainties are not considered. In [40], the authors have proposed an MPC-based volt/var optimization (MP-VVO) for voltage control in ADNs by employing the OLTC, CBs, EVs, and PV-DG units in the presence of conservation voltage reduction (CVR). Furthermore, the authors have considered the stochasticity using pre-defined probability distribution functions (PDFs) of PV generation and loads, using the beta distribution and normal distribution, respectively. The Monte-Carlo simulation is used for scenario generation, and the scenarios are reduced using K-means clustering. The stochastic optimization is carried out using discrete particle swarm optimization. A distributionally robust chance-constrained formulation is proposed in [71] to eliminate reliance on pre-defined or known probability distributions of uncertainties. However, the absence of detailed time-domain

simulations with real-time control under dynamic high-loading scenarios limits validation. Additionally, the coordinated control potential of other inverter-based devices, such as DSTATCOMs and EVCSs, remains unexplored. While the measurements are a prerequisite for real-time control, the uncertainties/errors in the measurements are widely ignored in [40, 71, 74–76]. For regulating the voltages in LV distribution networks, a coordinated voltage control scheme using PEV inverters and BESS is studied in [77], for urban and rural scenarios (having different R/X ratios). The work carried out establishes a voltage regulation strategy in which the voltage violation is checked after every hour. It is shown that for urban scenario (i) $R/X=1$, the PV inverter reactive power capabilities prove to be sufficient for regulating the voltages; however, for the rural scenario (ii) $R/X=2.8$, the coordination of droop-based BES systems and PV inverters is required [77]. The uncertainties in the load and PV generation are also considered by employing probabilistic estimation models, and simulations are carried out to find out the optimal battery size and critical R/X ratio, for efficient performance.

Under high penetration and uncertainty levels, the solution tends to deviate from the optimum; thus, the coordinated control scheme is better suited for lower control time steps. To account for the uncertainties, robust constrained model predictive control (RC-MPC) for voltage regulation in ADNs is proposed in [58]. Knowing the boundary values of uncertainties, a method called the direct method is proposed to quantify the worst-case transitions of stochastic resources, which avoids the need for computationally heavy Monte-Carlo simulations. The use of robust MPC, unlike stochastic MPC, relaxes the need for probability distribution functions (PDFs) for incorporating the uncertainties in generation or load, and instead modifies the constraints of the optimization. Unlike the consideration of uncertainties in the literature, the study conducted in [65] focuses on voltage control in ADNs while taking into account the uncertain line parameters, specifically the admittance matrix. Voltage sensitivity bounds for robust optimization are determined using Monte-Carlo simulation. Furthermore, considering the impact on the power quality of sensitive loads, due to voltage fluctuations, authors in [78, 79] have studied the methods for voltage regulation and optimal operation of ADNs, considering the voltage dependence of loads. The work is extended in [61] to incorporate the time-varying features of voltage-sensitive loads based on the load models with constant impedance, constant current, and constant power

(ZIP model).

1.3.3 Distributed Voltage Control

Under heavy DG integration and the large-scale control, centralized control schemes become complex due to the need for increased and reliable communication, transparency in information exchanged by different stakeholders, computational complexity, increased cost of implementation, and increased vulnerability to cyber-physical threats [80]. Furthermore, centralized control lacks scalability or plug-and-play functionality for further advancements [8]. Distributed control schemes emerge as promising techniques for achieving real-time coordinated control of various control equipment. These strategies involve sharing the communication and computation burden among multiple distributed controllers, with only neighbor-to-neighbor communication, thus resilient to communication failures. However, the solutions provided may be sub-optimal and may require more execution time than centralized control. An efficient network partitioning is preliminary to allocating controllers in different zones. The partition needs to be done sensibly so that the nodes in a zone are strongly coupled, and nodes in different zones are weakly coupled with each other [81]. Numerous kinds of network partitioning methods and indices are proposed in the literature, based on the topology, location of the control devices, electrical distances between the nodes, or based on some other proximity measure for clustering criterion [82]. Electrical distance quantifies the coupling between the nodes of a network, based on voltage sensitivities. The electrical distance (D_{ij}) between nodes i and j in a network is given by,

$$D_{ij} = -\text{Log}(\alpha_{ij} \cdot \alpha_{ji}), \quad \forall i, j \in \text{network nodes} \quad (1.28)$$

where, $\alpha_{ij} = \frac{\Delta V_i}{\Delta V_j}$, $\alpha_{ji} = \frac{\Delta V_j}{\Delta V_i}$ are the attenuation of voltage deviations caused due to control variables at the node j and node i , respectively. Numerous clustering algorithms are used for zoning/clustering of network nodes, such as the hierarchical clustering algorithm, spectral K-way clustering algorithm, fuzzy k-means clustering algorithm, Louvain algorithm, and affinity propagation clustering algorithm [81]. Distributed coordination is studied in literature using consensus-based algorithms [26,83,84], multi-agent system-based coordination algorithms [80,85],

or decomposition coordination based algorithms [60, 62, 86]. In consensus-based algorithms, a common consensus is reached among the various control resources for a desired voltage level. Multi-agent-based coordination is achieved based on local decisions by the agents. The agents collaborate and communicate with each other to exchange information regarding their local decisions. Furthermore, decomposition coordination is achieved by dividing the control problem into manageable sub-problems/subsystems, which are solved independently.

Distributed optimization techniques, such as the alternating direction method of multipliers (ADMM) [8, 87], Lagrangian dual theory [88], and auxiliary problem principle, have been used for decomposition coordination in ADNs. ADMM decomposes the OPF problem of a clustered network into multiple sub-problems (as in [8, 87]), thus providing distributed coordination of various distributed controllers. A bidirectional communication framework is proposed in [89] for CVC, using multi-agent distributed coordination of a multi-energy storage system, considering thermal and electric loads. A distributed MPC strategy is provided in [60], leveraging V2G reactive power capabilities for real-time voltage control in low-voltage DNs. However, the frameworks in [60, 89] do not incorporate legacy devices like OLTC and multi-time scale coordination of PV and EVCS inverters. A fully distributed multi-time scale, volt/var control (VVC) strategy is proposed in [87], leveraging ADMM for zonal coordination and computational tractability. However, the network partitioning is done based on topology and observational heuristics, rather than considering electrical coupling among the nodes. Distributed voltage control based on network partition has been studied on single-time scale coordination in [67, 82, 90], and based on double-time scale coordination in [8]. Authors in [62] presented a cooperative distributed MPC-based voltage control framework of a multi-microgrid distribution system that works under active supervisory control of an automatic voltage regulator, for acquiring voltage sensitivity matrices, while each microgrid communicates with neighboring parts for distributed coordination of control resources. A distributed model predictive control based regulation strategy is studied in [60], considering the V2G capabilities of EV chargers. Each charger solves its own optimization, utilizing data from neighboring chargers, using a peer-to-peer communication network. A modularity function-based index called the comprehensive index, based on electrical distances, is used for network partitioning in [90], to reduce computational complexity. Keeping in view the EV applications and

their V2G services, the distributed control mechanisms still lack sufficient studies. To study high penetration of EVs, a two-level distributed voltage control strategy exploiting active/reactive power injection/absorption capability of EVCSs is proposed in [67]. To establish a compromise between decentralized control and centralized control in ADNs, authors in [8] have proposed a distributed voltage control strategy with two control stages working in a complementary manner. The network partitioning for distributed MPC-based control is carried out based on the position of OLTCs. The control scheme considers multiple OLTCs for a discrete slow control mechanism at the first stage and DERs as continuous fast controllers at the second stage using ADMM. A distributed control mechanism is studied in [82], wherein the network is dynamically subdivided into an optimal number of controllable zones using an improved modularity index and enhanced community detection algorithm. The community with the highest voltage violated node serves as the first zone for voltage control. The optimization problem formulated for each zone/community is solved using particle swarm optimization (PSO).

1.3.4 Hybrid Voltage Control

The aforementioned control strategies exhibit distinct strengths and limitations across varying ADN scenarios. Recent research has increasingly explored the strengths of hybrid control architectures. Such approaches, leveraging multi-layered control schemes, integrate centralized, local, and distributed methods within a unified framework. For instance, centralized control may deliver optimal setpoints on an hourly basis, while local controllers independently manage DG inverter responses at faster time resolutions of a few seconds. A hybrid centralized and local control is proposed in [3], wherein the local control mechanism runs continuously, while the central controller dispatches optimal set-points to local controllers at a comparatively longer time scale. Coordination of diverse voltage regulation devices such as OLTC, DG units, CBs, and BESSs for large-scale networks is proposed in [66], in which the control devices (OLTC, DG units, and CBs) are centrally controlled based on the MPC framework. A multi-agent-based real-time distributed control is used at the second level for active/reactive power control and coordination of PV inverters and BESSs. Hybrid control using centralized control and local control is used in [40] based on model predictive control, to optimally control resources in PV and EV integrated distribution

networks. It is quite apparent that centralized control schemes find it hard and sometimes intractable to coordinate resources for real-time control in large networks, particularly with heavy distributed penetration of PVs. A hybrid of centralized and distributed voltage control architecture is presented in [91], wherein an OPF problem is solved at the centralized control level, after each hour. The convex relaxation of the OPF problem of the network is based on current injection (CI) and McCormick envelopes for unbalanced distribution networks. At the second level, a distributed volt-var optimal control is performed under various DER penetration levels, after a 5-minute time interval. A control scheme has been proposed in [92] for simultaneous hierarchical frequency and voltage control, using a hybrid control architecture, wherein preference is given to the voltage control. To address the issue of communication failures, authors in [93] have present a hybrid voltage control model that employs distributed as well as local control to coordinate DERs throughout the network. The control scheme is communication-cognizant due to the utilization of attractive features of both control schemes to effectively manage the resources.

In addition to the above-mentioned voltage control techniques, there are other techniques that have acquired a lot of interest among researchers. The conventional, as well as most of the advanced techniques require a precise distribution network model and line parameters, which may not be available in practical situations. To address these issues, deep reinforcement learning-based techniques have gained interest in distribution voltage control, utilizing the coordination capabilities of the above-mentioned methods as in references [27, 94, 95]. Moreover, there are control strategies that employ VVC coordination jointly with network reconfiguration [55, 96, 97]. Network reconfiguration changes the topology of flexible distribution networks to alter power flow paths to minimize losses, reduce voltage deviations, promote DG integration, and enhance economical operation.

1.4 Real-time Voltage Control based on Model Predictive Control

Since most of the coordinated control techniques use predicted data of renewable DG units, the uncertainties significantly rises under large DG penetration. If the time step for optimization

is large, the uncertainties may lead to sub-optimal solutions. Under this scenario, day-ahead coordination becomes infeasible, raising the need for real-time control and coordination. For real-time control in ADNs, the model predictive control (MPC) technique has received significant attention in recent times, as evident from Table 1.2. At the heart of MPC lies multi-step optimization, which provides an optimal control sequence over multiple steps in the future. MPC can effectively tackle model inaccuracies due to its measurement-based closed-loop operation, and can coordinate multiple control devices having diverse response times [62]. The model predictive control approach is being studied in various forms. Notably, deterministic MPC (D-MPC) is used in most of the centralized control strategies. However, other variants such as stochastic MPC and robust MPC have also been studied for voltage control in ADNs. The uncertainties in generation and load are neglected in the deterministic MPC formulation, and they are somehow mitigated by MPC closed-loop performance, while considering small time steps. The uncertainties in stochastic MPC are generally modeled using beta distribution and a normal distribution, for PV generation and load, respectively. Single-time scale coordinated control based on MPC has been studied in [2, 3, 68]. The coordination of OLTC and DG units is carried out using an MPC-based central controller in [2], and a local control scheme is integrated in [3]. In addition, EVs have also been studied for voltage control in [69, 70] in coordination with PV inverters, OLTC, and custom power devices. Furthermore, conservation voltage reduction (CVR) and demand response have been incorporated to achieve an effective control. The slow control devices are dispatched after a longer time step (after every hour), and the fast control devices are dispatched in a shorter time period of 1 minute (or even less), in a multi-time scale control structure in [48, 69, 70].

1.5 Motivation Behind the Thesis

As mentioned in the introductory section, voltage control in ADNs constitutes one of the primary challenges in ADNs. The intense and quite frequent voltage violations may cause serious issues to the voltage-sensitive loads and may restrict the integration of renewable DG units, if not addressed. Over the recent years, much of the research in ADN control has predominantly focused on control schemes to maintain voltages within acceptable limits. Various devices, such as OLTC,

shunt capacitors, and DG units, have been explored to mitigate the voltage violations; however, without coordinated control implementation, the control decisions of various equipment lead to unnecessary control actions. This may lead to the under-utilization or over-utilization of certain control devices (such as OLTC), oscillations in the system due to competing control resources, or may not even achieve the proper voltage regulation. Moreover, under the uncoordinated control of various resources, the other network aspects, such as energy loss minimization cannot be properly incorporated. The advanced coordinated control approaches are optimization-based, offering superior performance in terms of optimal operation, control cost minimization, energy loss minimization, and voltage regulation. While significant research has been devoted to the real-time voltage control of ADNs using centralized control for small and medium-sized networks, and distributed control for medium and comparatively larger networks, various aspects of practical distribution networks need to be considered in detail. The centralized optimization frameworks rely on reliable communication and system-wide measurement infrastructure, which increases the cost and computational complexity. Moreover, the increasing penetration of PVs and EVs aggravates the voltage control problem due to their stochastic nature, requiring detailed uncertainty consideration in distributed control schemes. These shortcomings of the existing voltage control schemes are the main motivation behind the work carried out in this thesis. For more clarity, the major research gaps in the existing literature are enumerated as follows.

- Although the existing optimization-based control schemes largely employ single-time scale control coordination, certain works, such as in [39, 48, 48, 63, 70] employ multi-time scale optimal coordination. This enables to exploitation of varying temporal characteristics of various control devices, to avoid suboptimal operation and resource over-utilization of discrete operating devices, such as OLTC. However, the control capabilities of all the control resources, such as PVs, EVs, STATCOM, and OLTC, are rarely studied in a single control framework, with multi-time scale and MPC-based real-time coordination.
- The existing control schemes based on the MPC framework, notably the multi-time scale-based control schemes, such as in [48, 57, 68, 69, 72], generally rely on network-wide measurement infrastructure and extensive communication overhead, particularly in large-scale

ADNs. This increases the cost and also increases the complexity and computational time, particularly in large networks. The extensive communication and measurement infrastructure may also increase the vulnerability to single-point failures and cyber-physical threats. Furthermore, none of the existing work considers the utilization of strategically chosen control resources in order to reduce the number of control resources employed in the network. Deploying an effective set of reduced control resources can help in efficient resource utilization, while also reducing the control complexity.

- The existing literature on centralized real-time voltage control does not explicitly consider various uncertainties in an ADN, while employing multi-time scale coordination of diverse control resources. Existing schemes often rely on deterministic models that fail to account for uncertainties in nodal power injections, inherent in EV charging demand, renewable PV generation, and conventional loads. While few existing works, such as [74–76], consider the power uncertainties, the reliance on day-ahead optimization in [75] disregards the advantages of real-time control facilitated by advanced measurement infrastructure, to account for frequent violations due to nodal power uncertainties. Robust optimization [74], on the other hand, may over-utilize the available control resources due to the consideration of worst-case scenario. Moreover, the coordinated multi-time scale control with diverse devices and domestic EV charging is not studied in any of the centralized control studies, which take into account the nodal power uncertainties in PVs, EVs, and loads. Thus, there is a need for a more sophisticated, real-time solution that embraces uncertainty in nodal power injections, while utilizing diverse control resources.
- While numerous studies with multi-time scale coordination are carried out for centralized control, the existing studies in distributed voltage control predominantly adopt single-time scale approaches. Furthermore, realistic EV behavioral data is rarely incorporated. Network partitioning techniques in distributed control typically rely on heuristic or pre-defined rules, with only a few works considering electrical coupling for enhanced zonal coordination. In addition, few centralized control frameworks have considered addressing uncertainties in ADNs; however, the existing distributed control studies have not considered

chance-constrained MPC-based control to account for uncertainties.

1.6 Contributions of the Thesis

Based on the research gaps in the existing literature, the main contributions of the thesis are enumerated as follows:

1. A dual-stage model predictive control (MPC) with a reduced model centralized control framework has been developed for voltage control and energy loss minimization in ADNs, having control devices of different temporal characteristics. The requirement for the number of measurement devices and communication overhead for centralized control is significantly reduced. Network partitioning is employed to identify critical buses for measurements (termed as observation buses). The available control resources are ranked using a novel ranking index (RI), by utilizing numerical voltage sensitivity analysis, so as to identify a global control resource set.
2. A novel real-time and chance-constrained MPC-based centralized control model has been developed for voltage control and energy loss minimization in ADNs, with nodal power uncertainties. The multi-time scale coordination of control devices such as PVs, EVs, and OLTC is considered. Detailed uncertainties in the conventional loads, EV loads, and renewable PV are considered, with their individual quantification of uncertainties, using known probability distributions. A scenario-based solution approach has been utilized to solve the chance-constrained problem. The computational efficiency is enhanced by using a scenario reduction method on the large set of scenarios generated using Monte-Carlo simulation.
3. A chance-constrained MPC-based centralized control framework has been developed, with robustness in probability distributions, to take into account the system uncertainties with unknown probability distributions. Both nodal power uncertainties and real-time measurement uncertainties are considered, and a scenario-independent solution approach is provided. The uncertainties are considered using an analytical solution to the distributionally

robust CC problem, requiring partial information about the uncertainties, wherein the CCs are transformed into deterministic ones using a dynamically adjusted safety margin.

4. A two-stage MPC-based centralized-distributed hybrid control framework has been developed for large ADNs with high renewable and EV penetrations. A modified clustering index is introduced, incorporating cluster diameter, in addition to cluster average voltage sensitivity, and device regulation capacity, to ensure uniform and efficient network clustering, for distributed coordination of inverter-driven control devices. The coordination scheme of distributed controllers is developed using the alternating direction method of multipliers (ADMM) based distributed optimization, with reduced information exchange between the neighboring clusters.
5. Similar to the scenario-based solution to the chance-constrained problem in centralized control, an MPC-based framework has been developed for the distributed coordination of inverter-driven control devices (IDCDs), in ADNs with nodal power uncertainties. An ADMM-enabled distributed optimization is used for reduced information exchange and communication overhead, while providing near-optimal zonal coordination in large networks.

In this thesis, certain performance metrics are employed to assess the operational efficacy of the proposed control frameworks and to enable comparison with existing control strategies. These indices are chosen to capture the critical aspects of distribution network performance, and comprise the following:

- Network energy loss: A key operational objective considered in this thesis is the minimization of power loss at each control step. The net energy loss over the whole 24-hour simulation period is considered as performance metric.
- Extreme voltage magnitudes: The minimum and maximum voltage magnitudes across all network buses are evaluated to ensure operation within the predefined normal operation limits.
- Comprehensive voltage deviation: The comprehensive voltage deviation index is considered to evaluate the overall deviation of bus voltages from the nominal value, across the entire

network and simulation time horizon.

- Control resource utilization: The controllable resources leveraged in this work include active and reactive power set-points of PV and EVCS inverters, tap position of OLTC, and reactive power exchange of DSTATCOM. The net active/reactive exchange is evaluated throughout this thesis.
- Number of measuring devices: The total number of sensors and monitoring devices installed across the network for real-time measurements is considered to evaluate the performance of some of the proposed control schemes.

All the simulations are performed on a system with a 12th Gen Intel Core i5-12500 processor (3.00 GHz) and 16.0 GB of RAM. The time-domain simulations are performed using the Power System Analysis (PSAT) toolbox in MATLAB, and all the optimizations are carried out using IBM ILOG CPLEX software with MATLAB interface.

1.7 Organization of the Thesis

The organization of the thesis is as follows:

- In Chapter 2, a two-time-scale deterministic MPC-based centralized control strategy is proposed for voltage regulation in ADNs, wherein OLTC is optimally operated at a slower time-scale, and inverter-driven control devices (IDCDs), such as PVs and EVCSs, are optimally coordinated at a second time-scale. The objective function involves the minimization of bus voltage deviations and the utilization of control resources. The control framework employs a reduced model control framework that reduces the need for system-wide measurement and communication infrastructure. The ranking of control resources is also carried out using the ranking index (RI) utilizing voltage sensitivity analysis. A global group of control resources, able to control voltages in real-time even under worst-case scenarios.
- The control framework in Chapter 2 is extended in Chapter 3, with the incorporation of network energy loss minimization, in addition to the minimization of voltage deviations and control resource utilization. The network line currents are also considered as outputs

of the MPC model, in addition to the bus voltages. The detailed quadratic formulation of the problem is provided, and the proposed reduced model performance is compared to the full order model and other state-of-the-art MPC-based control methods.

- The nodal power uncertainties, mainly due to renewable DG units and EV loads, may lead to the violation of network voltage constraints, or even thermal limit violations of lines in ADNs, if not taken into account. Chapter 4 focuses on the MPC-based real-time control model considering power uncertainties in nodal power injections in ADNs, due to PVs, EVs, and conventional loads, with known probability distributions. A stochastic real-time control model is proposed based on chance-constrained model predictive control (CC-MPC), for voltage regulation and loss minimization. A scenario-based solution approach is leveraged to solve the chance-constrained (CC) problem. The computational efficiency is enhanced by employing the backward scenario reduction technique while maintaining the solution accuracy using a pre-defined confidence parameter.
- In addition to the nodal power uncertainties, the uncertainties in real-time measurements are also considered, using a distributionally robust CC-MPC framework, in Chapter 5. Unlike the scenario-based solution approach to the chance-constrained (CC) formulation, requiring pre-defined probability distributions of uncertain parameters, as in Chapter 4, the study in Chapter 5 provides a scenario-independent tractable solution approach to the CC problem. The solution does not require pre-defined probability distributions of the uncertain parameters, thus providing a distributionally robust solution approach to the system with uncertainties. Moreover, the control capabilities of the distribution static synchronous compensator (DSTATCOM) are utilized in coordination with other control devices. In addition, a local control layer is added at a time scale of a few seconds, to enhance the control, and serve as a backup for the centralized controller.
- Chapter 6 presents a hybrid control structure of centralized and distributed control paradigms, at varying time scales considering the temporal characteristics of control equipment. At the first stage, OLTC is centrally coordinated with sparse communication from a set of strategically selected pilot buses, which facilitate real-time measurements. At the second

stage, a distributed MPC-driven coordination framework is employed for IDCs (PV and EVCS inverters), optimizing both reactive and active power support. Distributed control is employed to enhance privacy preservation, control reliability, and reduce communication overhead in large networks. A modified modularity metric is proposed, incorporating cluster diameter, in addition to the device regulation capacities, and average voltage sensitivities within the cluster, for effective partitioning, so as to achieve efficient distributed control. Alternating direction method of multipliers (ADMM) is employed for distributed coordination.

- The control framework presented in Chapter 6 is extended in Chapter 7 to consider nodal power uncertainties, using chance-constrained MPC. Assuming the known probability distributions, the scenario-based control approach discussed in Chapter 4 is employed, while considering the distributed coordination of IDCs.
- The conclusions of the whole work carried out in this thesis are provided in Chapter 8, along with a brief discussion on the future research directions.



Chapter 2

Centralized voltage control in ADNs with dual-stage MPC-based reduced model framework

This chapter presents a two-time-scale MPC-based centralized control strategy for voltage control in ADNs. The control framework optimally controls OLTC at a slower time scale of 1 hour, and inverter-driven control devices (IDCDs), such as PV inverters and EVCS inverters, at a faster time scale of 1 minute. The objective function involves the minimization of bus voltage deviations and the minimisation of utilization of control resources. The control framework employs a reduced model control framework, with only limited buses used in the system model, requiring a reduced number of measuring devices, and reduced communication infrastructure. The available control resources are ranked using the ranking index (RI), utilizing voltage sensitivity analysis. Based on this ranking, a global group of control resources is identified and utilized for voltage control in the network.

2.1 Introduction

The voltage rise problem forms one of the prominent issues in active distribution networks.

Over the years, considerable research has been carried out for real-time voltage and reactive power

control so as to deal with uncertain and frequent voltage violations. The volt/var optimization (VVO) is a critical feature of ANM, wherein the control capabilities of fast-acting devices, such as PV and EV charger inverters, storage devices, and other power electronic interfaced devices, such as soft open points (SOPs), are utilized for voltage regulation and energy loss minimization [40]. Over the years, various voltage control strategies have been proposed for voltage control and VVO in active distribution networks, such as local, centralized, distributed, and hybrid [53]. Centralized control forms a widely studied method in small/medium distribution networks, owing to its rule-based or optimization-based coordination among control resources.

Recent years have seen a significant rise in predictive control approaches, notably MPC, driven by the abundance of data logs and enhanced by recent advances in short-term forecasting [98]. MPC employs a system model for iterative computation of control variables at each control step and strategically optimizes the anticipated future behavior of the underlying system. Within the existing literature, studies exploring MPC-driven voltage control have been investigated using local [52], decentralized [99], centralized [2, 48, 57, 68, 69, 72] as well as distributed [98, 100, 101] frameworks. Centralized MPC-based techniques are relatively easier to implement than distributed control mechanisms for small and medium-sized networks. In [48, 57, 69, 72] the active/reactive power exchange leveraging smart inverters is used along with an on-load tap changer (OLTC), however, the measurements are assumed to be available from every node, so that the controller apprehends the system state for real-time control. Moreover, all control resources are utilized, increasing the communication burden. A distributed solution is proposed in [98] with optimality features of centralized control; however, in a distributed setting full set of network measurements is needed. Using diverse control equipment, authors in [101] have proposed a distributed MPC-based control strategy employing the gradient projection method to find the optimal solution. A decentralized approach utilizing coordination among different clusters is proposed in [99]. The control approach mitigates the communication requirements; however, nothing has been said about the optimality of the solution as compared to centralized approaches. Since centralized control demands extensive two-way communication with each controllable device, scaling this centralized approach becomes cost-prohibitive with the increasing number of control devices. Distributed control algorithms offer a viable alternative, requiring sparse communication, but optimal solutions may not always

be guaranteed. Moreover, in future distribution networks with highly penetrated distributed generation (DG) units and EVs, the coordination of all control resources with different temporal characteristics will increase the complexity of computation and coordination. The work in this chapter proposes a voltage control strategy leveraging an MPC-based reduced model framework that requires less network information, less communication, and control needs, thus encompassing the benefits of both distributed as well as centralized control structures, discussed above. A dual-stage MPC strategy is used in [48] to coordinate control devices with different temporal characteristics; however, the measuring infrastructure is assumed to be installed throughout the network, and all control resources are used for voltage regulation. Authors in [68] have carried out MPC-based real-time voltage control in ADNs in which the need for measuring infrastructure throughout the network is reduced. However, all the control resources available in the network are monitored and used for voltage regulation. Furthermore, the MPC framework is single-stage and designed for the coordination of only fast-acting control resources, such as DG units and energy storage systems (ESS). Authors in [56] have proposed an index for identifying the most effective control resources for voltage regulation. However, for the identification of the nodes with voltage violations, the monitoring of all nodes in the network is required. Furthermore, for different voltage violation cases, different sets of effective control resources are needed, which requires the availability of all control resources. Hence, to address these research gaps, this paper presents a real-time voltage control strategy in ADNs based on dual-stage model predictive control (MPC) with a reduced model framework. A comparison with existing work is drawn in Table 2.1. The control strategy uses minimum measuring infrastructure and a global minimum set of available control resources for voltage regulation throughout the network. The critical nodes for measurements are identified using the network partitioning based on the hierarchical clustering

Table 2.1: Comparison of existing works with the proposed control framework.

Reference	Control approach	Reduced number of sensors and measuring infrastructure	Reduced number of control resources
[48]	Dual-stage MPC	×	×
[68]	Single-stage MPC	✓	×
[56]	Index based	×	✓
Proposed	Dual-stage MPC	✓	✓

algorithm (HCA) [81]. A global set of control resources is identified by ranking the control resources using numerical voltage sensitivity analysis, to provide a reduced model framework in order to bring down the number of sensors and measuring devices, as well as the communication infrastructure. The proposed reduced model framework reduces the computational complexity and response speed of the controller. It is to be noted that a system model is imperative for employing MPC, however, a distribution network model is rarely available. Existing literature commonly assumes the availability of the network model, and thus extracts the necessary parameters like voltage sensitivity coefficients from Newton-Raphson (NR) power flow [2, 3, 48] or other analytical methods [58, 68, 102], relying on known line parameters. In case the network model is not available, the sensitivities can be extracted experimentally if the measurements are available throughout the network. However, the proposed method, featuring a reduced model structure, demands sensitivity coefficients for selected nodes (control and observation nodes) only. These required nodal sensitivities can be experimentally computed using measured-data-based sensitivity calculation approaches, as in [103, 104], with the limited number of devices present. The main objectives of this work are-

1. Development of dual-stage MPC with a reduced model framework for voltage control in ADNs having control devices of different temporal characteristics.
2. Network partitioning to identify critical nodes for measurements (termed as observation nodes) and ranking of available control resources using a novel ranking index (RI), by utilizing numerical voltage sensitivity analysis.
3. Identification of global control resource set among the ranked control resources and implementation of the MPC-based control framework on the radial 33-bus distribution network and modified IEEE 123-bus test network.

The rest of this chapter is arranged as follows: section 2.2 provides modelling of the distribution. The MPC control framework is discussed in section 2.3, and the optimization problem formulation in section 2.4. Section 2.5 formulates the reduced model control framework, with reduced measurement and communication infrastructure, and use of a reduced number of control resources.

Section 2.6 provides test system description, and section 2.7 presents the simulation results and

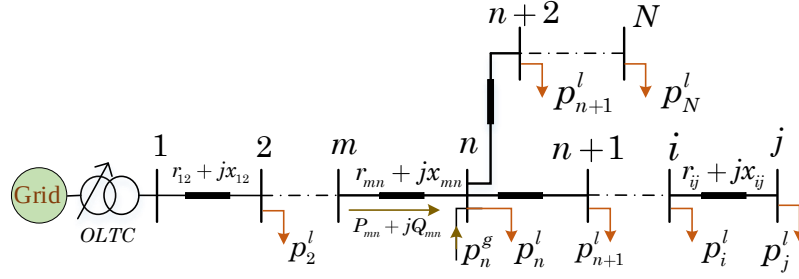


Fig. 2.1: A simple distribution network with radial topology.

related discussion of the 33-bus network and IEEE-123 bus distribution network. Finally, Section 2.8 provides the conclusion of this chapter.

2.2 Modelling of Radial Distribution Network

Consider an $N + 1$ node DN with radial topology as shown in Fig. 2.1. The $N + 1$ nodes are represented by set $\mathcal{N} \cup \{n_0\}$, where $\mathcal{N} := \{n_1, n_2, \dots, n_N\}$, and node n_0 represents the substation node. The branches $\mathcal{L} := \{(m, n)\}$ of the network are given by set $\mathcal{E}$, where m and n are node indices and line $\mathcal{L}_{mn} \in \mathcal{E} \subset (\mathcal{N} + 1) \times (\mathcal{N} + 1)$ has line impedance $\bar{z}_{mn} = r_{mn} + jx_{mn}$. Here, r_{mn} denotes line resistance and $x_{mn} = 1/j2\pi f L_{mn}$ denotes line inductive reactance corresponding to line inductance L_{mn} and system frequency f Hertz. Since in an ADN, DG units are integrated at various nodes, the net power injection at node n depends on the DG power generation and local power demand. Let, $\bar{s}_n = p_n + jq_n = (p_n^g - p_n^l) + j(q_n^g - q_n^l)$ be the net complex power injected at node n , where p_n^g and p_n^l are the active power generation and active power demand at node n , respectively. q_n^g and q_n^l are the reactive power generation and reactive power demand at node n , respectively. The complex power flow in each line $\mathcal{L}_{mn} \in \mathcal{E}$ is represented by $\bar{S}_{mn} = P_{mn} + jQ_{mn}$, where P_{mn} and Q_{mn} are active power and reactive power flow in the branch (m, n) , respectively. For every node $n \in \mathcal{N}$, $v_n := |\bar{V}_n|^2 = V_n^2$ represents the square of the node voltage V_n and for each branch $(m, n) \in \mathcal{E}$, $\ell_{mn} := |\bar{I}_{mn}|^2 = I_{mn}^2$ is the square of the line current I_{mn} . The complex power flow in each branch $(m, n) \in \mathcal{E}$ can be represented by distribution flow (Distflow) as [63]:

$$\bar{S}_{mn} = \sum_k (\bar{S}_{nk} - \bar{s}_n + \bar{z}_{mn}\ell_{mn}) \quad , \quad \forall k \in \mathcal{N}_k \quad (2.1)$$

$$v_n = v_m - 2(r_{mn}P_{mn} + x_{mn}Q_{mn}) + (r_{mn}^2 + x_{mn}^2)\ell_{mn} \quad (2.2)$$

$$\ell_{mn} = \frac{P_{mn}^2 + Q_{mn}^2}{v_n} \quad (2.3)$$

where, $\mathcal{N}_k$ is the set of downstream nodes connected to the node n and $(n, k) \in \mathcal{E}$ is the set of branches connected between node n and node k . The power flow in Eq. (2.1) can be expressed in active and reactive components as,

$$P_{mn} = \sum_{k \in \mathcal{N}_k} (P_{nk}) - p_n + r_{mn}\ell_{mn} \quad (2.4)$$

$$Q_{mn} = \sum_{k \in \mathcal{N}_k} (Q_{nk}) - q_n + x_{mn}\ell_{mn} \quad (2.5)$$

The terms with ℓ_{mn} in these power flow equations correspond to the network power losses. The loss terms are negligibly small as compared to the terms corresponding to the line power flows, introducing a small error of around 1% [105]. The above model can thus be linearized by ignoring the terms with ℓ_{mn} , which introduce non-convexity in the Distflow model. Assuming a relatively flat voltage profile (voltages close to the nominal value), the linear approximation introduces a small modelling error of 0.25% (1%) for 5% (10%) change in approximated voltage magnitudes [105].

Thus, eliminating ℓ_{mn} from Eq. (2.4) and Eq. (2.5), and linearizing Eq. (2.2) around the operating point ($V^0 = 1$ p.u.) using the first-order Taylor series expansion, the linearized Distflow is written as,

$$P_{mn} = \sum_{k \in \mathcal{N}_k} (P_{nk}) - p_n \quad (2.6)$$

$$Q_{mn} = \sum_{k \in \mathcal{N}_k} (Q_{nk}) - q_n \quad (2.7)$$

$$v_n = v_m - 2(r_{mn}P_{mn} + x_{mn}Q_{mn}) \quad (2.8)$$

Using the first-order Taylor series expansion of v_n around an operating point $V^0 = 1$ p.u.,

$$v_n = V_n^2 \simeq V^0 + 2V^0(V_n - V^0) = 2V_n - 1 \quad (2.9)$$

Therefore,

$$v_m - v_n = 2V_m - 1 - 2V_n + 1 = 2(V_m - V_n) \quad (2.10)$$

Thus, Eq. (2.2) can be expressed in the linear form as,

$$V_n = V_m - (r_{mn}P_{mn} + x_{mn}Q_{mn}) \quad (2.11)$$

2.2.1 Compact Form Representation of Distflow Model

To effectively and efficiently incorporate volt/var optimization and other algorithms, the Distflow model is represented in compact form with vectors and matrices. For all the nodes in set $\mathcal{N}$, the voltages are represented by vector $\mathbf{V} := [V_1 \ V_2 \ \dots \ V_N]^\top$, and the voltage of node 0 is represented by V_0 . Similarly, $\mathbf{I}$, $\mathbf{P}$ and $\mathbf{Q}$ represent the vector of currents, vector of active power flows, and vector of reactive power flows in all distribution lines $(m, n) \in \mathcal{E}$. The DN radial interconnection is contained in the matrix $\tilde{\mathbb{A}}$, where $\tilde{\mathbb{A}} = [\mathbf{a}_0 \ \mathbb{A}^\top]^\top$ is the bus incidence matrix of the given network topology. The bus incidence matrix $\tilde{\mathbb{A}}$, with size $(N + 1) \times N$ represents a connected graph and thus is a full rank matrix. Hence, the sub-matrix $\mathbb{A}$, which is a square matrix of size N , is invertible. The element $a_{mn} \in \tilde{\mathbb{A}} = 1$, if n^{th} line in $\mathcal{L}$ leaves the node m , and $a_{mn} = -1$ if the line is incoming at node m . All the remaining elements of matrix $\tilde{\mathbb{A}}$ are 0. The first row ($\mathbf{a}_0^\top$) of the matrix $\tilde{\mathbb{A}}$ corresponds to the substation node. Furthermore, if $\mathbf{r}$ and $\mathbf{x}$ are the vectors of line resistances and line reactances, respectively, we define matrix $\mathbf{R}_l := \text{diag}(\{\mathbf{r}\}) \in \mathbb{R}^{N \times N}$ and $\mathbf{X}_l := \text{diag}(\{\mathbf{x}\}) \in \mathbb{R}^{N \times N}$ with l^{th} diagonal elements corresponding to resistance and reactance of l^{th} branch, respectively. The linearized Distflow model given by Eq. (2.6), Eq. (2.7), and Eq. (2.11) is thus written in compact form as,

$$\mathbb{A}\mathbf{P} = \mathbf{p} \quad (2.12)$$

$$\mathbb{A}\mathbf{Q} = \mathbf{q} \quad (2.13)$$

$$\begin{bmatrix} \tilde{\mathbb{A}} \end{bmatrix}^\top \begin{bmatrix} V_0 & \mathbf{V}^\top \end{bmatrix}^\top = \mathbf{R}_l \mathbf{P} + \mathbf{X}_l \mathbf{Q} \quad (2.14)$$

Substituting Eq. (2.12) and Eq. (2.13) in Eq. (2.14) we have the following equation:

$$\mathbf{V} = \mathbb{D}_r \mathbf{p} + \mathbb{D}_x \mathbf{q} - \mathbb{A}^{-\top} \mathbf{a}_0 \mathbf{V}_0 \quad (2.15)$$

or precisely at any discrete time-step κ , the voltage vector as per Eq. (2.15) can be expressed as,

$$\mathbf{V}(\kappa) = \mathbb{D}_r \mathbf{p}(\kappa) + \mathbb{D}_x \mathbf{q}(\kappa) - \mathbb{A}^{-\top} \mathbf{a}_0 \mathbf{V}_0(\kappa) \quad (2.16)$$

If $\Delta \mathbf{V}$ is the change in voltage vector from time step κ to $\kappa + 1$, corresponding to the change in active power and reactive power injection at buses, and change in OLTC tap position as $\Delta \mathbf{p}$, $\Delta \mathbf{q}$ and $\Delta \mathbf{V}_0$, respectively, the linear evolution of voltages at time step $\kappa + 1$ can be expressed as,

$$\mathbf{V}(\kappa + 1) = \mathbb{D}_r \mathbf{p}(\kappa) + \mathbb{D}_x \mathbf{q}(\kappa) - \mathbb{A}^{-\top} \mathbf{a}_0 \mathbf{V}_0(\kappa) + \mathbb{D}_r \Delta \mathbf{p} + \mathbb{D}_x \Delta \mathbf{q} - \mathbb{A}^{-\top} \mathbf{a}_0 \Delta \mathbf{V}_0 \quad (2.17)$$

We can write the above equation as,

$$\mathbf{V}(\kappa + 1) = \mathbf{V}(\kappa) + \mathbf{S}_v^p \Delta \mathbf{p} + \mathbf{S}_v^q \Delta \mathbf{q} + \mathbf{S}_v^{\text{tap}} \Delta \mathbf{V}_0 \quad (2.18)$$

where, $\mathbf{V}(\kappa) = \mathbb{D}_r \mathbf{p}(\kappa) + \mathbb{D}_x \mathbf{q}(\kappa) - \mathbb{A}^{-\top} \mathbf{a}_0 \mathbf{V}_0(\kappa)$ is acquired through measurements at network nodes. The coefficient matrices $\mathbf{S}_v^p = \mathbb{D}_r$, $\mathbf{S}_v^q = \mathbb{D}_x$ and $\mathbf{S}_v^{\text{tap}} = -\mathbb{A}^{-\top} \mathbf{a}_0$ correspond to the voltage sensitivity matrices and incorporate sensitivities with respect to the change in real power injection, reactive power injection, and OLTC tap position, respectively.

It can be seen that the node voltages are linearly dependent on the net active and reactive power injections, thus making the linearized MPC framework (discussed next in Section 2.3) suitable for regulating node voltages. The linear model discussed and the proposed control strategy consider the distribution network as a balanced three-phase system. However, without the loss of generality, the proposed control scheme can be implemented on 3-phase unbalanced networks as well. The linear model for DN's discussed can be suitably used to model the unbalanced phases in the network. A similar mathematical formulation follows in which the network quantities like voltages, currents, and line power flows represent 3×1 complex vector, wherein each element

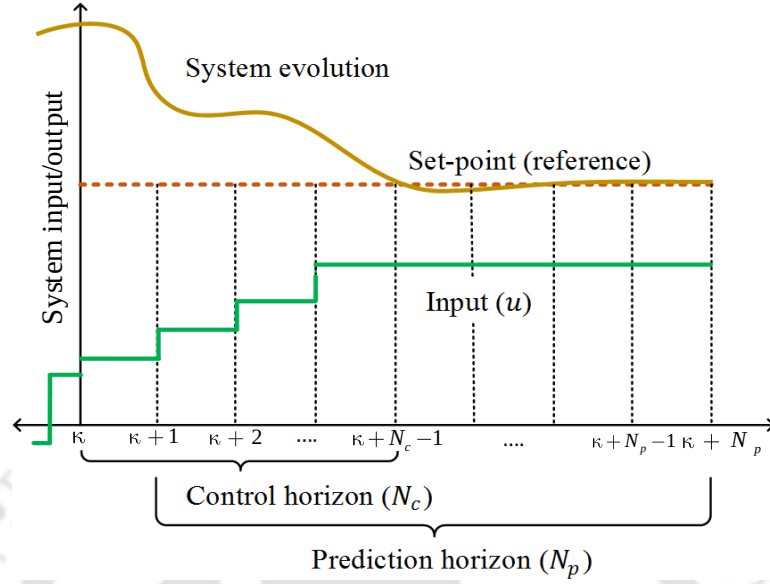


Fig. 2.2: MPC-based system evolution over the prediction horizon.

corresponds to the individual phase of the unbalanced network. The detailed linear modelling of the unbalanced networks is provided in [71].

2.3 Model Predictive Control Framework

Model Predictive Control (MPC) efficaciously deals with complex dynamic systems to predict the system behavior. MPC employs the system model and current system state to determine the optimal control sequence over multiple time steps called the control horizon (N_c). The system behavior is predicted based on the optimal control sequence over the prediction horizon (N_p). The system evolution is depicted in Fig. 2.2. This linear distribution system model serves as the bedrock for the model predictive control (MPC) framework. The generalized discrete state-space MPC model given by,

$$\xi(\kappa + 1) = \hat{\mathbf{A}}\xi(\kappa) + \hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) \quad (2.19)$$

$$\mathbf{y}_p(\kappa) = \hat{\mathbf{C}}\xi(\kappa) \quad (2.20)$$

where, $\hat{\mathbf{A}}$, $\hat{\mathbf{B}}$ are the system matrix and input matrix, respectively, and $\hat{\mathbf{C}}$ is the output matrix. System matrix $\hat{\mathbf{A}}$ governs the linear dependence of state variables, while the input matrix $\hat{\mathbf{B}}$ captures the sensitivity of state variables (monitored variables) with respect to the control variables

(control inputs). The model represented by Eq. (2.19) and Eq. (2.20) drives the system output ($\mathbf{y}_p$) to reach the set-point at the end of a future time window, called the prediction horizon (N_p), with the evolution of state vector (ξ) at each next time step, given the current system states (acquired through measurements). The system output is driven to the set point reference based on the optimal control sequence over the future time window called the control horizon (N_c). If $\mathcal{O}$, $\mathcal{I}$, and $\mathcal{S}$ refer to the number of system output variables, input variables, and state variables, respectively, in the prediction model, then the dimensions of the various matrices and vectors in the MPC model are given as, $\xi \in \mathbb{R}^{\mathcal{S} \times 1}$, $\mathbf{u} \in \mathbb{R}^{\mathcal{I} \times 1}$, $\hat{\mathbf{A}} \in \mathbb{R}^{\mathcal{S} \times \mathcal{S}}$, $\hat{\mathbf{B}} \in \mathbb{R}^{\mathcal{S} \times \mathcal{I}}$, $\hat{\mathbf{C}} \in \mathbb{R}^{\mathcal{O} \times \mathcal{S}}$, and $\mathbf{Y}_p \in \mathbb{R}^{\mathcal{O} \times 1}$. Based on the linear discrete model of the system given in Eq. (2.19), the state variables are obtained sequentially over N_p as,

$$\begin{aligned} \xi(\kappa + 1|k) &= \hat{\mathbf{A}}\xi(\kappa) + \hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) \\ \xi(\kappa + 2|k) &= \hat{\mathbf{A}}^2\xi(\kappa) + \hat{\mathbf{A}}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) + \hat{\mathbf{B}}\Delta\mathbf{u}(\kappa + 1) \\ &\vdots \\ \xi(\kappa + N_p|k) &= \hat{\mathbf{A}}^{N_p}\xi(\kappa) + \hat{\mathbf{A}}^{N_p-1}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) + \dots + \hat{\mathbf{A}}^{N_p-N_c}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa + N_c - 1) \end{aligned} \quad (2.21)$$

The outputs of the prediction model are linked to the system states through the output matrix $\hat{\mathbf{C}}$. Using the above-obtained states, the predicted outputs of the system, over the whole prediction horizon can be obtained as,

$$\begin{aligned} \mathbf{y}_p(\kappa + 1|k) &= \hat{\mathbf{C}}\hat{\mathbf{A}}\xi(\kappa) + \hat{\mathbf{C}}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) \\ \mathbf{y}_p(\kappa + 2|k) &= \hat{\mathbf{C}}\hat{\mathbf{A}}^2\xi(\kappa + 1) + \hat{\mathbf{C}}\hat{\mathbf{A}}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) + \hat{\mathbf{C}}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa + 1) \\ &\vdots \\ \mathbf{y}_p(\kappa + N_p|k) &= \hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p}\xi(\kappa) + \hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p-1}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa) + \dots + \hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p-N_c}\hat{\mathbf{B}}\Delta\mathbf{u}(\kappa + N_c - 1) \end{aligned} \quad (2.22)$$

The compact representation of the predicted output over the predicted horizon (N_p) can be expressed in terms of measurements, and the optimal sequence of inputs over the control horizon (N_c) as,

$$\mathbf{Y}_p = \chi\xi(\kappa) + \psi\Delta\mathbf{U} \quad (2.23)$$

where,

$$\chi = \begin{bmatrix} (\hat{\mathbf{C}}\hat{\mathbf{A}})^\top & (\hat{\mathbf{C}}\hat{\mathbf{A}}^2)^\top & (\hat{\mathbf{C}}\hat{\mathbf{A}}^3)^\top & \dots & (\hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p})^\top \end{bmatrix}^\top \quad (2.24)$$

and,

$$\psi = \begin{bmatrix} \hat{\mathbf{C}}\hat{\mathbf{B}} & 0 & \dots & 0 \\ \hat{\mathbf{C}}\hat{\mathbf{A}}\hat{\mathbf{B}} & \hat{\mathbf{C}}\hat{\mathbf{B}} & \dots & 0 \\ \hat{\mathbf{C}}\hat{\mathbf{A}}^2\hat{\mathbf{B}} & \hat{\mathbf{C}}\hat{\mathbf{A}}\hat{\mathbf{B}} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p-1}\hat{\mathbf{B}} & \hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p-2}\hat{\mathbf{B}} & \dots & \hat{\mathbf{C}}\hat{\mathbf{A}}^{N_p-N_c}\hat{\mathbf{B}} \end{bmatrix} \quad (2.25)$$

The control sequence over the control horizon, and consequently the predicted output sequence over the whole prediction horizon, are represented by,

$$\Delta \mathbf{U} = [\Delta \mathbf{u}(\kappa)^\top \ \Delta \mathbf{u}(\kappa+1)^\top \ \dots \ \Delta \mathbf{u}(\kappa+N_c-1)^\top]^\top \quad (2.26)$$

$$\mathbf{Y}_p = [\mathbf{y}_p(\kappa+1|\kappa)^\top \ \mathbf{y}_p(\kappa+2|\kappa)^\top \ \dots \ \mathbf{y}_p(\kappa+N_p|\kappa)^\top]^\top \quad (2.27)$$

Here, $\chi \in \mathbb{R}^{\mathcal{O}.N_p \times \mathcal{S}}$, $\mathbf{U} \in \mathbb{R}^{\mathcal{I}.N_c \times 1}$, $\Omega \in \mathbb{R}^{\mathcal{D}.N_c \times 1}$, $\psi \in \mathbb{R}^{\mathcal{O}.N_p \times \mathcal{I}.N_c}$, and $\mathbf{Y}_p \in \mathbb{R}^{\mathcal{O}.N_p \times 1}$. It is to be mentioned that in this work, only the first control actions are applied using the receding horizon control strategy to incorporate the renewed system states at each optimization step. Incorporating fresh measurements at each step alleviates the model inaccuracies, if any. The system state vector $\xi(\kappa)$ is acquired through real-time measurements at time step κ . It is to be noted that the MPC model uses the change in control inputs to predict the system behavior; however, the actual control inputs over the control horizon N_c are given by,

$$\begin{aligned} \mathbf{u}(\kappa) &= \mathbf{u}(\kappa-1) + \Delta \mathbf{u}(\kappa) \\ \mathbf{u}(\kappa+1) &= \mathbf{u}(\kappa-1) + \Delta \mathbf{u}(\kappa) + \Delta \mathbf{u}(\kappa+1) \\ &\vdots \\ \mathbf{u}(\kappa+N_c-1) &= \mathbf{u}(\kappa-1) + \Delta \mathbf{u}(\kappa) + \dots + \Delta \mathbf{u}(\kappa+N_c-1) \end{aligned} \quad (2.28)$$

Which reduces to the compact form as,

$$\mathbf{U}(\kappa) = \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) + \hat{\mathbf{H}}\Delta\mathbf{U} \quad (2.29)$$

where,

$$\hat{\mathbf{G}} = \begin{bmatrix} \mathbf{I} \\ \mathbf{I} \\ \vdots \\ \mathbf{I} \end{bmatrix}; \quad \hat{\mathbf{H}} = \begin{bmatrix} \mathbf{I} & 0 & 0 & \dots & 0 \\ \mathbf{I} & \mathbf{I} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{I} & \mathbf{I} & \mathbf{I} & \dots & \mathbf{I} \end{bmatrix} \quad (2.30)$$

The previous input $\mathbf{u}(\kappa - 1)$ cumulatively adds all previous input changes in Eq. (2.28), thus the input changes at the previous time steps, such as $\{\Delta\mathbf{u}(\kappa - 1), \Delta\mathbf{u}(\kappa - 2) \dots\}$, are implicitly considered by the value of $\mathbf{u}(\kappa - 1)$. The vector of optimal sequence control inputs ($\Delta\mathbf{U}$) is the change in active and reactive power at control nodes, or the change in voltage due to tap operation of OLTC. The state vector $\boldsymbol{\xi}$ corresponds to the network bus voltages. The input matrix $\hat{\mathbf{B}}$ represents the sensitivities of monitored variables with respect to control variables. The voltage sensitivity coefficients can be obtained using analytical voltage sensitivity analysis to power flow equations [102], or can be extracted from numerical techniques, such as Newton-Raphson (NR) power flow. In this chapter, the voltage sensitivity coefficients are extracted from the inverse of the Jacobian matrix, using the offline NR load flow method. Sensitivities with respect to tap operations of OLTC are obtained by calculating the voltage deviations at the network buses due to two successive tap operations.

It is worth mentioning that the choice of control horizon and prediction horizon involves a trade-off between computational complexity and how rigorously the controller should act. The control actions are taken such that the output meets the set point target at the end of the prediction horizon [2], as shown in Fig. 2.2. Since it is assumed that the measurements are available quite frequently due to advanced metering infrastructure, the optimal control actions are determined over a small time window. For this purpose, the prediction horizon is considered as 3 (which is relatively low), so that the controller action is more aggressive than spreading the control action over a large time window. From the computational perspective, the prediction

horizon is chosen to be equal to the control horizon ($N_p = N_c = 3$) in this work.

2.4 Problem Formulation

The optimal changes in inputs are found by solving an optimization problem, which lies at the core of MPC. The objective function is formulated as a quadratic programming (QP) problem as,

$$\min \left(\sum_{i=1}^{N_p} \left(\|\hat{\mathbf{y}}_p - \mathbf{y}_p(\kappa + i)\|_{\mathbf{w}_y}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 \right) + \sum_{i=1}^{N_c} \|\Delta \mathbf{u}(\kappa + i)\|_{\mathbf{w}_u}^2 \right) \quad (2.31)$$

where, $\mathbf{y}_p$ is the system output vector, which in this case is the vector of magnitude of bus voltages ($\mathbf{V}$), vector $\hat{\mathbf{y}}_p$ is the desired/reference voltage vector which is set as 1 p.u., for every bus, and $\boldsymbol{\sigma} = [\sigma_1 \ \sigma_2]^\top$ is the slack variable vector added to the objective function so that the controller does not stop under solution infeasibility. Since the output of the prediction model ($\mathbf{y}_p$) linearly depends on the decision variables, and the weight matrices are positive diagonal matrices, the Hessian of the standard quadratic form is positive semi-definite. Thus, the problem is solved as a standard quadratic programming (QP) problem. It is to be noted that the proposed control strategy is deterministic in nature. The heavy penetration of renewables and load may render the controller with insufficient control capabilities. Thus, voltage constraints are relaxed using slack variables, with minimum possible values, to secure the MPC controller from being stopped unexpectedly.

The weighting matrices $\mathbf{w}_u$ ($\mathbf{w}_p$, $\mathbf{w}_q$, and $\mathbf{w}_{tap}$) correspond to the objective weights of control efforts using active power exchange, reactive power exchange and OLTC tap operation, respectively. Similarly, the weight matrices $\mathbf{w}_y$ and $\mathbf{w}_s$ correspond to the weights of objectives corresponding to the minimization of voltage deviations and slack variables, respectively. These matrices are diagonal matrices, with the same element at each diagonal entry of a given matrix. For example, if w_y represents a scalar value, then the weight matrix corresponding to the output voltage deviations is $\mathbf{w}_y = w_y \mathbf{I}$, where matrix $\mathbf{I}$ represents an identity matrix. The values of the weight coefficients are determined empirically through recursive simulations, so that the trade-off between the minimization of voltage deviation and control cost is tuned suitably.

The MPC framework in this thesis adopts a rule-based structure for these scalar weights, wherein

Table 2.2: Weights associated with the different objectives of the MPC-based control problem.

Range of bus voltages (p.u.)	Objective weights				
	w_y	w_{tap}	w_q	w_q	w_s
$\max(\mathbf{V}) \geq 1.1$ or $\min(\mathbf{V}) \leq 0.9$	100	0.1	0.1	1	1000
$1.05 \leq \max(\mathbf{V}) \leq 1.1$ or $0.9 \leq \min(\mathbf{V}) \leq 0.95$	100	1	1	10	1000
$\max(\mathbf{V}) \leq 1.05$ and $\min(\mathbf{V}) \geq 0.95$	100	10	10	100	1000

three voltage-dependent operating conditions are defined via conditional logic. These rules govern dynamic tuning of objective function weights, as given in Table 2.2.

When the voltages are beyond the normal operation limits, the weight associated with the control resource utilization is reduced to bring the voltages quickly back to the normal operation range, and the weights associated with the voltage deviation from the nominal value are increased. Control actions are weighted according to their relative cost. Active power curtailment is deemed most expensive and thus pertains to the highest weight, e.g., $w_p = 100$, which is 10 times that of w_q , when the voltages are within an acceptable range. For large voltage deviations, the value of w_p is set lower to allow greater flexibility. Reactive power actions, being less costly, are weighted less ($1/10^{\text{th}}$) than that of active power, under all voltage conditions. Moreover, the slack variables are highly weighted so that they take values only under emergency conditions. These values may be adjusted by system operators based on preferential objectives or limitations on control devices. The optimal control actions are obtained under the following system and input constraints:

$$\underline{\underline{\Delta \mathbf{u}}} \leq \Delta \mathbf{u}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{u}}} \quad (2.32a)$$

$$\underline{\underline{\mathbf{u}}} \leq \mathbf{u}(\kappa + i) \leq \overline{\overline{\mathbf{u}}} \quad (2.32b)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} + \sigma_2 \mathbf{1} \quad (2.32c)$$

$$\mathbf{I}(\kappa + 1) \leq \overline{\overline{\mathbf{I}}} \quad (2.32d)$$

where $\mathbf{I}$ represents the vector of line currents. Therefore, Eq. (2.32d) corresponds to the thermal limit constraints of the distribution lines, and $\mathbf{1}$ in constraint Eq. (2.32c) represents a unitary

vector. The symbols $\overline{(\cdot)}$ and $\underline{(\cdot)}$ represent the maximum and minimum value of a quantity, respectively, and N_c represents the control horizon. The model equality constraints and line thermal limits constraints are expressed as,

$$\mathbf{V}(k+i) = \mathbf{V}(\kappa+i-1) + \left(\frac{\delta \mathbf{V}}{\delta \mathbf{u}} \right) \Delta \mathbf{u}(\kappa+i-1) \quad (2.33a)$$

$$\mathbf{I}(\kappa+i) = \mathbf{I}(\kappa+i-1) + \left(\frac{\delta \mathbf{I}}{\delta \mathbf{u}} \right) \Delta \mathbf{u}(\kappa+i-1) \quad (2.33b)$$

where, $i = 0, 1, 2, \dots, N_c - 1$. The matrices $\left(\frac{\partial \mathbf{V}}{\partial \mathbf{u}} \right)$ and $\left(\frac{\partial \mathbf{I}}{\partial \mathbf{u}} \right)$ contain voltage and current sensitivities. The MPC-based optimization is carried out in two stages. The optimal operation of OLTC is carried out each hour at the first stage, wherein $\Delta \mathbf{u}$ in Eq. (2.31) is given as,

$$\Delta \mathbf{u} = \Delta \mathbf{V}_{\text{tap}} \quad (2.34)$$

The variable $\Delta \mathbf{V}_{\text{tap}}$ (change in OLTC reference voltage) is treated as a continuous variable. The appropriate action taken by the OLTC is determined by rounding off the value of the continuous variable obtained to the nearest discrete tap position of the OLTC. At the second stage, controllable PV and EV inverters are coordinated after each minute, wherein the control input $\Delta \mathbf{u}$ in Eq. (2.31) is given by,

$$\Delta \mathbf{u} = \left[\Delta \mathbf{Q}_{\text{PV}}^\top \quad \Delta \mathbf{Q}_{\text{EV}}^\top \quad \Delta \mathbf{P}_{\text{PV}}^\top \quad \Delta \mathbf{P}_{\text{EV}}^\top \right]^\top \quad (2.35)$$

It is to be noted that the reactive power, as well as active power from PV inverters and EV charging stations (EVCSs), are used as control variables. The active power from EVCS is considered to be available through EVCS smart inverters by assessing the control capabilities of V2G technology. The use of active power curtailment (APC) from PVs involves the curtailment of renewable energy, which is generally discouraged by the DG owners. Similarly, active power exchange by the EVCS involves the degradation of battery life and customer willingness to participate in V2G. Thus, a maximum of 10% of the available active power is used for control purposes. Moreover, the weights attributed to the control inputs associated with active powers are considered significantly greater

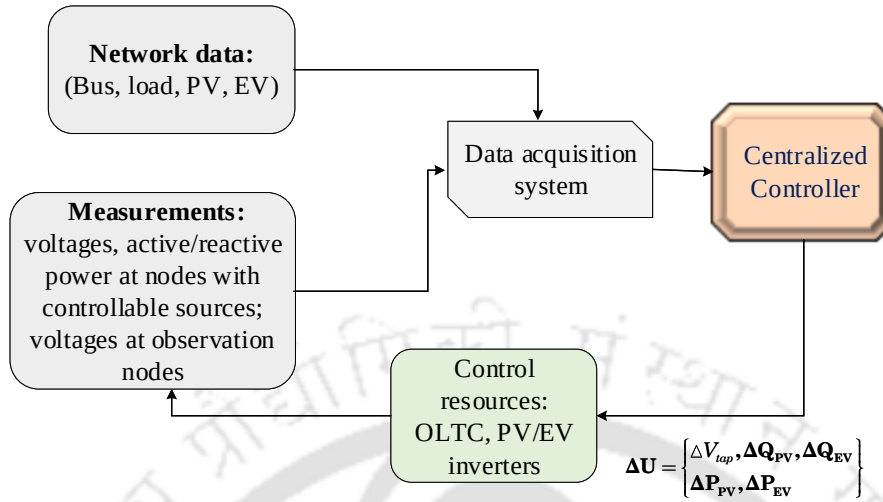


Fig. 2.3: Schematic of the proposed voltage control framework in ADNs.

compared to those pertaining to reactive power control inputs, to exhibit minimal preference for the active power.

2.5 Reduced Model Control Framework

The reduced model framework uses only selected nodes in the MPC linear model formulation to reduce the model size for fast computation. This involves the identification of critical nodes and ranking of control resources, as discussed in this section.

2.5.1 Selection of Observation Nodes

The multi-step corrective control using MPC needs real-time measurements to update the system state. For large-scale networks with substantial amounts of control resources, the need for measuring infrastructure increases significantly. The need for a wide communication network and measuring infrastructure throughout the network elevates the cost and complexity of real-time coordinated control. To have effective control with the requirement of minimum measurement infrastructure, we need to nominate network nodes that are more sensitive to deviations in network quantities, such as voltage. For the identification of sensitive nodes, network partitioning using the hierarchical clustering algorithm (HCA) [81] is used to divide the network into the optimal number of zones.

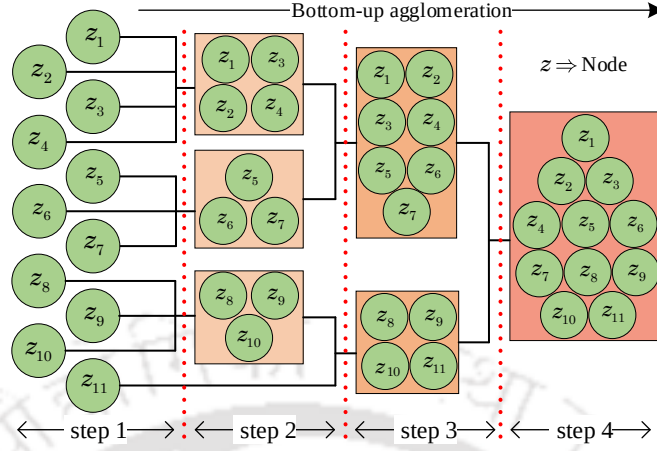


Fig. 2.4: Illustration of the hierarchical clustering method.

The clustering algorithm utilizes the concept of electrical distances defined by Eq. (2.37). If α_{ij} and α_{ji} are the voltage attenuation at node i and j due to the change in reactive power injection, and given as,

$$\alpha_{ij} = \frac{\partial V_i}{\partial Q_j} \left(\frac{\partial V_j}{\partial Q_j} \right)^{-1}; \quad \alpha_{ji} = \frac{\partial V_j}{\partial Q_i} \left(\frac{\partial V_i}{\partial Q_i} \right)^{-1} \quad (2.36)$$

Then, the electrical distance quantifying the coupling among network nodes using voltage sensitivity [68], is defined as,

$$D_{ij} = -\ln(\alpha_{ij} \cdot \alpha_{ji}), \quad \forall i, j \in \mathcal{N} \quad (2.37)$$

where, $\alpha_{ij} = \frac{\Delta V_i}{\Delta V_j}$, $\alpha_{ji} = \frac{\Delta V_j}{\Delta V_i}$ are voltage deviations at node i and node j with respect to voltage deviation at node j and node i , respectively.

2.5.1.1 Hierarchical Clustering Algorithm (HCA)

The clustering approach initially assumes all nodes of the network as individual clusters. The clusters are subsequently merged using bottom-up agglomeration based on electrical distances, in a hierarchical manner as shown in Fig. 2.4. If $\mathcal{K} = \{\mathcal{C}_1, \mathcal{C}_2, \dots, \mathcal{C}_k\}$ denotes the set of clusters at a particular clustering stage with k number of clusters, the inter-cluster distance (D_{ij}^c) is defined as,

$$D_{ij}^c = \max[D_{mn} : m \in \mathcal{C}_i; n \in \mathcal{C}_j] \quad \forall \mathcal{C}_i, \mathcal{C}_j \in \mathcal{K} \quad (2.38)$$

The successive aggregation of clusters at a given clustering stage proceeds as,

$$\mathcal{C}_i \cup \mathcal{C}_j = \min(D_{ij}^c) \quad \forall D_{ij}^c \in \mathcal{D} \quad (2.39)$$

The merging of zones of the network subsequently proceeds to form a single cluster. The appropriate clustering results are identified based on the measure of relative diameter at each clustering stage. The diameter of cluster $\mathcal{C}_i$ is given by

$$d_i^c = \max\{D_{mn} : m, n \in \mathcal{C}_i\} \quad (2.40)$$

Here $\mathcal{C}_i$ represents the cluster for which the diameter is to be calculated. Let, there be g number of clustering stages, the relative diameter (d_s^r) of the network for a particular clustering stage (s) is given by,

$$d_s^r = \frac{\sum_{i=1}^k (d_i^c)}{k_n} \quad ; \quad s = 1, 2, \dots, g \quad (2.41)$$

The change in relative diameter at two successive clustering stages is expressed as,

$$\Delta d_s^r = |d_s^r - d_{s-1}^r| \quad ; \quad s = 1, 2, \dots, g \quad (2.42)$$

The appropriate clustering result with k clusters corresponds to the clustering stage (s) where the value of Δd_s^r is maximum, i.e.,

$$k_n := \max\{|d_2^r - d_1^r|, |d_3^r - d_2^r|, \dots, |d_{end}^r - d_{end-1}^r|\} \quad (2.43)$$

In VAr control space, the clusters are linked based on the average linking criterion [81], wherein the inter-cluster distance is the average of electrical distances between the nodes of two clusters, given as,

$$D_{ij}^c = \frac{1}{\sum_{l=1}^{m_{max}} (n_m^k) \sum_{l=1}^{n_{max}} (n_n^k)} \sum_{i \in C_m} \sum_{j \in C_n} D_{mn} \quad (2.44)$$

where, $n_i^k \in \mathcal{C}_i$ and $n_j^k \in \mathcal{C}_j$ are l^{th} nodes in cluster $\mathcal{C}_i$ and $\mathcal{C}_j$, respectively. m_{max} and n_{max} are total number of nodes in cluster $\mathcal{C}_i$ and cluster $\mathcal{C}_j$, respectively. The appropriate clustering (with

k_n clusters) is decided based on the maximum value of the average zone distance of the network at each stage.

Within each partition of the network, a node is chosen to represent the whole partition for any voltage variations. The representative nodes are named as observation nodes, as in [102], which are chosen based on their location in the zone. For each zone, the PV node that lies towards the end of the feeder is chosen as the observation node [68]. However, if no PV node happens to be present in a zone, the node at the end of the feeder in the host zone is selected as the observation node. It is worth mentioning that for enhanced observability, we can choose multiple observation nodes from each zone so that the solution is closer to the system-wide optimal solution. However, due to the close geographical proximity of nodes in a zone in a distribution network, the generation profiles of all PV-DG units are almost identical. Thus, choosing the single most critical observation node is seen to be sufficient for measurement for voltage control. Moreover, the slight change in sensitivity coefficients due to changes in network conditions has a negligible effect on electrical distances, and almost no effect on the network partitioning. Thus, the partitioning remains the same under different load scenarios. It is to be noted that all observation nodes and nodes where controlled resources like PVs or EV charging stations are connected are necessarily equipped with measuring devices for real-time control. The communication infrastructure is laid out only for nodes where control resources are connected.

2.5.2 Selection of Set of Minimum Control Resources

To minimize communication and the need for control of all voltage control resources, the control infrastructure is reduced by choosing the control nodes that are more significant in reducing the voltage violations with minimum control actions. For choosing the control resources for real-time control, the resources are ranked based on voltage sensitivities to the observation node. The ranking utilizes the numerical voltage sensitivity analysis carried out using offline power flow. Corresponding to each PV bus, the value of the ranking index (RI) is calculated, which is the summation of voltage sensitivities at all observation nodes due to the reactive power change by a control resource. If $\mathcal{N}_{obsv} = \{o_1, o_2, o_3, \dots, o_m\}$ is the set of observation nodes and $\mathcal{N}_c = \{c_1, c_2, \dots, c_n\}$ is the set of control resources available in the network, then the ranking index RI

is given by,

$$RI_i = \frac{\partial V_{o1}}{\partial q_{c_i}} + \frac{\partial V_{o2}}{\partial q_{c_i}} + \dots + \frac{\partial V_{or}}{\partial q_{c_i}} + \dots + \frac{\partial V_{om}}{\partial q_{c_i}} \quad (2.45)$$

where, RI_i is the ranking index value corresponding to i_{th} control resource and $\frac{\partial V_{or}}{\partial q_{c_i}}$ is the voltage sensitivity of r_{th} observation node corresponding to reactive power change by i_{th} control resource. The control resource with a higher value of RI is more effective in controlling the voltage at observation nodes. For the determination of the minimum set among all ranked control resources, a simulation is performed to observe the highest voltage violation in the network. To eliminate this extreme violation, resources from the ranked set are progressively deployed until the voltage falls within the acceptable range of $[1.05, 0.95]$ p.u. The control resources effective in addressing the largest violation remain adequate for controlling voltages across the entire network. The bi-directional communication network is laid for the central controller connecting the nodes where the control resources are placed, and the substation node ($\mathcal{N}_c \cup \{1\}$). If $\mathcal{N}_c$ is the global set of resources identified corresponding to $\mathcal{N}_{obsv}$, the measuring devices are placed at node set $\mathcal{N}_{meas} = \mathcal{N}_c \cup \mathcal{N}_{obsv} \cup \{1\}$. The node voltages, injected currents, and power injections at the nodes $\mathcal{N}_{meas}$ are measured and gathered by the data acquisition system and fed to the controller. It is to be noted that the proposed model does not consider any pseudo-measurements; thus, the nodes in $\mathcal{N}_{meas}$ are only modelled for the MPC-based controller to reduce computation burden, communication, and the need for extensive measuring infrastructure.

2.6 Test System Description

To validate the proposed control strategy on a distribution network, a description of the test networks used is given with the modified network configuration and added components. The 33-bus network used in [48] and modified IEEE 123-bus network [106] are used as test networks in this article, as shown in Fig. 2.5 and Fig. 2.6, respectively. The peak active and reactive power demand of the 33-bus test network is 3.715 MW and 2.30 MVar, respectively. The network is modified to accommodate 16 PVs of 550 kVA each, with peak generation of 500 kW, and 2 EVCSs of capacities 1 MVA each. Similarly, the peak active and reactive power demand of the IEEE 123-bus network is 3.49 MW and 1.92 MVar, respectively. A total of 21 PV sources,

where x_t is the state variable (tap position), and H_{tap} , K_{tap} are integral deviation and inverse time constant, respectively. The variable x corresponding to the tap operation is treated as a continuous variable; however, the value of x depends on V_{tap} , which is determined by the optimization at the first stage. The OLTC has 32 tap steps and each tap change increases or decreases the voltage by 0.00625 p.u. and a maximum of 2 tap steps are allowed at a given time instant. Thus, OLTC can step up or bring down the voltage by 0.1 p.u. when all tap positions are utilized. The parameters K_{tap} and H_{tap} are tuned so that the OLTC control action is completed in 3 seconds. It is to be mentioned that the tap operation is carried out only when the maximum voltage deviation in the network is more than 2.5% of the nominal value, and the total number of tap operations in a day is restricted to 10, to enhance its life. Furthermore, PV sources are connected to the balanced three-phase distribution network at various nodes, which are assumed to be interfaced by smart inverters, so that they can exchange active as well as reactive power with the network. The nodes where PV sources are connected are represented by the node set $\mathcal{N}^{PV} \subset \mathcal{N}$. The PV power generation relies on PV capacity and irradiance at a given location and time. The available reactive power of PVs and EV stations is constrained by active power generation and EV charging load as given in Eq. (2.47) and Eq. (2.48), respectively. The inverters are assumed to have grid support functions to exchange reactive power under very little or no active power generation.

$$Q_{PV}(\kappa) = \pm \sqrt{S_{PV}^2 - P_{PV}^2(\kappa)} \quad (2.47)$$

$$Q_{EV}(\kappa) = \pm \sqrt{S_{EV}^2 - P_{EV}^2(\kappa)} \quad (2.48)$$

The power profile of PVs can significantly vary with geographic location. Since distribution networks are located in a small geographical area, the generation profile is assumed to be uniform for all PVs in both the 33-bus network and the IEEE 123-bus network. The loads are connected to all nodes. These are classified as residential loads, industrial loads, and commercial loads, as shown in Fig. 2.7(b). The PV generation profile and EV load profile are shown in Fig. 2.7(a).

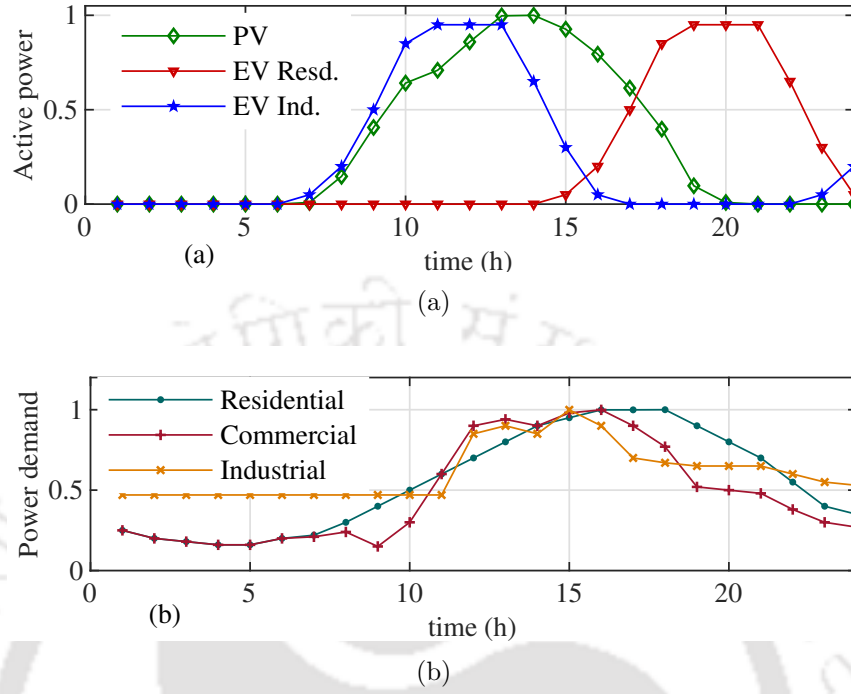


Fig. 2.7: Power profiles: (a) PV generation profile and EV load profile (b) Load demand profile.

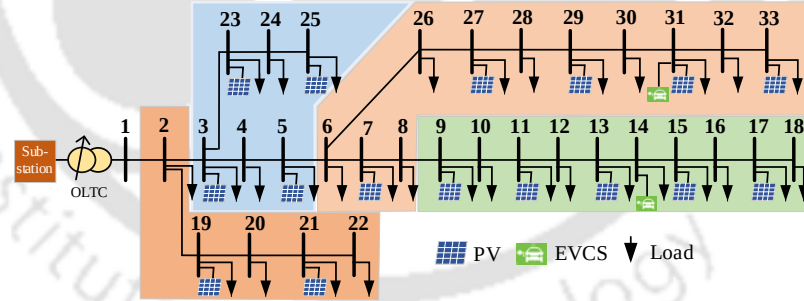


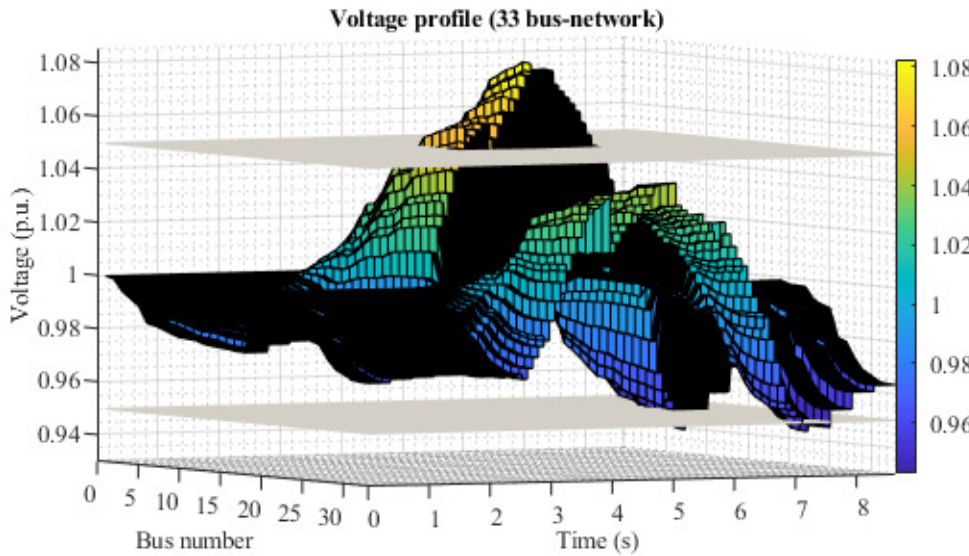
Fig. 2.8: Partitioning of the 33-bus distribution network.

2.7 Simulation Results and Discussion

The proposed dual-stage MPC-based voltage control is validated on both test networks. The networks are modeled using the Power System Analysis (PSAT) toolbox in the MATLAB environment, and optimizations are carried out using the CPLEX solver with the MATLAB interface.

Table 2.3: Ranking of control resources (PV inverters) in the 33-bus distribution network

Rank	PV node	RI	Rank	PV node	RI
01	33	0.5047	09	07	0.2291
02	17	0.4878	10	27	0.2246
03	31	0.4429	11	21	0.1365
04	15	0.4008	12	5	0.1229
05	13	0.3527	13	25	0.0563
06	29	0.3526	14	23	0.0553
07	11	0.3022	15	3	0.0549
08	09	0.2695	16	19	0.0208

**Fig. 2.9:** Voltage profile under no control action.

2.7.1 33-Bus Radial Distribution Network

Simulations are performed on the 33-bus radial distribution network shown in Fig. 2.8. The network is fed from a 63.3 kV/12.66 kV substation at node 1. The system base power is considered as 10 MVA and the base voltage is 12.66 kV. The PV sources are distributed throughout the network with 2 EVCSs located at node 14 and node 31 as in [48], an OLTC at the substation, and industrial, commercial, and residential loads (Fig. 2.8). Initially, the distribution network is partitioned into 4 zones using HCA to identify the observation nodes, as depicted in Fig. 2.8. The set of network nodes $\mathcal{N}_{obs} \subset \mathcal{N} = \{17, 33, 05, 21\}$ are chosen as observation nodes, based on their location at the feeder end in a zone [68]. Corresponding to these observational nodes,

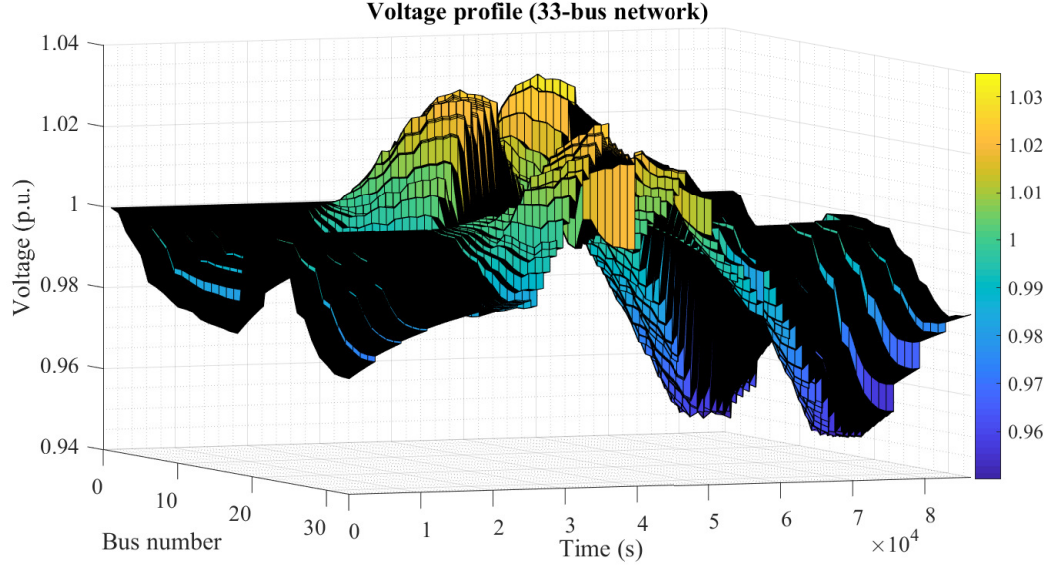


Fig. 2.10: Voltage profile with coordinated control of PV inverters.

all PV control sources are ranked based on the value of RI . The ranking of PV inverters for voltage control is shown in Table 2.3. To effectively choose an optimal set of controllable PV resources $\mathcal{N}_{cont} \subset \mathcal{N}^{PV}$, a time domain simulation over 24 hours is run to determine the instant of extreme voltage violations in the network. The simulation is carried out assuming there is no voltage control available in the network. The voltage profile without any control action is shown in Fig. 2.9. The extreme voltages are seen to be 1.0826 p.u. and 0.9429 p.u. at node 17 and node 18, respectively. Since the peak over-voltage violation is greater than the peak under-voltage violation, the over-voltage scenario under the given network conditions and available reactive power from PV inverters is considered for voltage correction. The control resources from the ranked set are serially added for extreme voltage correction, to bring down the node voltage below the normal operation limit (1.05 p.u.). The voltage correction for extreme over-voltage scenario requires the 5 top-ranked PV sources $\mathcal{N}_{cont} = \{33, 17, 31, 15, 13\}$ for bringing the voltage within limits. The voltage control for the test network is studied considering two cases:

- **Case (A):** Only PV inverters and coordinated control of PV inverters and OLTC are used for voltage control, assuming no EV load is present in the network.
- **Case (B):** EV loads are added to the 33-bus network at node 14 and node 31 and are

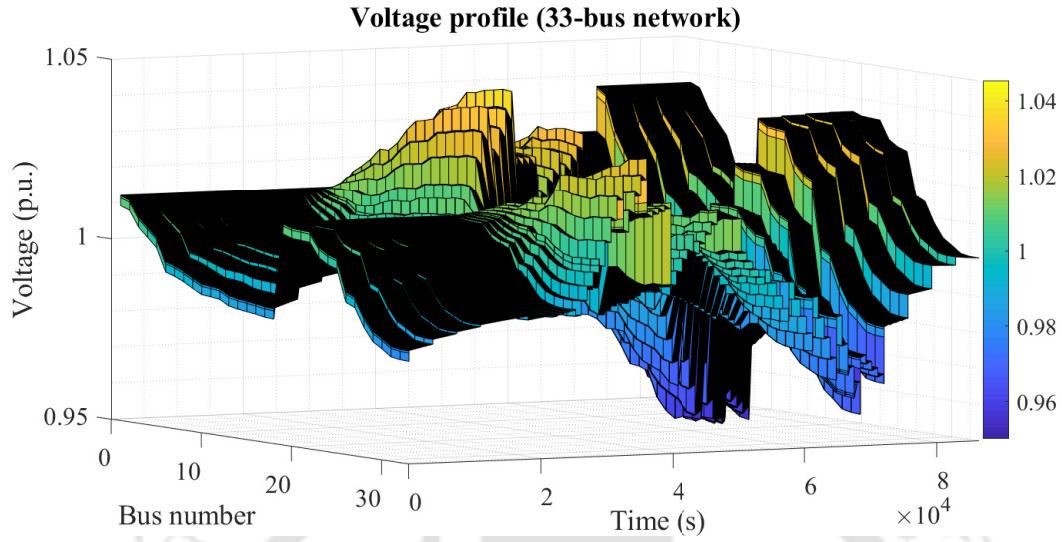


Fig. 2.11: Voltage profile with coordinated control of OLTC and PV inverters.

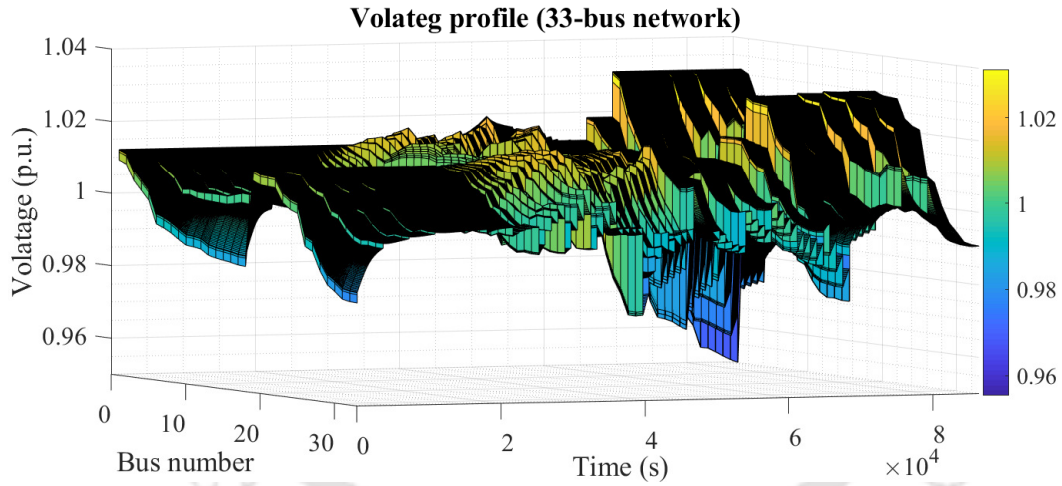


Fig. 2.12: Voltage profile under coordinated control of OLTC, PVs, and EVCSs.

centrally coordinated with PV inverters and OLTC for voltage control.

2.7.1.1 Case A

The network is modelled for observation nodes and node-set $\mathcal{N}_{cont}$. It is considered that the measuring devices are placed at all nodes modeled and at the substation, while communication infrastructure is laid for $\mathcal{N}_{cont}$ node-set and the substation node. The PV inverters of PV set $\mathcal{N}_{cont}$ are used to eliminate voltage violations corresponding to the PV generation profile in Fig. 2.7(a) and load profile in Fig. 2.7(b) using single-stage MPC, assuming no OLTC control. The voltage

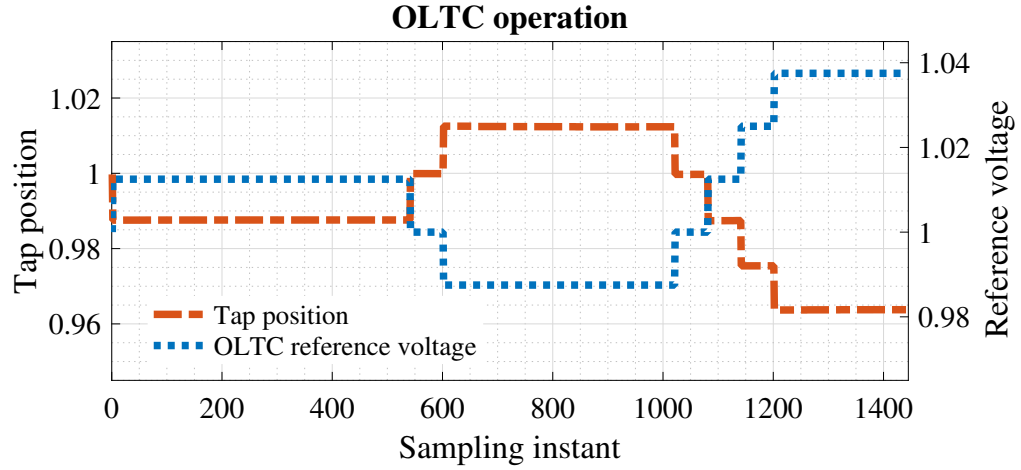


Fig. 2.13: OLTC tap operation with coordination of PV inverters and OLTC.

profile with the selected control set is shown in Fig. 2.10. It can be seen that the voltages remain within the safe operation limits $[0.95, 1.05]$ p.u. It is to be noted that only selected control resources are sufficiently able to maintain voltages within limits. The reactive power exchange by these resources is large from the available inverter reactive power. Furthermore, the controller tries to bring the voltages closer to the nominal value when the voltages are within limits so that the power losses are reduced; however, we can relax this objective to reduce reactive power exchange for any economical or operational constraints of the inverters. The highest and lowest voltage seen after PV control without APC is 1.0460 p.u. and 0.9503 p.u., respectively. Under added control using APC, the minimum/maximum voltage is 1.0349/0.9510 p.u. and the total active power curtailed is 8.5 kWh, as shown in Fig. 2.14(a). Fig. 2.11 shows the voltage profile with PV and OLTC coordinated control using the dual-stage MPC framework. The OLTC tap operation is carried out using if-then-else rules in addition to being centrally coordinated with the controlled PV inverters. The OLTC operation is optimally determined after each hour, and it is seen that 6 tap operations are dispatched by the central controller (Fig. 2.13). The OLTC takes 3s to apply each tap control action. It is to be understood that the OLTC operates with primary winding control, thus, increasing the tap position reduces the voltage at the secondary. Since the reference voltage corresponds to the secondary voltage, the reference voltage above 1 p.u. results in a decrease in tap position and vice versa. The voltage at the primary is always 1 p.u., and with each tap step, the voltage at the secondary changes by 0.00625 p.u. Since

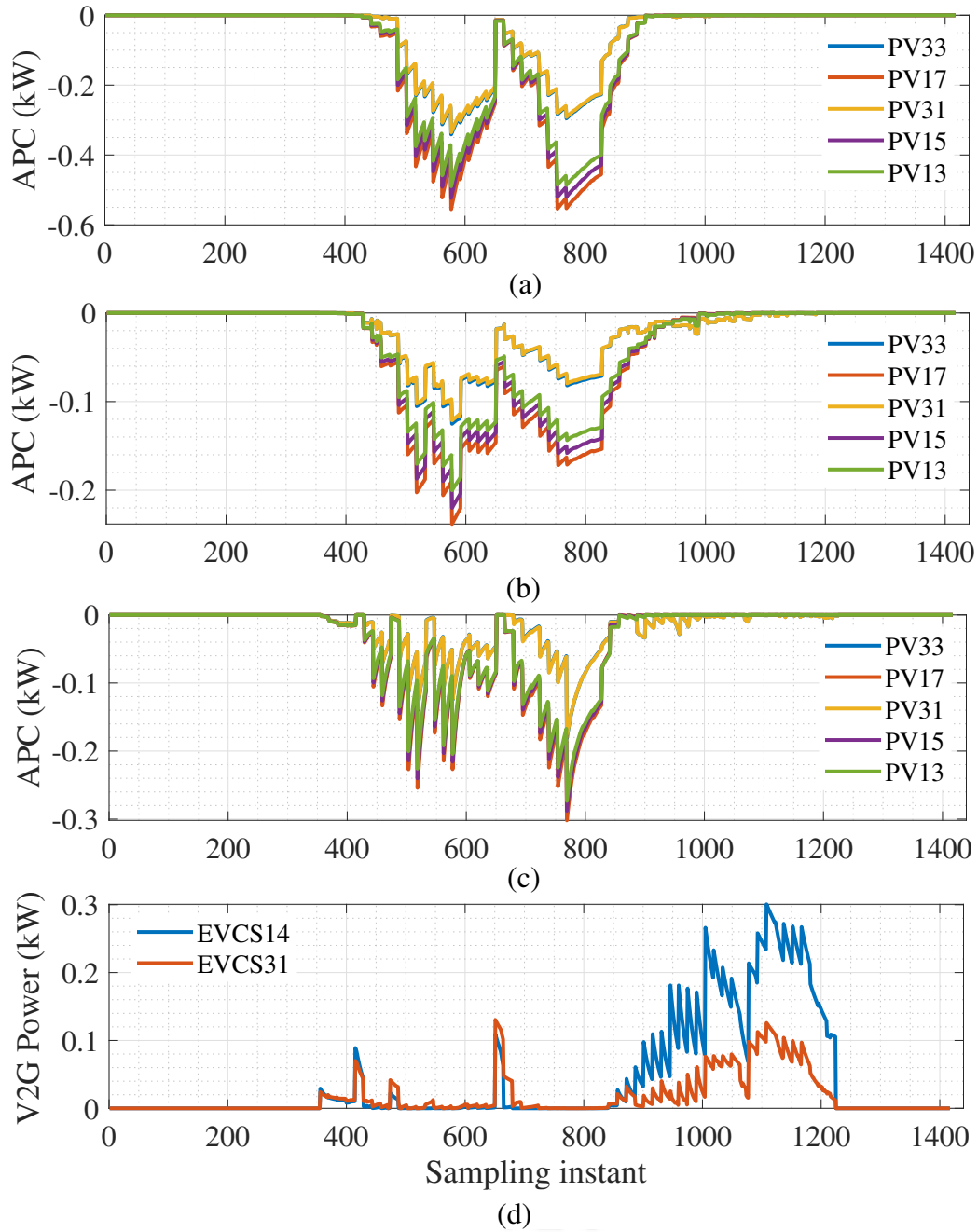


Fig. 2.14: Active power exchange by the control resources with sampling rate of 1-minute: (a) APC in case A with only PV control (b) APC in Case A with PVs and OLTC control (c) APC in Case B with PVs, EVCSs, and OLTC control (d) Active power injection from EV stations using V2G in case B.

the voltages are maintained within limits by PV inverters only, the coordination of OLTC tries to bring voltages closer to the nominal value and reduces the net reactive power injection and absorption significantly. The tap operation can be further reduced by relaxing the objectives of

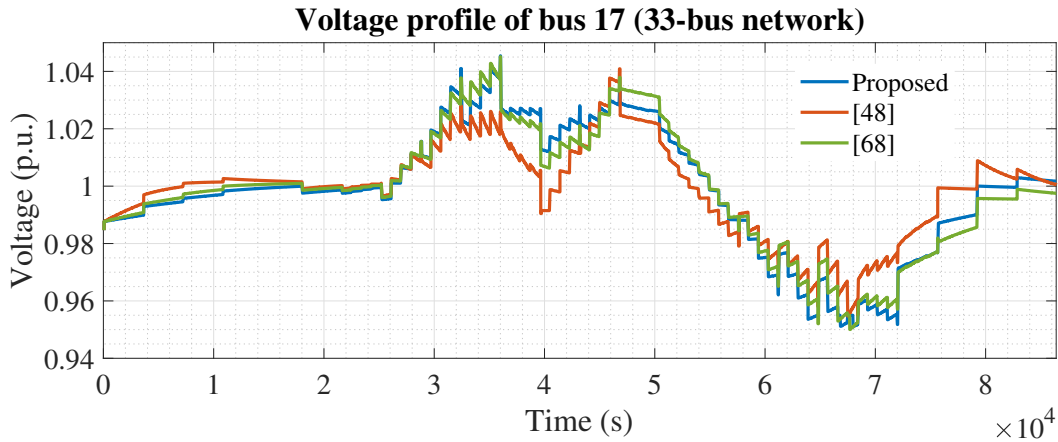


Fig. 2.15: Comparison of voltage using the proposed reduced order model with full order system models.

voltage deviations from the nominal value, however, we may have other objectives, such as power loss minimization, in the optimization formulation. The maximum and minimum voltages after coordinated control of PV inverters and OLTC are 1.0454 p.u. and 0.9504 p.u., respectively, and net curtailed power is 3.6 kW, as shown in Fig. 2.14(b). The APC reduces the reactive power injection/absorption requirement by 0.6411/ 1.5983 MVarh, respectively, as compared to the control without leveraging APC.

2.7.1.2 Case B

An EV load is added to the network in the residential and industrial sections. The EV charging stations are positioned at node 14 and node 31 of the network, each rated 1 MVA. The EV demand profile is shown in Fig. 2.7(a). Simulations are carried out to observe the effects of adding EV load. The EV inverters are brought in for actively controlling voltages with active as well as reactive power exchange in coordination with OLTC and PV inverters, to show their effectiveness in voltage regulation and V2G capabilities. The EV inverters are coordinated with PV inverters and OLTC, assuming that they are equipped with measuring devices and communication to other control devices, and with the centralized controller (at the substation). The voltage profile with EV coordinated control is shown in Fig. 2.12, with minimum and maximum voltages as 1.0312 p.u. and 0.9554 p.u., respectively. By leveraging reactive power from the PV inverters, the minimum voltage is brought up from 0.9700 p.u. to 0.9742 p.u. The net APC and active power injection

Table 2.4: Comparison table of proposed approach with the existing approaches.

Control approach	Test network	Voltage min./max. (p.u.)	Q injection/absorption (MVarh)	Power loss (MWh)
[48]	33-bus	0.9520/1.0425	2.8859/8.7592	2.8295
	123-bus	0.9786/1.0250	9.9426/7.2572	5.5326
[68]	33-bus	0.9511/1.0454	2.9802/8.3960	2.8166
	123-bus	0.9760/1.0250	8.0654/6.9671	5.5618
Proposed	33-bus	0.9521/1.0476	2.1937/8.2233	2.7488
	123-bus	0.9757/1.0204	6.1761/6.8278	5.7884

Table 2.5: Comparison between the full order system model and the proposed reduced order model.

Test system	system model	number of nodes modelled	optimization run time (s) per sample	voltage deviation (p.u.)	
				μ	σ
33-bus network	full order model	33	0.0312	0.0067 (node 17)	0.0085
	reduced order model	08	0.0186		
123-bus network	full order model	123	0.0505	0.0034 (node 94)	0.0043
	reduced order model	07	0.0183		

from EVCS are 3.1 kW and 1.4 kW, respectively, as shown in Fig. 2.14(c) and Fig. 2.14(d), respectively. Even though the active power exchange is less, it significantly reduces the need for reactive power exchange.

To validate the efficacy of the proposed model with reduced measuring infrastructure and control resources as compared to the full-order models, a comparison is made with single-stage MPC in [68] and dual-stage MPC framework in [48]. Bus 17 is chosen for analysis due to its highest voltage violation, and the voltage profiles are shown in Fig. 2.15. Various metrics such as minimum/maximum observed voltage, net reactive power injection/absorption, and total network power losses are used to compare the proposed approach as given in Table 2.4. It is seen that the proposed reduced-order model performs efficiently with all the metrics and is quite comparable to the full-order system models. The net reactive power exchange using the proposed approach in the IEEE 123-bus network is reduced by 23% and 13.3%, compared to the full-order models

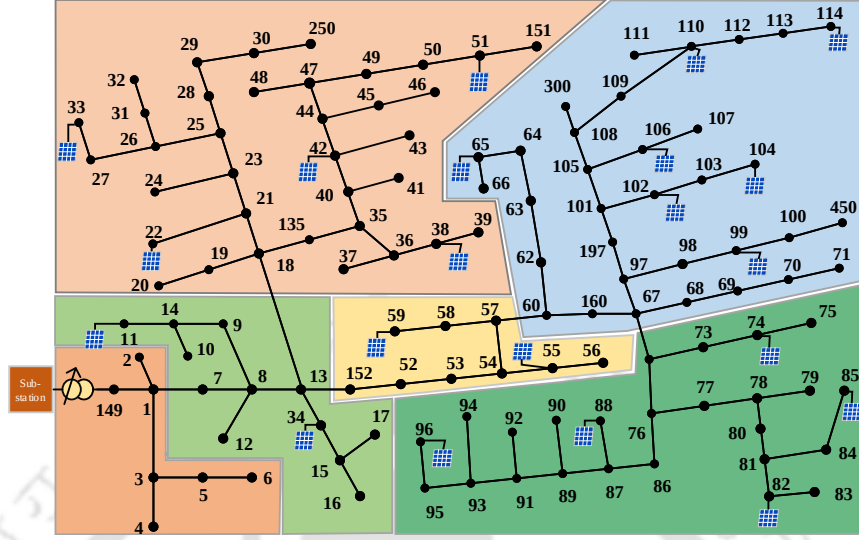


Fig. 2.16: Partitioning of IEEE 123-bus test network using HCA.

in [48] and [68], respectively. Furthermore, it can be seen from the table that the energy losses using the existing approaches are comparable to the proposed reduced-order model. However, the losses in the proposed approach are slightly higher, owing to the reduction in reactive power exchange. Furthermore, a numerical comparison of the proposed model is provided in Table 2.5 with the full-order model in [48], to quantify the voltage deviation in both approaches. In the table, μ refers to the mean voltage difference, and σ is the standard deviation of the voltage difference between the full-order model and the reduced model, over the whole simulation period of 24 hours. Both means as well as standard deviations are quite low, which implies that the proposed reduced-order model performs similarly to the full-order system model.

It can be seen from Table 2.5 that the optimization run time is 18.6 ms for the reduced order model in comparison to 31.2 ms for the full order model for each control step. Considering the communication latency of 150 ms for transferring the set of measurements to the central controller, the complete execution of the control action by the inverters requires 0.3186 s using the proposed control scheme. Nevertheless, the time step for the MPC controller is chosen as 1 minute; the controller can be efficiently used for small time steps if the fast variation in generation and load is considered.

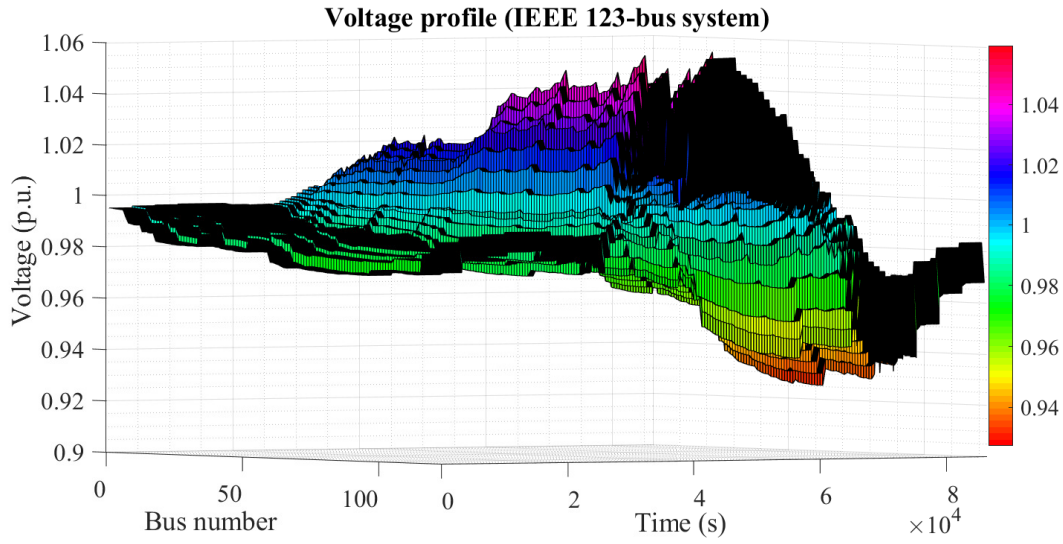


Fig. 2.17: Voltage profile under no control action.

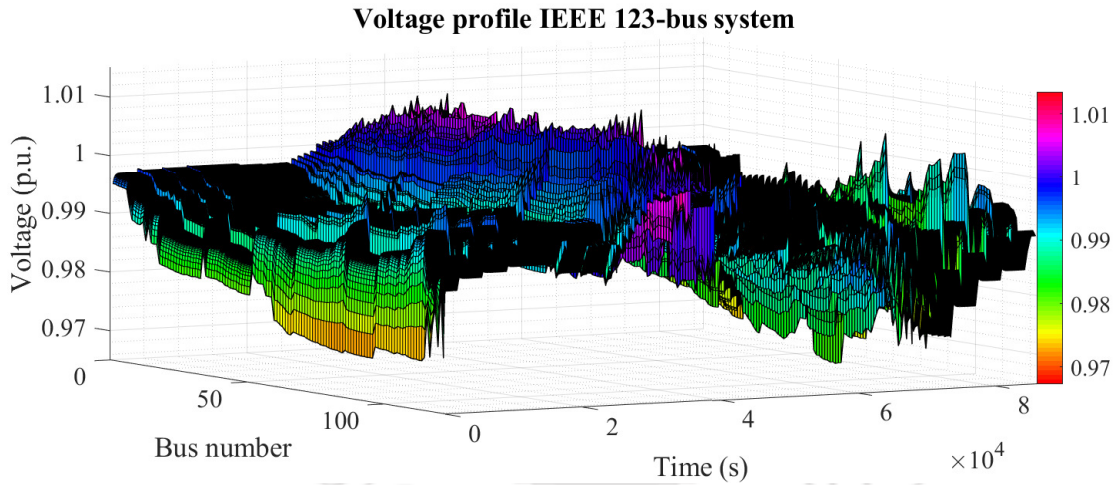


Fig. 2.18: Voltage profile using coordinated control of PV inverters.

2.7.2 IEEE 123-Bus Distribution Network

The proposed model is further validated on a larger IEEE-123 bus distribution network. The modified network is a balanced three-phase network with a nominal voltage of 4.16 kV. The system base power and base voltage are chosen as 1 MVA and 4.16 kV, respectively. The network is fed through an OLTC at node 149, and PVs are distributed as shown in Fig. 2.6 with ratings as described in section V. The network is partitioned into 6 zones as shown in Fig. 2.16, using HCA,

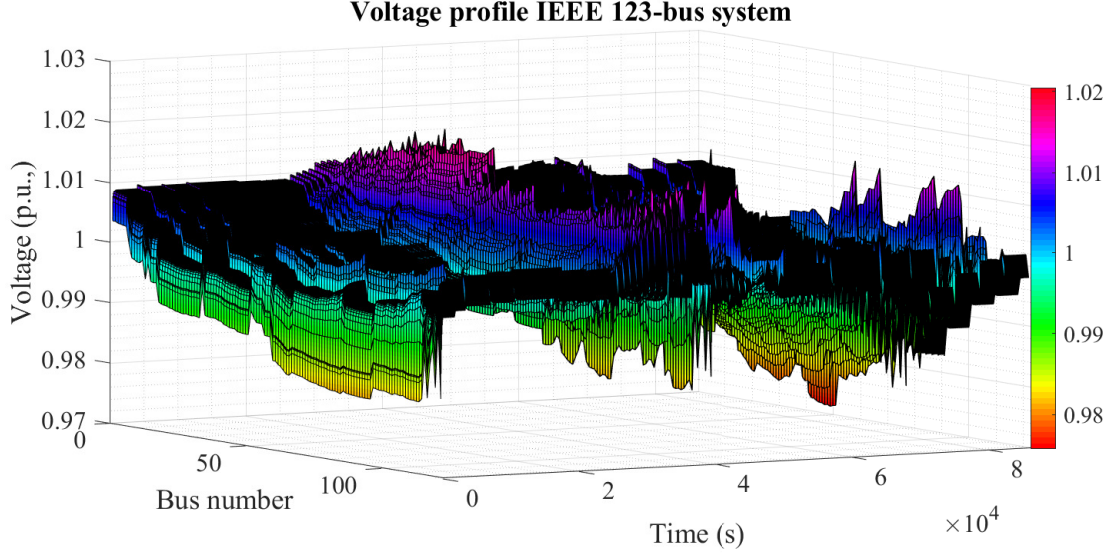


Fig. 2.19: Voltage profile with coordinated control of PV inverters and OLTC.

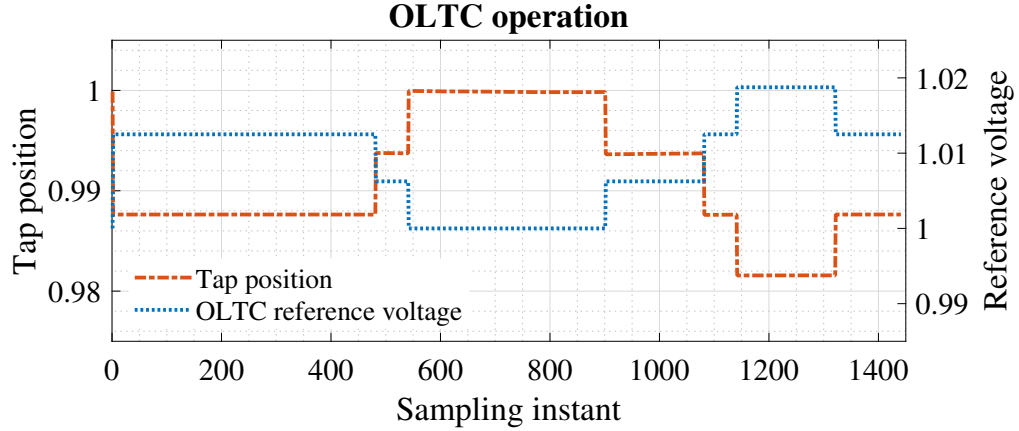


Fig. 2.20: OLTC tap operation with coordination of PV inverters and OLTC corresponding to the sampling rate of 1 minute over the whole time domain simulation.

and the identified set of observation nodes is $\mathcal{N}_{obsv} \subset \mathcal{N} = \{114, 85, 59, 51, 11, 06\}$. Corresponding to observation nodes, the PVs are ranked as shown in Table 2.6. The voltage profile under no voltage regulation is shown in Fig. 2.17, the minimum and maximum voltages are seen to be 0.9272 p.u. and 1.0592 p.u., respectively. The minimum control resource set $\mathcal{N}_{cont} = \{85, 114, 110\}$ is seen to be sufficient to eliminate the extreme voltage violation in the network. The voltage profile using $\mathcal{N}_{cont}$ control resource set (PVs only) with single-stage MPC is shown in Fig. 2.18. The minimum and the maximum voltages after PV control are seen to be 0.9673 p.u. and 1.0135

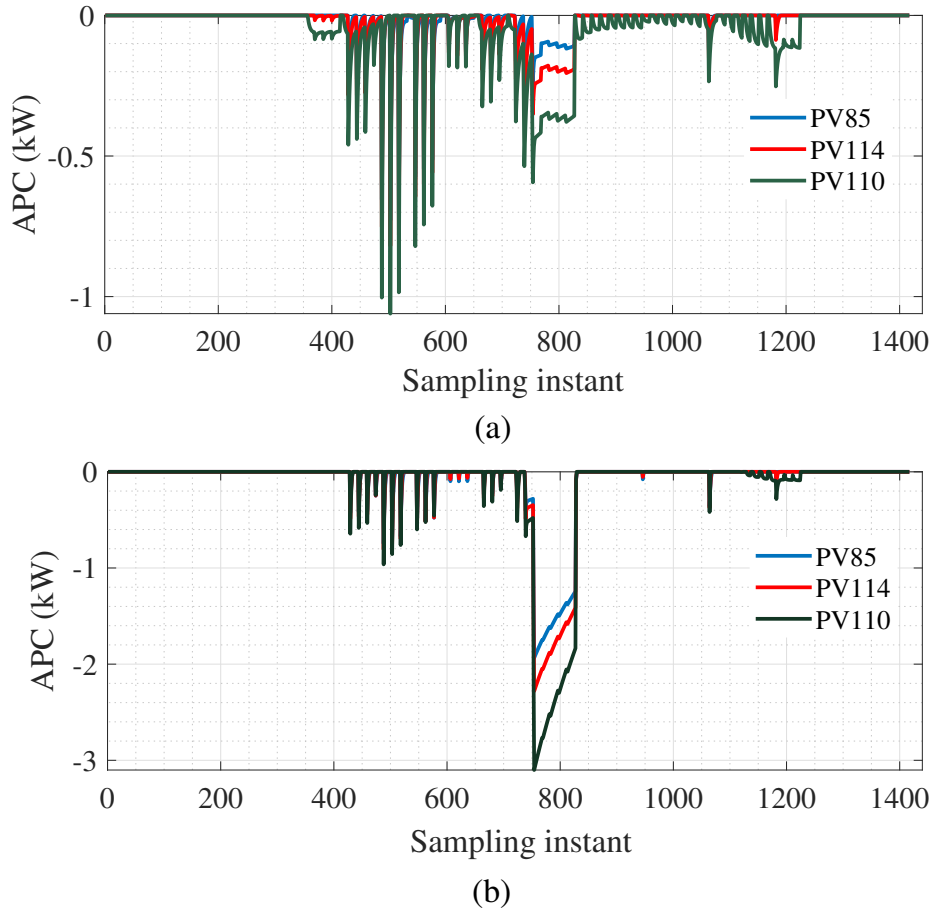


Fig. 2.21: Active power curtailment at the sampling rate of 1-minute: (a) Control action using only PV inverters (b) Control action using PV inverters and OLTC.

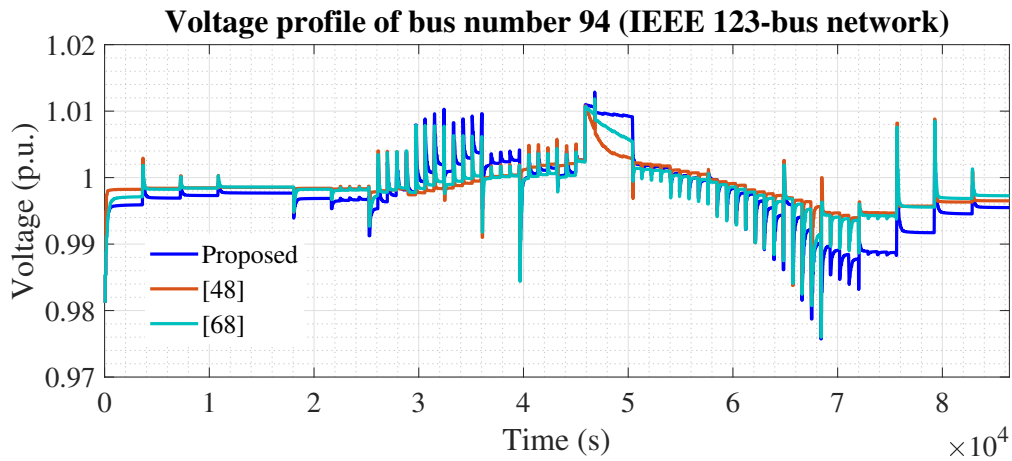


Fig. 2.22: Comparison of voltage profile of bus number 94.

Table 2.6: Ranking of control resources in the IEEE 123-bus distribution network.

Rank	PV node	RI	Rank	PV node	RI
01	85	0.2161	12	65	0.1592
02	114	0.2133	13	59	0.1422
03	110	0.1969	14	51	0.1273
04	82	0.1967	15	55	0.1187
05	106	0.1798	16	42	0.1113
06	96	0.1778	17	38	0.1043
07	88	0.1774	18	33	0.0993
08	104	0.1763	19	22	0.0990
09	102	0.1760	20	34	0.0893
10	74	0.1736	21	11	0.0659
11	99	0.1726			

p.u., respectively, with a net APC of 2.3545 kW. The voltage profile using coordinated control of OLTC and controlled PVs with dual-stage MPC is shown in Fig. 2.19. The maximum and minimum voltages are seen to be 1.0187 p.u. and 0.9756 p.u., respectively, with 7 tap operations as shown in Fig. 2.20, maintaining voltages within the normal operation limits. The total curtailed power from PVs is 2.0228 kW. The coordinated use of OLTC and PVs reduces the reactive power injection from 7.0257 MVarh to 4.6071 MVarh. A comparison of the full order models proposed in [48] and [68] with the proposed reduced order model is provided in Fig. 2.22. The numerical results of the comparison are provided in Table 2.5.

2.8 Conclusion

In this chapter, a dual-stage MPC-based voltage control strategy is presented using a reduced model framework, which utilizes a minimal set of available control resources to mitigate the need for system-wide communication, measuring infrastructure, and computation time. Unlike the full-order system model, the observation and control nodes are only modeled using the linear model for the MPC framework. Furthermore, the controllable nodes and critical observation nodes are assumed to have the necessary measuring infrastructure for real-time control. The minimal set of control resources is identified by ranking the system nodes with control resources, corresponding to critical observation nodes. This is achieved using the numerical voltage sensitivity analysis-based

novel index called the ranking index. The efficacy of the proposed control strategy is verified on the 33-bus network and the IEEE 123-bus distribution network. Compared to the full-order model, the mean and standard deviation of the voltages over the whole simulation period of 24 hours at the critical bus are 0.0034 p.u. and 0.0043 p.u., respectively. Furthermore, the computation time per sample is reduced by 40.38% and 63.73% for the 33-bus network and IEEE 123-bus network, respectively. The comparative results with the existing full-order model approaches show that the power losses are slightly increased in the proposed approach by around 4% in the 123-bus network; however, there is a reduction in the net reactive power exchange by the control resources by 13.3%, while the network voltages are maintained well within the limits.



Chapter 3

A centralized voltage control framework with network energy loss minimization using dual-stage MPC with reduced-model framework

This study extends the work discussed in Chapter 02 to incorporate network energy loss minimization, in addition to the voltage control in ADNs, with high renewable penetration. The MPC model with reduced dimensionality is used with reduced measurement and communication infrastructure, and the use of a reduced number of control resources. The MPC model is modified to incorporate line currents as state variables, in addition to the bus voltages. The quadratic problem formulation including energy loss minimization and the solution strategy is discussed in detail.

3.1 Introduction

The promotion of low-carbon and energy-efficient systems is highly encouraged worldwide, by turning to renewable energy resources, such as photovoltaic (PV) sources. Distributed generation

(DG) units provide functionalities, such as network flexibility, sustainability, and reduced cost of energy loss in addition to the provision of green energy [66]. However, the DN operators may face many technical challenges in active network management (ANM), such as large and frequent voltage deviations, demanding considerable attention. The conventionally employed voltage regulation methods using OLTC and reactive power from switched capacitors show incompetence in dealing with frequent voltage fluctuations, due to their slow operation [108]. Thus, reactive power from DG units with power electronic inverter interface offers viable and fast real-time voltage support, so as to avoid network reinforcements. A voltage regulation algorithm is proposed in [109] with proportional power compensation leveraging voltage sensitivity analysis. The active and reactive power of PVs and battery energy storage systems (BESSs) are utilized to address regional voltage violations in ADNs. Considering the reliability of PV inverters employed in ADNs for volt/var control (VVC), a reliability-constrained VVC scheme is proposed in [110] for voltage regulation and energy loss minimization in ADNs, utilizing the reactive power capability of PV inverters, as well as active power curtailment (APC). It is worth mentioning that over-voltages can easily and effectively be mitigated by active power curtailment of PV sources; however, it is discouraged by PV owners due to loss of revenue [111]. To centrally coordinate fast-acting devices like PV and EV charging station inverters, storage units, and slow-acting devices like OLTC and CBs, the control scheme needs to incorporate the temporal characteristics of these devices. For this purpose, multi-time scale optimal coordination has been studied in [48,69], wherein the slow-acting devices are coordinated at a slow time scale while fast response control devices are regulated at a faster time scale.

As mentioned in the previous chapter, centrally coordinated control schemes are widely studied and easy to implement; however, they require large communication and measurement infrastructure throughout the network [112]. Furthermore, during the large over-voltages the PV inverters draw large lagging currents to lower voltages, thus deteriorating the feeder power factor and consequently leading to a remarkable increase in line power losses [3]. MPC-based voltage control is proposed in [68], wherein all PV buses, and the buses at the end of the feeder are monitored. However, the energy loss minimization is not considered, and the MPC framework is single-stage.

Furthermore, the OLTC is operated based on the voltage at the local bus, and is not considered

Table 3.1: Comparison of existing works with the proposed work.

Ref.	Control approach	Reduced number of sensors and measuring infrastructure	Reduced number of control resources	Energy loss Minimization
[48]	Dual-stage MPC	×	×	✓
[68]	Single-stage MPC	✓	×	×
[66]	Two-time Scale MPC	×	×	×
[63]	Double-layer MPC	×	×	×
[56]	Index-based	×	✓	×
Proposed	Dual-stage MPC	✓	✓	✓

in the optimization problem of the central controller. Even though the control mechanism of the OLTC used is simpler, the excessive and unnecessary tap operations may be triggered under simultaneous over-voltage and under-voltage conditions in the network. However, in the presented control scheme, the optimization is carried out at two stages, and the optimal operation of the OLTC considers the states throughout the network, rather than the voltage of the local bus. To identify the effective control resources in the network, an index-based voltage control strategy is proposed in [56]. However, monitoring of all the network nodes is needed to identify voltage violations, and different cases require different sets of control resources among all the available resources. Furthermore, the energy loss minimization is not taken into account. Double-layer stochastic MPC is used in [63] to regulate voltages using OLTC, capacitor banks (CBs), and active power curtailment (APC). Though power loss minimization is also carried out with real-time control, however, all the control resources present in the network are used for control purposes. Thus, in the existing works, either all the devices present in the network are assumed to be controllable for real-time voltage regulation, or the energy loss minimization is not considered. To the best of the authors' knowledge, there is no multi-time scale centralized scheme that controls voltages and minimizes network power losses, with minimum use of control resources and reduced number of sensors and measuring infrastructure. To address the above-mentioned research gaps, the work carried out in this chapter presents a dual-stage MPC-based reduced model framework for voltage control that relieves the number of sensors and measurement devices required (as explained in the previous chapter), and performs the network energy loss minimization as well. A

comparison of the proposed control model with the existing control schemes is given in Table 3.1.

The main objectives of the work carried out in this chapter are -

1. Development of dual-stage MPC-based control framework with reduced dimensionality of the system model, for voltage control in ADNs with high PV penetration, and EV charging stations.
2. Incorporation of network energy loss minimization using the proposed reduced order model framework, along with the voltage control using only the most effective control resources.

This chapter is organized as follows: Section 3.2 provides the MPC framework with energy loss minimization. Section 3.3 discusses the problem formulation, Section 3.4 provides a brief discussion on the control model with reduced dimensionality, and Section 3.5 provides the simulation results on the two test networks and the related discussion. Finally, Section 3.6 provides the conclusive remarks of this chapter.

3.2 MPC Control Framework

The linearized model used by the MPC for voltages is given by Eq. (6.3), which is expressed as,

$$\mathbf{V}(\kappa + 1) = \mathbf{V}(\kappa) + \mathbf{S}_V^p \Delta \mathbf{p} + \mathbf{S}_V^q \Delta \mathbf{q} + \mathbf{S}_V^{\text{tap}} \Delta \mathbf{V}_0 \quad (3.1)$$

The voltage sensitivity coefficients ($\mathbf{S}_V^p$, $\mathbf{S}_V^q$ and $\mathbf{S}_V^{\text{tap}}$) in Eq. (3.1), and derived from the linearized model depend upon the line parameters, given by vector $\mathbf{r}$ and vector $\mathbf{x}$, corresponding to line resistances and line reactances, respectively. However, the sensitivity coefficients may slightly vary due to the variation in complex power injection at the network nodes, if the non-linear dynamics of the system are considered. For MPC-based real-time control, the sensitivities are treated as constant in this study. Furthermore, $\Delta \mathbf{p}$ and $\Delta \mathbf{q}$ correspond to controllable power and do not consider the uncertain disturbance in power injection. The disturbances and modelling inaccuracies are handled by the closed-loop nature of MPC, and by the receding horizon control with real-time measurements, at every control step. Similar to the voltages, we can write the linear evolution of line currents with change in active and reactive power injections and change

in OLTC tap position as [63],

$$\mathbf{I}(\kappa + 1) = \mathbf{I}(\kappa) + \mathbf{S}_I^p \Delta \mathbf{p}(\kappa) + \mathbf{S}_I^q \Delta \mathbf{q}(\kappa) + \mathbf{S}_I^{\text{tap}} \Delta \mathbf{V}_0(\kappa) \quad (3.2)$$

where, the vector of line currents $\mathbf{I}(\kappa)$ at time step κ are measured state inputs to the MPC-based controller. The vectors $\mathbf{S}_I^p$, $\mathbf{S}_I^q$, and $\mathbf{S}_I^{\text{tap}}$ are the current sensitivities with respect to change in active power injection, reactive power injection, and OLTC voltage, respectively. The sensitivities of currents with respect to the complex power injections are functions of the power injection at the buses, and thus need to be evaluated at each step of control action, under the current system state. The linearized distribution network model detailed in Eq. (2.19) and Eq. (2.20) is utilized for the MPC-based control framework, and is written as,

$$\boldsymbol{\xi}(\kappa + 1) = \hat{\mathbf{A}}\boldsymbol{\xi}(\kappa) + \hat{\mathbf{B}}\Delta \mathbf{u}(\kappa) \quad (3.3)$$

$$\mathbf{y}_p(\kappa) = \hat{\mathbf{C}}\boldsymbol{\xi}(\kappa) \quad (3.4)$$

The state variable vector $\boldsymbol{\xi}(\kappa + 1)$ in the state space model in Eq. (3.3) corresponds to the bus voltages and line currents. The output vector $\mathbf{y}_p(\kappa) = [\mathbf{y}_{p1}^\top(\kappa) \ \mathbf{y}_{p2}^\top(\kappa)]^\top$ represents the system voltages and currents, corresponding to the output matrix $\hat{\mathbf{C}} = [\hat{\mathbf{C}}_1^\top \ \hat{\mathbf{C}}_2^\top]^\top$. The vector of system states $\boldsymbol{\xi}(\kappa)$, at time step κ is acquired through real-time measurements. The vector of measured states can be written as $\boldsymbol{\xi}(\kappa) = [\boldsymbol{\xi}_1^\top(\kappa) \ \boldsymbol{\xi}_2^\top(\kappa)]^\top$, where the vector $\boldsymbol{\xi}_1(\kappa)$ corresponds to the voltage measurements at specified nodes, and $\boldsymbol{\xi}_2(\kappa)$ corresponds to the line current measurements. The output vector $\mathbf{y}_{p1}(\kappa)$ represents the predicted node voltages corresponding to output matrix $\hat{\mathbf{C}}_1$, and $\mathbf{y}_{p2}(\kappa)$ represents the predicted line currents corresponding to output matrix $\hat{\mathbf{C}}_2$. The voltages of certain buses and currents are chosen as state variables for the MPC model in this study. Thus, the predicted output over the prediction horizon (N_p) can be expressed in terms of measurements and optimal inputs (over the whole control horizon (N_c)) as,

$$\mathbf{Y}_p = \boldsymbol{\chi}\boldsymbol{\xi}(\kappa) + \boldsymbol{\psi}\Delta \mathbf{U} \quad (3.5)$$

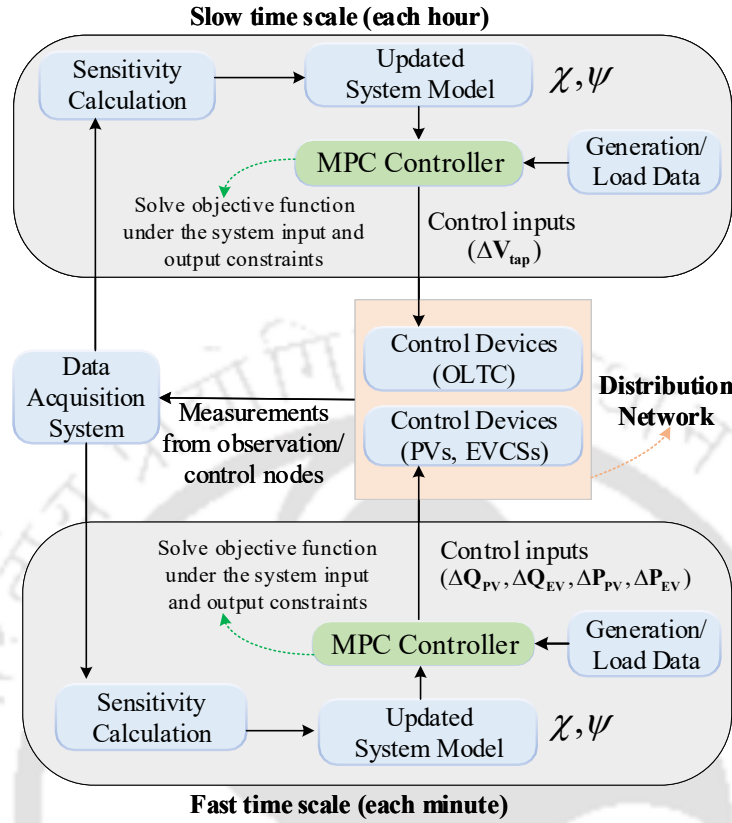


Fig. 3.1: Architecture of the proposed MPC-based control scheme.

where, $\mathbf{Y}_p = [\mathbf{Y}_{p1}^\top \ \mathbf{Y}_{p2}^\top]^\top$, $\chi = [\chi_1^\top \ \chi_2^\top]^\top$, $\psi = [\psi_1^\top \ \psi_2^\top]^\top$. The detailed structure of the matrices χ and ψ based on the system matrix $\hat{\mathbf{A}}$, input matrix $\hat{\mathbf{B}}$, and system output matrix $\hat{\mathbf{C}}$ is given by Eq. (2.24) and Eq. (2.25), respectively, in Section 2.3. Since the model uses change in control input to predict the system behavior, the control inputs themselves are given by,

$$\mathbf{U}(\kappa) = \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) + \hat{\mathbf{H}}\Delta\mathbf{U} \quad (3.6)$$

The dimensions of the matrices used in Eq. (3.5) and Eq. (3.6) are given as: $\mathbf{Y}_p \in \mathbb{R}^{\mathcal{O}.N_p \times 1}$, $\mathbf{U} \in \mathbb{R}^{\mathcal{O}.N_c \times 1}$, $\chi \in \mathbb{R}^{\mathcal{O}.N_p \times \mathcal{S}}$, $\psi \in \mathbb{R}^{\mathcal{O}.N_p \times \mathcal{I}.N_c}$, $\hat{\mathbf{G}} \in \mathbb{R}^{\mathcal{I}.N_c \times \mathcal{I}}$, and $\hat{\mathbf{H}} \in \mathbb{R}^{\mathcal{I}.N_c \times \mathcal{I}.N_c}$. The schematic of the proposed control architecture is shown in Fig. 3.1. Nevertheless, the optimal control sequence is determined over the whole control horizon; however, only the control inputs at the first time step are assimilated by the receding horizon control strategy. The moving horizon window with receding horizon control enables incorporating fresh measured system states quite frequently, at each control step, to recompense for any modelling inaccuracies or deviations in the

sensitivity coefficients.

3.3 Problem Formulation

The objectives considered for coordinated control involve the minimization of output deviations (voltage deviations) from the reference vector $\tilde{\mathbf{Y}}_{\mathbf{p1}}$, minimization of control actions ($\Delta\mathbf{U}$), and minimization of line losses ($\mathbf{p}_l$). The objective function is formulated as a quadratic programming problem given as,

$$\min \|\tilde{\mathbf{Y}}_{\mathbf{p1}} - \mathbf{Y}_{\mathbf{p1}}\|_{\mathbf{w}_v}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 + \|\Delta\mathbf{U}\|_{\mathbf{w}_u}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1} \quad (3.7)$$

subjected to the system input constraints and output constraints as,

$$\underline{\underline{\Delta\mathbf{U}}} \leq \Delta\mathbf{U} \leq \overline{\overline{\Delta\mathbf{U}}} \quad (3.8a)$$

$$\underline{\underline{\mathbf{U}}} \leq \mathbf{U} \leq \overline{\overline{\mathbf{U}}} \quad (3.8b)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{Y}_{\mathbf{p1}}}} \leq \mathbf{Y}_{\mathbf{p1}} \leq \overline{\overline{\mathbf{Y}_{\mathbf{p1}}}} + \sigma_2 \mathbf{1} \quad (3.8c)$$

$$0 \leq \mathbf{Y}_{\mathbf{p2}} \leq \overline{\overline{\mathbf{Y}_{\mathbf{p2}}}} + \sigma_3 \mathbf{1} \quad (3.8d)$$

The output constraints are relaxed under solution infeasibility, by using a highly penalized slack variable vector $\boldsymbol{\sigma} = [\sigma_1 \ \sigma_2 \ \sigma_3]^\top$ in the objective function. The output vectors $\mathbf{Y}_{\mathbf{p1}}$ and $\mathbf{Y}_{\mathbf{p2}}$ correspond to the bus voltages and line currents, respectively. The matrices $\mathbf{w}_v, \mathbf{w}_u, \mathbf{w}_s, \mathbf{w}_1$ are diagonal weight matrices associated with different objectives, as discussed in Section 2.4. The matrix $\mathbf{w}_s$ is highly weighted so that the slack variables take values only when the optimal solution is not found within the constraint limits. The objective function in Eq. (3.7) consists of terms corresponding to output variables (voltages/currents), power losses, control inputs, and slack variables. Using Eq. (3.5) the objective function given in Eq. (3.7) can be written as,

$$\min \|\tilde{\mathbf{Y}}_{\mathbf{p1}} - \chi_1 \boldsymbol{\xi}(\kappa) - \psi_1 \Delta\mathbf{U}\|_{\mathbf{w}_v}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 + \|\chi_2 \boldsymbol{\xi}(\kappa) + \psi_2 \Delta\mathbf{U}\|_{\mathbf{w}_1}^2 + \|\Delta\mathbf{U}\|_{\mathbf{w}_u}^2 \quad (3.9)$$

The objective function given in Eq. (3.9) can be written in expanded form as,

$$\begin{aligned} & \left(\tilde{\mathbf{Y}}_{\mathbf{p1}} - \chi_1 \boldsymbol{\xi}(\kappa) - \psi_1 \Delta \mathbf{U} \right)^\top \mathbf{w}_v \left(\tilde{\mathbf{Y}}_{\mathbf{p1}} - \chi_1 \boldsymbol{\xi}(\kappa) - \psi_1 \Delta \mathbf{U} \right) + \\ & (\chi_2 \boldsymbol{\xi}(\kappa) + \psi_2 \Delta \mathbf{U})^\top \mathbf{w}_l \mathbf{R}_l (\chi_2 \boldsymbol{\xi}(\kappa) + \psi_2 \Delta \mathbf{U}) + (\Delta \mathbf{U})^\top \mathbf{w}_u (\Delta \mathbf{U}) + (\boldsymbol{\sigma})^\top \mathbf{w}_s (\boldsymbol{\sigma}) \end{aligned} \quad (3.10)$$

The objective function, as given in Eq. (3.10) is solved as a box-constrained standard quadratic programming (QP) problem as,

$$\min \frac{1}{2} \begin{bmatrix} \Delta \mathbf{U} \\ \boldsymbol{\sigma} \end{bmatrix}^\top \mathbf{H} \begin{bmatrix} \Delta \mathbf{U} \\ \boldsymbol{\sigma} \end{bmatrix} + \mathbf{f} \begin{bmatrix} \Delta \mathbf{U} \\ \boldsymbol{\sigma} \end{bmatrix} \quad (3.11)$$

subjected to,

$$\mathbf{M} \Delta \mathbf{U} \leq \mathbf{m} \quad (3.12)$$

where, the Hessian matrix $\mathbf{H}$ and the matrix $\mathbf{f}$ are given as,

$$\mathbf{H} = \begin{bmatrix} 2(\psi_1^\top \mathbf{w}_v \psi_1 + \psi_2^\top \mathbf{w}_l \mathbf{R}_l \psi_2 + \mathbf{w}_u) & \mathbf{0} \\ \mathbf{0} & \mathbf{w}_s \end{bmatrix} \quad (3.13)$$

$$\mathbf{f} = \begin{bmatrix} 2([\chi_1 \boldsymbol{\xi}(\kappa) - \tilde{\mathbf{Y}}_{\mathbf{p1}}]^\top \mathbf{w}_v \psi_1 + [\chi_2 \boldsymbol{\xi}(\kappa)]^\top \mathbf{w}_l \mathbf{R}_l \psi_2)^\top \\ \mathbf{0} \end{bmatrix}^\top \quad (3.14)$$

Here $\mathbf{0}$ is the null matrix and $\mathbf{R} := \text{diag}[\mathbf{r}_{(1)}^\top \mathbf{r}_{(2)}^\top \dots \mathbf{r}_{(N_p)}^\top]^\top$, corresponding to the vector $\mathbf{r}$ of line resistances. The constraint matrices $\mathbf{M}$ and $\mathbf{m}$ are expressed as

$$\mathbf{M} = \begin{bmatrix} \mathbf{H} \\ -\mathbf{H} \\ \hat{\psi}_1 - \mathbf{S}_{v2} \\ -\hat{\psi}_1 - \mathbf{S}_{v1} \\ \hat{\psi}_2 - \mathbf{S}_i \\ \mathbf{I} \\ -\mathbf{I} \end{bmatrix}; \quad \mathbf{m} = \begin{bmatrix} \overline{\overline{\mathbf{U}}} - \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) \\ -\underline{\underline{\mathbf{U}}} + \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) \\ \overline{\overline{\mathbf{Y}}_{\mathbf{p1}}} - \chi_1 \boldsymbol{\xi}(\kappa) \\ -\underline{\underline{\mathbf{Y}}_{\mathbf{p1}}} + \chi_1 \boldsymbol{\xi}(\kappa) \\ \overline{\overline{\mathbf{Y}}_{\mathbf{p2}}} - \chi_2 \boldsymbol{\xi}(\kappa) \\ \underline{\underline{\Delta \mathbf{U}}} \\ -\underline{\underline{\Delta \mathbf{U}}} \end{bmatrix} \quad (3.15)$$

where,

$$\mathbf{H} = \begin{bmatrix} \hat{\mathbf{H}} & \mathbf{0}_1 \\ \mathbf{0}_1^\top & \mathbf{I}_1 \end{bmatrix}; \hat{\boldsymbol{\psi}}_1 = \begin{bmatrix} \boldsymbol{\psi}_1^\top \\ \mathbf{0}_2 \end{bmatrix}^\top \quad (3.16)$$

The matrices $\mathbf{0}_1, \mathbf{0}_2$ are null matrices and $\mathbf{I}, \mathbf{I}_1, \mathbf{I}_2$ are identity matrices. Matrices $\mathbf{S}_{v1}, \mathbf{S}_{v2}, \mathbf{S}_i$ are related as: $\mathbf{S}_{v1}\Delta\mathbf{U} = \sigma_1\mathbf{1}$, $\mathbf{S}_{v2}\Delta\mathbf{U} = \sigma_2\mathbf{1}$ and $\mathbf{S}_i\Delta\mathbf{U} = \sigma_3\mathbf{1}$.

The time-decomposition of the coordinated control scheme optimizes the operation of OLTC at the first layer (each hour) and fast devices such as PV and EVCS inverters at the second layer (each minute). The MPC-based control effectively addresses the different temporal characteristics of control devices, thus preventing the excessive tap operation of OLTC. At the first stage, the OLTC operation is optimized with the following objective function:

$$\min \sum_{i=1}^{N_p} \left(\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1} \right) + \sum_{i=1}^{N_c} \|\Delta\mathbf{V}_{\text{tap}}(\kappa + i)\|_{\mathbf{w}_u}^2 \quad (3.17)$$

subjected to the constraints,

$$\underline{\underline{\Delta\mathbf{V}_{\text{tap}}}} \leq \Delta\mathbf{V}_{\text{tap}} \leq \overline{\overline{\Delta\mathbf{V}_{\text{tap}}}} \quad (3.18a)$$

$$\underline{\underline{\mathbf{V}_{\text{tap}}}} \leq \mathbf{V}_{\text{tap}}(\kappa + i) \leq \overline{\overline{\mathbf{V}_{\text{tap}}}} \quad (3.18b)$$

$$-\sigma_1\mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} + \sigma_2\mathbf{1} \quad (3.18c)$$

$$\mathbf{I}(\kappa + 1) \leq \overline{\overline{\mathbf{I}}} + \sigma_3\mathbf{1} \quad (3.18d)$$

where, $\boldsymbol{\sigma} = [\sigma_1 \ \sigma_2 \ \sigma_3]^\top$. It is to be mentioned that the change in OLTC tap position is treated as a continuous variable in the optimization; however, the actual position is obtained by rounding off the optimal value to the nearest discrete tap position. The tap position remains constant for 1 hour and is updated at the beginning of the next hour. In the second stage, fast-acting PV and EVCS inverter operations are optimized with the following objective function:

$$\min \sum_{i=1}^{N_p} \left(\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1} \right) + \sum_{i=1}^{N_c} \left(\|\Delta\mathbf{Q}_{\text{PV}}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta\mathbf{Q}_{\text{EV}}(\kappa + i)\|_{\mathbf{w}_q}^2 \right) \quad (3.19)$$

subjected to the constraints,

$$\underline{\underline{\Delta Q_{PV}}} \leq \Delta Q_{PV}(\kappa + i) \leq \overline{\overline{\Delta Q_{PV}}} \quad (3.20a)$$

$$\underline{\underline{\Delta Q_{EV}}} \leq \Delta Q_{EV}(\kappa + i) \leq \overline{\overline{\Delta Q_{EV}}} \quad (3.20b)$$

$$\underline{\underline{Q_{PV}}} \leq Q_{PV}(\kappa + i) \leq \overline{\overline{Q_{PV}}} \quad (3.20c)$$

$$\underline{\underline{Q_{EV}}} \leq Q_{EV}(\kappa + i) \leq \overline{\overline{Q_{EV}}} \quad (3.20d)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} + \sigma_2 \mathbf{1} \quad (3.20e)$$

$$\mathbf{I}(\kappa + i) \leq \overline{\overline{\mathbf{I}}} + \sigma_3 \mathbf{1} \quad (3.20f)$$

It is to be noted that the operation of PV inverters and EVCS inverters is essentially the same for distribution network voltage regulation. However, the availability of the reactive power is dependent on the active power exchange by the inverter. During the day, the reactive power availability of the PV inverters is less due to high active power exchange, while the reactive power availability of EVCS inverters is different in residential and industrial sections of the network, due to varying charging patterns (i.e. arrival time, departure time, and time of charging of electric vehicles) at the charging station. Furthermore, the PV inverters are kept slightly overrated so as to provide reactive power of at least 44% of the active power exchange, even under peak generation, as recommended for DG units in IEEE standard 1547 [17]. However, the EVCSs are not considered as overrated in this study; thus, the reactive power availability may be zero under the conditions when the charging demand (kW) is equal to the KVA rating of the inverter.

3.4 Control Model with Reduced Dimensionality

The MPC-based control framework needs real-time estimates of system states to predict and optimize the system behavior. The imperative communication among all resources and measuring infrastructure that spans the whole network increases both cost as well as complexity in real-time control. Achieving an efficacious coordinated control, while minimizing the required measurement

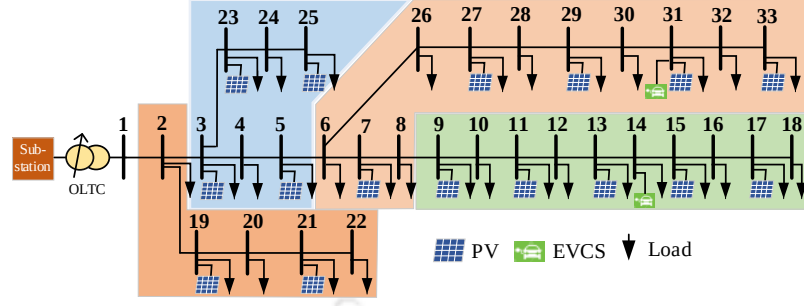


Fig. 3.2: 33-bus test network with partitioning using HCA.

infrastructure, necessitates the sensible identification of network nodes exhibiting more sensitivity to deviations in network voltages. Furthermore, the identification of the most effective control resources from the available resources and their coordination can reduce the need for an expansive communication setup. The reduced model framework, discussed in Section 2.5 in the previous chapter, uses only selected nodes in the MPC linear model formulation, thus making the multi-step corrective control effective for successfully regulating the network voltages with fewer sensors and less communication setup. The critical nodes (observation nodes) are identified based on network clustering using HCA, as discussed in Section 2.5.1.1. Furthermore, the identification of a minimal set of available control resources is carried out by ranking the resources using the ranking index, as explained in Section 2.5.2.

3.5 Simulation Results and Discussion

The proposed dual-stage MPC-based voltage control strategy is validated on the 33-bus distribution network and IEEE 123-bus distribution network as shown in Fig. 3.2 and Fig. 3.3, respectively. Both the test networks considered are assumed to be three-phase balanced systems. The substations are equipped with an OLTC, which is centrally coordinated for regulating the system voltage. The OLTC has 32 tap steps with primary winding control, as discussed in Chapter 2. The PV generation profile, EV load profiles, and load profiles considered in Chapter 2, and shown in Fig. 3.4 and Fig. 3.5 are considered here as well. The charging profiles are determined based on the number of electric vehicles arriving/departing from the EV charging station, time of arrival/departure, charging time, and state of charge of the EV battery. The arrival/departure

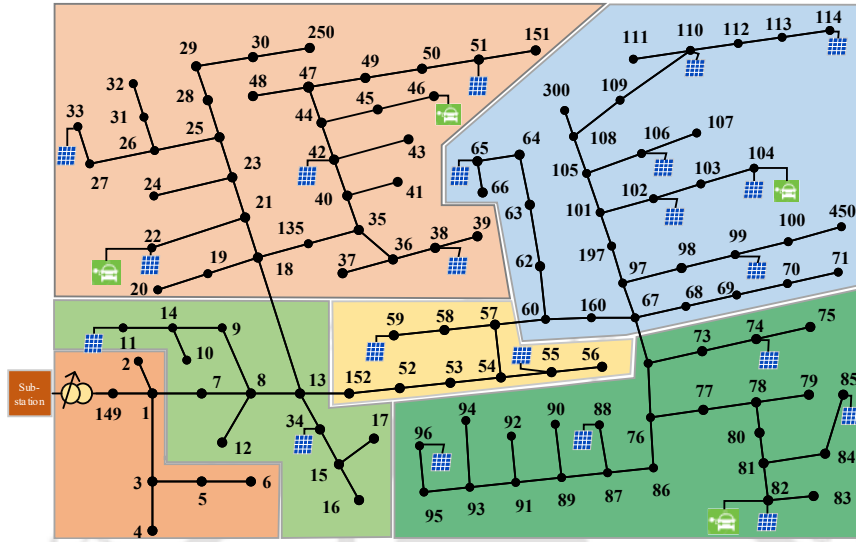


Fig. 3.3: IEEE 123-bus test network with partitioning using hierarchical clustering algorithm (HCA).

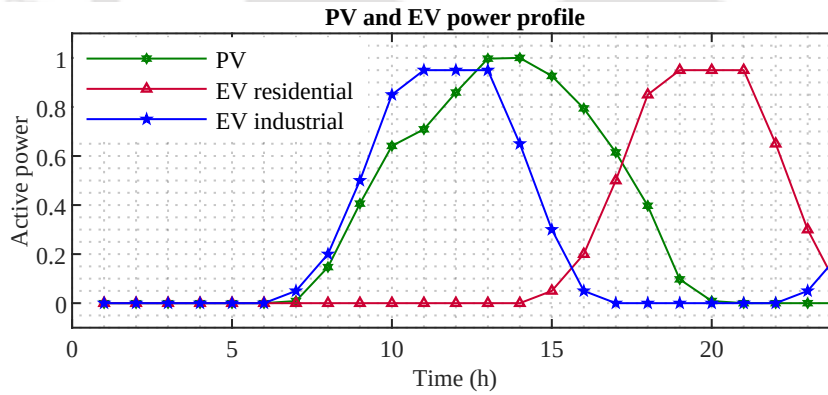


Fig. 3.4: PV generation profile and EV demand profile.

times for EVs in the residential section and the industrial section are different. The number of EVs arriving during the day, both in the residential section as well as the industrial section are depicted in Fig. 3.6. Since the sampling time for the fast time scale MPC (corresponding to PV and EVCS inverters) is considered as 1 minute, the measurements from the network and the charging stations are taken at each sampling instant. It is assumed that the EV demand has small variations from the assumed load profile within the sampling period considered. Furthermore, the small uncertainties and modeling inaccuracies are mitigated by the closed-loop nature of MPC and the receding horizon control strategy, which incorporates fresh measurements at each

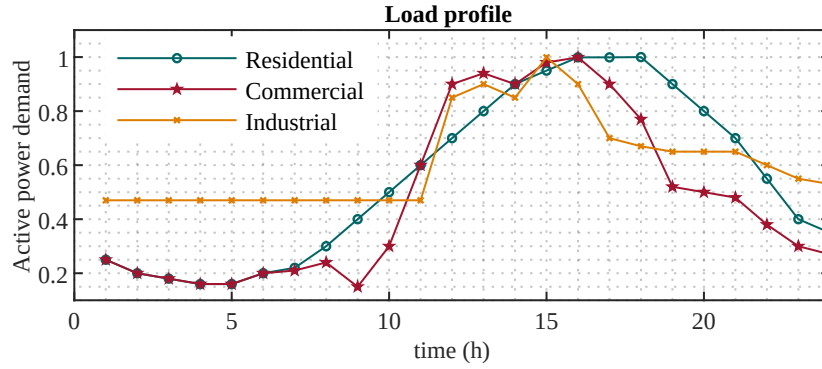


Fig. 3.5: Load demand profiles for residential, commercial, and industrial loads.

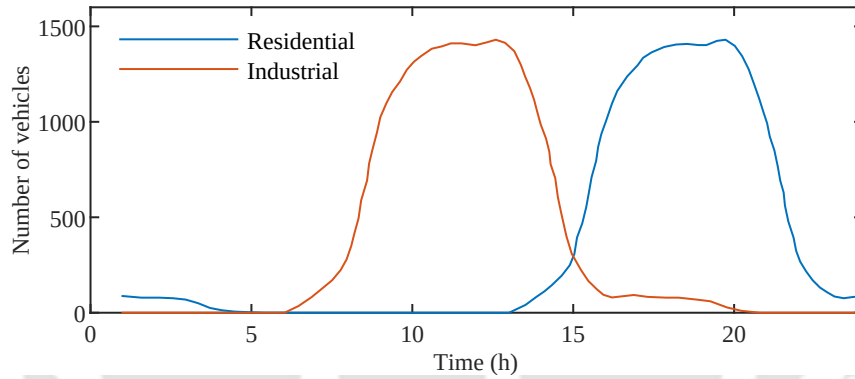


Fig. 3.6: Number of vehicles arriving at EV charging station.

sampling instant. The proposed work depicts the control capabilities of EVCSs in distribution system voltage control; however, the consideration of large uncertainties needs detailed modelling and further investigation.

3.5.1 33-Bus Radial Distribution Network

The network is modified to accommodate 16 PVs of 550 kVA each, with peak generation of 500 kW, and 2 EVCSs of capacities 1 MW each. The PV sources are distributed throughout the network with 2 EVCSs located at node 14 and node 31, as in ref. [48]. It is to be noted that inverters in both test systems are kept slightly overrated by 10% so as to meet the reactive power demand at peak generation. The DN is partitioned into 4 zones using HCA, as depicted in Fig. 3.2, so as to identify the observation nodes. To effectively choose an optimal set of PV resources

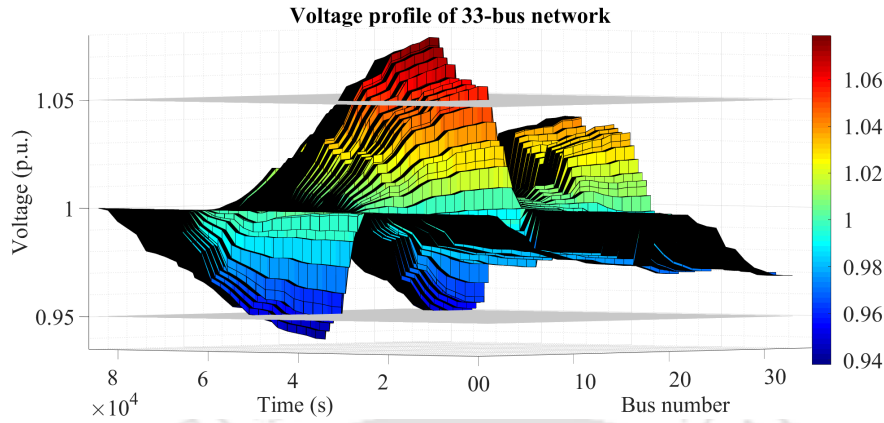


Fig. 3.7: Voltage profile of 33-bus network under no control action.

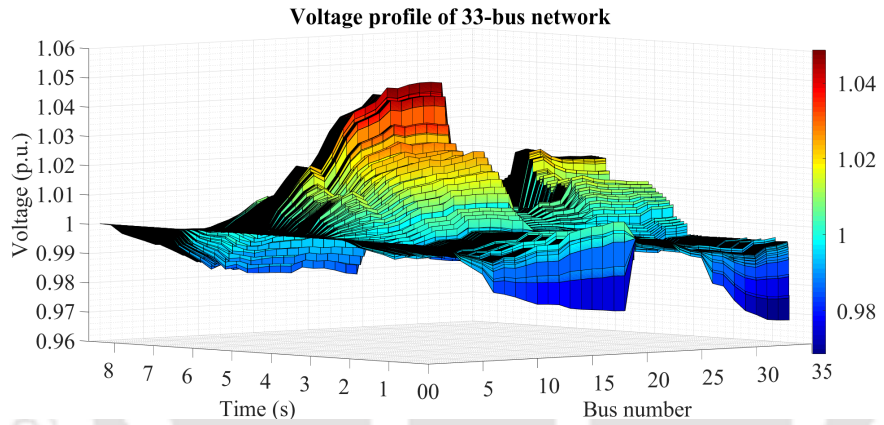


Fig. 3.8: Voltage profile with coordinated control of PV inverters (case A).

($\mathcal{N}_{cont}$), a time domain simulation over 24 hours is run to determine the instant of extreme violations, under no control action. The voltage profile is shown in Fig. 3.7 with extreme voltage violations seen as 1.0826 p.u. and 0.9429 p.u., at node 17 and node 18, respectively. Given that the over-voltage issue is more severe than the under-voltage case, the minimum control resource set is chosen to eliminate the extreme over-voltage. The voltage control of the test network is carried out under the following case studies:

- *Case (A)*: Only PV inverters are employed for controlling the network voltages with the proposed approach.
- *Case (B)*: PV inverters and OLTC are used for control with OLTC at a slow time-scale and PV inverters at a fast time-scale.

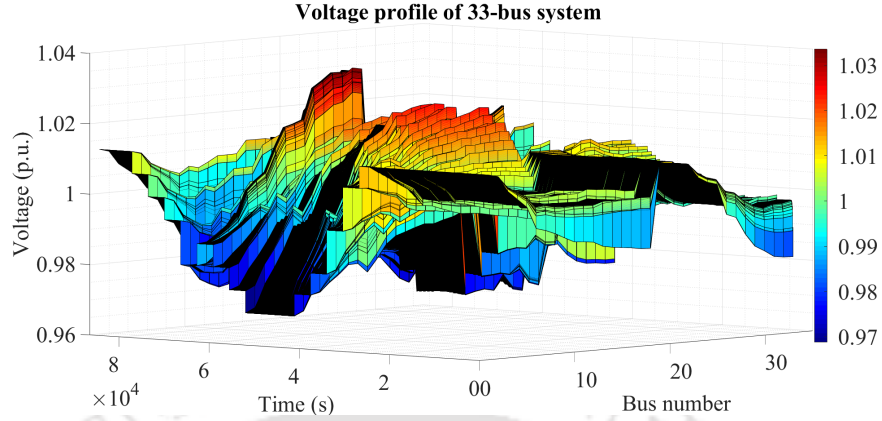


Fig. 3.9: Voltage profile with coordination of OLTC and PV inverters (case B).

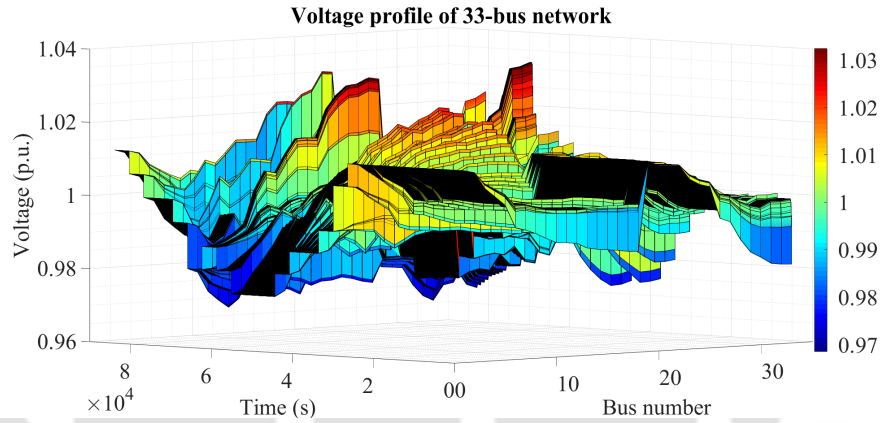


Fig. 3.10: Voltage profile with control of OLTC, PV, and EV inverters (case C).

Table 3.2: Numerical results obtained for the two test networks.

Test system	Case	Voltage (p.u.)		Energy loss (MWh)
		Min/Max	Tap operations	
33-bus system	No control	0.8832/1.0709	-	2.1176
	Case A	0.9686/1.0488	-	2.9420
	Case B	0.9688/1.0336	14	2.4600
	Case C	0.9684/1.0324	13	2.5710
123-bus system	No control	0.9272/1.0600	-	5.5863
	Case A	0.9712/1.0427	-	6.0068
	Case B	0.9680/1.0445	9	5.8892
	Case C	0.9754/1.0250	8	5.9148

- *Case (C)*: EV loads are added to the 33-bus network at node 14 and node 31, and are centrally coordinated with PV inverters and OLTC for voltage control using dual-stage MPC.

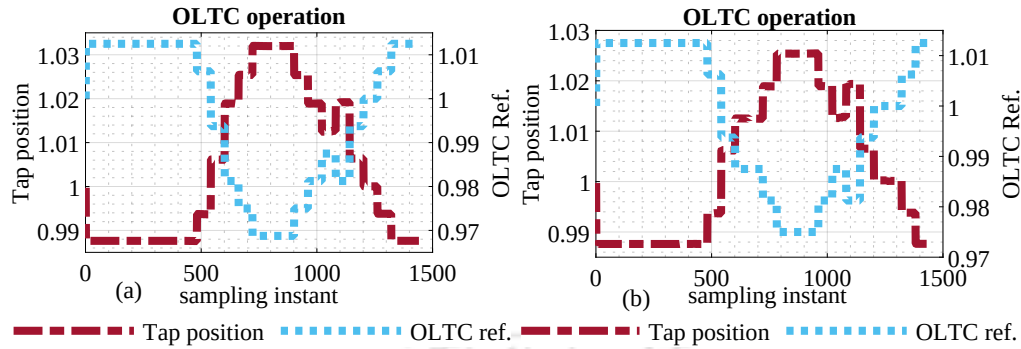


Fig. 3.11: OLTC operation of 33-bus network at sampling rate of 1-minute: (a) coordinated control of PV inverters and OLTC (b) coordinated control of PV inverters, EV inverters, and OLTC.

3.5.1.1 Case A

The PV inverter set ($\mathcal{N}_{cont}$) is deployed to regulate voltages using single-stage MPC, with control action after every minute. The voltage profile over 24 hours with the PV inverter control is shown in Fig. 3.8. The voltages remain within safe operation limits of $[0.95, 1.05]$ p.u. The total energy loss over 24 hours is seen to be 2.9420 MWh.

3.5.1.2 Case B

In this case, the PVs and OLTC are coordinated at two time scales using the proposed model. The voltage profile with the coordinated control is shown in Fig. 3.9 and the OLTC tap operation is shown in Fig. 3.11(a). It is to be noted that the voltages are maintained within the normal operation limits using only PV inverters; however, with the coordination of PV inverters and OLTC, the voltage profile is brought closer to the nominal value of 1 p.u. Furthermore, the energy losses are reduced to 2.46 MWh with a 16.4% reduction in energy losses, as compared to case A.

3.5.1.3 Case C

An EV load is added to the network; the interfacing EV inverters are controlled in coordination with PV inverters and OLTC, using dual-stage MPC. The nodes where EVCSs are positioned are assumed to be equipped with measuring devices. The voltage profile and OLTC tap operation

**A centralized voltage control framework with network energy loss minimization
using dual-stage MPC with reduced-model framework**

Table 3.3: Comparison table for voltage regulation with and without energy loss minimization.

Test network	Without energy loss minimization		With energy loss minimization	
	Voltage (p.u.) Min/Max	Energy loss (kWh)	Voltage (p.u.) Min/Max	Energy loss (kWh)
33-bus	0.9777/1.0277	3353.8	0.9684/1.0324	2571.0
123-bus	0.9800/1.0240	6134.0	0.9795/1.0248	5914.8

Table 3.4: Comparison between the full order model and the proposed reduced model.

Test system	Model type	Optimization run time (s) per sampling instant	Voltage difference (p.u.)	
			μ	σ
33-bus	Full order model	0.0332	0.0038	0.0059
	Reduced model	0.0156		
IEEE 123-bus	Full order model	0.0285	0.0045	0.0035
	Reduced model	0.0139		

Table 3.5: Comparison table of proposed approach with the existing approaches.

Control approach	Test network	Voltage min./max. (p.u.)	Power loss (MWh)
[48]	33-bus	0.9580/1.030	2.6619
	123-bus	0.9721/1.0273	5.6630
[68]	33-bus	0.950/1.0317	2.6480
	123-bus	0.9760/1.02730	5.6897
Proposed	33-bus	0.9684/1.0324	2.5710
	123-bus	0.9754/1.0250	5.9148

with coordinated control are shown in Fig. 3.10 and Fig. 3.11(b), respectively. It can be seen from Table 3.2 that the power losses are slightly increased by 4.5% as compared to case B, due to additional reactive currents from EVCS inverters, but the voltage profile is improved and brought closer to 1 p.u.

Furthermore, a simulation is carried out in which the objective corresponding to energy loss minimization is not considered. The controller focuses on minimizing the voltage deviations only, ignoring the simultaneous energy loss minimization. The net energy losses are seen to be 3.3538 MWh as compared to the case when energy losses are minimized in addition to the minimization of voltage deviations, with minimum and maximum voltages as 0.9777 p.u. and 1.0277 p.u., respectively. The net energy losses are reduced by 23.24% when power losses are minimized;

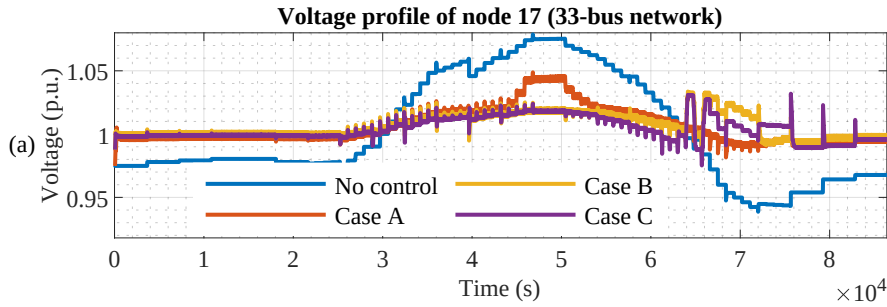


Fig. 3.12: Comparison of voltage profile of node 17 in 33-bus network for all the case studies.

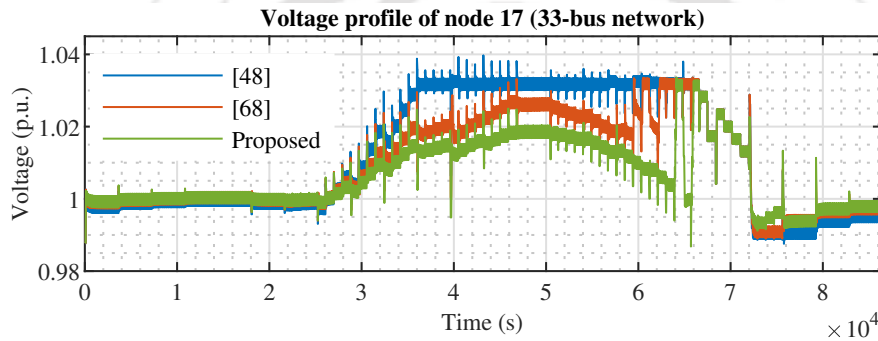


Fig. 3.13: Comparison between full order system model and proposed reduced order model corresponding to voltage profile at node 17 of the 33-bus distribution network.

however, the minimum and maximum voltages over the whole simulation period of 24 hours are seen to be 0.9684 p.u. and 1.0324 p.u., respectively, as shown in Table 3.3. Thus, the controller makes a trade-off between the minimization of voltage deviations and the minimization of energy losses, while ensuring that the voltages remain within normal operation limits. For comparison purposes, node 17 is chosen because of the highest violation at this node. The voltage profiles with all the case studies are shown in Fig. 3.12 along with voltages under no control. To validate the efficacy of the proposed model, a comparison has been drawn with full-order MPC models proposed in [48] and [68]. Fig. 3.13 shows that the proposed model is efficient in regulating the voltages with reduced sensors and measurement devices, reduced communication setup, and reduced model size, as compared to the other approaches. The net energy losses are slightly lower in the proposed control approach in the 33-bus network, as shown in the Table 3.5. It is to be mentioned that the proposed control approach assumes the same generation profile for all the PV sources present in the network (considering the DN spans over a small geographical

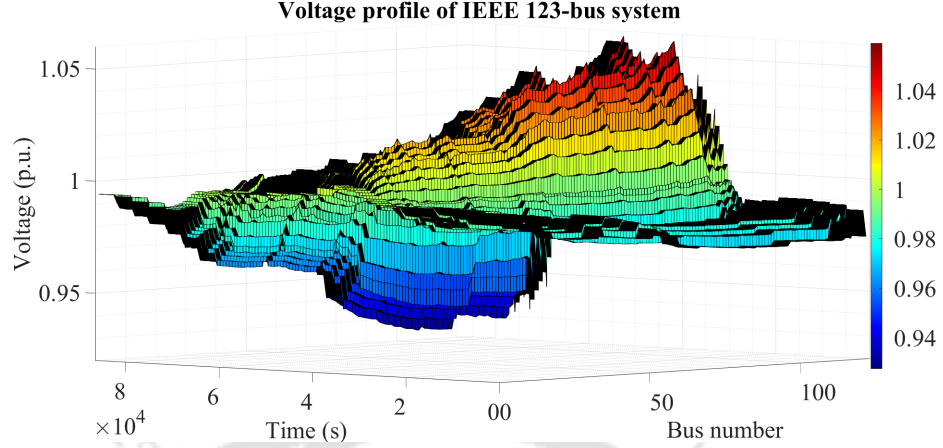


Fig. 3.14: Voltage profile of IEEE 123-bus system under no control action.

area), but only limited resources are assumed to be controlled and equipped with the measuring infrastructure. Thus, if the PV profiles are different in the various PV sources, the optimal values may slightly vary in the proposed control approach. Table 3.4 provides a numerical comparison of the proposed model with the full-order model in [48], in terms of node voltages, where μ is the mean voltage difference and σ is its standard deviation of the voltages in the proposed model from the voltages in the full-order model. For each control step, the optimization run time is 15.6 ms for the reduced order model in comparison to 33.2 ms for the full order model in [48] (Table 3.4). Considering the communication latency of 150 ms in sending data to the central controller, the control execution takes 315.6 ms with the proposed model. Due to the slow variability of PV and EV power, the control step is chosen as 1 minute; however, the controller can efficiently regulate the voltages with a time step of a few seconds if the frequent variations in generation and load are accounted for.

3.5.2 IEEE 123-Bus Distribution Network

The proposed control strategy is further validated on a modified IEEE-123 bus distribution network, fed through an OLTC with primary winding control at node 149. The peak active and reactive power demands of the network are 3.49 MW and 1.92 MVar, respectively. The network is modified by integrating 21 distributed PVs with inverters rated at 650 kVA for peak generation of 585 kW, and partitioned as shown in Fig. 3.3, in a similar way as explained in Section 2.7.2.

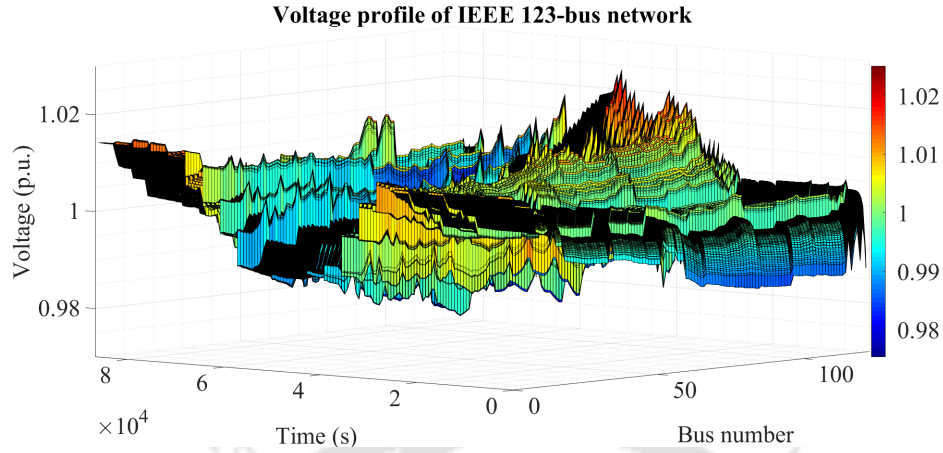


Fig. 3.15: Coordinated control using OLTC and reactive power from PV and EVCS inverters.

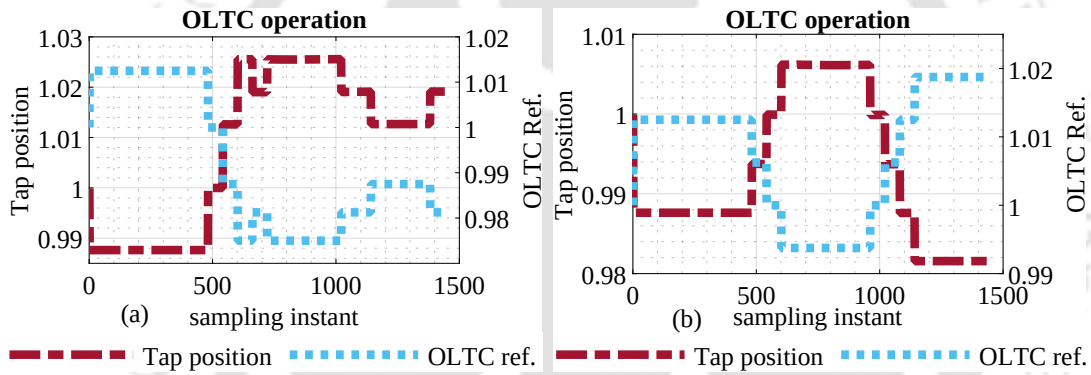


Fig. 3.16: OLTC operation of 123-bus network at sampling rate of 1-minute: (a) coordinated control of PV inverters and OLTC (b) coordinated control of PV inverters, EV inverters, and OLTC.

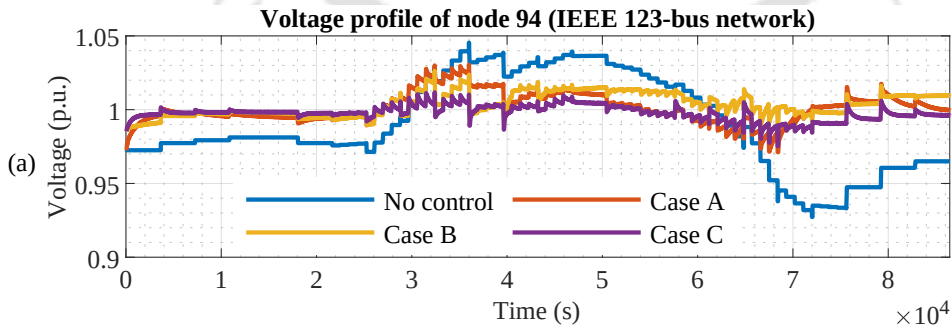


Fig. 3.17: Comparison of voltage profile of node 94 in IEEE 123-bus network for all the case studies.

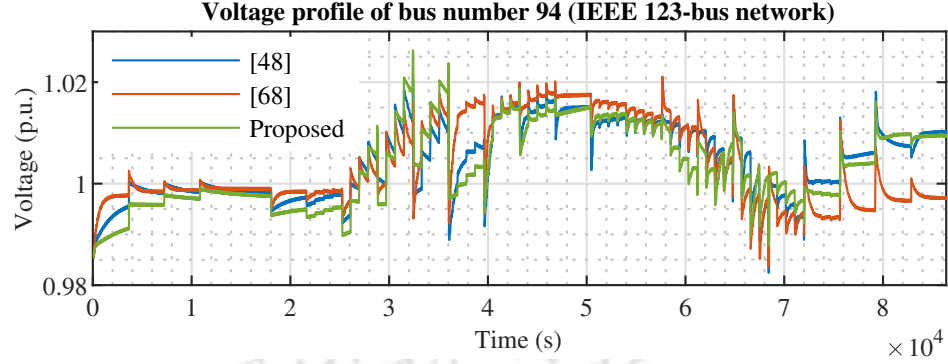


Fig. 3.18: Comparison between full order system model and proposed reduced order model corresponding to voltage profile at node 94 (IEEE 123-bus system).

Furthermore, 4 EVCSs are placed at bus numbers 22, 46, 82, and 104 as in [113], each rated as 610 kVA. The voltage profile under no control is shown in Fig. 3.14, with minimum and maximum voltages as 0.9272 p.u. and 1.0592 p.u., respectively. The minimum control resource set $\mathcal{N}_{cont} = \{85, 114, 110\}$ suffices to eliminate all the voltage violations. The control strategy is studied under three case studies as done for the 33-bus network. The voltage profile in all case studies remains within accepted limits. For instance, the voltage profile for case C is shown in Fig. 3.15. It can be seen from Table 3.2 that the losses are slightly reduced in case B and increase in case C, due to additional reactive power exchange by EV charging stations; however, the voltage profile is improved. Furthermore, it is seen that when the minimization of energy losses is not considered, the minimum and maximum voltages are seen to be 0.9800 p.u. and 1.0240 p.u., and the net energy losses are 6.1340 MWh. However, under the simultaneous optimization of voltage deviations and energy loss minimization, the energy losses are reduced to 5.9148 MWh. The minimum and maximum voltages are seen to be 0.9795 p.u. and 1.0248 p.u., respectively, as shown in Table 3.3. These are slightly higher than the case in which energy loss minimization is not considered. The OLTC operations for case B and case C are shown in Fig. 3.16(a) and Fig. 3.16(b), respectively. Fig. 3.17(a) shows the comparison of the voltage profile of the sensitive node number 94 under all case studies. Furthermore, the proposed model is compared with MPC models in [48] and [68], as shown in Fig. 3.18(b). The numerical results are provided in Table 3.4. It can be seen that the proposed model with less measuring and communication infrastructure and reduced model size performs efficiently to regulate network voltages, as compared to the

full-order model. Considering the voltage profile of the full-order model as a reference, the mean and standard deviation in voltages in the proposed model are seen to be 0.0045 p.u. and 0.0035 p.u., respectively, which are practically quite low.

3.6 Conclusion

In this chapter, the dual-stage MPC with a reduced model framework is employed for voltage control as well as energy loss minimization. The validation of the proposed model on the 33-bus network shows that the mean (μ) and standard deviation (σ) of the voltages at the most critical node are merely 0.0038 p.u. and 0.0059 p.u., respectively, as compared to the full order model of the network used in [48]. The network losses are reduced by 23.24% in the 33-bus network, and 4% in the IEEE 123-bus network, while considering the power loss minimization along with voltage regulation, as compared to the case when energy loss minimization is not incorporated in the proposed reduced order model. Moreover, it is seen that the energy losses slightly increase by 4% and 0.5%, for the 33-bus network and IEEE 123-bus network when EV charging stations are incorporated; however, the voltage profile is improved. Furthermore, due to the reduced dimensionality, the computation is improved, with a reduction in computation time per sample by 53% and 51%, for the 33-bus network and IEEE 123-bus network, respectively, as compared to the full-order model in [48]. Compared to the existing full-order model, the net energy loss is slightly reduced by 3.5% in the 33-bus network, and increased slightly by 3.8% in the IEEE 123-bus network, respectively. Thus, the performance of the proposed control framework is comparable to the full-order model in terms of performance in voltage control and energy loss minimization; however, the proposed model has the advantage of a reduced number of measurement devices and computational time.

Chapter 4

Centralized voltage control and energy loss minimization of ADNs with nodal power uncertainties using chance-constrained model predictive control

The nodal power uncertainties may lead to violations of network voltage constraints or even thermal limit violations of lines, if not taken into account. This study mainly focuses on the real-time control model considering power uncertainties in nodal power injections, due to PVs, EVs, and conventional loads. A stochastic real-time control model is proposed based on chance-constrained model predictive control (CC-MPC) for voltage control and energy loss minimization in ADNs. A scenario-based approach is used to solve the intractable chance-constrained problem. The computational efficiency is enhanced by employing the backward scenario reduction technique while maintaining the solution accuracy using a pre-defined confidence parameter.

4.1 Introduction

The large penetration of distributed RESs and EV loads introduces significant variability and uncertainties in the current distribution networks [114, 115], instigating various challenges for secure and reliable network operation. Voltage regulation emerges as one of the main challenges in highly penetrated active distribution networks. Thus, the network operators call upon both economically viable and robust control strategies to overcome the issues due to variability and volatility in renewable generation and EV loads.

The control devices with different temporal characteristics are coordinated together using various multi-time-scale optimization-based methods, generally leveraging comprehensive system data like network parameters, generations, and loads. PV inverters' reactive power compensation capability is widely used for mitigating frequent voltage deviations in ADNs, such as in [75, 116]. Nonetheless, control capability using reactive power constrained by active power generation may not be adequate during peak generation hours, further exacerbated by the high R/X ratio prevalent in distribution systems. Active power curtailment (APC) in PV systems is an alternative under these cases [110, 117], at the expense of losing renewable energy. Both reactive power and APC are utilized in [110] for VVC and loss minimization, considering the reliability of PV inverters, while authors in [117] present a decentralized solution to the voltage control problem in LV distribution networks, considering the fairly distributed APC among various PV systems.

The rapid proliferation of EVs evokes load uncertainties; however, the reactive power from EVCSs and active power exchange from EV batteries using V2G functionality makes them useful assets for supporting various grid requirements, such as control, stability, resilience, and reliability [41]. The flexibility in charging and discharging of EVs can offset PV active power curtailment under effective coordination with PV inverters. While EVs augment grid flexibility and offer multifaceted benefits, challenges persist in erratic driving patterns and charging infrastructure. Model predictive control (MPC) based real-time coordinated voltage control (CVC) is studied in [40] and [74] with PV and EV coordination; however, the vast uncertainties in EVs are not considered. Considering EVs as controllable assets, coordinated EV charging with grid voltage support is studied in [41]; however, the stochasticity in charging/discharging and EV allocation in parking

lots is randomly distributed. A model-free control approach based on multi-agent reinforcement learning is proposed in [64] to coordinate EVs with PV inverters. A partially observable Markov decision process is used to formulate the coordination problem of EV active/reactive power exchange. Coordinated control schemes studied in [40, 64, 70, 74, 99] consider EVCSs for sustaining the network node voltages, with a detailed charging scheduling in [64, 99] using decentralized control structures; however, the impact of residential EV charging is not studied. Furthermore, the realistic EV data structures with detailed uncertainties associated with both PV and EV loads are not incorporated.

The diverse time responses of control equipment and high DG and EV integration create complex challenges in ADNs. Day-ahead coordination becomes infeasible and insecure, thus necessitating real-time control with multi-time scale coordination. In recent years, MPC-based multi-step optimization has garnered considerable attention due to abundant data logs and advancements in short-term forecasting, thus addressing real-time control demands within inherently uncertain networks. MPC-driven voltage control has been investigated within decentralized [99], centralized [40, 57, 70] as well as distributed [98, 101] frameworks. These MPC-based control schemes are deterministic in nature and do not consider the detailed uncertainties in the nodal power injections and the growing impact on residential EV charging. A robust optimization technique is introduced in [74], designed to encompass uncertainties related to system demand and EV behavior. A robust optimization approach is employed to contain EV uncertainties using deterministic uncertainty sets; however, the lack of real-time control may over-utilize or under-utilize control resources. Furthermore, the proposed control approach in [74] does not consider other control resources, such as PV inverters and legacy devices like OLTC. A two-stage optimal coordination framework is proposed in [75], employing a scenario-based chance-constrained VVC. Nodal power uncertainties are addressed through a multi-scenario methodology, generating scenarios based on predetermined probability distributions. The exactness of the solution obtained using the proposed scenario-based approach is maintained by a predefined confidence parameter. Nonetheless, this method overlooks the integration of EVs and their control capabilities. Moreover, it relies on day-ahead optimization, thus neglecting the advantages of real-time control facilitated by advanced measurement infrastructure. To this end, a real-time stochastic

MPC framework is proposed in [76] to consider uncertainty in renewable generation by formulating the voltage constraints as chance constraints. The uncertainties in renewable generation are contained using the affine-disturbance feedback control policy; however, the EV penetration and the associated uncertainties are not considered. The comparison of VVO approaches considering nodal power uncertainties is given in Table 4.1. To the best of the authors' knowledge, there is no study for MPC-based voltage control that considers the penetration of domestic EVs along with uncertainty modelling in PVs, EVs, and loads. To address these research gaps, a real-time scenario-based CC-MPC control approach is proposed in this chapter. The various controllable resources with different temporal characteristics are considered with multi-time scale coordination. The detailed uncertainties in nodal power injections are considered with real EV data sets. The uncoordinated domestic EV charging and coordinated EVCSs with V2G functionality are considered in the proposed approach. The objectives of the proposed work can be summarized as follows:

- A novel real-time and MPC-based chance-constrained CVC model is proposed with multi-time scale coordination of control devices such as PV inverters, EV inverters, and OLTC.
- Detailed uncertainties in the conventional loads, EV loads, and renewable generations are considered, with their individual quantification of uncertainties corresponding to the different levels of uncertainty.
- The real-time CVC optimization problem is formulated as a chance-constrained MPC model, and a scenario-based approach is utilized to solve the problem deterministically.

Table 4.1: MPC-based VVO approaches.

Reference	Real-time control	Consideration of uncertainties		
		PV	Load	EV
[70]	✓	×	×	×
[75]	×	✓	✓	×
[41]	✓	×	×	✓
[74]	×	×	×	✓
[76]	✓	✓	×	×
[40]	✓	✓	✓	×
Proposed	✓	✓	✓	✓

The computational efficiency is enhanced by using a scenario reduction method. The exactness and confidence of the solution under uncertainty are maintained with proper scenario generations, considering a pre-defined confidence parameter.

The rest of this chapter is arranged as follows: Section 4.2 discusses the ADN model with nodal power uncertainties, Section 4.3 provides the MPC framework under nodal power uncertainties, and Section 4.4 discusses the CC-MPC and D-MPC problem formulations for the proposed control framework. Section 4.5 discusses the EV data characterization, Section 4.6 provides simulation results and discussions, and finally, Section 4.7 provides conclusive remarks.

4.2 Network Model with Nodal Power Uncertainties

Consider an $N + 1$ node distribution network with a radial topology, represented by a set $\mathcal{N} \cup \{0\}$, $\mathcal{N} := \{1, 2, 3, \dots, N\}$, as explained in Section 2.2. Let, $\bar{s}_n = p_n + jq_n = (p_n^g - p_n^{ev} - p_n^l) + j(q_n^g - q_n^{ev} - q_n^l)$ be the net complex power injected at node n , where the superscript g , ev and l denotes the DG power, EV demand, and load demand, respectively. If only PV-DG units are present in the network, then p_n^g is denoted by p_n^{pv} . Consider that the net power injections at the network nodes are associated with uncertainties in PVs, EVs, and loads. If $\hat{p}_n^{pv}(t)$, $\hat{p}_n^{ev}(t)$, and $\hat{p}_n^l(t)$ denote the predicted PV, EV, and load powers at time instant t , then,

$$p_n^{pv}(t) = \hat{p}_n^{pv}(t) + \zeta_n^{pv}(t), \forall n \in \mathcal{N}^{PV}, \zeta_n^{pv} \in \mathcal{B}(0, \sigma^{pv}) \quad (4.1)$$

$$p_n^{ev}(t) = \hat{p}_n^{ev}(t) + \zeta_n^{ev}(t), \forall n \in \mathcal{N}^{EV}, \zeta_n^{ev} \in \mathcal{N}(0, \sigma^{ev}) \quad (4.2)$$

$$p_n^l(t) = \hat{p}_n^l(t) + \zeta_n^l(t), \forall n \in \mathcal{N}, \zeta_n^l \in \mathcal{N}(0, \sigma^l) \quad (4.3)$$

where, $\zeta_n^{pv}(t) = \Delta p_n^{pv}(t)$, $\zeta_n^{ev}(t) = \Delta p_n^{ev}(t)$, $\zeta_n^l(t) = \Delta p_n^l(t)$ are the uncertainties in PV, EV, and load powers, respectively, and $\mathcal{N}$ denotes the normal distribution. The linearized Distflow model equations, explained in Section 2.2, can thus be written as,

$$\begin{bmatrix} \mathbf{p} \\ \mathbf{q} \end{bmatrix} = \begin{bmatrix} \mathbb{A}\mathbf{P} \\ \mathbb{A}\mathbf{Q} \end{bmatrix} \quad (4.4)$$

$$\begin{bmatrix} \tilde{\mathbf{A}} \end{bmatrix}^\top \begin{bmatrix} \mathbf{V}_0 & \mathbf{V}^\top \end{bmatrix}^\top = [\mathbf{R}_l][\mathbf{P}] + [\mathbf{X}_l][\mathbf{Q}] \quad (4.5)$$

This linearized model of DNs is used to develop the proposed CC-MPC based control framework, as explained in the next section.

4.3 MPC framework with Nodal Power Uncertainties

The linear evolution of voltages using the sensitivity-based linearized model is given by,

$$\mathbf{V}(\kappa + 1) = \mathbf{V}(\kappa) + \mathbf{S}_V^p \Delta \mathbf{p} + \mathbf{S}_V^q \Delta \mathbf{q} + \mathbf{S}_V^{\text{tap}} \Delta \mathbf{V}_0 \quad (4.6)$$

Similarly, the line currents and power losses are given by the following linearized model [63] as,

$$\mathbf{I}(\kappa + 1) = \mathbf{I}(\kappa) + \mathbf{S}_I^p \Delta \mathbf{p} + \mathbf{S}_I^q \Delta \mathbf{q} + \mathbf{S}_I^{\text{tap}} \Delta \mathbf{V}_0 \quad (4.7)$$

$$\mathbf{L}(\kappa + 1) = \mathbf{L}(\kappa) + \mathbf{S}_L^p \Delta \mathbf{p} + \mathbf{S}_L^q \Delta \mathbf{q} + \mathbf{S}_L^{\text{tap}} \Delta \mathbf{V}_0 \quad (4.8)$$

The vectors $\mathbf{I}(\kappa)$ and $\mathbf{L}(\kappa)$ correspond to measured state inputs at time step κ . The coefficient matrices $\mathbf{S}_I^p, \mathbf{S}_I^q$ and $\mathbf{S}_I^{\text{tap}}$ are the current sensitivity coefficients with respect to active power, reactive power, and tap operations, respectively. Similarly, $\mathbf{S}_L^p, \mathbf{S}_L^q$ and $\mathbf{S}_L^{\text{tap}}$ are the loss sensitivity coefficients with respect to active power, reactive power, and tap operations, respectively. These current sensitivities and power loss sensitivities are functions of nodal power injections and need to be updated at each control step. The linear distribution model given in Eqs. (4.6), (4.7), and (4.8) serves as the bedrock for the MPC-based control in this study. The generalized discrete state-space MPC model [118], with power uncertainties, is given by,

$$\boldsymbol{\xi}(\kappa + 1) = \hat{\mathbf{A}}\boldsymbol{\xi}(\kappa) + \hat{\mathbf{B}}\Delta \mathbf{u}(\kappa) + \hat{\mathbf{D}}\Delta \boldsymbol{\omega}(\kappa) \quad (4.9)$$

$$\mathbf{y}_p(\kappa) = \hat{\mathbf{C}}\boldsymbol{\xi}(\kappa) \quad (4.10)$$

The output vector $\mathbf{y}_p(\kappa) = [\mathbf{y}_{p1}^\top(\kappa) \mathbf{y}_{p2}^\top(\kappa) \mathbf{y}_{p3}^\top(\kappa)]^\top$ is structured alongside the system output matrix $\hat{\mathbf{C}} = [\hat{\mathbf{C}}_1^\top \hat{\mathbf{C}}_2^\top \hat{\mathbf{C}}_3^\top]^\top$ corresponding to the evolution of the system state vector $\boldsymbol{\xi}(\kappa + 1)$, and

real-time measurement vector $\xi(\kappa)$. Output vectors $\mathbf{y}_{\mathbf{p}1}$, $\mathbf{y}_{\mathbf{p}2}$, and $\mathbf{y}_{\mathbf{p}3}$ are predicted node voltages, line currents, and power losses, respectively. Since the state variables in the model comprise node voltages, line currents, and network power losses. For the real-time control, the measurements corresponding to node voltages and line currents are assumed to be available throughout the network. Detailed structures of matrices $\hat{\mathbf{A}}, \hat{\mathbf{B}}, \hat{\mathbf{C}}$ are provided in [118]. The matrix $\hat{\mathbf{D}}$ of the model contains sensitivity coefficients, considering nodal power deviations due to uncertainties. The dimensions of the various matrices and vectors in the MPC model are given as; $\xi \in \mathbb{R}^{S \times 1}$, $\mathbf{u} \in \mathbb{R}^{I \times 1}$, $\omega \in \mathbb{R}^{D \times 1}$, $\hat{\mathbf{A}} \in \mathbb{R}^{S \times S}$, $\hat{\mathbf{B}} \in \mathbb{R}^{S \times I}$, $\hat{\mathbf{C}} \in \mathbb{R}^{O \times S}$, $\hat{\mathbf{D}} \in \mathbb{R}^{S \times D}$, and $\mathbf{y}_{\mathbf{p}} \in \mathbb{R}^{O \times 1}$. The net nodal power deviations due to uncertainties in predicted values are contained in the uncertainty vector $\Delta\omega$, where,

$$\Delta\omega = \zeta^{pv}(\kappa) + \zeta^{ev}(\kappa) + \zeta^l(\kappa), \quad \forall \mathcal{N} \quad (4.11)$$

where $\zeta^{pv}(\kappa)$, $\zeta^{ev}(\kappa)$, and $\zeta^l(\kappa)$ denote the uncertainty vectors corresponding to PVs, EVs, and loads at time step κ . The optimal control sequence $\Delta\mathbf{U}$ is predicted over control horizon N_c ($\leq$ prediction horizon N_p). The predicted output over the prediction horizon N_p can be expressed in terms of measurements and the optimal input sequence as,

$$\mathbf{Y}_{\mathbf{p}} = \chi\xi(\kappa) + \psi\Delta\mathbf{U} + \Sigma\Delta\Omega \quad (4.12)$$

where, $\mathbf{Y}_{\mathbf{p}} = [\mathbf{Y}_{\mathbf{p}1}^\top \mathbf{Y}_{\mathbf{p}2}^\top \mathbf{Y}_{\mathbf{p}3}^\top]^\top$, $\chi = [\chi_1^\top \chi_2^\top \chi_3^\top]^\top$, $\psi = [\psi_1^\top \psi_2^\top \psi_3^\top]^\top$ and $\Sigma = [\Sigma_1^\top \Sigma_2^\top \Sigma_3^\top]^\top$. $\Delta\Omega = [\Delta\omega_{(1)}^\top \Delta\omega_{(2)}^\top \dots \Delta\omega_{(N_p)}^\top]^\top$ is the disturbance vector corresponding to the nodal power uncertainties. Here, $\chi \in \mathbb{R}^{O.N_p \times S}$, $\mathbf{U} \in \mathbb{R}^{I.N_c \times 1}$, $\Omega \in \mathbb{R}^{D.N_c \times 1}$, $\psi \in \mathbb{R}^{O.N_p \times I.N_c}$, and $\mathbf{Y}_{\mathbf{p}} \in \mathbb{R}^{O.N_p \times 1}$. The MPC model uses the change in control input to predict the system behavior. Thus the actual control inputs over N_c are given by,

$$\mathbf{U}(\kappa) = \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) + \hat{\mathbf{H}}\Delta\mathbf{U} \quad (4.13)$$

The matrices χ , ψ , Σ , $\hat{\mathbf{G}}$ and $\hat{\mathbf{H}}$ are developed over the prediction/control horizon using matrices $\hat{\mathbf{A}}$, $\hat{\mathbf{B}}$, and $\hat{\mathbf{C}}$ as discussed in Section 3.2. Centralized control is achieved by the coordination of PV and EVCS inverters using their active and reactive power, and using OLTC tap operations.

The active power control through APC, or V2G applications of EVs are considered as expensive control resources, thus only 20% of the available active power is assumed to be available for active power control [70]. Additionally, the R/X ratio in distribution lines is high, making the voltages more sensitive to active power exchange. Thus, a small active power exchange can avoid a larger amount of reactive power for voltage control [118]. Since the curtailment of active power is generally discouraged, the control action due to active power exchange is highly penalized as compared to the reactive power. The controller uses a receding horizon control strategy, assimilating only the control inputs at the initial time step.

For calculating the voltage, current, and loss sensitivity coefficients, the Z-bus method tailored for active distribution networks is leveraged [119]. Z-bus-based methodology enables system linearization with high computational efficiency and accuracy. Unlike Jacobian-based approaches, which rely on voltage magnitudes and angles, Z-bus sensitivity coefficients are explicitly expressed in terms of bus voltages and bus power injections [119]. Within the premise of acceptable errors, the simplified Z-bus method is well-suited for real-time estimation tasks. Moreover, the dependence on voltages and nodal power injections enables the incorporation of network information regarding renewed voltage levels and changing generation and loads at each control step [76], thus reducing the error due to linearization. Utilizing estimated network states, the voltage sensitivity coefficients with respect to the reactive power injections, delineated in the state space model in Eq. (4.9) are computed as,

$$\frac{\partial V_i}{\partial q_k} = \frac{1}{V_i} \Re \left(\bar{V}_i^* \frac{\partial \bar{V}_i}{\partial q_k} \right), \quad i \in \mathcal{N} \quad (4.14)$$

$$\frac{\partial \bar{V}_i}{\partial q_k} = \sum_{j \neq k} \left(-\frac{\bar{z}_{ij} \bar{s}_j^*}{\bar{V}_j^2} \frac{\partial V_j}{\partial q_k} \right) + \frac{\bar{Z}_{ik} V_k}{V_k^2}, \quad j, k \in \mathcal{N} \quad (4.15)$$

where, $\Re$ represents the real part. Similarly, the current and loss sensitivity coefficients corresponding to nodal reactive power injections [120] are expressed as,

$$\frac{\partial I_{ij}}{\partial q_k} = \frac{1}{|\bar{I}_{ij}|} \Re \left(\bar{I}_{ij}^* \frac{\partial \bar{I}_{ij}}{\partial q_k} \right), \quad (i, j) \in \mathcal{L} \quad (4.16)$$

$$\frac{\partial \bar{I}_{ij}}{\partial q_k} = y_{ij} \left(\frac{\partial \bar{V}_i}{\partial q_k} - \frac{\partial \bar{V}_j}{\partial q_k} \right), \quad (i, j) \in \mathcal{L} \quad (4.17)$$

$$\frac{\partial \mathbf{P}_l}{\partial q_k} = 2 \cdot \Re \left(\tilde{\mathbf{V}}^{*T} \mathbf{Y}_G \frac{\partial \tilde{\mathbf{V}}}{\partial q_k} \right) \quad (4.18)$$

Detailed derivations and explanations of the voltage, current, and loss sensitivities with respect to the active/reactive power injections are given in [76] and [121].

4.4 Problem Formulation

This section discusses the chance-constrained formulation and scenario-based solution approach to solve the problem, considering deterministic constraints.

4.4.1 Chance Constrained MPC Formulation

The objective function for the MPC framework involves the minimization of voltage deviations and line currents ($\mathbf{Y}_p$), minimization of control actions ($\Delta \mathbf{U}$), and minimization of line losses ($\mathbf{p}_l$). Each objective involves a weight matrix to dynamically change the preferences as per the system state. It is to be mentioned that the model is based on sensitivity coefficients, and the power flow equations are not explicitly employed as constraints. Thus, to enforce constraints corresponding to the maximum allowable line currents in the system, the minimization of line currents is incorporated as an objective within the optimization framework. The objective function is formulated as a quadratic programming problem as,

$$\min \|\tilde{\mathbf{Y}}_p - \mathbf{Y}_p\|_{\mathbf{w}_y}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1}^2 + \|\Delta \mathbf{U}\|_{\mathbf{w}_u}^2 \quad (4.19)$$

subjected to the following constraints,

$$\underline{\underline{\Delta \mathbf{U}}} \leq \Delta \mathbf{U} \leq \overline{\overline{\Delta \mathbf{U}}} \quad (4.20a)$$

$$\underline{\underline{\mathbf{U}}} \leq \mathbf{U} \leq \overline{\overline{\mathbf{U}}} \quad (4.20b)$$

$$\mathbb{P}(\underline{\underline{\mathbf{Y}_p}} \leq \mathbf{Y}_p \leq \overline{\overline{\mathbf{Y}_p}}) = 1 - \varepsilon \quad (4.20c)$$

The weight matrices $\mathbf{w}_y, \mathbf{w}_u, \mathbf{w}_s, \mathbf{w}_l$ are empirically determined considering the required control actions for minimization of losses and voltage deviations. Through recursive simulations, the optimal weights corresponding to output voltage deviations and control inputs are determined, ensuring a suitable trade-off between voltage magnitudes, power losses, and control actions. The matrix $\mathbf{w}_s$ is highly weighted so that the slack variables $\boldsymbol{\sigma} = [\sigma_1 \ \sigma_2 \ \sigma_3]^\top$ take values only under solution infeasibility corresponding to network security constraints. All other weight matrices are changed using if-then-else rules, corresponding to the network voltage conditions, as given in Table 4.2. The weights associated with control inputs are chosen less if voltages lie outside the normal operation bounds, so that the control rigorously aims at bringing the voltages within limits. Moreover, the weights corresponding to active power inputs are chosen 10 times more than the weights associated with reactive power inputs. This enables minimum APC and V2G actions if needed.

The chance-constrained formulation given in Eqs. (4.19), (4.20a)-(4.20c) incorporates the inherent variability of the uncertain parameter ζ , ensuring that the security constraints are upheld to a prescribed probability threshold $(1 - \varepsilon)$. The resulting solutions are said to be ε -level robustly feasible [75]. However, computing the precise probability spaces corresponding to the constraint in Eq. (4.20c) is computationally challenging, thus restricting the ability to solve the problem directly. This can be handled by leveraging the scenario method to transform probabilistic constraints into hard constraints. It is illustrated in [122] that if a minimum number N_s of randomly selected samples of the uncertain parameter (sampled within its probability space) are chosen, and the constraints of the chance-constrained problem are satisfied for all these samples, the re-

Table 4.2: Weights associated with different objectives for MPC

Range of bus voltages (p.u.)	Objective weights					
	w_v	w_i	w_q	w_p	w_l	w_s
$\max(\mathbf{v}) \geq 1.1$ or $\min(\mathbf{v}) \leq 0.9$	0.01	100	0.01	0.1	100	1000
$1.05 \leq \max(\mathbf{v}) \leq 1.1$ or $0.9 \leq \min(\mathbf{v}) \leq 0.95$	0.01	100	0.1	1	100	1000
$\max(\mathbf{v}) \leq 1.05$ and $\min(\mathbf{v}) \geq 0.95$	0.01	100	10	100	0.01	1000

sultant solution becomes feasible for the original problem with a predetermined confidence level. The performance is guaranteed if the deterministic counterpart of the chance-constrained problem is a convex function or a mixed integer convex program [75]. Corresponding to c number of continuous variables and b number of binary variables, the minimum number of random samples to be generated for the solution to be ε -level robustly feasible (with pre-specified confidence level γ) is given by the relation:

$$2^b \sum_{i=0}^{c-1} \binom{N_s}{i} \varepsilon^i (1 - \varepsilon)^{N_s-i} \leq \gamma \quad (4.21)$$

where γ is the confidence parameter, which is generally quite small and is assumed very close to zero. It is worth noting that the adoption of a scenario-based approach for a chance-constrained framework preserves the problem structure, and works effectively well with any kind of probability distribution of uncertain parameter.

4.4.2 Scenario Reduction

The scenario approach involves the optimization of the whole scenario set over the optimization time window. The computational burden significantly increases with an increasing number of scenarios. Leveraging the scenario reduction technique to reduce the original scenario set to minimum representative scenarios helps to relax the computational burden while maintaining accuracy. Here, the backward reduction method [123] is utilized to reduce the computational complexity while preserving the quality of the original scenario set. The pseudo-code of the backward reduction technique is given in Algorithm 4.1.

4.4.3 Deterministic-MPC Reformulation

Thus, the chance-constrained formulation given in Eqs. (4.19), (4.20a)-(4.20c) is reformulated as its deterministic counterpart using the scenario-based approach as,

$$\min \sum_{s=1}^{N^R} p^s \left(\|\tilde{\mathbf{Y}}_{\mathbf{p}} - \mathbf{Y}_{\mathbf{p}}\|_{\mathbf{w}_y}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1}^2 + \|\Delta \mathbf{U}\|_{\mathbf{w}_u}^2 \right) \quad (4.22)$$

subjected to the following constraints,

$$\underline{\underline{\Delta \mathbf{U}}} \leq \Delta \mathbf{U} \leq \overline{\overline{\Delta \mathbf{U}}} \quad (4.23a)$$

$$\underline{\underline{\mathbf{U}}} \leq \mathbf{U} \leq \overline{\overline{\mathbf{U}}} \quad (4.23b)$$

$$\underline{\underline{\mathbf{Y}_p}} \leq \mathbf{Y}_p \leq \overline{\overline{\mathbf{Y}_p}} \quad (4.23c)$$

The formulation given in Eq. (4.22) is restructured as a standard quadratic programming problem with box constraints as,

$$\min \frac{1}{2} \begin{bmatrix} \Delta \mathbf{U} \\ \sigma \end{bmatrix}^\top \mathbf{H} \begin{bmatrix} \Delta \mathbf{U} \\ \sigma \end{bmatrix} + \mathbf{f} \begin{bmatrix} \Delta \mathbf{U} \\ \sigma \end{bmatrix} \quad (4.24)$$

Algorithm 4.1 Backward Scenario Reduction Technique

INITIALIZE:

$\mathcal{S}^G \leftarrow \{s^1, s^2, \dots, s^{N_s}\}$ Set of N_s generated scenarios

$\mathcal{S}^R \leftarrow$ Set of reduced scenarios;

$|\mathcal{S}^R| = 0 \leftarrow$ Initially

$N^R \leftarrow$ Required reduced number of scenarios

$p^i \leftarrow$ Probability of i^{th} scenario (s^i)

while $|\mathcal{S}^G| > N^R$ **do**

$d_k(s^i, s^j) \leftarrow \|s^i - s^j\|, \forall s^i, s^j \in \mathcal{S}^G, i \neq j$

$\mathbf{D}_k \leftarrow [d_k]_{i,j}$; ($d_k =$ Kantorovich distance)

$d'_k(i) \leftarrow \min d_k(i, j), \forall d_k \in \mathbf{D}_k$

$\mathbf{d}'_k \leftarrow [d'_k]_i$

$r(j) \leftarrow \arg \min_j d_k(i, j)$

$\mathbf{r} \leftarrow [r]_j$

$d_k^p(i) \leftarrow p^i \times d'_k(i), \forall d'_k \in \mathbf{d}'_k$

$\mathbf{d}_k^p \leftarrow [d_k^p]_i$

$f \leftarrow \arg \min \mathbf{d}_k^p$

$e \leftarrow \mathbf{r}(f)$

$\mathcal{S}^G \leftarrow \mathcal{S}^G - \{s^e\}$

$\mathcal{S}^R \leftarrow \mathcal{S}^R + \{s^e\}$

$|\mathcal{S}^G| \leftarrow |\mathcal{S}^G| - 1$

$|\mathcal{S}^R| \leftarrow |\mathcal{S}^R| + 1$

$p^i \leftarrow p^i + p^e$

end while

return

$\mathcal{S}^R$

subjected to,

$$\mathbf{M}\Delta\mathbf{U} \leq \mathbf{m} \quad (4.25)$$

where, the Hessian matrix $\mathbf{H}$ and matrix $\mathbf{f}$ are expressed as,

$$\mathbf{H} = \begin{bmatrix} 2(\psi_1^\top \mathbf{w}_v \psi_1 + \psi_2^\top \mathbf{w}_i \psi_2 + \psi_3^\top \mathbf{w}_1 \psi_3 + \mathbf{w}_u) & \mathbf{0} \\ \mathbf{0} & \mathbf{w}_s \end{bmatrix} \quad (4.26)$$

$$\mathbf{f} = \sum_{s=1}^{S^R} p^s * \mathbf{f}^s ; \mathbf{f}^s = \begin{bmatrix} \mathbf{f}_1^s & \mathbf{0} \end{bmatrix} \quad (4.27)$$

$$\mathbf{f}_1^s = 2((\chi_1 \xi + \Sigma_1 \Delta \Omega^s - \tilde{\mathbf{V}})^\top \mathbf{w}_v \psi_1 + (\chi_2 \xi + \Sigma_2 \Delta \Omega^s)^\top \mathbf{w}_i \psi_2 + (\chi_3 \xi + \Sigma_3 \Delta \Omega^s)^\top \mathbf{w}_1 \psi_3) \quad (4.28)$$

Here, $\mathbf{0}$ is the null matrix, $\tilde{\mathbf{V}}$ is the reference voltage vector, and $\mathbf{w}_y = \begin{pmatrix} \mathbf{w}_v \\ \mathbf{w}_i \end{pmatrix}$. The vector $\Delta \Omega^s$ represents the uncertainty vector over whole prediction horizon corresponding to scenario s . The constraint matrices $\mathbf{M}$ and $\mathbf{m}$ are expressed as,

$$\mathbf{M} = \begin{pmatrix} \mathbf{H} \\ -\mathbf{H} \\ \hat{\psi}_1 - \mathbf{S}_{v2} \\ -\hat{\psi}_1 - \mathbf{S}_{v1} \\ \hat{\psi}_2 - \mathbf{S}_i \\ \mathbf{I} \\ -\mathbf{I} \end{pmatrix} ; \mathbf{m} = \begin{pmatrix} \bar{\bar{\mathbf{U}}} - \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) \\ -\underline{\underline{\mathbf{U}}} + \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) \\ \bar{\bar{\mathbf{Y}}}_{p1} - \chi_1 \xi(\kappa) \\ -\underline{\underline{\mathbf{Y}}}_{p1} + \chi_1 \xi(\kappa) \\ \bar{\bar{\mathbf{Y}}}_{p2} - \chi_2 \xi(\kappa) \\ \Delta \bar{\bar{\mathbf{U}}} \\ -\Delta \underline{\underline{\mathbf{U}}} \end{pmatrix} \quad (4.29)$$

where,

$$\mathbf{H} = \begin{pmatrix} \hat{\mathbf{H}} & \mathbf{0}_1 \\ \mathbf{0}_1^\top & \mathbf{I}_1 \end{pmatrix} ; \hat{\psi}_1 = \begin{pmatrix} \psi_1^\top \\ \mathbf{0}_2 \end{pmatrix}^\top \quad (4.30)$$

The matrices $\mathbf{0}_1, \mathbf{0}_2$ are null matrices and $\mathbf{I}, \mathbf{I}_1, \mathbf{I}_2$ are identity matrices. Matrices $\mathbf{S}_{v1}, \mathbf{S}_{v2}, \mathbf{S}_i$ are related as; $\mathbf{S}_{v1}\Delta\mathbf{U} = \sigma_1 \mathbf{1}$, $\mathbf{S}_{v2}\Delta\mathbf{U} = \sigma_2 \mathbf{1}$ and $\mathbf{S}_i\Delta\mathbf{U} = \sigma_3 \mathbf{1}$. Since the objective weights are positive, the quadratic norm makes the Hessian matrix positive definite; thus, the objective function

is convex. Furthermore, all the constraints are linear, thus Eq. (4.21) ensures the feasibility of the solution within the probabilistic bounds. The temporal stratification within the MPC control framework optimizes the functioning of OLTC on an hourly basis, due to slow temporal characteristics. PV and EVCS inverters' operations are optimized at a fast time scale with a time step of 2 minutes, to respond quickly to dynamic changes in the nodal power variations. Leveraging MPC, this approach accommodates the temporal dynamics of control mechanisms, effectively mitigating undue OLTC tap operations. The OLTC operation is optimized at a slower time scale, with the controller input as the change in OLTC reference, while at a faster time scale, the control inputs are active/ reactive power of PV and EVCS inverters. The OLTC operation is optimized at a slower time scale with the following objective function:

$$\min \sum_{s=1}^{N^R} p^s \left(\sum_{i=1}^{N_p} (\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\mathbf{I}(\kappa + i)\|_{\mathbf{w}_i}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_l}^2) + \sum_{i=1}^{N_c} \|\Delta \mathbf{V}_{\text{tap}}(\kappa + i)\|_{\mathbf{w}_{\text{tap}}}^2 \right) \quad (4.31)$$

subjected to the constraints,

$$\underline{\underline{\Delta \mathbf{V}_{\text{tap}}}} \leq \Delta \mathbf{V}_{\text{tap}} \leq \overline{\overline{\Delta \mathbf{V}_{\text{tap}}}} \quad (4.32a)$$

$$\underline{\underline{\mathbf{V}_{\text{tap}}}} \leq \mathbf{V}_{\text{tap}}(\kappa + 1) \leq \overline{\overline{\mathbf{V}_{\text{tap}}}} \quad (4.32b)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + 1) \leq \overline{\overline{\mathbf{V}}} + \sigma_2 \mathbf{1} \quad (4.32c)$$

$$\mathbf{I}(\kappa + 1) \leq \overline{\overline{\mathbf{I}}} + \sigma_3 \mathbf{1} \quad (4.32d)$$

The variable associated with the OLTC ($\Delta \mathbf{V}_{\text{tap}}$) is modeled as a continuous variable within the objective. The precise adjustment of the OLTC is then determined by rounding off the resulting value to the nearest discrete tap position. At a faster time scale, PV and EVCS inverter operations are optimized with the following objective function:

$$\min \sum_{s=1}^{N^R} p^s \left(\sum_{i=1}^{N_p} (\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\mathbf{I}(\kappa + i)\|_{\mathbf{w}_i}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_l}^2) + \sum_{i=1}^{N_c} (\|\Delta \mathbf{Q}_{\text{PV}}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{Q}_{\text{EV}}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{P}_{\text{PV}}(\kappa + i)\|_{\mathbf{w}_p}^2 + \|\Delta \mathbf{P}_{\text{EV}}(\kappa + i)\|_{\mathbf{w}_p}^2) \right) \quad (4.33)$$

subjected to the constraints,

$$\underline{\underline{\Delta Q_{PV}}} \leq \Delta Q_{PV}(\kappa + 1) \leq \overline{\overline{\Delta Q_{PV}}} \quad (4.34a)$$

$$\underline{\underline{\Delta Q_{EV}}} \leq \Delta Q_{EV}(\kappa + 1) \leq \overline{\overline{\Delta Q_{EV}}} \quad (4.34b)$$

$$\Delta P_{PV}(\kappa + 1) \leq \overline{\overline{\Delta P_{PV}}}(\kappa) \quad (4.34c)$$

$$\underline{\underline{Q_{PV}}} \leq Q_{PV}(\kappa + 1) \leq \overline{\overline{Q_{PV}}} \quad (4.34d)$$

$$\underline{\underline{Q_{EV}}} \leq Q_{EV}(\kappa + 1) \leq \overline{\overline{Q_{EV}}} \quad (4.34e)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{V}} \leq V(\kappa + 1) \leq \overline{\overline{V}} + \sigma_2 \mathbf{1} \quad (4.34f)$$

$$\mathbf{I}(\kappa + 1) \leq \overline{\overline{\mathbf{I}}} + \sigma_3 \mathbf{1} \quad (4.34g)$$

4.5 EV Characterization

With the global rise in EV adoption and technological advancements, leveraging the latest trial data and accounting for EV diversity becomes imperative to comprehend EV user behavior. This work considers data from 461 residential EVs from the UK's Electric Nation project [124], and realistic domestic EV demand profiles developed by the EV Integration Project, University of Melbourne [125]. Individual residential charger demands are created using charging duration and start time, daily charging times, daily plug-in factor, and EV charger sizes. The parameters like charging time, charging duration, daily charging time, and merely ascertain the charging status (ON/OFF), whereas the EV charger size determines the actual power demand. Two commercially available chargers for home use [124], termed "Level 1" and "Level 2" are considered with power ratings of 3.68 kW (16A, 230V) and 7.36kW (32A, 230V), respectively. The charging time and durations are used to transform single or multiple daily charging events into binary profiles. The charging duration depends on the type of EV and the battery capacity. Three types of EVs considered [124] include battery EVs (BEV), plug-in hybrid EVs (PHEVs), and range-extended PHEVs (REX-PEVs). The battery capacities of the vehicles considered vary between 6 kWh

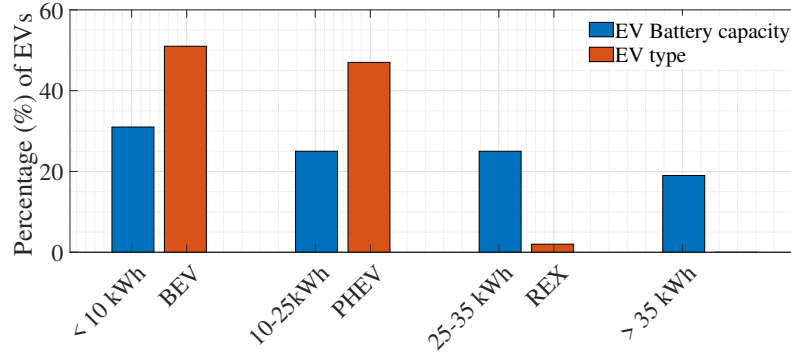


Fig. 4.1: Classification of EVs used based on the type and battery capacity.

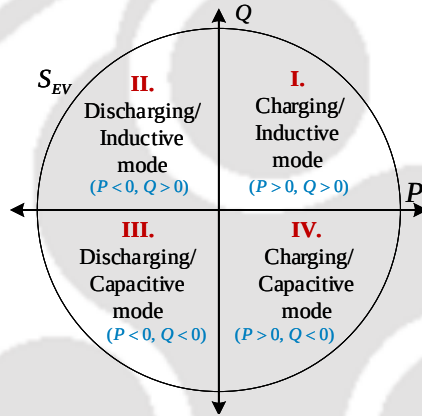


Fig. 4.2: Capability curve of electric vehicle charger.

to 100 kWh as given in Fig. 4.1. The required probability distributions concerning the charging times and durations corresponding to the charger rating and type of the day are provided in [125]. Assigning the binary EV profile to the corresponding charger size, enables to determination of the required EV demand profile. The EV penetration is considered 100% if for every 3 kW residential load, an EV charger is installed. The EV chargers are assumed to be installed in residential homes. The residential load of each house is assumed to be 3 kW, and 60% of the houses are assumed to be installed with EV chargers of both kinds. Level 1 chargers, characterized by slower charging rates and predominantly adopted by short to medium-range EVs, are presumed to constitute only 20% of the market by 2050 [125]. In contrast, the Level 2 chargers are projected to dominate with around 80% market share for equipping long-range EVs. Thus, 20% of the total residential chargers are assumed to be Level 1 and the rest as Level 2.

In addition, EVCSs are assumed to be installed at certain locations. Due to the lack of

communication and measuring infrastructure, the residential chargers are assumed to be incapable of active network control; however, the EVCSs are assumed to be centrally coordinated, utilizing the reactive power from EVCS inverters. The aggregate EV model is considered with a group of EVs as a single equivalent load. Upon arrival at EVCS, drivers submit the EV data like state-of-charge, electric range, and battery specifications to the local aggregator. Since the proposed work considers the network impact assessment regarding voltages and corresponding control in MV distribution networks, the aggregated model is preferred to simplify the analysis. However, EVs in the trial data are assumed to be uncontrolled loads with the following assumptions: (a) EVs commence charging at the maximum rated power of the charger immediately upon connection, (b) Charging is uncontrolled, continuing at maximum power until the battery is fully charged or the driver opts to depart. Thus, EV charging operates independently of network requirements. The charging demand at any instant is the sum of the charger ratings in use in an EVCS. The reactive power exchange is assumed controllable based on the capability curve (Fig. 4.2). The reactive power available at a given time instant κ is given by,

$$Q_{EV}(\kappa) = \sqrt{S_{EV}^2 - P_{EV}^2(\kappa)} \quad (4.35)$$

where, S_{EV} is the kVA rating of the EVCS. The stochasticity is considered in the demand profiles developed under uncontrolled EV integration. An in-depth analysis, including the development and implementation of a coordinated charging strategy, is beyond the scope of this current study.

4.6 Simulation Results and Discussion

The proposed voltage control strategy is validated on 33-bus and IEEE 123-bus balanced distribution networks with PVs and EVs, and equipped with centrally coordinated OLTC, as shown in Fig. 4.3 and Fig. 4.4, respectively. The PV generation and demand profiles of conventional loads, EVCSs, and domestic chargers are shown in Fig. 4.5. The daily load profile corresponds to the data obtained from Pecan Street Inc. [71], and the solar power data corresponds to the data of the southwestern state of Arizona (US) and is obtained from the NREL data center [126]. It is to be mentioned that the PV inverters are overrated slightly by around 10% so that they can

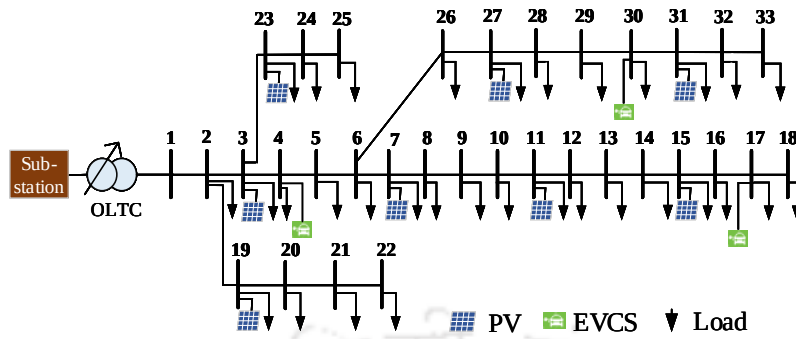


Fig. 4.3: 33-bus distribution network.

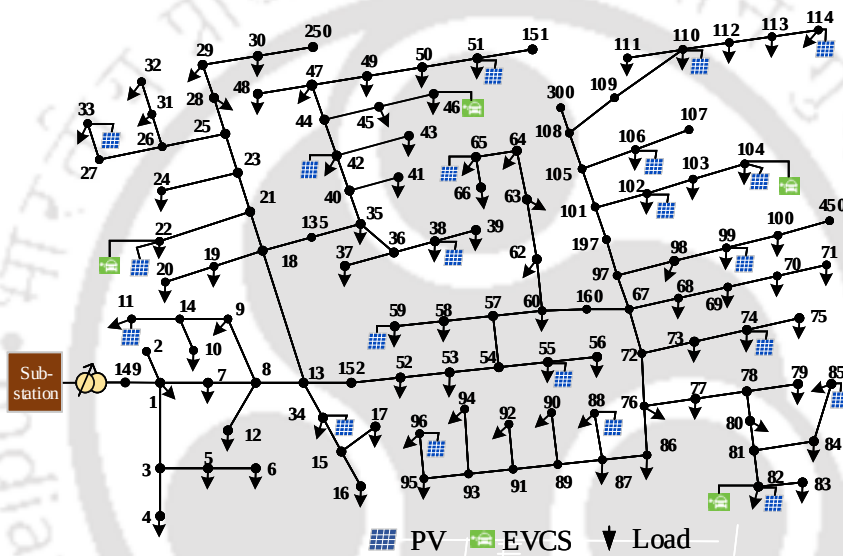


Fig. 4.4: Modified IEEE 123-bus distribution network.

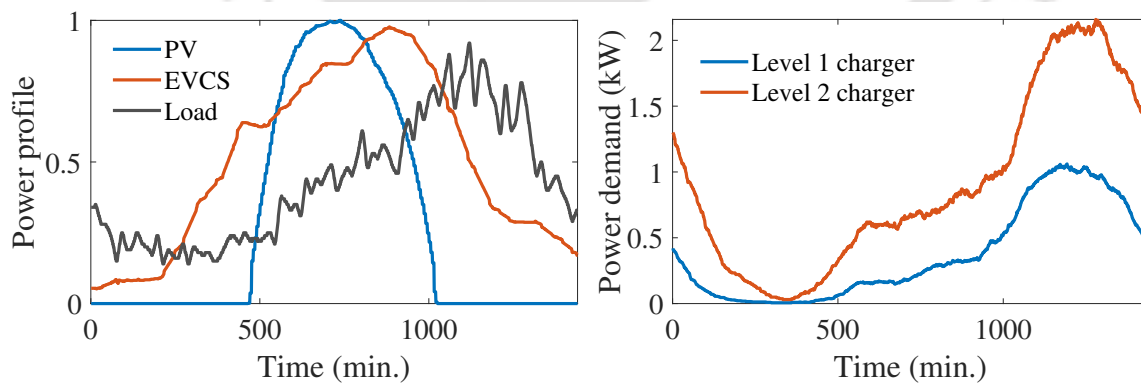


Fig. 4.5: (a) Power profiles of conventional load, PVs, and EVCSs (b) Diversified average power demand of domestic chargers.

exchange at least 44% reactive power as well, under the peak power injections, as recommended by IEEE standard 1547 (2018) [17] for DG units. With primary winding control, the OLTC provides

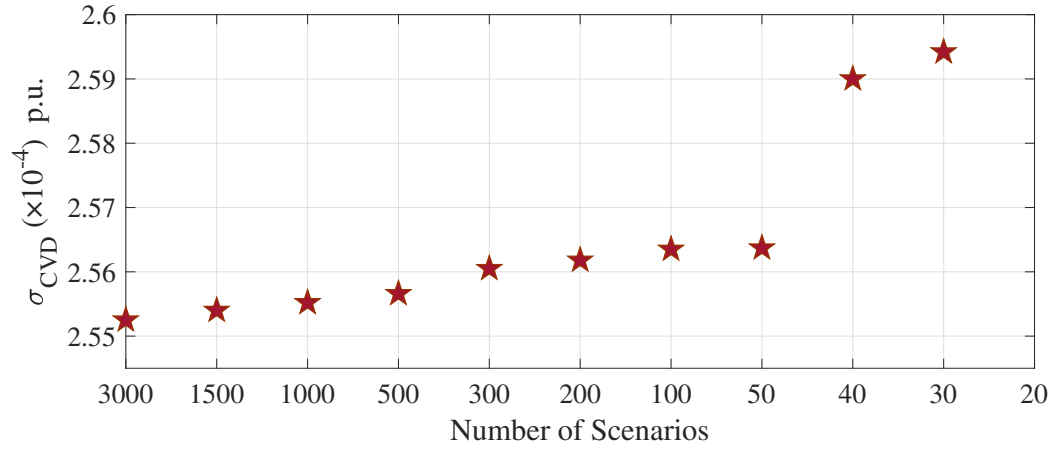


Fig. 4.6: Sensitivity of voltage deviations in the 33-bus network using σ_{CVD} corresponding to the different number of representative scenarios.

32 discrete tap adjustments with each step corresponding to 0.00625 p.u. The voltage variation range of OLTC is set as 20%, with 10% above and below the nominal value. Furthermore, only 2 tap steps are allowed at a given instant. Moreover, the OLTC operation is restricted when the maximum voltage deviation remains within 3% of the nominal value.

Initially, $N_s = 3100$ random scenarios are generated using Monte-Carlo simulation, based on Eq. (4.21), corresponding to confidence parameter $\gamma = 10^{-8}$ and $\varepsilon = 0.02$. The uncertainties in predicted PV generation, conventional load demand, EVCS demand, and residential EV demand are assumed to be normally distributed [75]. The standard deviation (σ^{ev}) of EV uncertainty is considered as 10%, while a standard deviation of 5% is assumed for residential load (σ^l) and PV generation (σ^{pv}). Using the backward reduction technique, 50 representative scenarios are considered. Repeated simulations are carried out at various reduced scenario sets to choose the required set feasibly. Furthermore, sensitivity analysis is carried out, quantified using σ_{CVD} , corresponding to different reduced scenario sets, as shown in Fig. 4.6. It is seen that the value of σ_{CVD} increases only by 0.44% from the original number of scenarios to the reduced scenario set with 50 representative scenarios. However, there is a 1.02% deviation in σ_{CVD} when the number of representative scenarios changes from 50 to 40. Thus, 50 scenarios are considered in the final simulations while highly maintaining the solution accuracy. All the simulations are carried out for 24 hours using Power System Analysis Toolbox (PSAT) with MATLAB interface.

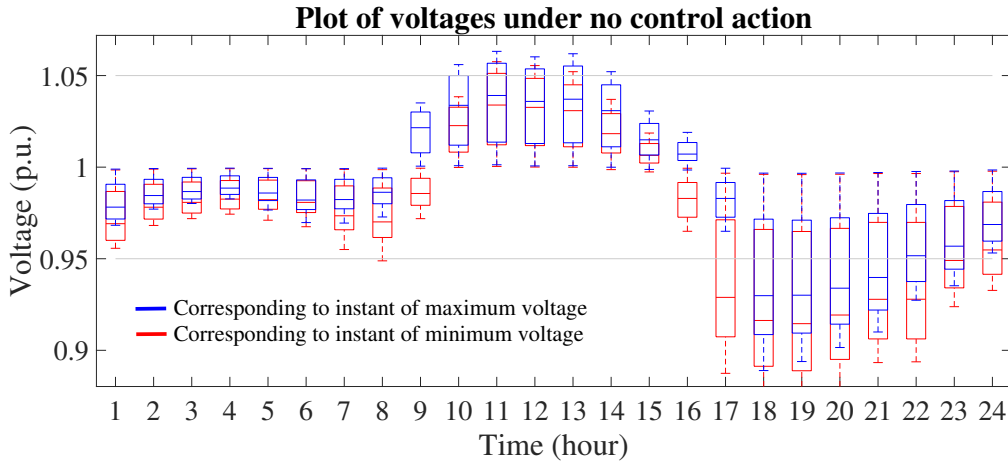


Fig. 4.7: Voltage plots of 33-bus system corresponding to the instant of minimum/ maximum voltage occurrence in each hour, under no control action.

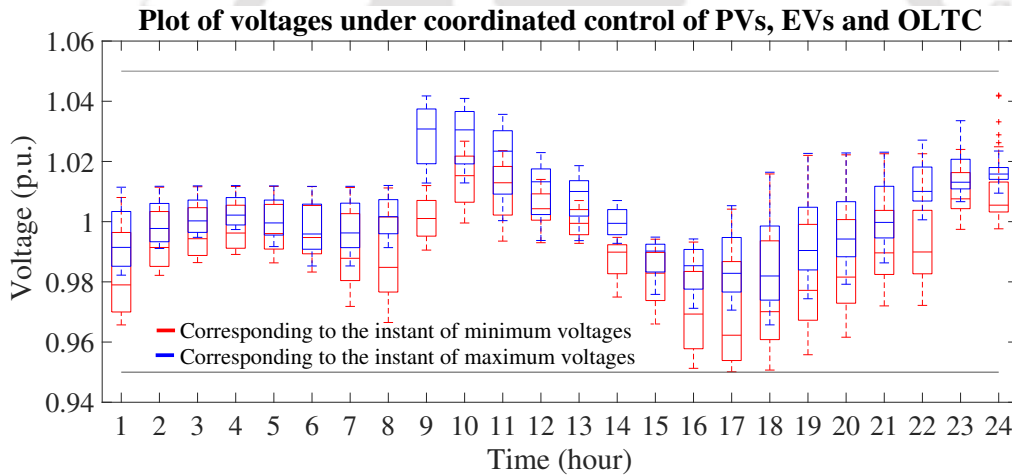


Fig. 4.8: Voltage plots of the 33-bus system corresponding to the instant of minimum and maximum voltage occurrence in each hour, under the CC-MPC.

4.6.1 Simulation Results of 33-Bus Distribution System

The network is modified to accommodate 8 PVs of 550 kVA and a peak generation of 500 kW. The network is fed from a 63.3 kV/12.66 kV substation, with a base power of 10 MVA. Three EVCSs are added as shown in Fig. (4.3), each having a capacity of 500 kVA. The residential EV chargers are assumed to be installed in every LV network connected to the nodes. A detailed description of residential EV integration is given in Section III. Considering a penetration level of 60%, a total of 750 chargers with 150 level 1 chargers and 600 level 2 chargers are assumed to be installed throughout the network. Initially, a time domain simulation of the network with PVs

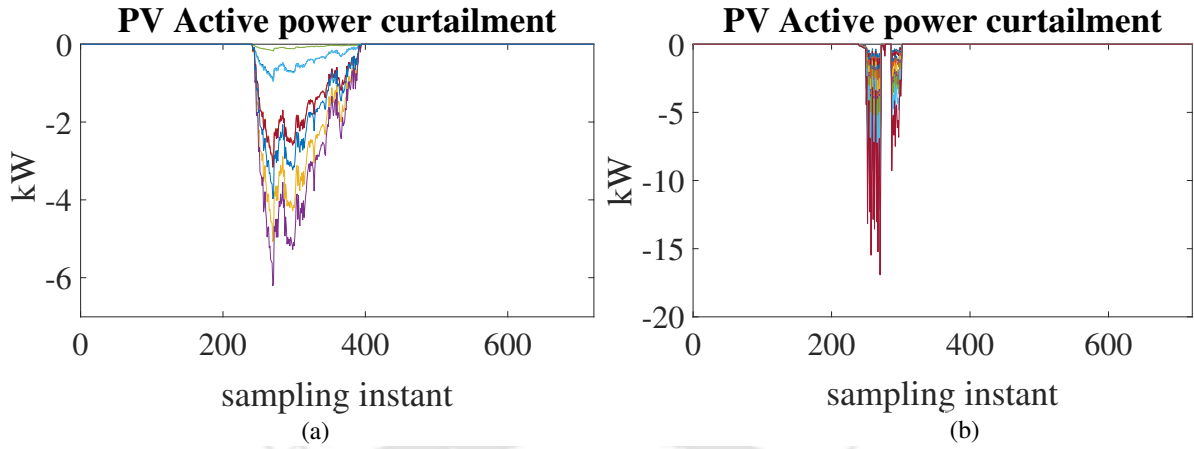


Fig. 4.9: Active power curtailment at 60% EV penetration levels with sampling rate of 2-minutes: (a) 33-bus network (b) IEEE 123-bus network.

Table 4.3: Numerical results obtained for the 2 test networks.

Attributes	33-bus network		IEEE 123-bus network	
	CC-MPC	D-MPC	CC-MPC	D-MPC
Net Energy loss (MWh)	1.7595	1.3565	4.9767	4.7522
Q_{PV} exchange (MVarh)	12.6252	12.273	18.733	18.2867
Q_{EV} exchange (MVarh)	5.4727	5.3218	3.3586	3.172
Net APC of PVs (kWh)	56.93	87.63	74.93	87.62
Net V2G injection (kWh)	70.98	75.21	53.45	34.03
Min./ max. voltage (p.u.)	0.95/1.042	0.94/1.054	0.95/1.034	0.94/1.038
Tap operations	07	04	07	07
Computation time (s) per sampling instant	0.0422	0.0332	0.053	0.040

and EVs is carried out under no control action. The instants of minimum and maximum voltages in each hour are recorded, and the corresponding node voltages at that instant are represented by box plots as shown in Fig. 4.7. Significant over/under voltage violations can be seen; the over-voltages are significant from 11 am to 1 pm due to PV generation and relatively less demand. Similarly, the under-voltages are significantly high from 5 pm to 11 pm, due to evening peak demands and high EV charging demands during evening hours. Using the proposed scenario-based control approach with coordinated control of PVs, EVCSs, and OLTC, the voltages are limited within the safe operation limits as shown in Fig. 4.8. A total of 7 tap operations are observed (Fig. 4.11), and net active power exchange from PVs and EVCSs is observed to be 56.9 kWh and 70.98 kWh, respectively, as shown in Table 4.3. Fig. 4.9 (a) shows the active power

Table 4.4: Numerical results under CC-MPC considering the beta distribution of PV uncertainty (ζ^{pv}).

Attributes	33-bus network	IEEE 123-bus network
Net Energy loss (MWh)	1.7858	4.9821
Min./ max. voltage (p.u.)	0.9500/1.0466	0.9500/1.0399
Tap operations	7	7
σ_{CVD} p.u.	2.5573×10^{-4}	3.7548×10^{-4}

Table 4.5: Comprehensive voltage deviation index (σ_{CVD}) for the CC-MPC approach and D-MPC approach with and without coordinated control of OLTC.

Test network	$\sigma_{CVD} (\times 10^{-4})$ p.u.			
	CC-MPC		D-MPC	
	Without OLTC	With OLTC	Without OLTC	With OLTC
33-Bus	3.4893	2.5637	3.5881	2.6592
IEEE 123-Bus	4.7546	3.7502	4.8739	3.8868

curtailment of PVs. To evaluate the effects of the slow-acting OLTC within the CVC framework, simulations are conducted without engaging the OLTC, and the results demonstrate an increase in network energy losses from 1.7595 MWh to 2.4750 MWh. Additionally, the network experiences greater deviations from nominal voltage levels. These are quantified by the comprehensive voltage deviation (σ_{CVD}) defined in [60], and expressed as,

$$\sigma_{CVD} = \sqrt{\frac{\sum_{\tau=1}^{\mathcal{T}_s} (\sigma_{VD}(\tau))^2}{\mathcal{T}_s}} \quad (4.36)$$

where, the voltage deviation (σ_{VD}) is given as,

$$\sigma_{VD}(\tau) = \sqrt{\frac{\sum_{n=1}^N (V_n(\tau) - V_{ref})^2}{N}} \quad (4.37)$$

Here, $\mathcal{T}_s$ is the number of time samples. The value of σ_{CVD} is lower when the OLTC operation is optimized along with the inverter-based control resources, as seen from Table 4.5. In addition, a case study is carried out while considering the beta distribution of the PV uncertainty (ζ^{pv}), wherein the shape parameters are determined as given in [63]. It can be seen from Table 4.4 that the value of σ_{CVD} is comparable to the case when σ^{pv} is modeled using the normal distribution.

It is seen that certain scenarios in the beta distribution have more deviation from the predicted

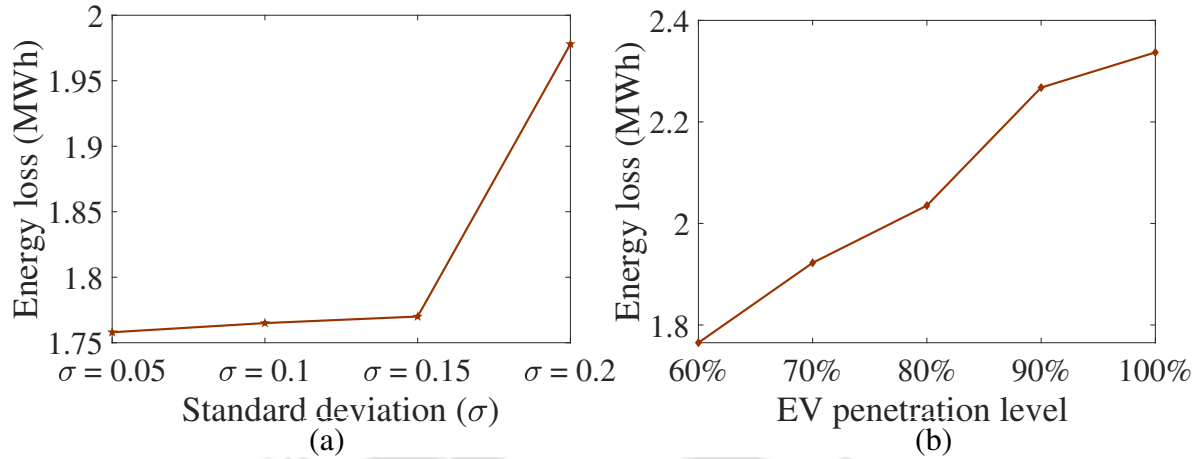


Fig. 4.10: Variation of net energy losses in the 33-bus network: (a) With varying degrees of uncertainties (b) With varying domestic EV penetration levels.

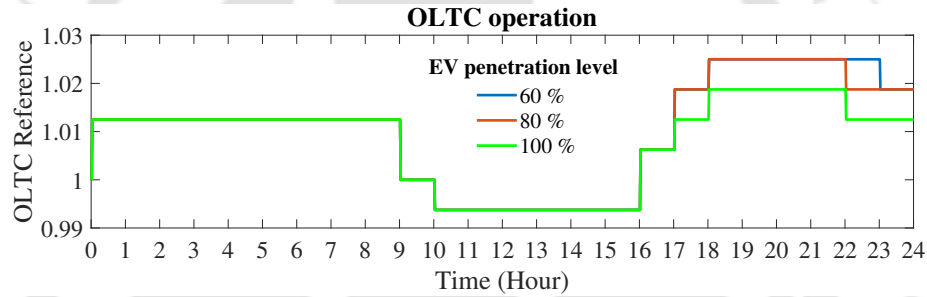


Fig. 4.11: OLTC reference voltage for different EV penetration levels.

data as compared to that of the normal distribution, due to which the energy losses are slightly increased in the case of the beta distribution.

4.6.1.1 System Response with Varying Degrees of EV Uncertainties

The impact of EV uncertainty on energy loss and reactive power compensation is studied by varying the standard deviation (σ^{ev}) associated with domestic EVs and EVCSs. The variation of net energy losses corresponding to different values of σ^{ev} is shown in Fig. 4.10(a). The net energy losses are seen to be 1.758 MWh, 1.765 MWh, 1.770 MWh, and 1.978 MWh corresponding to $\sigma = 0.05, 0.1, 0.15$, and 0.2 , respectively. Moreover, with increased levels of EV uncertainties, there is an increase in net reactive power exchange, due to the fact that the controller optimizes the control inputs corresponding to all scenarios. Thus, if the uncertainty level increases, there are certain scenarios with increased deviation from the predicted scenario. To compensate for these

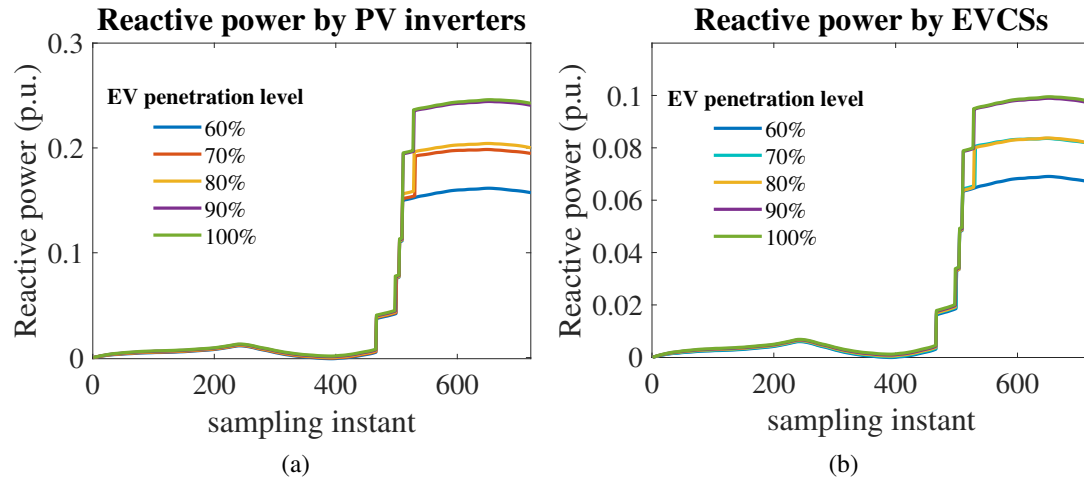


Fig. 4.12: Net reactive power exchange from inverter-based devices under various residential EV penetration levels with sampling rate of 2-minutes: (a) Net reactive power exchange by PV inverters (b) Net reactive power exchange by EV charging stations.

scenarios with higher deviations, the net reactive power exchange also increases. It is seen that the proposed control approach effectively maintains the voltages within limits for all the studied uncertainty levels.

4.6.1.2 System Response with Varying Levels of EV Penetration

The proposed approach is further studied under varying degrees of EV penetration levels. The penetration level is gradually increased from the base case of 60% up to 100%. The energy losses with varying domestic EV penetrations are shown in Fig. 4.10(b). It is seen that compared to the base case of 60% penetration level with net energy loss equal to 1.765 MWh, the energy losses increase by 15.74%, 27.02%, 50.26%, and 57.19% corresponding to penetration levels of 70%, 80%, 90%, and 100%, respectively. The voltages remain within normal operation limits corresponding to all penetration levels. The net reactive power exchange by PV inverters and EVCSs is shown in Fig. 4.12(a) and Fig. 4.12(b), respectively. As compared to the base case (60% penetration level), the net reactive power exchange increases by 19.179%, 22.483%, 44.063%, and 45.628% for penetration levels of 70%, 80%, 90%, and 100%, respectively. Fig. 4.11 shows the tap operation under different EV penetration levels.

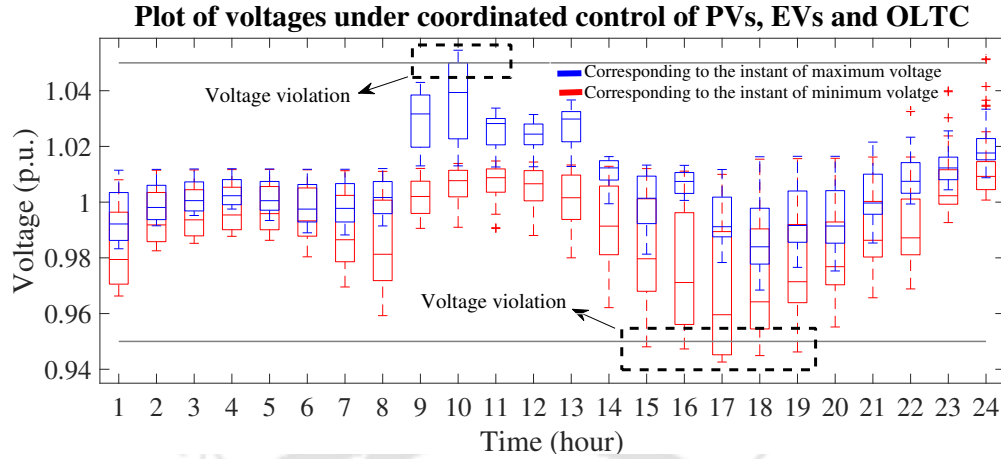


Fig. 4.13: Voltage plots of the 33-bus system corresponding to the instant of minimum and maximum voltage occurrence in each hour, using D-MPC.

4.6.1.3 Comparison with a Deterministic (D-MPC) Control Approach

The proposed scenario-based CC-MPC framework is compared with the deterministic MPC (D-MPC) approach for validation under nodal power uncertainties. The predictive control under D-MPC considers the given generation and load profiles, however, the actual simulations are carried out on the randomly chosen scenarios from the generated scenario set. It is to be noted that there will be no voltage violations if the simulations are carried out on the given data (ignoring the uncertainty). The voltage profile is shown in Fig. 4.13. There are multiple over-voltage and under-voltage violations seen, corresponding to the randomly chosen scenarios. The mitigation of voltage violations due to uncertain nodal powers comes at the cost of slightly increased losses and increased reactive power injections. The power losses are increased by around 403 kWh, and the net reactive power exchange is increased by 513 KVarh.

4.6.2 Simulation Results of IEEE 123-Bus Distribution System

To validate the scalability of the proposed approach, simulations are further carried out on the modified IEEE-123 bus network shown in Fig. 4.4. The total connected active and reactive power load demand is 3.49 MW and 1.92 MVar, respectively. The network is fed through a 4.16 kV substation, and the base voltage and base power are 4.16 kV and 1 MVA, respectively. The network is modified to accommodate distributed PVs with inverter ratings of 330 kVA, and peak

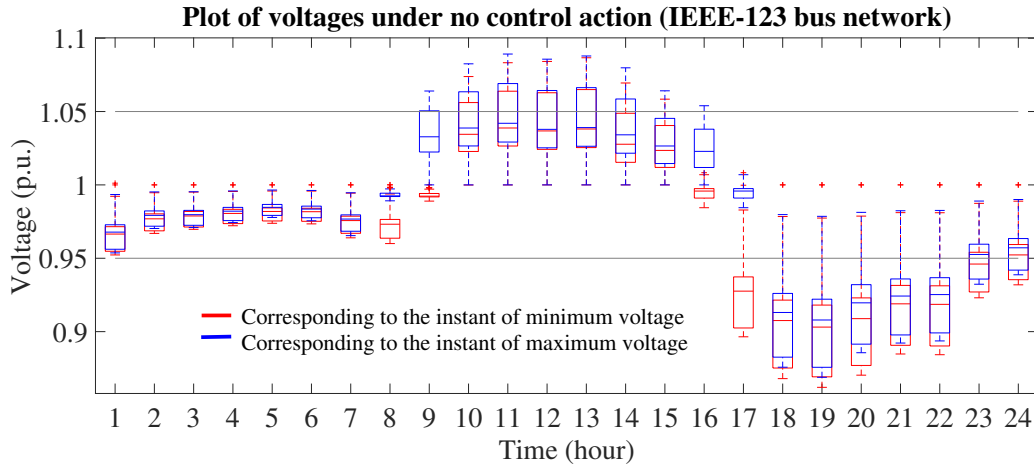


Fig. 4.14: Voltage plots of IEEE-123 bus network corresponding to the instant of minimum/ maximum voltage occurrence in each hour, under no control.

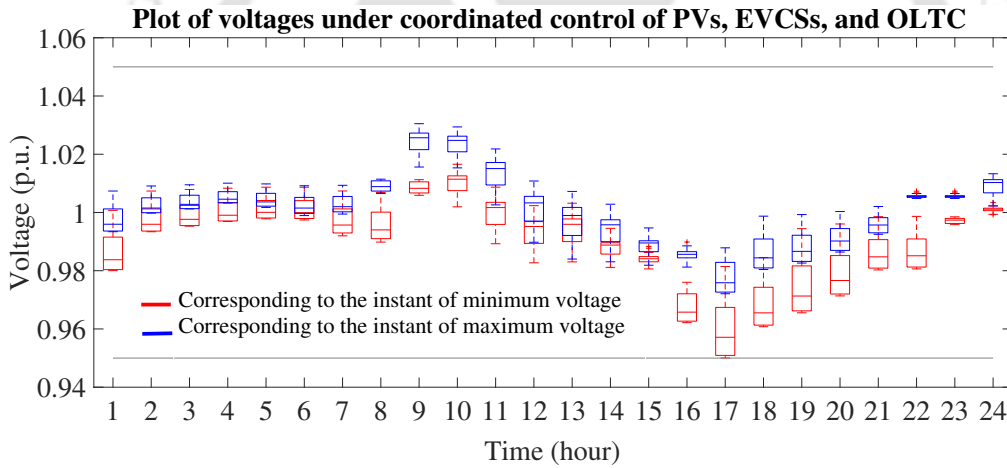


Fig. 4.15: Voltage plots of IEEE-123 bus network corresponding to the instant of minimum and maximum voltage occurrence in each hour, under CC-MPC.

generation of 300 kW [127]. Moreover, 4 EV EVCSs are placed in the network as per locations in [113], each rated as 300 kVA. The power capacity of each line is 5000 kVA, as considered in [127], corresponding to which the current carrying capacity of each line is 1.202 kA. The residential chargers are assumed to be installed in every LV network connected. Considering the domestic EV penetration level of 60%, 140 and 560 chargers of level 1 and level 2 are assumed to be installed throughout the network based on connected load demand (as explained in Section III). Fig. 4.14 shows a plot of voltages under no control action. Significant over/under voltage violations are seen throughout the day, with over-voltages dominant during peak PV generation,

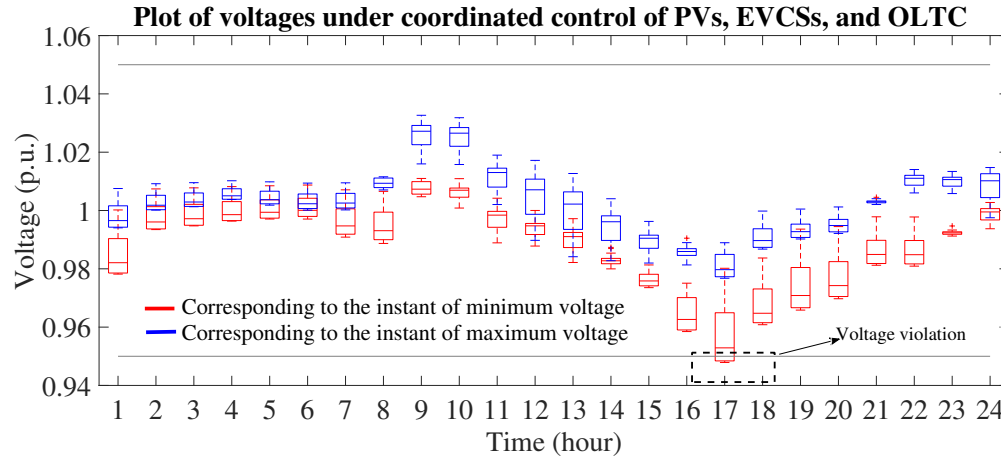


Fig. 4.16: Voltage plots of IEEE-123 bus network corresponding to the instant of minimum and maximum voltage occurrence in each hour, under D-MPC.

and under-voltages significant during high load and EV demands. The thermal limit of a few lines is also violated due to high PV active power injection, as shown in Fig. 4.17. With the proposed CC-MPC control approach coordinating PVs, EVCSs, and OLTC, the voltages are maintained within the range $[1.05, 0.95]$ p.u., while maintaining the thermal limits of the lines, as shown in Fig. 4.18. For the base case of 60% penetration of domestic EVs, the plot of voltages corresponding to instants of minimum/maximum voltage occurrence in each hour is shown in Fig. 4.15. The controller demands a higher reactive power injection due to dominantly higher under-voltages; however, the reactive power absorption from the controllable inverters is comparatively low. The active power exchange by PV inverters and EVCSs is shown in Fig. 4.9(b), and is 74.93 kWh and 53.45 kWh, respectively (Table 4.3). Under varying degrees of domestic EV uncertainties, the variations of net energy loss corresponding to different values of σ^{ev} are shown in Fig. 4.20(a). The voltages are effectively maintained within limits for all EV uncertainty levels. The net energy losses are seen to be 4.977 MWh, 4.983 MWh, 4.994 MWh, and 4.9958 MWh corresponding to $\sigma^{ev} = 0.05, 0.1, 0.15$, and 0.2 , respectively. Moreover, with increased levels of EV uncertainties, there is an increase in net reactive power injection. The increased reactive power injection is to maintain the voltages within the specified limits. Moreover, the EV penetration is varied between 60% and 100%, and the corresponding energy loss variations with different EV penetration levels are shown in Fig. 4.20(b). Compared to the base case of 60% EV penetration level with net

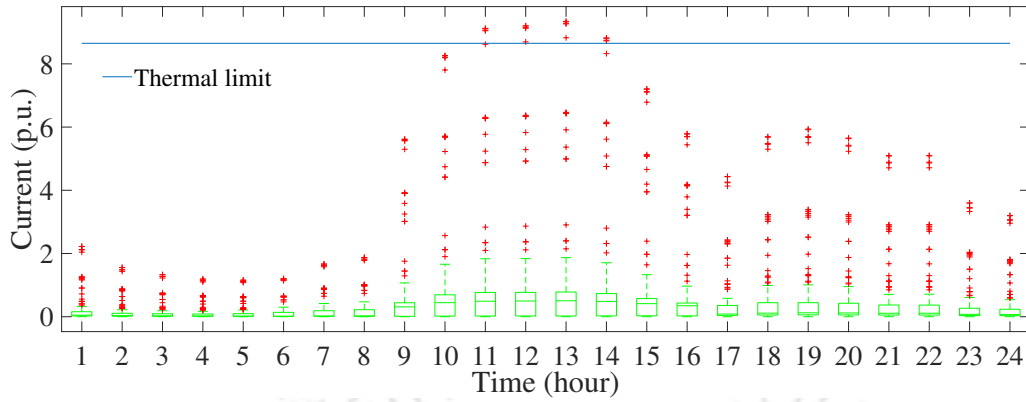


Fig. 4.17: Plot of line currents corresponding to the instant of maximum current in each hour, under no control.

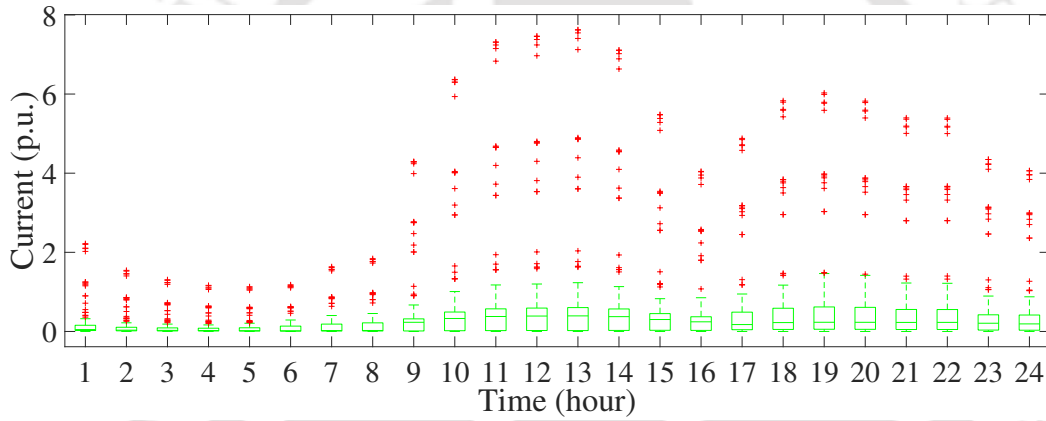


Fig. 4.18: Plot of line currents corresponding to the instant of maximum current in each hour using the CC-MPC approach.

energy loss equal to 4.9832 MWh, the energy losses increase by 2%, 3.922%, 6.025%, and 8.587% corresponding to EV penetration levels of 70%, 80%, 90%, and 100%, respectively. The voltages remain within normal operation limits corresponding to all EV penetration levels. The net reactive power exchange by PV and EVCS inverters is shown in Fig. 4.19(a) and Fig. 4.19(b), respectively. As compared to the base case (60% penetration), the net reactive power exchange increases by 4.084%, 6.38%, 10.74%, and 13.44% for EV penetration levels of 70%, 80%, 90%, and 100%, respectively. The CC-MPC model is compared to the D-MPC approach. There are under-voltage violations seen at the evening peak hour. The plot of minimum/maximum voltages in each hour is shown in Fig. 4.16. With slightly increased reactive power exchange (0.6234 MVarh), the voltage violations are eliminated using the CC-MPC approach.

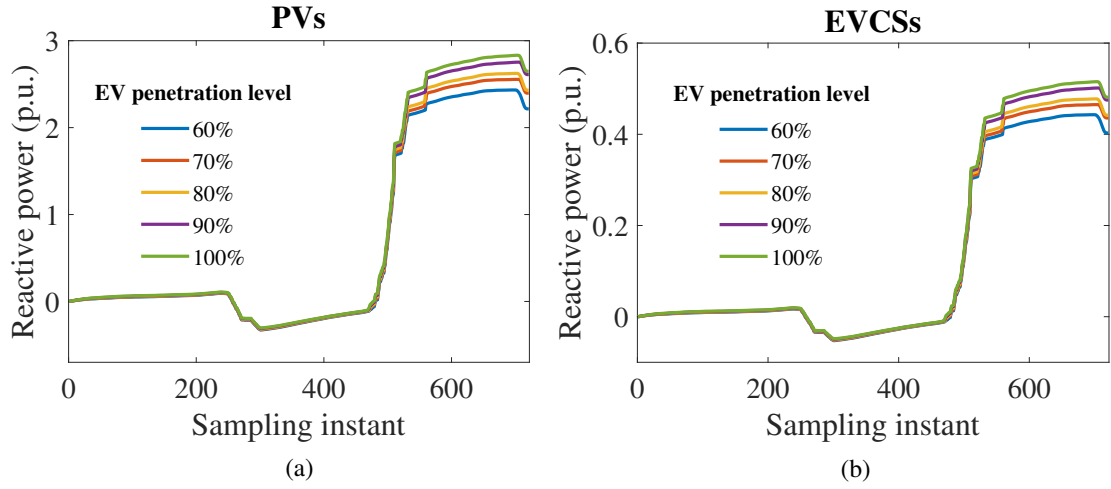


Fig. 4.19: Net reactive power exchange under various residential EV penetration levels with sampling rate of 2-minutes: (a) by PV inverters (b) by EVCSs.

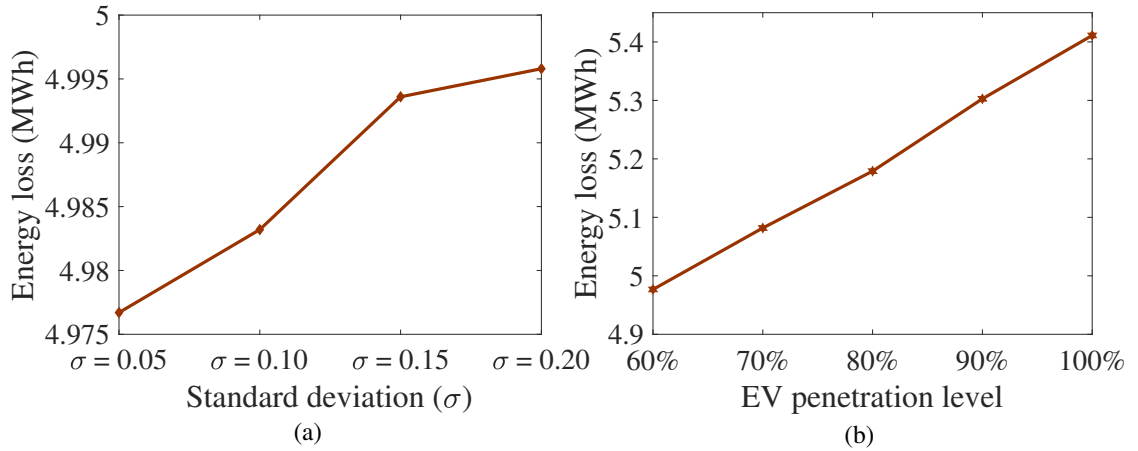


Fig. 4.20: Variation of net energy losses: (a) Under varying degrees of uncertainties (b) Under varying domestic EV penetration levels.

4.7 Conclusion

This work proposes a real-time CC-MPC approach for CVC in ADNs. A multi-time scale co-ordination approach has been used with high domestic EV penetration, by coordinating devices with different temporal characteristics (PVs, EVCSs, and OLTC), to ensure rapid adaptability to dynamic power system conditions, while limiting the over-utilization of slow control devices. The proposed model effectively considers uncertainties inherent in conventional loads, EV loads, and PVs, quantifying them individually to account for varying levels of uncertainties. A scenario-based approach (using Monte-Carlo simulation) is leveraged to reformulate the chance-constrained prob-

lem as a deterministic counterpart while maintaining computational efficiency using the backward scenario reduction technique. The proposed approach considers the nodal power uncertainties, unlike the other D-MPC approaches, under varying degrees of uncertainties and EV penetration levels. The simulations have been performed on the 33-bus network and IEEE-123 bus network to validate the performance of uncertainty handling and the scalability of the proposed control approach.

- The proposed approach maintains the voltages within limits for all EV penetration levels in both test networks. The energy losses increase by 19.179%, 22.483%, 44.063%, and 45.628% for penetration levels of 70%, 80%, 90%, and 100%, respectively, for 33-bus network.
- The net increase in reactive power exchange and energy losses as compared to D-MPC is seen to 513 kVarh and 403 kW, respectively, for the 33-bus network. For the IEEE 123-bus network, the net increase in reactive power is seen to be 623.4 kVarh. However, the voltages are maintained within safe operation limits using CC-MPC, while voltage violations are seen in the D-MPC approach.

Chapter 5

Centralized voltage control and energy loss minimization of ADNs with nodal power uncertainties using distributionally robust chance-constrained MPC

This study extends the work discussed in Chapter 4 for the voltage control and energy loss minimization under system uncertainties. In addition to the nodal power uncertainties, the uncertainties in real-time measurements are also considered, using a distributionally robust CC-MPC framework. Unlike the scenario-based solution approach to the chance-constrained formulation, requiring pre-defined probability distributions of uncertain parameters, this study provides a scenario-independent tractable solution approach to the chance-constrained problem. The solution does not require pre-defined probability distributions of the uncertain parameters, thus providing a distributionally robust solution approach to the system with uncertainties. Moreover, the control capabilities of the distribution static synchronous compensator (DSTATCOM) are utilized in coordination with other control devices. In addition, a local control layer is added at

a time scale of a few seconds to enhance the control and serve as a backup for the centralized controller.

5.1 Introduction

ANSI Standard C84.1-2016 [9] specifies that voltage deviations in each bus must be maintained within $\pm 5\%$ of the nominal value. Failure to comply with the voltage constraints can lead to the mandatory disconnection of RESs, thereby reducing the PV hosting capacity [128]. These uncertainties are further enhanced by electric vehicle charging stations (EVCSs), which require advanced coordinated voltage control (CVC) schemes [129].

PV reactive power is generally used to regulate node voltages, however, during peak generation, reactive power control may be rendered insufficient, constrained by active power generation. In such cases, active power curtailment (APC) [110] is a viable alternative but results in a loss of energy. Additional control provisions can be provided by EVCSs, using reactive power from inverters, and active power from EV batteries using V2G functionality [70]. A multi-time scale optimization framework using model predictive control (MPC) is proposed in [70], utilizing V2G services from EVCSs, in addition to PVs for voltage control. EVCSs are considered for CVC in [41], with random stochasticity in parking lot allocation and power exchange. In addition, V2G functionality is also utilized in [60, 64] for coordinated voltage control. Utilizing DSTATCOM, a coordinated voltage control is proposed in [130], along with PVs and OLTC in [48] using the current injection model, and energy storage systems [68] but the advantages of adding a local control structure are not considered in [48, 130]. The CVC frameworks in [41, 48, 60, 64, 70, 130] do not consider the control of PV inverters, EVCS inverters, DSTATCOM, and domestic EV charging in a single control framework.

Since the centralized control schemes require reliable communication and information transparency, and may be affected by single-point failure. The advantages of the hybrid control mechanism, with a fast local control layer, are largely ignored. To leverage the advantages of local and centralized control schemes, a hybrid control structure is utilized in [3] employing a fast local control layer, in addition to the centralized control of DG units. A hybrid CVC strategy is proposed

in [93] that combines distributed and local designs efficiently, to coordinate DERs. Nonetheless, the control capabilities of EVCSs and DSTATCOMs are not explored in [3,93]. A two-time scale hybrid control scheme based on MPC is proposed in [131], utilizing PVs, EVCSs, and OLTC for voltage control and energy loss minimization, while ignoring the control capabilities of DSTATCOM. The existing CVC schemes mentioned rely on network-wide measurement infrastructure and communication overhead, which might not be practically economical. Authors in [64] propose a model-free multi-agent reinforcement learning-based approach to coordinate EVs and PVs using a partially observable Markov decision process.

The aforementioned works provide coordinated single and multi-stage control frameworks, however, they predominantly consider deterministic PV and load profiles and do not account for the inherent uncertainties in nodal power injections. This may lead to unreliable control actions and, consequently, violation of network security constraints [75]. Several advanced methods such as robust optimization (RO) [74, 132], and chance-constrained (CC) programming [75, 76] have been employed to address voltage control under uncertainties. RO approaches ensure solution feasibility under uncertainties using worst-case conditions. RO framework is introduced in [74], considering uncertainties in load demand and EV charging, using deterministic sets. The control approach does not consider OLTC and renewable PVs, and lacks real-time control. A multi-objective robust control scheme is proposed in [132] considering PV uncertainties; however, a CVC with different devices, such as EVCSs and DSTATCOM, are not considered. Despite the computational efficiency, solutions using robust optimization are often over-conservative, thus may over-utilize the control resources. Chance-constrained (CC) approaches, on the other hand, ensure that probabilistic constraints are satisfied with a predefined confidence level [75,133]. However, the inherent complexity of probabilistic constraints renders them analytically intractable, necessitating scenario-based approximations that involve extensive sampling. A two-stage CC optimization framework is used in [75] to model the nodal power uncertainties with a pre-defined probability distribution. However, the formulation uses a day-ahead optimization framework, and the capabilities of other fast-acting control resources are not taken into account. A two-time scale chance-constrained model predictive control (CC-MPC) based control framework is proposed in [133], considering nodal power uncertainties, which employs a scenario-based solu-

tion approach. The real-time control is enabled by advancements in short-term forecasting and measurement infrastructure. Nevertheless, the CVC schemes [48, 75, 76, 118, 133] do not consider the erroneous measurements, which may render the solution suboptimal, or even violate voltage constraints. Furthermore, the CC optimization problems utilizing a scenario-based approach to eliminate the intractability may be computationally demanding. In addition, the CC approaches in [75, 133] rely on predefined probability distributions; however, the determination of the actual distribution may be practically hard. A tractable approximation of the original CC problem is proposed in [76], using affine disturbance parameterization, to reformulate chance-constraints (CCs) into second-order cone constraints. While the solution strategy is computationally efficient, the uncertainties in measurements, for central coordination are not taken into account. While robust optimization approaches tend to produce overly conservative actions with higher operational costs, the scenario-based methods, on the other hand, depend on the quality of selected scenarios and incur significant computational burden, limiting applicability in large networks with a large number of control variables. A scenario-independent chance-constrained formulation avoids these limitations by eliminating the need for extensive scenario generation. To this end, a distributionally robust CC formulation is proposed in [71] to avoid dependence on pre-defined uncertainty distributions; however, detailed time domain simulations with real-time control actions are not depicted to show the controller performance under dynamic high loading conditions. Moreover, the control capabilities of DSTATCOM and EVCSs under coordinated control are not evaluated, and the uncertainties in measurements are not taken into account. The comparison of existing CVC

Table 5.1: Coordinated voltage control approaches in ADNs.

Reference	Real-time control	Domestic EV charging	DSTATCOM control	EVCS control	Local control layer	Consideration of uncertainties	
						Nodal powers	Measurements
[70]	✓	×	×	✓	×	×	×
[75]	×	×	×	×	×	✓	×
[76]	✓	×	×	×	×	✓	×
[68]	✓	×	×	×	×	✓	×
[131]	✓	✓	×	✓	✓	×	×
[74]	×	×	×	✓	×	×	×
Proposed	✓	✓	✓	✓	✓	✓	✓

frameworks with the proposed approach is given in Table 5.1. Based on the existing literature discussed above, the research gaps addressed in this work are as follows.

- Existing real-time control schemes have not considered the inherent uncertainties in real-time measurements required for centralized control.
- Although few of the existing real-time control schemes have considered power uncertainties, they have either employed robust optimization or a scenario-based approach to the chance-constrained problem. A scenario-independent solution to the CC problem, considering measurement and nodal power uncertainties, is not studied.

In this chapter, a CC-MPC-based control scheme is proposed for CVC in ADNs, with slow-acting OLTC and fast-acting PVs, EVCSs, and DSTATCOM. The proposed model considers nodal power and measurement uncertainties using a distributionally robust CC-MPC with receding-horizon control. Unlike robust optimization and scenario-based approaches, the CC formulation is solved analytically while ensuring robustness for uncertainty distributions. Network modularity-based clustering is used to partition the network using the Louvain algorithm to identify the critical nodes for reduced measurement and communication. In addition, a local fast control layer is added to enhance the regulation flexibility. The main contributions are enumerated as follows:

1. An MPC-based control scheme is developed to coordinate devices of different time characteristics, and in the presence of realistic domestic EV data sets. In addition, the control capabilities of DSTATCOM are explored under the coordinated control framework.
2. The nodal power and measurement uncertainties are considered using an analytical solution to the distributionally robust CC problem, requiring partial information about the uncertainties. Detailed time domain simulations are carried out to depict the control capabilities under uncertainties and dynamic high loading conditions.
3. A local control layer is integrated, in addition to the centralized control structure. The local controllers embedded in PVs quickly respond to voltage fluctuations in a few seconds using local measurements, providing additional control flexibility.

The remaining part of this chapter is structured as follows: Section 5.2 gives a brief description of the control framework. The problem formulations and the solution approach are discussed in section 5.3. Section 5.4 provides the time-domain simulation results on the two test networks, and section 5.5 provides the conclusion of the chapter.

5.2 Control Framework

The MPC controller coordinates PVs, EVCSs, DSTATCOM, and OLTC in a multi-time scale optimization framework. The control action using PVs and EVCSs is achieved by adjusting the active/reactive power of the interfacing inverters and the reference voltage of DSTATCOM for reactive power control. Only 20% of the active power available is used for the control with APC of PVs and V2G while avoiding the reactive power adjustments. The control strategy employs a receding-horizon approach to integrate new measurements at each control step [70,133]. A current injection model, shown in Fig. 1.6 (Chapter 1) is used for DSTATCOM. The differential equation governing the dynamical operation of STATCOM corresponding to a given set point reference voltage is discussed in section 1.2.5, and is given as,

$$\dot{i}_{stat} = [K_{stat}(V_{ref} - V_g) - i_{stat}]/T_{stat} \quad (5.1)$$

Here, K_{stat} and T_{stat} are controller gain and time constant, and V_{stat} and V_g are DSTATCOM reference voltage and interfacing bus voltage, respectively. The net reactive power exchange for the given interfacing bus voltage is given by,

$$Q_{stat} = V_g i_{stat} \quad (5.2)$$

The direction of the DSTATCOM current governs whether the reactive power is injected or absorbed. The sensitivity coefficients corresponding to active and reactive power injections are obtained leveraging the Z-bus method. For the detailed expressions and derivations of voltage, current, and power loss sensitivities using the Z-bus method, refer to [76] and [121]. Voltage sensitivities with respect to OLTC tap changes are evaluated by varying taps above and below the

nominal position to determine corresponding bus voltage deviations and averaging the sensitivities for both cases. As their variation across different loading conditions is negligible, the coefficients are treated as constant throughout the simulation period in the proposed model.

5.3 Problem Formulations

The proposed control scheme employs a centralized architecture that operates in two stages. The operation of OLTC is carried out at a slower time scale of 1 hour. Power electronic-based devices, capable of frequent operation, are scheduled with a 4-minute control step (greater than 1-minute resolution of generation/load data) to illustrate uncertainty-handling capability. However, the time step can be feasibly reduced to a few seconds if the measurements are available within the time frame. Additionally, a rapid response local control structure is employed every 10 seconds, offering enhanced network control flexibility. It needs to be understood that the network voltages ($\mathbf{V}$) and power losses ($\mathbf{p}_l$) serve as the outputs of the prediction model. Thus, under the nodal power injection and measurement uncertainties, the system output may deviate from the predicted output. Thus, the output constraints are modeled as chance constraints.

5.3.1 Centralized Control

The objective function minimizes voltage deviations from the reference voltage vector ($\tilde{\mathbf{V}}$), change in control inputs ($\Delta \mathbf{U}$), and line losses ($\mathbf{p}_l$), and is expressed as,

$$\min \sum_{i=1}^{N_p} (\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_l}^2) + \sum_{i=1}^{N_c} \|\Delta \mathbf{V}_{\text{tap}}(\kappa + i)\|_{\mathbf{w}_{\text{tap}}}^2 \quad (5.3)$$

subjected to the constraints,

$$\underline{\underline{\Delta \mathbf{V}_{\text{tap}}}} \leq \Delta \mathbf{V}_{\text{tap}} \leq \overline{\overline{\Delta \mathbf{V}_{\text{tap}}}} \quad (5.4a)$$

$$\underline{\underline{\mathbf{V}_{\text{tap}}}} \leq \mathbf{V}_{\text{tap}}(\kappa + i) \leq \overline{\overline{\mathbf{V}_{\text{tap}}}} \quad (5.4b)$$

$$\mathbb{P} \left(\underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} \right) \geq 1 - \varepsilon \quad (5.4c)$$

where, slack variable vector $\sigma = [\sigma_1 \ \sigma_2]^\top$ is added to avoid the controller being stopped under solution infeasibility. Eq. (5.4a) and Eq. (5.4b) are operational constraints of OLTC. Eq. (5.4c) is the probabilistic constraint of the output variable, wherein ε represents the voltage violation probability. The control variable $\Delta \mathbf{V}_{\text{tap}}$ is handled as a continuous variable in the objective function. However, the operations are carried out by rounding off the input variable to the nearest discrete tap position. Similarly, at a faster time scale of the centralized controller, the objective function is given by,

$$\min \sum_{i=1}^{N_p} (\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1}^2) + \sum_{i=1}^{N_c} (\|\Delta \mathbf{Q}_{\text{PV}}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{Q}_{\text{EV}}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{V}_{\text{ref}}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{P}_{\text{PV}}(\kappa + i)\|_{\mathbf{w}_p}^2 + \|\Delta \mathbf{P}_{\text{EV}}(\kappa + i)\|_{\mathbf{w}_p}^2) \quad (5.5)$$

subjected to the following constraints,

$$\underline{\underline{\Delta \mathbf{Q}_{\text{PV}}}} \leq \Delta \mathbf{Q}_{\text{PV}}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{Q}_{\text{PV}}}} \quad (5.6a)$$

$$\underline{\underline{\Delta \mathbf{Q}_{\text{EV}}}} \leq \Delta \mathbf{Q}_{\text{EV}}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{Q}_{\text{EV}}}} \quad (5.6b)$$

$$\Delta \mathbf{P}_{\text{PV}}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{P}_{\text{PV}}}}(\kappa) \quad (5.6c)$$

$$\underline{\underline{\mathbf{Q}_{\text{PV}}}} \leq \mathbf{Q}_{\text{PV}}(\kappa + i) \leq \overline{\overline{\mathbf{Q}_{\text{PV}}}} \quad (5.6d)$$

$$\underline{\underline{\mathbf{Q}_{\text{EV}}}} \leq \mathbf{Q}_{\text{EV}}(\kappa + i) \leq \overline{\overline{\mathbf{Q}_{\text{EV}}}} \quad (5.6e)$$

$$\underline{\underline{\mathbf{Q}_{\text{ST}}}} \leq \mathbf{Q}_{\text{ST}}(\kappa + i) \leq \overline{\overline{\mathbf{Q}_{\text{ST}}}} \quad (5.6f)$$

$$\mathbb{P} \left(\underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} \right) \geq 1 - \varepsilon \quad (5.6g)$$

Equations (5.6a) - (5.6f) refer to the operational constraints over the control inputs, which are essentially related to the device operation and capacity limits, and Eq. (5.6g) corresponds to the probabilistic constraint on the system voltages, under system uncertainties.

5.3.1.1 Network Partitioning Based Identification of Pilot Nodes

The above MPC-based control model relies on state measurements and estimation for predictive optimization. However, extensive communication and network-wide measurement infrastructure increases both cost and complexity. For this purpose, a community detection based on the Louvain algorithm is employed, as given in Algorithm 5.2, for optimal network partitioning for the identification of pilot nodes. The Louvain algorithm is chosen for its computational efficiency, scalability, independence from a predefined number of partitions, and ability to quantify clustering quality by maximizing a modularity function at each stage. An improved modularity index is maximized at each stage for optimal partitioning [99]. The improved index considers voltage regulation capabilities and cluster voltage sensitivities for effective network partitioning, in addition to network topology considerations. The modified modularity index (ρ_{mod}) is calculated at a given clustering stage using the following function [99]:

$$\rho_{mod} = \alpha_1 \rho + \alpha_2 \frac{1}{n_C} \left(\sum_{m=1}^{n_C} (\alpha_3 S^{vp} + \alpha_4 S^{vq}) \cdot \Psi \right) \quad (5.7)$$

Algorithm 5.2 Louvain Algorithm for Network Clustering

Inputs: Network data, adjacency matrix, voltage sensitivity matrix, generation/load data
 Start with each node as its own cluster: $\mathcal{C}$
 Set current clustering $\mathcal{C}^s \leftarrow \mathcal{C}$, best clustering $\mathcal{C}^* \leftarrow \mathcal{C}$
 Initialize modularity improvement $\Delta \rho_{mod}^+ \geq 0$
while $\Delta \rho_{mod}^+ \geq 0$ **do**
 for each cluster c_i in $\mathcal{C}^s$ **do**
 Find all neighboring clusters $\mathcal{A}$ of c_i
 for each neighbor $c \in \mathcal{A}$ **do**
 Temporarily merge c_i and c
 Compute modularity gain for this merge
 end for
 end for
 Select the merge with the highest modularity gain and update $\mathcal{C}^s$
 Update $\Delta \rho_{mod}^+$ as the change in best modularity
end while
Return
 $\mathcal{C}^* \leftarrow \mathcal{C}^s$ (Optimal partition)

S^{vp} and S^{vp} represent mean voltage sensitivities with respect to active and reactive powers, respectively, and Ψ represents the regulation capacity within the cluster. ρ considers network topology and edge weights, and is defined as,

$$\rho = \frac{1}{2m} \sum_i \sum_j \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(i, j) \quad \forall i, j \in \mathcal{N} \quad (5.8)$$

where, A is the adjacency matrix, with $A_{ij} = 1$ if a line connects nodes i and j , and 0 otherwise. The term $k_i = \sum_j A_{ij}$, $m = \frac{1}{2} \sum_i \sum_j A_{ij}$, and $\delta(i, j)$ takes the value 1 if nodes i and j are in the same cluster, and 0 otherwise. The detailed description of the improved modularity index and application to the Louvain algorithm is given in [82,99]. The Silhouette Index (SI) is adopted as a quantitative metric to assess the clustering quality, particularly with respect to the number of network partitions [134]. For each bus i , the SI is defined as,

$$SI(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (5.9)$$

where $a(i)$ denotes the average electrical distance between bus i and all other buses within the same cluster, while $b(i)$ represents the minimum average distance of bus i to the elements of any other cluster. The index satisfies $SI(i) \in [-1, 1]$, where values close to unity indicate that bus i is strongly affiliated with its assigned cluster and well separated from neighboring clusters, and thus strong clustering. The values close to zero imply weak clustering, and negative values suggest potential misclassification of the network buses [134]. The overall clustering quality is characterized by the average silhouette coefficient across all buses, given as,

$$\overline{SI} = \frac{1}{N_0} \sum_{i=1}^{N_0} SI(i) ; \text{ where } N_0 = |\mathcal{C}^*| \quad (5.10)$$

A larger $\overline{SI}$ reflects stronger intra-cluster coupling and weaker inter-cluster coupling.

5.3.2 Local Control

The reactive power is allocated by the central controller to the local controllers embedded within each PV system by issuing optimal control signals. It needs to be mentioned that the

integration of a local control layer enables rapid mitigation of voltage deviations between central control intervals, improves resilience to forecast errors and disturbances [40], and provides a fail-safe voltage regulation mechanism in case of central controller failure or communication failure [3]. A piece-wise linear $Q(V)$ characteristic is considered for each local controller adjusted based on the optimal signal dispatched by the centralized controller [70]. Consider the optimal reactive power delivered by the centralized controller as Q_{PV} , the control action (ΔQ_{PV}^l) dispatched by the local controller within each PV system is given by,

$$\Delta Q_{PV}^l = \begin{cases} 0 & V_{low1} \leq V \leq V_{up1} \\ \overline{\overline{Q_{PV}}} - Q_{PV} & V \leq V_{low2} \\ -\overline{\overline{Q_{PV}}} + Q_{PV} & V \geq V_{up2} \\ \frac{\overline{\overline{Q_{PV}}} - Q_{PV}}{V_{low1} - V_{low2}} \cdot (V_{low1} - V) & V_{low2} < V < V_{low1} \\ \frac{\overline{\overline{Q_{PV}}} + Q_{PV}}{V_{up2} - V_{up1}} \cdot (\overline{\overline{V}}_{up1} - V) & V_{up1} < V < V_{up2} \end{cases} \quad (5.11)$$

where, Q_{PV} is the magnitude of maximum available reactive power from the PV inverter at a given time, $V_{low1} = 0.96$ p.u., $V_{low2} = 0.90$ p.u., $V_{up1} = 1.04$ p.u., and $V_{up2} = 1.1$ p.u.

5.3.3 Distributionally Robust Chance-constrained Formulation

The chance constraint in Eq. (5.4c) and Eq. (5.6g) is not tractable and lacks a closed-form solution. The CCs are typically approximated by a scenario-based reformulation into deterministic ones, as in the previous chapter. It is seen that a sufficiently large sample set guarantees constraint satisfaction with high confidence [75]. However, scenario-based evaluation of CCs demands a specific known probability distribution of uncertainties, and is computationally less efficient for large systems with a large number of decision variables. To address these limitations, the proposed method adopts a distributionally robust chance-constrained MPC framework, representing uncertainties via an ambiguity set defined by moment information and support bounds, considering all possible distributions. The proposed formulation is tractable, computationally efficient, and does not need a precise probability distribution. Rather, the uncertainties are represented by an ambiguity set requiring only the first-order moment (mean) and second-order moment (covariance

matrix) [135]. Assuming that the uncertainties in nodal powers represented by vector ζ are modeled as a multivariate normal distribution with zero mean (μ_p) and covariance matrix Σ_p , and the measurement errors represented by vector ω are modeled using Gaussian distribution with zero mean (μ_m) and covariance matrix Σ_m . These covariance matrices can thus be expressed as [71],

$$\Sigma_p = \mathbb{E}(\zeta\zeta') , \Sigma_m = \mathbb{E}(\omega\omega') \quad (5.12)$$

Thus, the bus voltages under the uncertain nodal powers and measurement errors can be approximated as,

$$\mathbf{V} \approx \mathbf{V}_0 + \left(\frac{\partial \mathbf{V}}{\partial \zeta} \right) \zeta + \left(\frac{\partial \mathbf{V}}{\partial \omega} \right) \omega \quad (5.13)$$

As, the uncertainties in nodal power injections and state measurements are independent, it follows from (5.13) that the variances of voltages in vector $\mathbf{V}$ are given by,

$$\text{Var}(\mathbf{V}) = \left(\frac{\partial \mathbf{V}}{\partial \zeta} \right) \text{Var}(\zeta) \left(\frac{\partial \mathbf{V}}{\partial \zeta} \right)^T + \left(\frac{\partial \mathbf{V}}{\partial \omega} \right) \text{Var}(\omega) \left(\frac{\partial \mathbf{V}}{\partial \omega} \right)^T \quad (5.14)$$

Let us define the sensitivity matrices $\mathbf{D}_p$ and $\mathbf{D}_m$, representing the sensitivity coefficients with respect to the nodal power uncertainties and measurement errors, respectively, then,

$$\mathbf{D}_p := \frac{\partial \mathbf{V}}{\partial \zeta} = \frac{\partial \mathbf{V}}{\partial \mathbf{p}} \cdot \frac{\partial \mathbf{p}}{\partial \zeta} , \mathbf{D}_m := \frac{\partial \mathbf{V}}{\partial \omega} \quad (5.15)$$

The sensitivity of active power at a given node is 1 corresponding to the uncertain power at that node, and 0 otherwise. Thus, $\frac{\partial \mathbf{p}}{\partial \zeta}$ represents essentially an identity matrix. The elements of matrix $\frac{\partial \mathbf{V}}{\partial \mathbf{p}}$ are obtained using the Z-bus method, as discussed in Section 4.3. Moreover, based on the linear MPC model [133], the deviation due to voltage error measurement is directly reflected in the predicted output voltage at a bus. Thus, $\frac{\partial \mathbf{V}}{\partial \omega}$ is treated as an identity matrix. Therefore, from Eq. (5.14), we have,

$$\text{Var}(\mathbf{V}) = \mathbf{D}_p \Sigma_p \mathbf{D}_p' + \mathbf{D}_m \Sigma_m \mathbf{D}_m' \quad (5.16)$$

Let $\mathbf{e}_i$ be the i^{th} canonical basis vector, then for i^{th} node voltage (V_i), the variance is given by,

$$\text{Var}(V_i) = \|\mathbf{e}_i^\top \mathbf{D}_p \Sigma_p^{1/2}\|_2^2 + \|\mathbf{e}_i^\top \mathbf{D}_m \Sigma_m^{1/2}\|_2^2 \quad (5.17)$$

The upper bound of the original chance constraint given in Eq. (5.4c) is equivalently expressed in robust form as,

$$\inf_{\Theta \in \mathcal{D}} \Theta(V_i \leq \bar{V}_i) \geq 1 - \varepsilon \quad (5.18)$$

where Θ represents the worst-case cumulative distribution function corresponding to the parameter ε in ambiguity set $\mathcal{D}$ [71]. The solution feasibility is assured with the probability threshold $1 - \varepsilon$ corresponding to the value of parameter ε [75]. Thus, the robust chance-constrained reformulation is given by,

$$\frac{V_i^2 - \bar{V}_i^2}{\|\mathbf{e}_i^\top \mathbf{D}_p \Sigma_p^{1/2}\|_2^2 + \|\mathbf{e}_i^\top \mathbf{D}_m \Sigma_m^{1/2}\|_2^2} \geq \Theta^{-1}(1 - \varepsilon) \quad (5.19)$$

For a moment-based ambiguity set ($\mathcal{D}_a$) with known mean and covariance, the inverse cumulative distribution function can be explicitly written as [71],

$$\Theta^{-1}(1 - \varepsilon) := \sqrt{\frac{1 - \varepsilon}{\varepsilon}} \quad (5.20)$$

Therefore, from Eq. (5.19) and Eq. (5.20) we obtain,

$$V_i \leq \left(\bar{V}_i^2 - \sqrt{\frac{1 - \varepsilon}{\varepsilon}} \left(\|\mathbf{e}_i^\top \mathbf{D}_p \Sigma_p^{1/2}\|_2^2 + \|\mathbf{e}_i^\top \mathbf{D}_m \Sigma_m^{1/2}\|_2^2 \right) \right)^{1/2} \quad (5.21)$$

Similarly, the lower bound constraint $\mathbb{P}(V_i \geq \underline{V}_i) \geq 1 - \varepsilon$ is reformulated as,

$$V_i \geq (\underline{V}_i^2 + \Lambda_i)^{1/2} \quad (5.22)$$

$$\Lambda_i = \sqrt{\frac{1 - \varepsilon}{\varepsilon}} \left(\|\mathbf{e}_i^\top \mathbf{D}_p \Sigma_p^{1/2}\|_2^2 + \|\mathbf{e}_i^\top \mathbf{D}_m \Sigma_m^{1/2}\|_2^2 \right) \quad (5.23)$$

These inequalities define the deterministic constraints resulting from the robust chance-constrained reformulation, where Λ_i acts as a risk-adjusted safety margin.

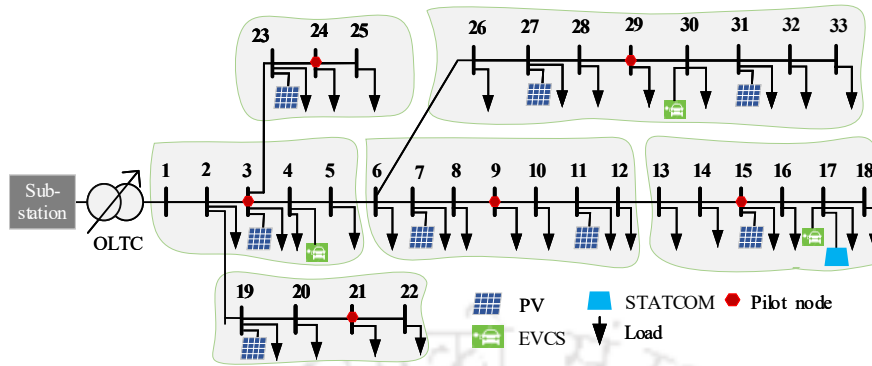


Fig. 5.1: 33-bus distribution network.

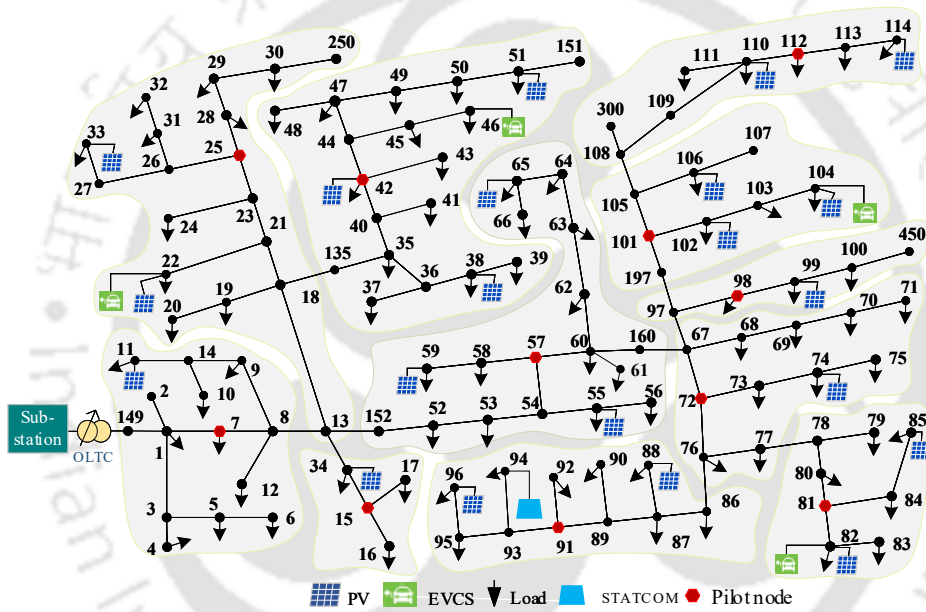


Fig. 5.2: IEEE 123-bus distribution network.

5.4 Simulation Results and Discussion

The proposed strategy is validated on 33-bus and IEEE 123-bus balanced distribution networks with PVs, EVs, and OLTC, as shown in Fig. 5.1 and Fig. 5.2. PV generation, EV demand, and load demand profiles are depicted in chapter 4. The OLTC provides 32 discrete tap adjustments, each with a 0.00625 p.u. voltage step, and a voltage variation range of $\pm 10\%$ of the nominal value. Only two tap steps are allowed at any instant, and OLTC operation is restricted if the voltage deviation is within 3% of the nominal value. This study also considers trial data from 461 residential EVs in the UK's Electric Nation project [124], as discussed in chapter 4. Detailed data

data are provided in [124] and [125]. Assuming the average residential load demand of each house as 3 kW, the EV penetration level is assumed to be 100% if a charger is installed for every 3 kW load. The work in this chapter considers a 50% EV penetration level, in which 80% of chargers are level 2 and the rest are level 1. The residential EV charging is assumed to be uncoordinated in the control scheme; however, EVCSs are considered as controllable resources. The uncertainties in the forecasted aggregated nodal powers and errors in measurements are contained in ambiguity sets, $\mathcal{D}_p$ and $\mathcal{D}_m$, respectively. The mean values of the uncertainties are assumed to be zero, and are considered to be independent. Thus, the covariance matrices Σ_p and Σ_m are diagonal matrices.

5.4.1 33-Bus Distribution Network

The network is integrated with PVs, DSTATCOM, and EVCSs as shown in Fig. 5.1, with a capacity of each PV and EVCS as 550 kVA and 330 kVA, respectively. Furthermore, residential EV loads are connected proportionally to the connected demand at each node. Considering the domestic EV penetration level of 50%, the total number of EV chargers is 620, with 124 and 496 of level 1 and level 2, respectively. In addition, an 800 kVA DSTATCOM is connected at bus 17 of the network, operating in current injection mode [48].

Significant and prolonged under/over voltages are seen under no control action in the network as shown in Fig. 5.3(a), with minimum and maximum voltages under the complete 24-hour time domain simulation identified as 0.8863 p.u. and 1.0737 p.u., respectively. Significant voltage deviations from the allowable normal limits are caused due to high penetration of PVs and EV loads, with net energy losses seen to be 2.6307 MWh.

To validate the control strategy, the proposed voltage control scheme is studied in the following case studies:

- **Case 1:** Considering the D-MPC and CC-MPC control schemes under measurement uncertainties
- **Case 2:** Considering the D-MPC and CC-MPC schemes under measurement and nodal power uncertainties.

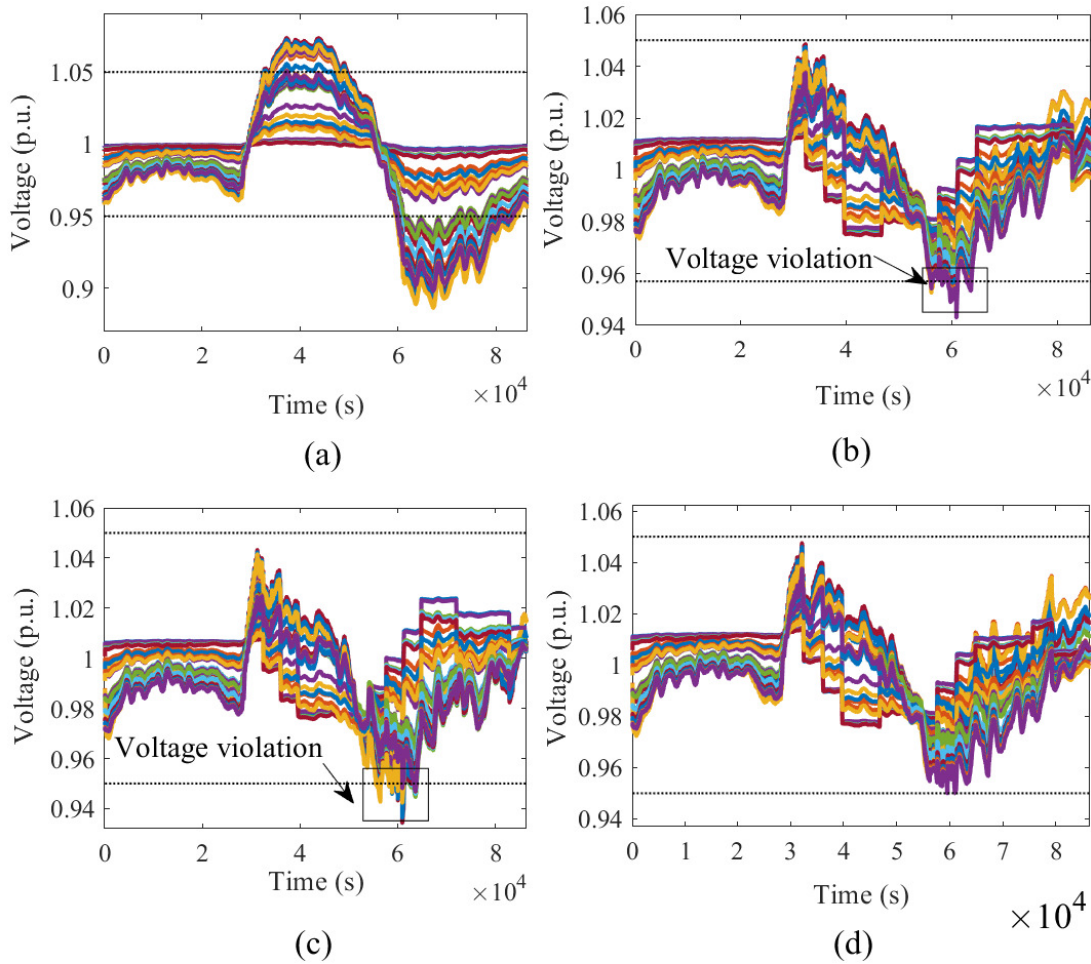


Fig. 5.3: Voltage profile of the 33-bus network with: (a) No control action (b) D-MPC approach under measurement uncertainties (c) D-MPC approach under nodal power and measurement uncertainties (d) Distributionally robust CC-MPC approach under nodal power and measurement uncertainties.

Comparison with the deterministic MPC scheme shows the effectiveness of the proposed distributionally robust CC-MPC control scheme in handling violations due to measurement and nodal power uncertainties. D-MPC assumes that all forecasted values of load demand, PV generation, and EV demand are exact, and enforces network voltage security constraints deterministically at each prediction step. However, the forecasted values have some uncertainties associated with them. This makes it prone to voltage violations under real-time nodal power and measurement uncertainties. In contrast, the proposed CC-MPC model treats voltage security constraints as probabilistic. Since CC-MPC optimization considers possible violations due to uncertainties, it provides more reliable and practical decisions.

5.4.1.1 Case 1: Considering D-MPC and CC-MPC Control Schemes under Measurement Uncertainties

The control scheme is evaluated assuming measurement uncertainties in the network, using the D-MPC framework. The uncertainties are incorporated in the real-time measurements using the Gaussian distribution. The voltage constraints are treated as deterministic with similar operation limits for each node. The network voltage profiles of all the buses are shown in Fig. 5.3(b), and it can be seen that there are voltage violations at certain time instants, due to the deterministic formulation under system uncertainties. It needs to be noted that the violations may be more severe and prolonged if the uncertainties are greater. The power losses are 1.5483 MWh. The aggregated reactive power exchanged by the control devices is summarized in Table 5.2. It can be seen that the control actions are predominantly taken by the PV inverters. Furthermore, it is observed that the net injection of reactive power from all control devices is significantly higher than the absorption of reactive power, as evident from Fig. 5.4, due to the occurrence of significant under-voltages. A significantly smaller amount of active power exchange is demanded under the severe voltage violation conditions, due to the high penalty (weights) associated with them in the objective function, thereby prioritizing reactive power control. However, using the proposed CC-MPC control scheme, the voltage violations due to measurement uncertainties are eliminated at the cost of higher reactive power exchange and slightly higher power losses by 191.8 kWh compared to the D-MPC case, as seen from Table 5.2. The net APC and V2G real-power injection of EVs is reduced compared to the D-MPC case study.

5.4.1.2 Case 2: Considering D-MPC and CC-MPC Schemes under Measurement and Nodal Power Uncertainties

The D-MPC scheme is assessed under network uncertainties in nodal powers and measurements, emulating realistic operational conditions. The uncertainties are incorporated using a Gaussian distribution with a predefined standard deviation of their respective uncertainty levels. Multiple voltage violations are seen, especially under severe generation and load demand. The voltage profile in this case study is shown in Fig. 5.3(c). The voltage violations due to uncertain-

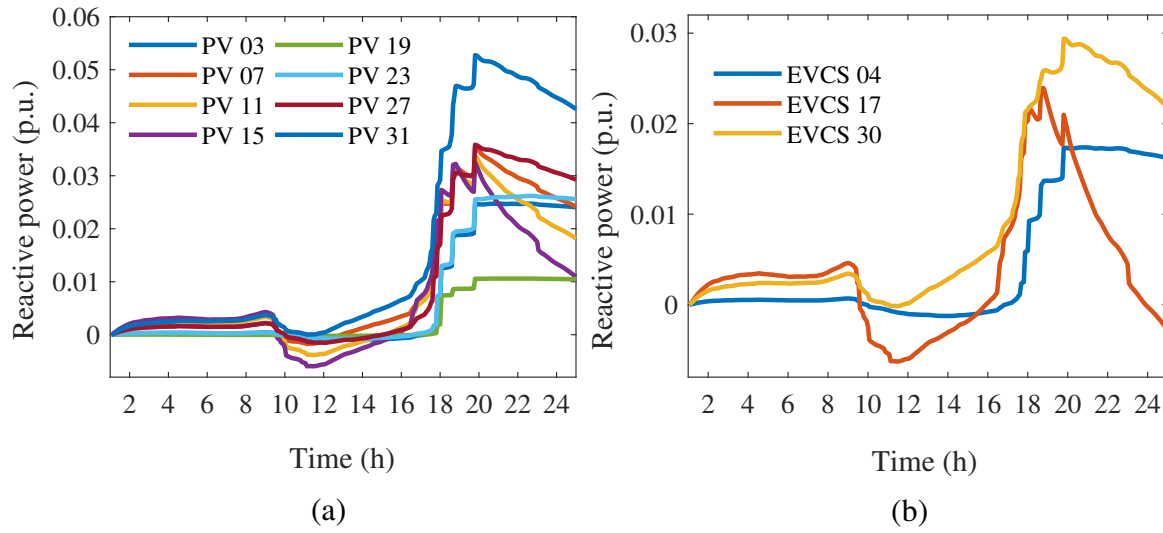


Fig. 5.4: Reactive power exchange in 33-bus distribution network under distributionally robust CC-MPC framework with nodal power uncertainties and measurement errors: (a) PV inverters (b) EVCSs.

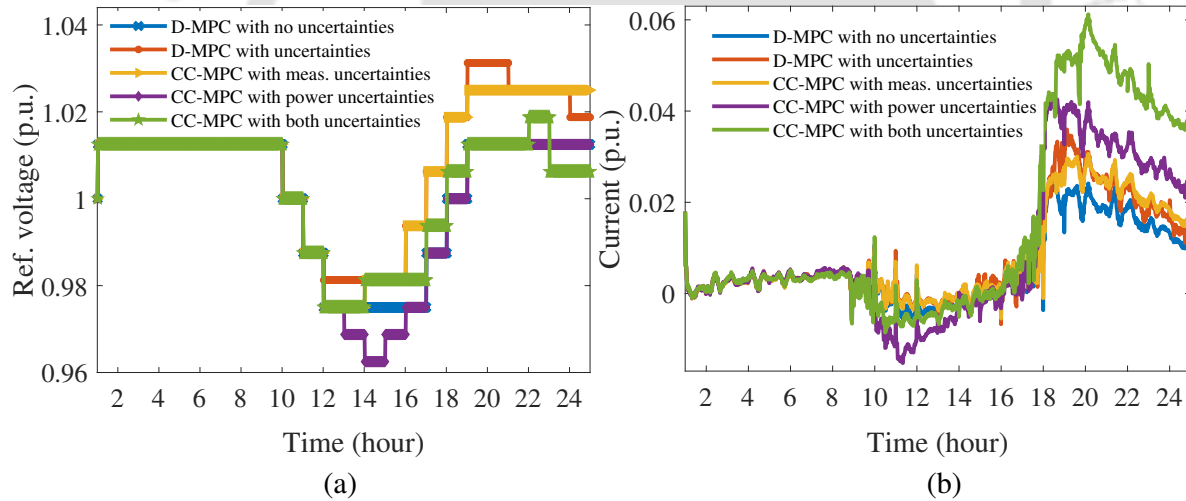


Fig. 5.5: Operation of OLTC and DSTATCOM in 33-bus network using CC-MPC approach with nodal power and measurement uncertainties: (a) Hourly optimal value OLTC reference voltage (V_{tap}) (b) DSTATCOM current (i_{stat}).

ties in nodal power injections are somewhat mitigated by the local control layer in the proposed control framework; however, due to the limited number of nodes with control resources, the action is localized to only these nodes. With the distributionally robust CC-MPC framework discussed in section 5.3.3, the voltage constraints are modified using the risk adjustment safety margin term (Λ). The constraint limits are modified in the CC-MPC framework with different values of Λ for

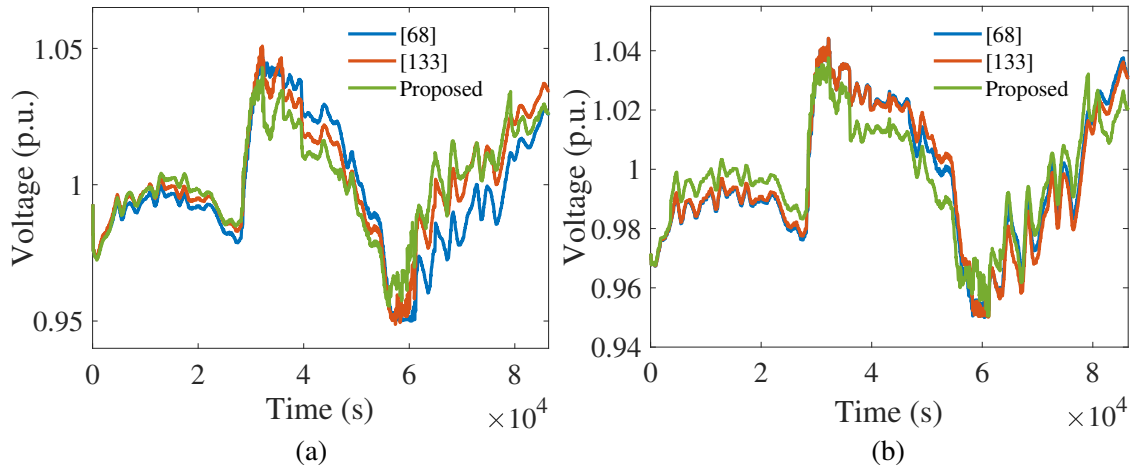


Fig. 5.6: Comparison with the existing works: (a) Voltage profile of node 18 in 33-bus network (b) Voltage profile of node 94 in IEEE 123-bus network.

each node, unlike the same values in D-MPC. The voltage profiles of the network nodes under nodal power and measurement uncertainties are shown in Fig. 5.3(d), and it can be seen that the node voltages are seen to be within the normal operation range. Since measurement errors are generally small (less than 1%), the possible voltage violations are relatively small compared to the uncertainties. Compared to the deterministic case study, it can be seen from Table 5.2 that the energy losses, as well as the aggregate reactive power exchange, increase by 112 kWh and 1.08 MVar, respectively. The reactive power exchanged by the PV inverters and EVCS inverters is shown in Fig. 5.4. They are increased to compensate for the constraint tightening in the CC-MPC

Table 5.2: Numerical values obtained from the simulations of the test systems under a random scenario of uncertainties.

Attributes	D-MPC scheme with measurement uncertainties		CC-MPC scheme with measurement uncertainties		D-MPC scheme with measurement and power uncertainties		CC-MPC with measurement and power uncertainties	
	33-Bus	123-Bus	33-Bus	123-Bus	33-Bus	123-Bus	33-Bus	123-Bus
Net Energy loss (MWh)	1.5483	4.9128	1.7401	5.1606	1.6673	5.010	1.7801	5.4514
Q_{PV} exchange (MVarh)	10.4138	14.8359	11.9304	15.4756	11.8753	14.5508	12.7011	16.0265
Q_{EV} exchange (MVarh)	4.451	2.7177	4.8933	2.7688	4.7971	2.6097	5.0198	3.0370
Q_{ST} exchange (MVarh)	1.4781	0.7796	1.9466	0.7977	1.9786	0.7051	2.0010	0.7740
Net APC of PVs (kWh)	86.55	109.3429	77.7867	93.6279	85.2937	134.7492	62.2139	77.0611
Net V2G injection (kWh)	102.31	92.920	85.0455	106.7184	90.2479	100.7279	68.6371	87.009
Minimum voltage (p.u.)	0.9430	0.9334	0.9502	0.9502	0.9392	0.9297	0.9500	0.9500
Maximum voltage (p.u.)	1.0484	1.0537	1.0477	1.0465	1.0482	1.0495	1.0474	1.0454
Dur. of voltage violation (h)	0.580	0.783	0	0	0.15	0.301	0	0
$\sigma_{CVD}(\times 10^{-4})$ p.u.	167	175	158	165	174	191	152	154
Comput. time (s)/sample	0.0416	0.0510	0.0416	0.0510	0.0416	0.0510	0.0416	0.0510

Table 5.3: Comparison table of the proposed control approach with the existing approaches.

Control approach	Test network	Voltage minimum/maximum (p.u.)	$\sigma_{CVD} \times 10^{-4}$ p.u.	Energy Loss (MWh)	Voltage deviation compared to proposed model σ/μ (p.u.)
[133]	33-bus	0.9502/1.050	177	2.0195	0.0042/ 0.0051
	123-bus	0.950/1.050	193	5.4525	0.0037/ 0.0083
[48]	33-bus	0.950/1.0483	176	2.0127	0.0041/ 0.0050
	123-bus	0.950/1.0504	191	5.3210	0.0038/ 0.0084
[68]	33-bus	0.950/ 1.051	190	2.0441	0.0065/0.0080
	123-bus	0.950/1.0505	198	5.5175	0.0033/ 0.0075
Proposed	33-bus	0.950/ 1.0474	152	2.0543	—
	123-bus	0.950/1.0454	154	5.4514	—

approach. Furthermore, the APC and V2G active power of EVs are reduced by 23.08 kWh and 21.21 kWh, respectively. The tap operations under different case studies are depicted in Fig. 5.5, wherein the reference voltage is the optimized control input. The effectiveness of the CVC control framework in different case studies is further evaluated with a performance evaluation metric called comprehensive voltage deviation (σ_{CVD}) [60], defined as,

$$\sigma_{CVD} = \sqrt{\frac{\sum_{\tau=1}^{\mathcal{T}_s} (\sigma_{VD}(\tau))^2}{\mathcal{T}_s}} \quad (5.24)$$

$$\text{where, } \sigma_{VD}(\tau) = \sqrt{\frac{\sum_{n=1}^N (V_n(\tau) - V^0)^2}{N}} \quad (5.25)$$

Here, $\mathcal{T}_f$ corresponds to the number of time samples. The values of (σ_{CVD}) represent the proximity of the voltages to the nominal value, and are given in Table 5.2 for different cases.

5.4.2 IEEE 123-Bus Distribution Network

The proposed scheme is further validated on the IEEE 123-bus network, shown in Fig. 5.2, with base power and voltage as 1 MVA and 4.16 kV, respectively. The network adapts equal-sized PVs and EVCSs, and 50% domestic EV penetration. In addition, a 500 kVA DSTATCOM is placed at bus number 94. The network exhibits significant and sustained voltage violations from the nominal operation range, in the absence of any voltage control, as evident from Fig. 5.7(a).

The minimum and maximum voltage magnitudes are seen to be 0.8863 p.u. and 1.0737 p.u., respectively. The resulting aggregated energy loss of the network, over the simulation period of 24 hours, is seen to be 6.4756 MWh. To regulate the voltages within the normal operation range and reduce net energy losses, the network is studied under the test cases mentioned in Section 5.4.1. The results corresponding to both the case studies are discussed in the following sub-sections.

5.4.2.1 Case 1: Considering D-MPC and CC-MPC Control Schemes under Measurement Uncertainties

Under measurement uncertainties using the D-MPC scheme, the voltage profile shown in Fig. 5.7(b) depicts violations at certain instants. The minimum voltage is seen to be 0.9430 p.u. It is to be mentioned that the voltage constraints are assumed to be deterministic, and the same constraint limits are considered for all nodes. The CVC is achieved with aggregated reactive power exchanged by the control agents shown in Table 5.2. With the proposed CC-MPC control scheme, the voltage violations are eliminated. The corresponding increase in reactive power control and power losses is given in Table 5.2. However, compared to the D-MPC approach, the APC, as well as the V2G active power demand from EVs, are reduced.

5.4.2.2 Case 2: Considering the D-MPC and CC-MPC Schemes under Measurement and Nodal Power Uncertainties

The control performance is evaluated under uncertainties in both nodal power injections and measurements, with deterministic voltage constraints. Forecasted powers and measurement uncertainties are considered using the Gaussian distribution, with a standard deviation of 1% and 5%, respectively. The voltage profiles under this scenario are shown in Fig. 5.7(c). It is seen that voltage violations are observed at several instances. It needs to be noted that the severity of the violation may be greater in certain scenarios or if the uncertainty level is higher. However, the simulations summarized correspond to a random scenario of uncertainties. Even though the fast-acting local control layer mitigates certain violations, the voltage violations persist as the local control takes into account the local bus voltages. With the proposed CC-MPC framework under

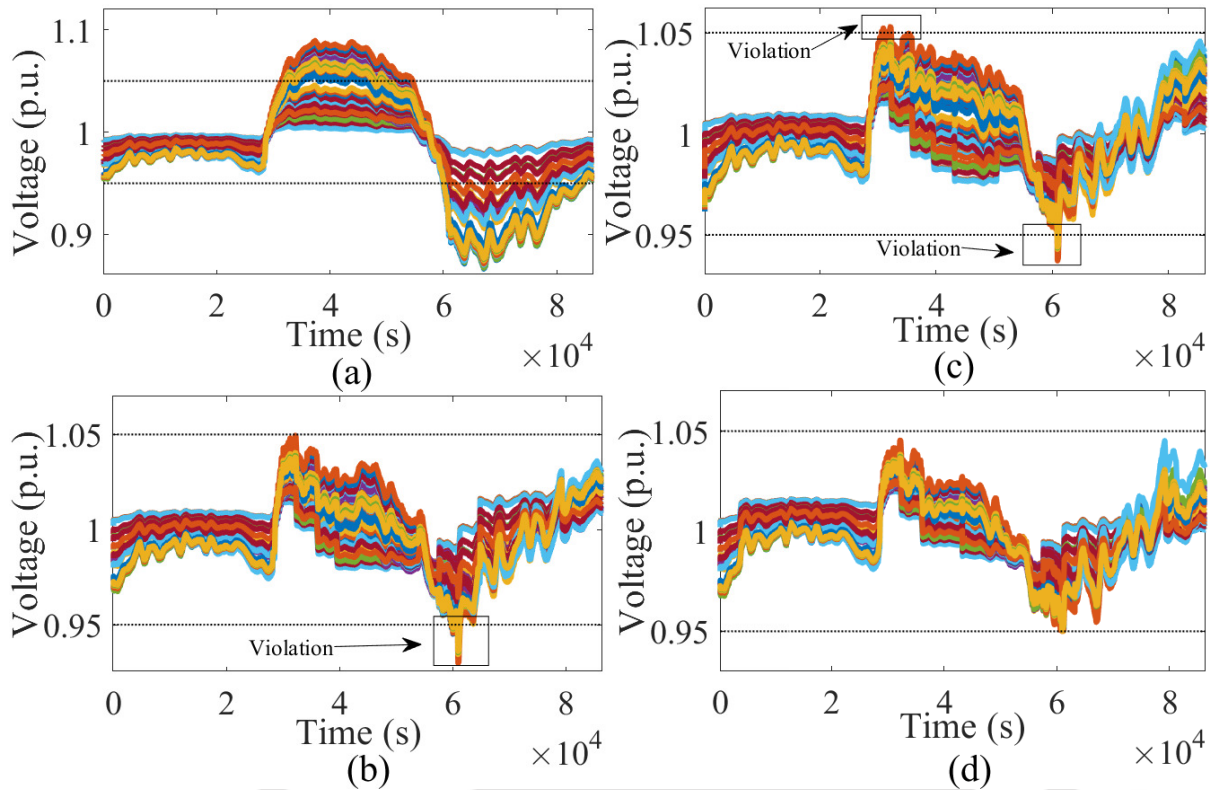


Fig. 5.7: Voltage profile of IEEE 123-bus network with: (a) No control action, (b) D-MPC approach under measurement uncertainties, (c) D-MPC approach under nodal power and measurement uncertainties, (d) Distributionally robust CC-MPC approach under nodal power and measurement uncertainties.

both uncertainties, the voltages are effectively regulated within the normal operation range. The corresponding voltage profile is depicted in Fig. 5.7(d). While the voltage violations due to uncertainties are eliminated, an increase in the control actions is seen, with a net increase in reactive power exchange by around 1.97 MWh, and a net increase in energy loss by 441.4 kWh (8.81%). The reactive power exchange by the control devices is shown in Fig. 5.8, depicting significant reactive power injection due to predominantly under-voltages in the network. The tap operations and DSTATCOM currents under different case studies are shown in Fig. 5.9. The control cost and power losses are increased in the proposed CC-MPC approach, as compared to the deterministic case study under uncertainties. Nonetheless, the network voltage security constraints are not violated in the proposed CC-MPC approach, and the active power curtailment is reduced compared to the deterministic case study. Furthermore, a comparative analysis is conducted between the proposed control strategy and existing approaches, including the scenario-based solution method

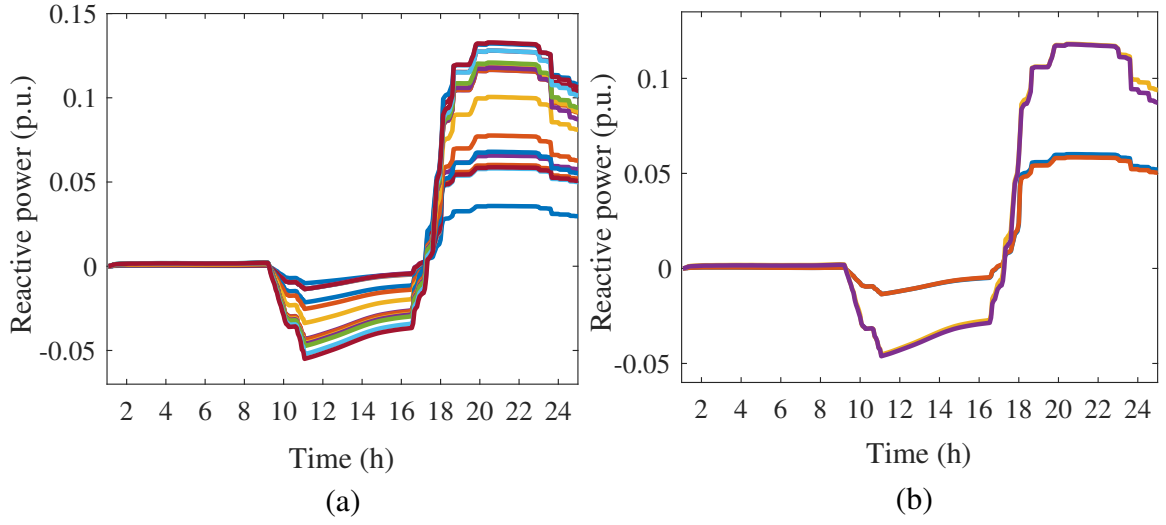


Fig. 5.8: Reactive power exchange in IEEE 123-bus distribution network under distributionally robust CC-MPC framework with nodal power uncertainties and measurement errors: (a) PV inverters (b) EVCSs.

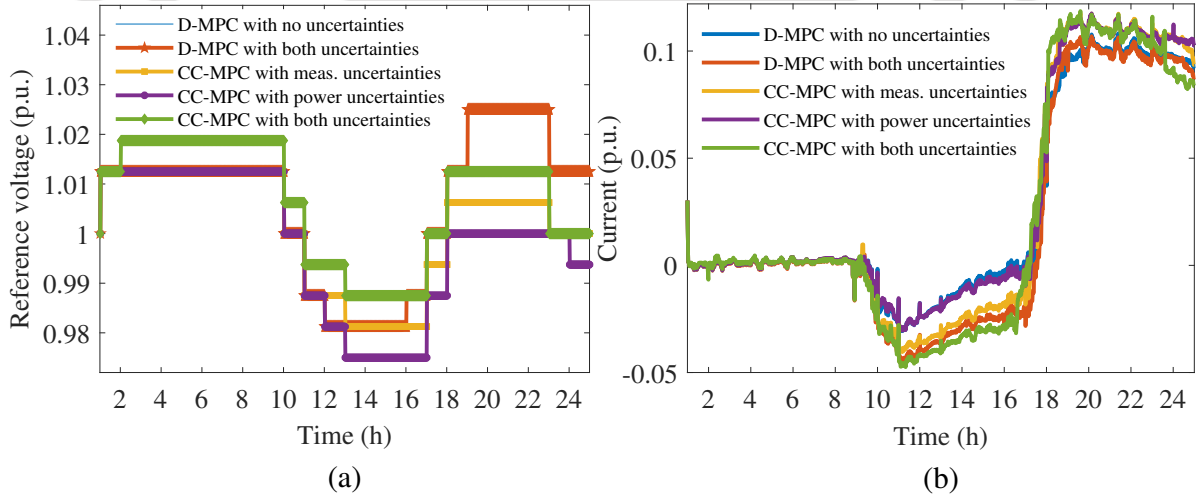


Fig. 5.9: Operation of OLTC and DSTATCOM in 123-bus network using CC-MPC approach with nodal power and measurement uncertainties: (a) Hourly optimal value OLTC reference voltage (V_{tap}) (b) DSTATCOM current (i_{stat}).

presented in [133], as well as control schemes employing varied measurement infrastructures as discussed in [68] and [48]. The voltage profile of the critical bus (bus 94) is depicted in Fig. 5.3(b). It is observed that the proposed method offers superior voltage regulation capabilities under the system uncertainties (Table 5.3).

5.4.3 Comparison with the Scenario-based Solution Approach

The effectiveness of the proposed control strategy is further validated through a comparison with the scenario-based approach presented in [133]. For evaluation, the voltage profile of a critical (bus 18) is selected as the reference. As illustrated in Fig. 5.6(a), the voltage profile using the proposed approach closely aligns with that of the scenario-based solution. Although the proposed method exhibits marginally higher power losses, as given in Table 5.2, it achieves a notably lower value of σ_{CVD} , depicting enhanced voltage regulation capability. In addition, the proposed approach is compared with MPC-based strategies in [48] and [68]. The approach in [48] relies on system-wide measurement infrastructure, whereas [68] uses fewer measurement devices. The comparative results, summarized in Table 5.3, indicate only a slight variation in power losses compared with the proposed method. However, the corresponding reduction in σ_{CVD} depicts the effectiveness of the proposed approach in mitigating voltage deviations under system uncertainties. The voltage profile of bus 18 is examined in Fig. 5.6(b). The mean (μ) and standard deviation (σ) of the voltage deviations compared to the proposed approach are much lower (Table 5.3). However, unlike deterministic control frameworks in [48] and [68], the proposed approach explicitly handles measurement and nodal power uncertainties.

5.5 Conclusion

In this work, a real-time, multi-timescale coordinated framework based on distributionally robust CC-MPC has been developed for voltage control and loss minimization in ADNs. The proposed framework explicitly addresses nodal power and measurement uncertainties by employing a hierarchical control with OLTC, and fast-acting PV inverters, EVCSs, and DSTATCOM via a multi-step receding horizon optimization. A fast-acting local control layer is incorporated to mitigate rapid voltage fluctuations and complement the centralized coordination mechanism. The proposed approach works under unknown probability distributions of uncertainty parameters, leveraging only partially available information. Comparative analysis with the deterministic solution approach depicts that the voltage constraints are successfully restrained within the normal operation limits, thus enhancing network security. Although the local control layer alleviates

some of the voltage violations, its limited spatial scope due to localized actions prevents comprehensive mitigation, allowing some voltage violations to persist within the network. The voltage violations caused by the uncertainties are successfully eliminated with the proposed approach, at the cost of an increase in reactive power control and a slight, but acceptable increase in power losses. Compared to the deterministic case study, the energy loss, as well as the aggregate reactive power exchange, increase by 112 kWh and 1.08 MVar, respectively, for the 33-bus system. However, the APC and V2G injection by EVCSs are reduced using the proposed control approach, employing the addition of a risk-adjusted safety margin to the chance constraints. The APC and V2G active power of EVs are reduced by 23.08 kWh and 21.21 kWh, respectively. However, the APC and V2G injection by EVCSs are reduced using the proposed control approach, with a safety margin (Δ) added to the chance constraints. This occurs due to the slightly conservative control actions through reactive power control, over the simulation period, waiving off the costly actions pertaining to the active power exchange. Furthermore, the proposed approach closely matches the scenario-based solution approach in [133], with a small increase in control cost and an increase in net energy loss by 1.7%, due to the consideration of the worst cumulative distribution function of uncertainties. However, the proposed solution approach shows better voltage regulation and does not need predefined probability distributions.



Chapter 6

A centralized-distributed MPC-based hybrid voltage control framework with improved network partitioning based distributed coordination of IDCDs

This chapter presents a hybrid control structure of centralized and distributed control paradigms, at varying time scales, considering the temporal characteristics of control equipment. At the first stage, OLTC is centrally coordinated with sparse communication from a set of strategically selected pilot buses, which facilitate real-time measurements. At the second stage, a distributed MPC-driven coordination framework is employed for IDCDs (PVs and EVCSs), optimizing both reactive and active power support. Distributed control is employed to enhance privacy preservation, control reliability, and reduce communication overhead in large networks. The network is partitioned into optimal clusters for distributed control, using a modified modularity-based community detection algorithm (employing the Louvain algorithm). A modified modularity metric is proposed, incorporating cluster diameter, in addition to the device regulation capacities and

average voltage sensitivities within the cluster, for effective partitioning, so as to achieve efficient distributed control. For distributed control, the decomposition coordination of the centralized model is used, corresponding to each controller in a cluster. To solve the distributed control problem, ADMM-based distributed optimization is employed, which enables parallel and localized decision-making of the distributed controllers.

6.1 Introduction

Voltage control problem in ADNs has been addressed through various optimal power flow (OPF) based and model predictive control (MPC) based centralized frameworks, necessitating a fully observable system and extensive communication. Multi-stage optimization models are employed for coordinated voltage control (CVC) using legacy devices like OLTC and fast-acting PVs [75, 76] while considering stochasticity. The Vehicle-to-Grid (V2G) paradigm that leverages bidirectional power flow enables EVs to also support grid operations. Multi-time scale coordination in the presence of PVs, EVs, and conventional devices is studied in [118, 133], wherein EV charging stations (EVCSs) are treated as control assets. For real-time control, MPC-driven multi-step optimization models [57, 118, 133] are increasingly used due to the availability of extensive data logs and advances in short-term forecasting [133]. While a system model is a prerequisite for MPC-driven systems, a multi-agent reinforcement learning based model-free voltage control framework is proposed in [64], employing a partially observable Markov decision process. With increasing size and the number of control resources in ADNs, communication overhead and computation time also increase in centralized control schemes [112]. A multi-time scale MPC-based control approach with reduced model framework is proposed in [118], to reduce the communication requirements and measuring infrastructure. However, in centralized control schemes, privacy concerns (such as operational constraints, critical resource parameters, scheduling profiles, etc.) emerge, as DG units are owned by different entities. Furthermore, centralized architectures are inherently vulnerable to cyber-physical threats, where a single point of failure can affect the entire network [87].

Consequently, voltage control problems in ADNs can be framed as constrained optimal power

flow problems [87], which can be solved in a distributed manner. Distributed coordination is achieved through various methods including algorithms based on multi-agent systems [85], decomposition-based coordination algorithms [8, 60, 87], consensus-based algorithms [83], and using optimization techniques, such as the alternating direction method of multipliers (ADMM) [8, 87] and Lagrangian dual theory [88]. ADMM decomposes the OPF problem of clustered network into multiple sub-problems (as in [8, 87]), thus providing distributed coordination. Distributed CVC mitigates the issues with centralized architecture by enabling localized coordination with reduced data exchange, privacy preservation, and enhancement of computational efficiency [112]. A bidirectional communication framework is proposed in [89] for CVC, utilizing multi-agent distributed coordination of a multi-energy storage system that considers both thermal and electric loads. A distributed MPC strategy is provided in [60], leveraging V2G reactive power capabilities for real-time voltage control in low-voltage DNs. However, the frameworks in [60, 89] do not incorporate legacy devices like OLTC. Moreover, the multi-time scale coordination of PVs and EVCSs with slow-acting devices is not studied. A fully distributed multi-time scale, volt/var control (VVC) strategy is proposed in [87], leveraging ADMM for zonal coordination and computational tractability. However, the network partitioning is done based on topology and observational heuristics, rather than considering electrical coupling among the nodes. Also, the control capabilities of EVs are not considered. Multi-time scale distributed control schemes are proposed in [101, 112], wherein the OLTC is coordinated at slow time scale (STS), while static synchronous compensators and DG units in [101], and PVs and storage devices in [112] are coordinated at faster time scale (FTS). Since the control resources are treated as individual controllers, the solution may significantly deviate from the optimal one, with an increase in the number of control variables. A VVC method in [136] utilizes machine learning-assisted distributed optimization, integrating long short term Memory (LSTM) model to improve ADMM convergence. However, the network partitioning is rule-based, and the use of OLTC and EVCSs using multi-time scale coordination is not considered. To this end, an MPC-based decentralized control framework is proposed in [99] with high penetration of EVs and PVs, wherein the network is partitioned into clusters based on the modified modularity index. However, it does not consider comprehensive coordination of different zones and multi-time scale coordination, incorporating OLTC. Thus, the

Table 6.1: Distributed control approaches for voltage control in ADNs.

Attributes	ADMM-based coordination			MPC-based coordination			MPC+ ADMM	
	[112]	[87]	[136]	[101]	[136]	[99]	[8]	Proposed
Optimal clustering	×	×	×	×	×	✓	×	✓
Consideration of EVCSs	×	×	×	×	×	✓	×	✓
Multi-time scale coordination	✓	✓	×	✓	×	×	✓	✓
Hybrid control structure	×	×	×	×	×	×	×	✓

existing research gaps in the distributed control can be summarized as follows:

- *Consideration of hybrid scheme for devices with varying temporal characteristics:* Existing frameworks do not consider the control capabilities of OLTC along with inverter-driven control devices (IDCDs), using hybrid control structure. The centralized-distributed hybrid control structure enhances solution optimality while ensuring reduced communication overhead.
- *Consideration of non-heuristic optimal network clustering for ADMM coordination:* The ADMM-based schemes either do not use zonal coordination [10], or primarily uses observational heuristics [2], [11], considering predefined rules or network topology, rather than leveraging electrical coupling for optimal clustering and enhanced zonal coordination. This may provide sub-optimal solution in ADMM-based distributed coordination.
- *Consideration of realistic EV data and V2G support of EVCSs:* The existing frameworks consider pre-defined EV profiles, or data generated using the processes, such as Markov chain process [64]. The control capabilities of EVCSs using active/ reactive power via V2G support, and the consideration of domestic EV loads based on the realistic trial data are not studied in detail.

Considering these gaps in the existing literature, this work presents a multi-stage MPC-based voltage control framework for ADNs with high penetration of PVs and EVs. A comparison of the proposed model with existing models is given in Table 6.1. The proposed control scheme leverages a hybrid control structure of centralized and distributed control paradigms, at varying time scales, to consider the temporal characteristics of control equipment. At the first stage,

OLTC is centrally coordinated with sparse communication from a set of strategically selected pilot nodes, facilitating limited real-time measurements. At the second stage, a distributed MPC-driven coordination framework is employed for IDCs (PVs and EVCSs), optimizing both reactive and active power support. Hierarchical clustering is used for optimal clustering of the network into coupled zones, using a modularity-based community detection algorithm. The modified modularity metric incorporates cluster diameter, in addition to the device regulation capacities, and average voltage sensitivity, within the cluster. For distributed control, the decomposition coordination of the centralized model is used for each controller in a cluster. An ADMM-based distributed optimization is employed, enabling parallel and localized decision-making for CVC with minimal communication overhead, enhanced computational efficiency, and scalability. The main contributions of the work presented in this chapter are as follows:

1. An MPC-based hybrid predictive control framework is proposed with multi-time scale adaptability for control devices with different temporal characteristics. Realistic EV data sets corresponding to domestic EV charging are considered to simulate the control scheme under real network conditions, with high renewable penetration.
2. A modified clustering index is introduced, incorporating cluster diameter, in addition to cluster voltage sensitivity, and device regulation capacities, to ensure uniform and efficient network clustering for distributed coordination.
3. An MPC-driven coordination scheme for distributed controllers is developed using ADMM-based distributed optimization, with reduced information exchange between neighboring clusters, corresponding to cluster boundary nodes. The coordination scheme uses reduced communication overhead to provide near near-optimal solution, while controlling reactive and active power. MPC-enabled receding horizon control enhances the performance of ADMM-based distributed coordination.

In the remaining part, Section 6.2 provides the MPC framework, Section 6.3 discusses network partitioning based on improved modularity index, Section 6.4 discusses centralized control of OLTC with limited communication to the pilot nodes, and Section 6.5 discusses the ADMM-based distributed coordination of inverter-driven control devices (IDCDs). Section 6.6 discusses

the simulation results on the test distribution networks, and finally, the Section 6.7 provides conclusive remarks.

6.2 MPC Framework

The compact matrix form representation of the linear Distflow model, as discussed in Chapter 2, is expressed as,

$$\begin{bmatrix} \mathbf{p}^\top & \mathbf{q}^\top \end{bmatrix}^\top = \begin{bmatrix} (\mathbb{A}\mathbf{P})^\top & (\mathbb{A}\mathbf{Q})^\top \end{bmatrix}^\top \quad (6.1)$$

$$\begin{bmatrix} \tilde{\mathbb{A}} \end{bmatrix}^\top \begin{bmatrix} \mathbf{V}_0 & \mathbf{V}^\top \end{bmatrix}^\top = [\mathbf{R}_l][\mathbf{P}] + [\mathbf{X}_l][\mathbf{Q}] \quad (6.2)$$

Based on this linear model in Eq. (6.1) and Eq. (6.2), the voltage vector corresponding to the changes in the nodal active and reactive power injections ($\Delta\mathbf{p}$ and $\Delta\mathbf{q}$), and change in the tap position of OLTC ($\Delta\mathbf{V}_0$), at time step $\kappa + 1$, is given by,

$$\mathbf{V}(\kappa + 1) = \mathbf{V}(\kappa) + \mathbf{S}_v^p \Delta\mathbf{p}(\kappa) + \mathbf{S}_v^q \Delta\mathbf{q}(\kappa) + \mathbf{S}_v^{\text{tap}} \Delta\mathbf{V}_0(\kappa) \quad (6.3)$$

where $\mathbf{S}_v^p$, $\mathbf{S}_v^q$, and $\mathbf{S}_v^{\text{tap}}$ represent the voltage sensitivity matrices corresponding to the change in active power, reactive power, and OLTC tap change, respectively. Knowing the voltages at κ (i.e., $\mathbf{V}(\kappa)$), the voltages at $\kappa + 1$ can be steered to the desired set point by changes in the nodal active/ reactive power injections, and changes in the tap position. The linearized distflow model serves as the basic structure for the linear, discrete MPC-driven voltage regulation paradigm [137]. Considering the prediction horizon (N_p) and control horizon (N_c) of the discrete MPC, the output voltages over N_p are given by,

$$\mathbf{Y}_p = \chi \xi(\kappa) + \psi \Delta\mathbf{U} \quad (6.4)$$

The prediction output is given by $\mathbf{Y}_p = [\mathbf{V}(\kappa + 1); \mathbf{V}(\kappa + 2); \dots; \mathbf{V}(\kappa + N_p)]$, $\mathbf{Y}_p \in \mathbb{R}^{N_p \times 1}$, and the predicted control sequence is $\Delta\mathbf{U} = [\Delta\mathbf{u}(\kappa); \Delta\mathbf{u}(\kappa + 1); \dots; \Delta\mathbf{u}(\kappa + N_c - 1)]$, $\Delta\mathbf{U} \in \mathbb{R}^{N_c \times 1}$, where $\mathcal{O}$, $\mathcal{I}$ represent the number of outputs and control inputs, respectively. Control vector $\Delta\mathbf{u}(\kappa)$ represents change in control inputs at time step κ . The matrix $\chi \in \mathbb{R}^{N_p \times \mathcal{S}}$ is the system matrix

corresponding to the linear system model (where $\mathcal{S}$ represent the number of state variables), and input matrix $\psi \in \mathbb{R}^{O_{N_p} \times I_{N_c}}$ incorporates voltage sensitivity coefficients corresponding to the control inputs. Since, the prediction model considers change in control inputs, the actual control inputs over the horizon N_c are given by,

$$\mathbf{U}(\kappa) = \hat{\mathbf{G}}\mathbf{u}(\kappa - 1) + \hat{\mathbf{H}}\Delta\mathbf{U} \quad (6.5)$$

The detailed structures of matrices χ , ψ , $\hat{\mathbf{G}}$, and $\hat{\mathbf{H}}$ have been discussed in Chapter 3.

6.3 Network Partitioning and Modified Modularity Index

Network clustering is fundamental to distributed control, wherein the network is divided into controllable zones. The Louvain algorithm introduced in [138] is employed due to its ability to quantitatively evaluate quality at each clustering step and its computational efficiency. Initially, all nodes are considered as individual clusters, and the nodes are successively merged such that the modularity (clustering performance) is maximized for each merge. The local communities formed are treated as virtual nodes and subsequently aggregated with other communities, as per Algorithm 6.3, till no further modularity improvement is seen, thus yielding an optimal clustering.

6.3.1 Modified Modularity Index with Cluster Voltage Sensitivity and Regulation Capability

The modularity index assesses the efficacy of a clustering and serves as a measure for its evaluation. A higher modularity value signifies a higher coupling among nodes within the cluster, and weak coupling between nodes of different clusters. The standard modularity index primarily considers the structure and edge weights of the network while evaluating cluster quality, and is given by,

$$\rho = \frac{1}{2m} \sum_i \sum_j \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(i, j) \quad (6.6)$$

where, A_{ij} is the adjacency matrix, with $A_{ij} \in \{0, 1\}$, $\forall i, j \in \mathcal{N}$, wherein $A_{ij} = 1$ if a distributed line connects nodes i and j , and $A_{ij} = 0$ otherwise. The term $k_i = \sum_j A_{ij}$ is sum of the edge weights connected to node i , while $m = \frac{1}{2} \sum_i \sum_j A_{ij}$ is the net weight of all edges. If nodes i and j are in the same cluster, the function $\delta(i, j)$ takes the value 1, and 0 otherwise. The effective determination of VAR control space [81] for distributed voltage control involves the proximity measure based on electrical information, rather than simply the structural nature of the network. To account for the electrical information, the standard modularity index is modified to incorporate voltage regulation capabilities and nodal voltage sensitivities in [82, 99]. It is to be noted that while determining the modularity of the network using the Louvain algorithm,

Algorithm 6.3 Louvain algorithm for network clustering using modified modularity index incorporating cluster diameter

Inputs: Network data, adjacency matrix, voltage sensitivity matrix, generation/load data

```

 $\mathcal{C} \leftarrow$  Set of clusters
 $\mathcal{C}^s \leftarrow$  Set of clusters stage with maximum modularity at a given clustering
 $\mathcal{C}^* \leftarrow$  Set of clusters with global maximum modularity
 $c_i \leftarrow$   $i$ th cluster in  $\mathcal{C}^s$ 
 $\mathcal{C} \leftarrow \{c_1, c_2, c_3, \dots, c_n\}$ ;  $n = |\mathcal{N}|$ 
Initialize:  $s, \Delta\rho_{mod}^+$ 
while  $\Delta\rho_{mod}^+ \geq 0$  do
    Initialize:  $k$ 
    for Every  $c_i \in \mathcal{C}^s$  do
         $\mathcal{A} \leftarrow$  Set of neighbor clusters of  $c_i$ ;  $\mathcal{A} \subset \mathcal{C}^s$ 
         $n_A \leftarrow |\mathcal{A}|$ 
        for Every  $c \in \mathcal{A}$  do
             $c_i \leftarrow c_i(k) \cup c(k)$ 
             $\rho_{mod}^+(k) \leftarrow \rho_{mod}^+$ ; Calculate
             $k = k + 1$ 
        end for
    end for
     $c_i \leftarrow c_i \cup c \Leftrightarrow \rho_{mod}^+ = \max(\rho_{mod}^+(k))$ 
     $\rho_{mod}^{+0} = \max(\rho_{mod}^+(k))$ 
     $\Delta\rho_{mod}^+ = \rho_{mod}^+(s) - \rho_{mod}^{+0}(s - 1)$ 
     $\mathcal{C}^s \leftarrow$  update
end while
return
 $\mathcal{C}^* \leftarrow \mathcal{C}^s$ ; Optimal partition

```

temporary clustering options are considered at each clustering stage until the maximum value of the index is achieved. If $\mathcal{N}^c$ denotes the set of nodes with IDCDs, and $\mathcal{N}_{C_m}^a$ and $\mathcal{N}_{C_m}^c \subset \mathcal{N}^c$ denote the set of all the nodes and the set of control nodes in m^{th} cluster, respectively, the mean voltage sensitivity of all the nodes within the cluster m is defined as,

$$S_{C_m}^{vp} = \begin{cases} \frac{1}{|\mathcal{N}_{C_m}^a| |\mathcal{N}_{C_m}^c|} \sum_{j \in \mathcal{N}_{C_m}^a} \sum_{k \in \mathcal{N}_{C_m}^c} (S_{j,k}^{vp}) & \text{if } \mathcal{N}_{C_m}^c \neq \emptyset \\ 0, & \text{if } \mathcal{N}_{C_m}^c = \emptyset \end{cases} \quad (6.7)$$

$$S_{C_m}^{vq} = \begin{cases} \frac{1}{|\mathcal{N}_{C_m}^a| |\mathcal{N}_{C_m}^c|} \sum_{j \in \mathcal{N}_{C_m}^a} \sum_{k \in \mathcal{N}_{C_m}^c} (S_{j,k}^{vq}), & \text{if } \mathcal{N}_{C_m}^c \neq \emptyset \\ 0, & \text{if } \mathcal{N}_{C_m}^c = \emptyset \end{cases} \quad (6.8)$$

where, $|\mathcal{N}_{C_m}^a|$ and $|\mathcal{N}_{C_m}^c|$ represent the cardinality of sets $\mathcal{N}_{C_m}^a$ and $\mathcal{N}_{C_m}^c$, respectively. The coefficients $S_{j,k}^{vp} = \frac{\partial V_j}{\partial P_k}$, $S_{j,k}^{vq} = \frac{\partial V_j}{\partial Q_k}$ depict the sensitivity coefficients corresponding to active and reactive power injections of control devices at node k . Higher values of $S_{C_m}^{vp}$ and $S_{C_m}^{vq}$ signify greater sensitivity [99] within the cluster exhibit, thus more coupling.

To account for the voltage regulation capability within a cluster, the control capabilities of control resources are evaluated corresponding to their maximum capacity and active power exchange at a given instant. The regulation capabilities are, thus, determined based on the resource availability and the extent of voltage deviation within the cluster [99]. If ΔV_m represents the maximum voltage deviation in cluster m at j^{th} node, at time instant τ , the voltage regulation capability in a cluster under a given operational condition is defined as,

$$\Psi_{C_m}(\tau) = \begin{cases} 1, & \text{if } |\Delta V_m(\tau)| \leq \sum_{k \in \mathcal{N}_{C_m}^c} S_{j,k}^{vq} \cdot Q_k^a(\tau) \\ \frac{\sum_{k \in \mathcal{N}_{C_m}^c} (S_{j,k}^{vq} \cdot Q_k^a(\tau))}{|\Delta V_m(\tau)|}, & \text{if } |\Delta V_m(\tau)| > \sum_{k \in \mathcal{N}_{C_m}^c} S_{j,k}^{vq} \cdot Q_k^a(\tau) \end{cases} \quad (6.9)$$

The maximum absolute voltage deviation within a cluster depends on the normal operation limits on voltages $[0.95, 1.05]$ p.u, and $Q_k^a(\tau) = \sqrt{(S_k^{\text{rated}})^2 - (P_k(\tau))^2}$ is the maximum reactive power available at time τ for active power P_k and inverter rating S_k^{rated} . To account for anticipated

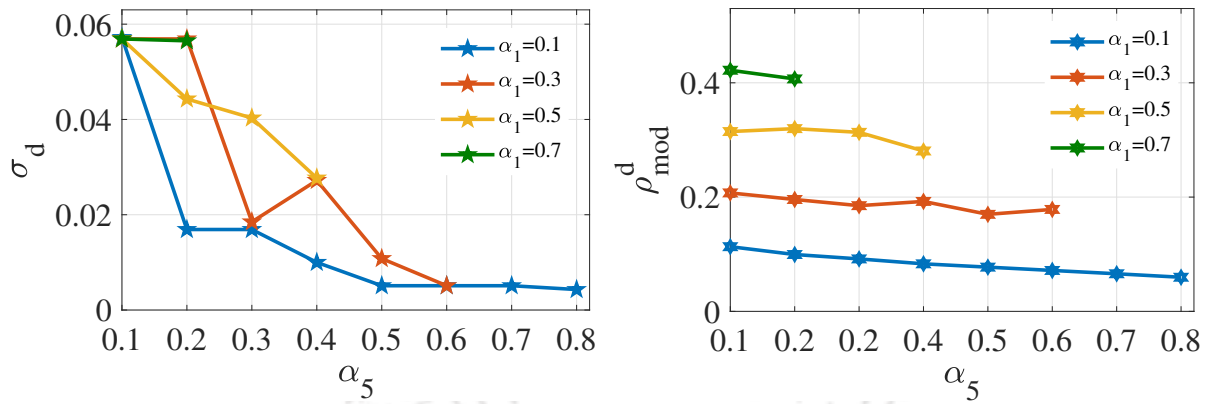


Fig. 6.1: Variation of σ_d and ρ_{mod}^d values with the weight coefficients.

operational conditions over the future horizon, the regulation capability over the entire horizon can be considered to ensure resilient operation. However, in this work the regulation capability under worst case of voltage violation is considered for network clustering. It needs to be mentioned that no reconfigurable switches are considered in the test networks, in this work. The network topology as well as the voltage sensitivities remain same, due to dependence on line parameters. Therefore, the same clustering is maintained throughout the time-domain simulation period, in this work, i.e. $\Psi_{C_m}(\tau) = \Psi_{C_m}, \forall \tau$. Thus, based on cluster voltage sensitivities and regulation capability [99], the modified index is given by,

$$\rho_{mod} = \alpha_1 \rho + \alpha_2 \frac{1}{n_C} \left(\sum_{m=1}^{n_C} (\alpha_3 S_{C_m}^{vp} + \alpha_4 S_{C_m}^{vq}) \cdot \Psi_{C_m} \right) \quad (6.10)$$

The weighting coefficients represented by α ensure normalization, and is constrained by $\alpha_1 + \alpha_2 = 1$ and $\alpha_3 + \alpha_4 = 1$.

6.3.2 Modification with Cluster Diameter

The modularity metric (ρ_{mod}) is further modified to enhance intra-cluster coupling, while reducing the relative variation in the cluster diameters. The cluster diameter is defined as the maximum electrical distance between any two nodes within a cluster, given by,

$$d_{C_m} = \max\{D_{i,j}\}, \forall i, j \in \mathcal{N}_{C_m}^a \quad (6.11)$$

The electrical distance $D_{i,j}$ between the node i and node j within the cluster m , $\forall i, j \in \mathcal{N}_{C_m}^a$, is defined as,

$$D_{i,j} = -\log(\alpha_{i,j} \cdot \alpha_{j,i}) \quad (6.12)$$

where, $\alpha_{i,j} = \partial V_i / \partial V_j = \frac{\partial V_i / \partial Q_k}{\partial V_j / \partial Q_k}$ and $\alpha_{j,i} = \partial V_j / \partial V_i = \frac{\partial V_j / \partial Q_k}{\partial V_i / \partial Q_k}$ represent the voltage deviation at node i due to deviation at node j and vice-versa, respectively, within the cluster. If d_C^{avg} and d_{C_m} represent average diameter and diameter of cluster m , respectively, the modified modularity index incorporating the cluster diameter is defined as,

$$\rho_{mod}^d = \alpha_1 \rho + \alpha_2 \frac{1}{n_C} \left(\sum_{m=1}^{n_C} (\alpha_3 S_{C_m}^{vp} + \alpha_4 S_{C_m}^{vq}) \cdot \Psi_{C_m} \right) - \alpha_5 \sigma_d \quad (6.13)$$

where, penalization term σ_d represents the standard deviation of the cluster diameters, and is given by,

$$\sigma_d = \sqrt{\frac{1}{n_C} \sum_{m=1}^{n_C} \left(\frac{d_{C_m} - d_C^{avg}}{d_C^{max}} \right)^2} \quad (6.14)$$

The diameter deviations are normalized to the maximum diameter (d_C^{max}), to ensure proper weighting, and uniformity among the different terms in the index. Incorporating cluster diameter prevents disproportionately large clusters that could affect control and data acquisition. The modified index integrates weight proportional to the normalized standard deviation of cluster diameters, thereby promoting more balanced and coupled clusters for distributed coordination. The weight parameter constrained by $\alpha_1 + \alpha_2 + \alpha_5 = 1$ and $\alpha_3 + \alpha_4 = 1$ can be optimally tuned to a trade-off between modularity maximization and diameter uniformity. The values of α_3 and α_4 are set to 0.5, so that the active and reactive power sensitivities are considered equally. However, the values of α_1 , α_2 , and α_5 can be optimized and dynamically adjusted while evaluating the modified index at each step. To avoid the dominated coefficients, the suitable values are pre-defined based on sensitivity analysis. The variation of σ_d and ρ_{mod}^d with the change in weight coefficients α_1 , α_2 , and α_5 are shown in Fig. 6.1. The variation of standard deviation in cluster diameters and the modified modularity values are plotted. It can be seen that the standard deviation in cluster diameter decreases with the increase in the value of its weight coefficient (α_5); however, the modularity value also decreases (which is not preferable). Thus, a suitable trade-off is made while

considering the higher modularity value and lower standard deviation in the cluster diameters. Corresponding to $\alpha_1 = 0.7$, the standard deviation is seen to be highest (≈ 0.06), which is not desirable; however, the modularity value is also seen to be maximum. Corresponding to the value of $\alpha_1 = 0.5$, and $\alpha_5 = 0.3$, the value of σ_d is moderately higher with reasonable value of ρ_{mod}^d . Thus, in the present case, the value of α_1 , α_2 and α_5 are chosen as 0.5, 0.2, and 0.3, respectively.

6.4 Centralized Coordination of OLTC

The control framework adopts a centralized architecture for OLTC at a slower time scale of 1 hour. Leveraging real-time voltage measurements and short-term forecasts of load and renewable generation, an optimal sequence of control inputs is determined by solving a multi-time-step constrained optimization problem. The optimization model aims to minimize OLTC switching actions and voltage deviations, given by,

$$\min \sum_{i=1}^{N_p} \left(\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + 1)\|_{\mathbf{w}_v}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 \right) + \sum_{i=1}^{N_c} \|\Delta \mathbf{V}_{\text{tap}}(\kappa + i)\|_{\mathbf{w}_{\text{tap}}}^2 \quad (6.15)$$

subjected to,

$$\underline{\underline{\Delta \mathbf{V}_{\text{tap}}}} \leq \Delta \mathbf{V}_{\text{tap}}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{V}_{\text{tap}}}} \quad (6.16a)$$

$$\underline{\underline{\mathbf{V}_{\text{tap}}}} \leq \mathbf{V}_{\text{tap}}(\kappa + i) \leq \overline{\overline{\mathbf{V}_{\text{tap}}}} \quad (6.16b)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} + \sigma_2 \mathbf{1} \quad (6.16c)$$

It is to be mentioned that the OLTC operation is decoupled from the distributed coordination of IDCs. However, due to fast control of IDCs the network states evolve at each sampling instant. The control decisions of IDCs are taken into account by real-time measurements for OLTC control. Sparse communication with information from limited pilot nodes is used for centralized control of OLTC. The pilot nodes are selected by finding the centroid node within each cluster, and are identified using the proximity index [81], given by,

$$L_i = \sum_{i,j \in m} D_{i,j} \quad (6.17)$$

Index L_i corresponds to the load node i within the cluster m . The load bus minimizing L_i is designated as the pilot node within a cluster. Thus the number of pilot nodes within the clustered network equals the number of network clusters.

It should be noted that IDCs may sufficiently regulate the voltages; however, the IDCs placed towards the load end have less pronounced effect on voltage regulation on the nodes near the substation. The OLTC being more effective in such cases reduces the control cost of IDCs. Moreover, the other control equipment, such as capacitor banks and static var compensators, can also be incorporated in the proposed control framework, but that may unnecessarily increase the cost.

6.5 Distributed Coordination of IDCs

The CVC optimal solution with minimization of voltage deviations and the control cost of IDCs inherently necessitates a centralized framework. The optimization problem for the MPC-based centralized model can be formulated as,

$$\min \sum_{i=1}^{N_p} \left(\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 \right) + \sum_{i=1}^{N_c} \left(\|\Delta \mathbf{Q}_{PV}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{Q}_{EV}(\kappa + i)\|_{\mathbf{w}_q}^2 + \|\Delta \mathbf{P}_{PV}(\kappa + i)\|_{\mathbf{w}_p}^2 + \|\Delta \mathbf{P}_{EV}(\kappa + i)\|_{\mathbf{w}_p}^2 \right) \quad (6.18)$$

subjected to,

$$\underline{\underline{\Delta \mathbf{Q}_{PV}}} \leq \Delta \mathbf{Q}_{PV}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{Q}_{PV}}} \quad (6.19a)$$

$$\underline{\underline{\Delta \mathbf{Q}_{EV}}} \leq \Delta \mathbf{Q}_{EV}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{Q}_{EV}}} \quad (6.19b)$$

$$\Delta \mathbf{P}_{PV}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{P}_{PV}}}(\kappa + i) \quad (6.19c)$$

$$\underline{\underline{\mathbf{Q}_{PV}}}(\kappa + i) \leq \mathbf{Q}_{PV}(\kappa + i) \leq \overline{\overline{\mathbf{Q}_{PV}}}(\kappa + i) \quad (6.19d)$$

$$\underline{\underline{\mathbf{Q}_{EV}}}(\kappa + i) \leq \mathbf{Q}_{EV}(\kappa + i) \leq \overline{\overline{\mathbf{Q}_{EV}}}(\kappa + i) \quad (6.19e)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} + \sigma_2 \mathbf{1} \quad (6.19f)$$

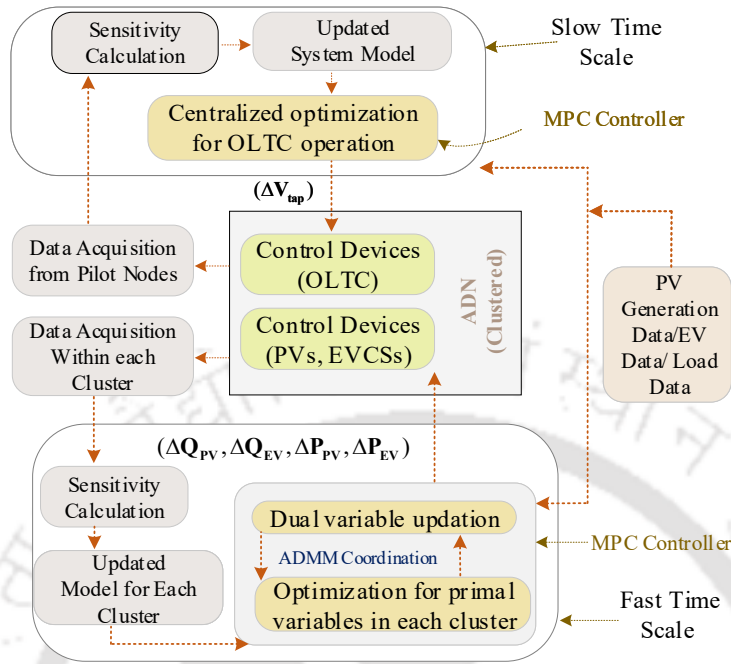


Fig. 6.2: Schematic of the proposed control framework.

Table 6.2: Weights associated with different objectives for MPC.

Range of bus voltages (p.u.)	Objective weights				
	w_y	w_{tap}	w_q	w_q	w_s
$\max(\mathbf{V}) \geq 1.1$ or $\min(\mathbf{V}) \leq 0.9$	100	0.1	0.1	1	1000
$1.05 \leq \max(\mathbf{V}) \leq 1.1$ or $0.9 \leq \min(\mathbf{V}) \leq 0.95$	100	1	1	10	1000
$\max(\mathbf{V}) \leq 1.05$ and $\min(\mathbf{V}) \geq 0.95$	100	10	10	100	1000

The objective function minimizes the voltage deviations and control inputs over the prediction and control horizons, respectively. The diagonal weights of matrices $\mathbf{w}_v$, $\mathbf{w}_q$, $\mathbf{w}_p$ and $\mathbf{w}_s$ are empirically determined and dynamically adjusted using if-then-else rules based on network voltages. The numerical values of weight coefficients considered under different voltage conditions are given in Table 6.2. A high weight on $\mathbf{w}_s$ restricts slack variables $\sigma (= [\sigma_1 \ \sigma_2]^T)$ and takes values only under solution infeasibility. Furthermore, active power input is heavily weighted, ensuring minimal APC and V2G interventions. To eliminate the need for network-wide observability, extensive communication, privacy concerns, and single-point failure, the distributed implementation of the centralized model in Eqs. (6.18), (6.19a)–(6.19f) can be employed by decomposing the problem into tractable sub-problems. This is implemented using an ADMM-based decomposition coordination

scheme, wherein global consensus is achieved through an iterative process of information exchange of boundary nodes with neighboring clusters and parallel solving of sub-problems. The topology of the proposed control scheme is depicted in Fig. 6.2.

6.5.1 ADMM Enabled Distributed Coordination

The quadratic programming (QP) problem in Eq. (6.18) comprises continuous decision variables. The different terms in the objective function are weighted with diagonal matrices having non-negative diagonal elements. The positive diagonal matrices make the Hessian matrix of the standard quadratic program positive definite. Therefore, the objective function in Eq. (6.18) is a convex program and separable into sub-problems. Thus, the original problem is decomposed into sub-problems based on network clusters, using ADMM [139] for distributed CVC. Each cluster has a distributed controller that independently solves the optimization sub-problem and communicates with neighboring clusters for coordination to achieve global consensus on the solution. The distributed controllers are assumed to be interconnected through inter-cluster communication channels. Detailed discussion on communication interoperability based on standard data models for information exchange, such as IEC 61850, can be found in [140]. Consider the vector $\Delta \mathbf{u} = [\Delta \mathbf{Q}_{\mathbf{PV}}; \Delta \mathbf{Q}_{\mathbf{EV}}; \Delta \mathbf{P}_{\mathbf{PV}}; \Delta \mathbf{P}_{\mathbf{EV}}]$ represents the control inputs of all the control resources in DN, corresponding to the centralized model. Since the IDCs are spread in different clusters, the vector of control variables within each cluster c can be represented as $\Delta \mathbf{u}_c = [\Delta \mathbf{Q}_{\mathbf{PV}}^c; \Delta \mathbf{Q}_{\mathbf{EV}}^c; \Delta \mathbf{P}_{\mathbf{PV}}^c; \Delta \mathbf{P}_{\mathbf{EV}}^c]$. Consider that the centralized model in Eq. (6.18) is represented by $f(\Delta \mathbf{u})$, the corresponding distributed implementation is given as,

$$\min \sum_{c \in \mathcal{C}^*} f_c(\Delta \mathbf{u}_c) \quad (6.20)$$

subjected to the constraints,

$$\Delta \mathbf{u}_c \in \Delta \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (6.21a)$$

$$\mathbf{u}_c \in \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (6.21b)$$

$$\mathbf{a}_c = \mathbf{g}_c, \quad \forall c \in \mathcal{C}^* \quad (6.21c)$$

Here, $\mathcal{C}^*$ represents the set of clusters at the optimal partitioning, $f_c(\Delta \mathbf{u}_c)$ represents the subproblem in cluster c , $\forall c \in \mathcal{C}^*$, and $\Delta \mathbf{u}_c$ represents the control input vector in cluster c . Thus, the formulation in Eq. (6.20) is equivalent to the centralized control formulation given in Eq. (6.18). The variable vector $\mathbf{a}_c$ represents the auxiliary variable vector corresponding to the cluster c , and the variable vector $\mathbf{g}_c$ corresponds to the global variables, for consensus. The constraints in Eqs. (6.21a)–(6.21b) are equivalent to the inequality constraints in Eqs. (6.19a)–(6.19e), wherein $\mathcal{U}_c$ and $\Delta \mathcal{U}_c$ represent the solution feasibility regions of the control variables within each cluster c . To achieve distributed coordination among clusters, we assign auxiliary variables represented by vector $\mathbf{a}_c$ in Eq. (6.21c), corresponding to the inter-cluster boundary nodes for each cluster $c \in \mathcal{C}^*$. The constraint in Eq. (6.21c) is used to enforce the equality boundary conditions (on node voltages) at the inter-cluster boundaries, through global variables represented by vector $\mathbf{g}_c$. If $\mathcal{B}_{cd}$ represents the set of boundary nodes of neighboring clusters $c, d \in \mathcal{C}^*$, interconnected through tie lines, then the constraint in Eq. (6.21c) acts as a consensus constraint enforcing,

$$a_c = a_d = g_c = g_d; \quad a_c \in \mathbf{a}_c \text{ \& } a_d \in \mathbf{a}_d \quad (6.22)$$

where, $a_c \in \mathbf{a}_c$ and $a_d \in \mathbf{a}_d$ are auxiliary variables corresponding to nodes in set $\mathcal{B}_{cd}$. The solution approach with ADMM commences with the determination of the primal variables (control variables), through the minimization of the augmented Lagrangian for each subproblem, individually. Subsequent steps involve the iterative update of dual variables, auxiliary variables, and global variables, till the termination criterion is met. The augmented Lagrangian of the decomposition coordination problem in Eq. (6.20) is defined as,

$$\min \mathcal{L}(\Delta \mathbf{u}, \boldsymbol{\lambda}, \mathbf{a}, \mathbf{g}) = \sum_{c \in \mathcal{C}^*} \mathcal{L}_c(\Delta \mathbf{u}_c, \boldsymbol{\lambda}_c, \mathbf{a}_c, \mathbf{g}_c) \quad (6.23)$$

subjected to the constraints,

$$\Delta \mathbf{u}_c \in \Delta \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (6.24a)$$

$$\mathbf{u}_c \in \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (6.24b)$$

$$\text{where, } \mathcal{L}_c = f_c(\Delta \mathbf{u}_c) + \boldsymbol{\lambda}_c^\top (\mathbf{a}_c - \mathbf{g}_c) + \frac{\rho}{2} \|\mathbf{a}_c - \mathbf{g}_c\|_2^2 \quad (6.25)$$

The symbol $\mathcal{L}$ represents the global augmented Lagrangian function of the problem containing all clusters, and $\mathcal{L}_c$ represents the local augmented Lagrangian of cluster c . The variable vectors $\boldsymbol{\lambda}$, $\mathbf{a}$, and $\mathbf{g}$ symbolize the general dual variables, auxiliary variables, and global variables of the whole problem. The variable vector $\boldsymbol{\lambda}_c$ in the linear term of Eq. (6.25) represents the dual variable vector corresponding to the cluster c . The equality boundary conditions within the cluster are structured through the incorporation of an augmented term (quadratic norm), weighted by the penalty parameter $\rho > 0$. This quadratic term is used to enforce the global consensus between the sub-problems in each cluster, using auxiliary variable vectors in each cluster, and the global variable vector $\mathbf{g}$. In this work, the auxiliary variables are the node voltage deviations at the boundary nodes of a cluster, which depend on the control inputs $\Delta \mathbf{u}_c$. Thus, the primal residual $\mathbf{r}_c = (\mathbf{a}_c - \mathbf{g}_c)$ corresponding to the cluster c can be written as,

$$\mathbf{r}_c = h(\Delta \mathbf{u}_c), \quad \forall c \in \mathcal{C}^* \quad (6.26)$$

The Eq. (6.26) implies that the primal residual (which essentially in this case corresponds to the node voltage deviations) of the cluster is a function of the control input vector in cluster c . Taking into account the linearized sensitivity-based model of ADN, the node voltage deviations of boundary nodes within the cluster c , represented by $\Delta \mathbf{v}_c^b$, can be linearly expressed in terms of control variables within the cluster c as,

$$\Delta \mathbf{v}_c^b = \boldsymbol{\Lambda}_c \Delta \mathbf{u}_c = \mathbf{a}_c, \quad \forall c \in \mathcal{C}^* \quad (6.27)$$

where the matrix $\boldsymbol{\Lambda}_c$ is the sensitivity matrix that contains the voltage sensitivity coefficients of the boundary nodes with respect to the control variables within the cluster c . Therefore, from Eq. (6.26) and Eq. (6.27) we have,

$$h(\Delta \mathbf{u}_c) = \boldsymbol{\Lambda}_c \Delta \mathbf{u}_c - \mathbf{g}_c \quad (6.28)$$

which implies,

$$\mathbf{r}_c = \Lambda_c \Delta \mathbf{u}_c - \mathbf{g}_c \quad (6.29)$$

The solution approach of the ADMM-based coordination problem involves updating primal variables, dual variables, and global variables iteratively till the solution converges.

The update of primal variables, dual variables, and global variables at $(k + 1)^{\text{th}}$ iteration proceeds with the following steps:

6.5.1.1 Determining Primal Variables (Control Variables)

The primal variables $\Delta \mathbf{u}_c$ are calculated in parallel for each cluster by minimizing the augmented Lagrangian in Eq. (6.25) as follows:

$$\Delta \mathbf{u}_c^{k+1} = \arg \min_{\Delta \mathbf{u}_c \in \Delta \mathcal{U}_c} \mathcal{L}_c(\Delta \mathbf{u}_c, \boldsymbol{\lambda}_c^k, \mathbf{a}_c^k, \mathbf{g}_c^k) \quad (6.30)$$

6.5.1.2 Updating Global Variables

The update of the global variables $\mathbf{g}_c$, $\forall c \in \mathcal{C}^*$ can be effectively done by averaging all the auxiliary variables (neighbor boundary variables) [8] corresponding to the node set $\mathcal{B}_{cd}$, $\forall c, d \in \mathcal{C}^*$. It is to be noted here that each cluster becomes capable of updating $\mathbf{g}_c$ independently, only by facilitating the exchange of $\mathbf{a}_c$ between adjacent clusters. If $\mathcal{A} = \{a_1, a_2, a_3, \dots, a_{|\mathcal{A}|}\}$ is the set of auxiliary variables such that $\mathcal{A} = \{a \mid \forall a \in \mathbf{a}_c, \forall c \in \mathcal{C}^*\}$, then for every global variable element $g \in \mathcal{G}$ corresponding to a boundary node b , where $\mathcal{G} = \{g \mid \forall g \in \mathbf{g}_c, \forall c \in \mathcal{C}^*\}$, the global variable g is updated at $(k + 1)^{\text{th}}$ step as,

$$g^{k+1} = \frac{1}{|\mathcal{B}_{cd}(b)|} \sum_{h=1}^{|\mathcal{B}_{cd}(b)|} (a_h^{k+1}), \quad a_h \in \mathcal{A}$$

where, set $\mathcal{B}_{cd}(b)$ represents the set of boundary nodes connected to boundary node b , including itself, a_h is the auxiliary variable corresponding to the h^{th} boundary node in set $\mathcal{B}_{cd}(b)$, and $|\mathcal{B}_{cd}(b)|$ represents cardinality (number of nodes) of set $\mathcal{B}_{cd}(b)$.

6.5.1.3 Updating Dual Variables

Knowing the values $\mathbf{a}_c^{k+1}$, $\mathbf{g}_c^{k+1}$, the dual variables can be updated as,

$$\lambda_c^{k+1} = \lambda_c^k + \rho(\mathbf{a}_c^{k+1} - \mathbf{g}_c^{k+1}) = \lambda_c^k + \rho(\mathbf{r}_c^{k+1}), \quad \forall c \in \mathcal{C}^* \quad (6.31)$$

The value of penalty parameter (ρ) is tailored dynamically during iterations to enhance the convergence rate and reduce sensitivity to the initial value of ρ [139]. At each iteration, the value of ρ is set as,

$$\rho^{k+1} := \begin{cases} \tau_a \rho^k, & \text{if } \|\mathbf{r}_c^k\|_2 > \mu \|\mathbf{g}_c^k - \mathbf{g}_c^{k-1}\|_2; \quad \forall c \\ \rho^k / \tau_b, & \text{if } \|\mathbf{g}_c^k - \mathbf{g}_c^{k-1}\|_2 > \mu \|\mathbf{r}_c^k\|_2; \quad \forall c \\ \rho^k, & \text{otherwise} \end{cases} \quad (6.32)$$

where, the parameters τ_a, τ_b and μ are > 1 . In this work, the parameter values are chosen as $\tau_a = \tau_b = 2$, and $\mu = 10$ [139].

6.6 Simulation Results and Discussion

The proposed methodology undergoes validation on highly penetrated 33-bus and IEEE 123-bus balanced DNs, integrated with PVs, EVs, and OLTC, as depicted in Fig. 6.3 and Fig. 6.4, respectively. Considering the PV penetration level as the ratio of peak PV generation to the total maximum load demand in the network, the penetration level in this study is more than 200%. The OLTC facilitates 32 tap adjustments, each with a 0.00625 p.u. voltage increment, thereby providing the range of $\pm 10\%$ around the nominal voltage value. Only two tap adjustments are allowed per operational cycle, and OLTC action is prevented if voltage deviations remain within 3% of the nominal value. The test networks are modeled in MATLAB employing the Power System Analysis Toolbox (PSAT), and optimizations are carried out in the IBM ILOG CPLEX Toolbox through MATLAB interface. The power profiles for PV generation, EV demand, and load demand are given in Fig. 6.5. This study considers trial data from 461 residential EVs from the Electric Nation project (UK) [124], and the demand profiles are extracted by the EV Integration Project [125]. Two residential EV charger types, Level 1 (3.68 kW) and Level 2

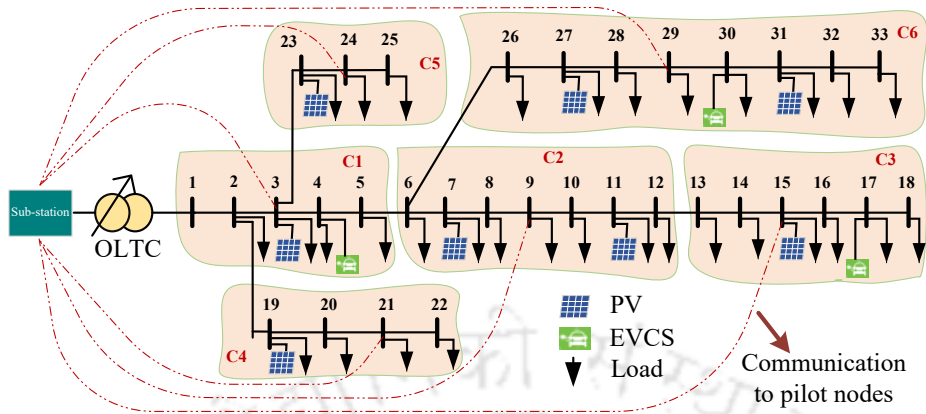


Fig. 6.3: 33-bus distribution network with clustering.

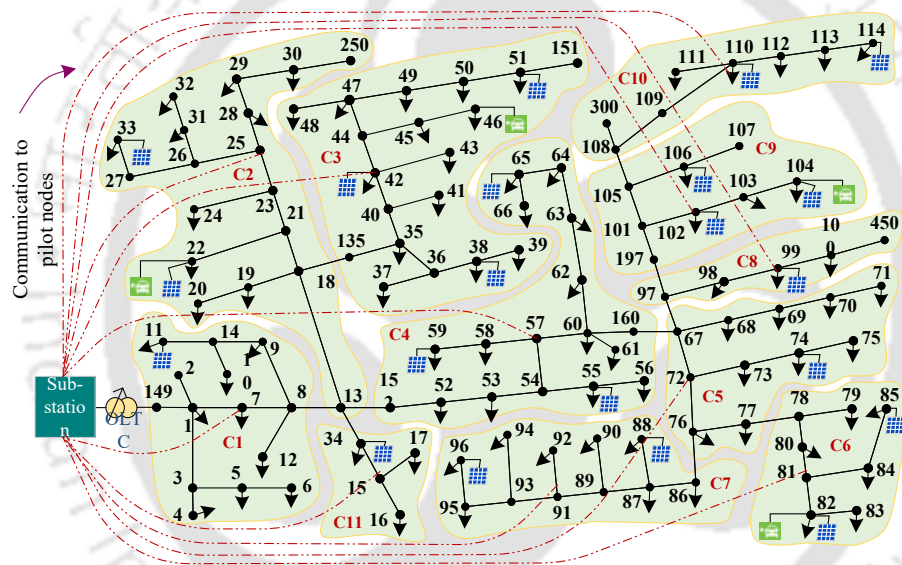


Fig. 6.4: Modified IEEE 123-bus distribution network with clustering.

(7.36 kW), are considered. The trial data encompasses Battery Electric Vehicles (BEVs), Plug-in Hybrid EVs (PHEVs), and Range-Extended EVs (REX-PEVs), with capacities ranging from 6 to 100 kWh. A detailed description of the EV data including battery types and their capacities are given in Chapter 4. Moreover, EV charging stations (EVCSs) are assumed to be located at various nodes. While residential EV charging is considered uncoordinated in the proposed control scheme, EVCSs are treated as controllable resources, capable of utilizing both reactive power and active power through V2G applications. To facilitate a simplified network impact assessment of EVs in medium voltage (MV) distribution systems, an aggregated EV model is considered with a group of EVs as a single equivalent entity. Upon arrival, drivers submit key parameters such

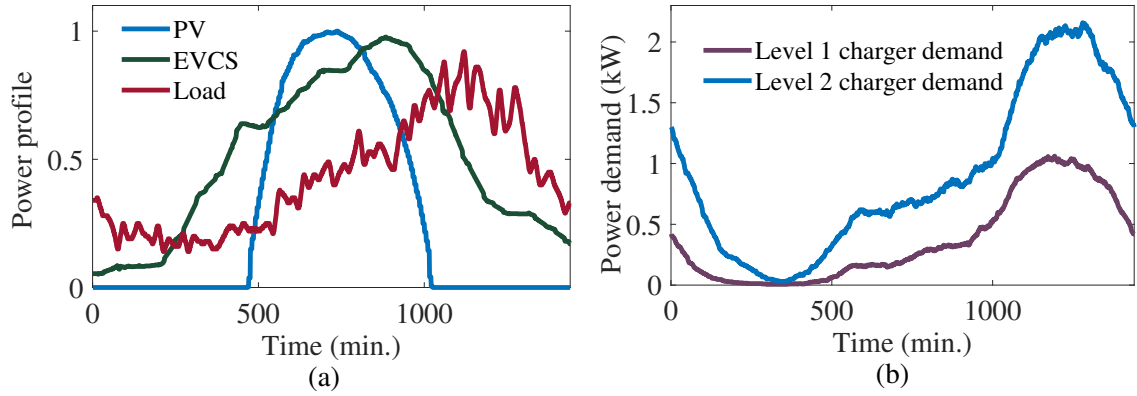


Fig. 6.5: (a) Power profiles of PVs, EVCSs and load demand (b) Diversified average power demand of domestic chargers.

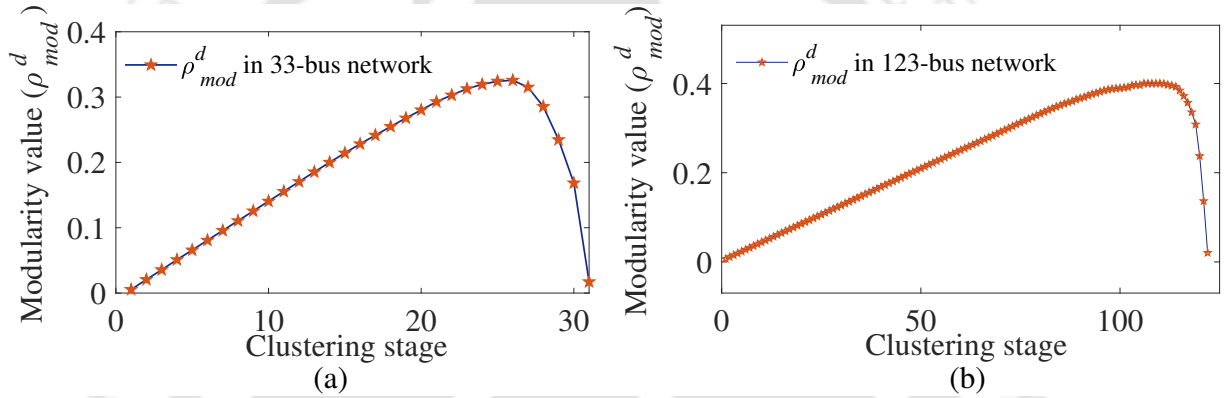


Fig. 6.6: Values of modularity metric ρ_{mod}^d at different clustering stages: (a) 33-bus network (b) IEEE 123-bus network.

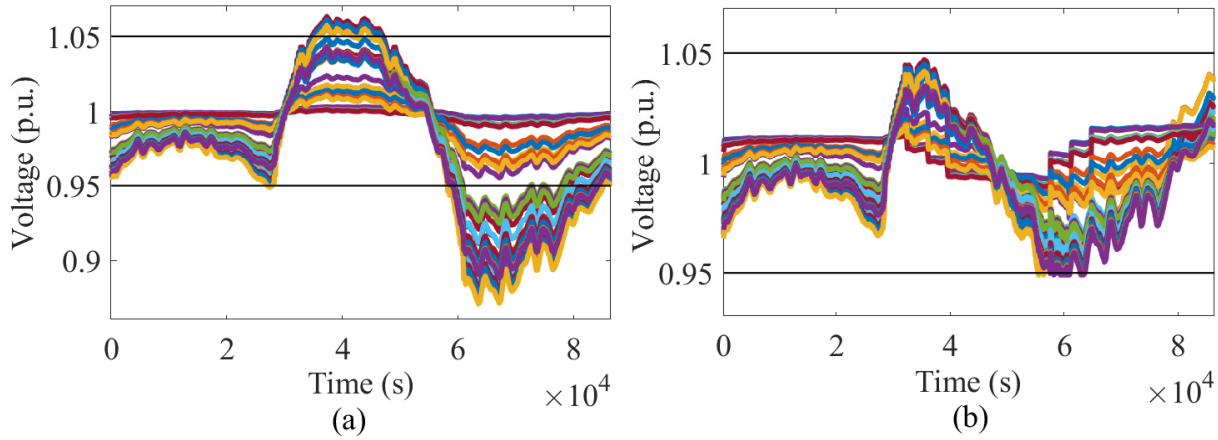
as electric range, battery SOC, and other specifications to a local aggregator. For this study, EVs are considered as uncontrolled loads with the following assumptions (as in trial data): (a) Charging commences immediately upon connection at rated power (b) The uncontrolled charging continues at rated power until the battery is fully charged, or the driver opts to disconnect. A detailed analysis of EV integration with a coordinated charging strategy is beyond the scope of this current study.

6.6.1 Simulations on 33-Bus Distribution Network

The network is considered with connected active and reactive demand of 3.715 MW and 2.3 MVar, and fed through a 63.3 kV/12.66 kV substation with a 10 MVA base capacity. Multiple distributed PVs and EVCSs are connected (as shown in Fig. 6.3), in addition to the domestic

Table 6.3: Comparison of different clustering metrics.

Attribute	Test network	Modularity metric			
		ρ [Standard]	ρ_{im} [82]	ρ_{mod} [99]	ρ_{mod}^d [proposed]
Structural modularity	33-bus	0.6037	0.6035	0.6035	0.6064
	123-bus	0.7677	0.7648	0.6618	0.8004
Maximum diameter	33-bus	15.5426	15.8739	15.8739	13.2354
	123-bus	9.2915	13.9537	14.3297	9.2915
Std. deviation in diameters	33-bus	5.4918	5.6894	5.6894	4.5813
	123-bus	3.4920	4.2456	4.1695	3.0988
Number of clusters	33-bus	06	06	06	06
	123-bus	12	11	12	11

**Fig. 6.7:** Voltage profiles of 33-bus system over 24 hours: (a) under no control action (b) under ADMM and MPC-based distributed coordination of IDCs.

EV loads in all low voltage networks connected to the nodes. A detailed description of the modified network, including the location and size of all PVs and EVCSs, is given in [133]. A 60% penetration of domestic EVs is assumed, entailing 150 Level 1 and 600 Level 2 chargers, distributed throughout the network [133]. Initially, the network is clustered based on the modified modularity metric ρ_{mod}^d into 6 optimal clusters as shown in Fig. 6.3. The evolution of clustering metric value ρ_{mod}^d with the clustering stages is shown in Fig. 6.6(a). The structural modularity (given by the standard modularity index ρ), maximum cluster diameter, and standard deviation in cluster diameters are evaluated for comparing the clustering results using each metric. The effectiveness of incorporating the cluster diameter is shown by comparing the clustering results obtained using the modified metric with existing indices, as shown in the Table 6.3. It can be

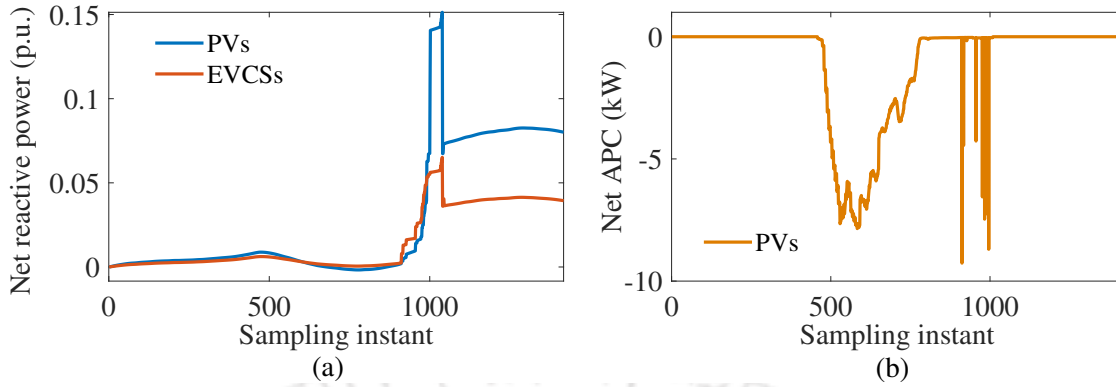


Fig. 6.8: Active and reactive power control inputs at the sampling rate of 1-minute, over the whole time domain simulation: (a) Net reactive power exchange of PVs and EVCSs (b) Net active power curtailment of PVs.

seen from Table 6.3 that the structural modularity using the proposed modified index is higher compared to the modularity metric ρ_{mod} . Furthermore, the values of maximum cluster diameter and the standard deviation in diameters are both lower, depicting the superiority of the clustering. The lower values of maximum diameter and standard deviation, and the high value of structural modularity imply that the clustering is more uniform, while maintaining the strong coupling among the cluster nodes.

An initial time-domain simulation over 24 hours depicts extreme voltage deviations with pronounced over-voltage conditions and significant under-voltages, as evident from Fig. 6.7(a). The proposed hybrid control under the prescribed operational constraints effectively eliminates the voltage violations and maintains them within normal operation limits ($[0.95, 1.05]$ p.u.), as depicted in Fig. 6.7(b).

6.6.1.1 Comparison With Centralized Control Architecture

To study the effectiveness of ADMM based coordination, the proposed distributed control is compared with the centralized dispatching of IDCDS. The reduced communication as compared to the centralized architecture is shown in Fig. 6.12. For comparison purposes bus 30 is chosen, and it is seen that the voltage profile closely matches with the centralized control scheme (Fig. 6.9), with a mean deviation of 0.0048 p.u. and standard deviation of 0.0064 p.u (Table 6.4). While in centralized control, the network is treated as fully observable, with the information available from

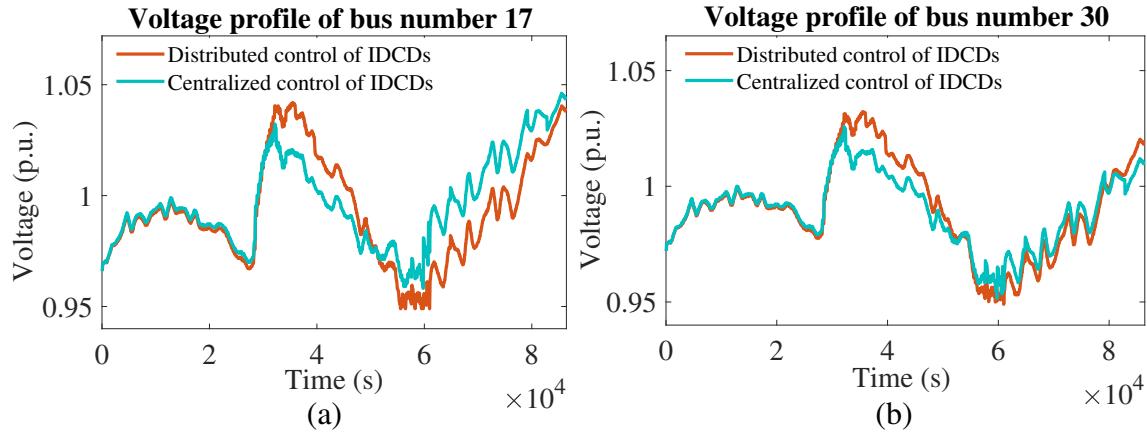


Fig. 6.9: Comparison of voltage profile of bus 30 of 33-bus network with centralized and distributed coordination of IDCs.

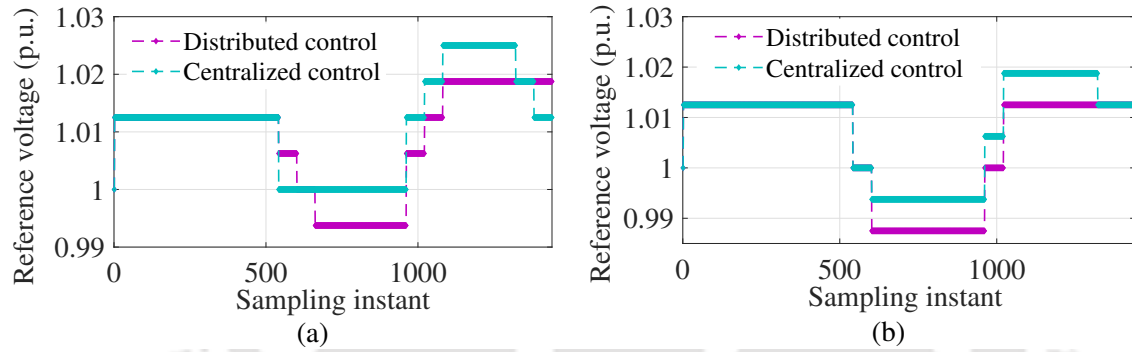


Fig. 6.10: OLTC reference voltage corresponding to centralized and distributed coordination of IDCs, with sample rate of 1-minute: (a) 33-bus network (b) IEEE 123-bus network.

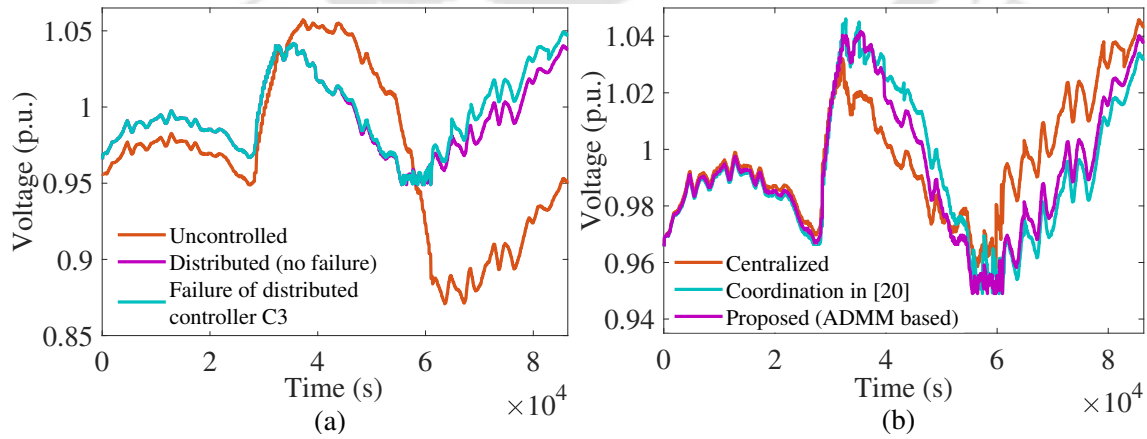


Fig. 6.11: Voltage profile of critical node 30 in 33-bus network considering: (a) failure of a distributed controller (b) distributed coordination mechanism.

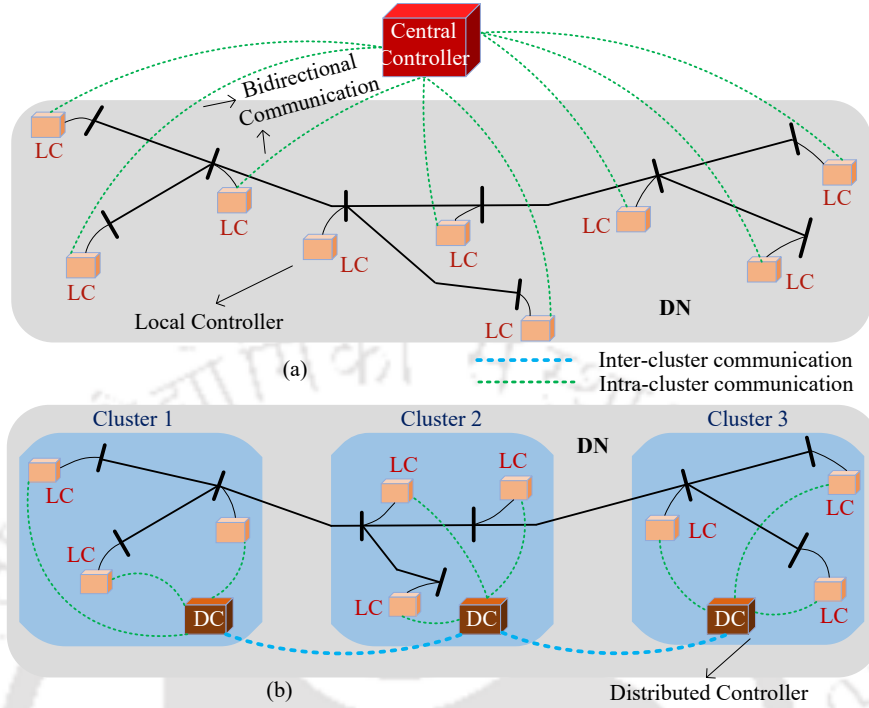


Fig. 6.12: Control architecture depicting communication links in ADN: (a) centralized control of IDCs (b) distributed control of IDCs.

each node (Fig. 6.12), distributed coordination requires limited inter-cluster information exchange between neighbor clusters, thus reduces communication burden and enhances data privacy. The tap operations corresponding to the distributed and centralized operation of OLTC are given in Fig. 6.10(a). It can be seen that the total number of tap operations remains same, however there is a little difference in the switching patterns. It needs to be noted that OLTC operation in the distributed scheme uses limited information from the pilot nodes but in centralized scheme the measurements are taken from all the nodes.

6.6.1.1.1 Data Privacy Preservation Data privacy preservation is intrinsically enhanced in distributed control due to localized control processing and minimal inter-cluster data exchange. Unlike centralized schemes which utilize comprehensive communication and measurement systems, inter-cluster communication is limited to the exchange of global variable values corresponding to the boundary nodes, thus reducing volume of transmitted data and bandwidth utilization.

Table 6.4: Quantitative comparison between distributed and centralized coordination of IDCDS.

Test network	Control scheme	Average time per optimization	Average nodes connected to the controller	μ	σ
33-bus	Centralized	0.0470 s	33	0.0048 p.u.	0.0064 p.u.
	Distributed	0.0310 s	6		
123-bus	Centralized	0.0630 s	123	0.0051 p.u.	0.0025 p.u.
	Distributed	0.0312 s	18		

6.6.1.1.2 Scalability and Reliability The decomposition coordination with parallel computation of localized sub-problems reduces the computational burden on any single controller, thereby enhancing scalability of ADNs. In contrast, the burden on centralized controller increases with increase in the network size and the number of control variables, increasing the computation time (as shown in Table 6.4). Furthermore, distributed control ensures system reliability by eliminating the risk of single point of failure. To study the reliable operation in distributed control, simulations are carried out assuming the failure of distributed controller in cluster C3 at 20:05 hours. The voltage profiles of critical node 30 are plotted in Fig. 6.11(a), and it is apparent that the voltages are regulated within limits due to the compensation of other functional controllers.

Furthermore, the proposed scheme is compared to the distributed scheme in [99], which utilizes partitioning based on modularity metric ρ_{mod} , and local MPC controllers, wherein neighboring clusters exchange renewed voltages via connection nodes information. In contrast, the proposed approach enforces global consensus on distributed controller solutions through ADMM. Although [99] does not consider OLTC control and comparison with centralized control, simulations are performed with OLTC in both schemes for comparison with centralized control solution. Fig. 6.11(b) demonstrates that the proposed scheme achieves a voltage profile closer to the centralized solution, due to the coordination mechanism considering global consensus. The mean and standard deviation of 0.0048 p.u., and 0.0043 p.u., in the proposed coordination scheme are lower, compared to 0.0066 p.u. and 0.0065 p.u., respectively, for the distributed coordination reported in [99].

Table 6.5: Numerical values obtained from the simulations under the distributed coordination of IDCs.

Attributes	33-bus network	IEEE 123-bus network
Q_{PV} exchange (MVarh)	6.9164	17.6242
Q_{EV} exchange (MVarh)	3.7199	2.1442
Net APC of PVs (kWh)	24.0083	30.9636
Net V2G injection (kWh)	24.4461	15.6444
Min./ max. voltage (p.u.)	0.95/1.047	0.95/1.0444
Tap operations	07	05

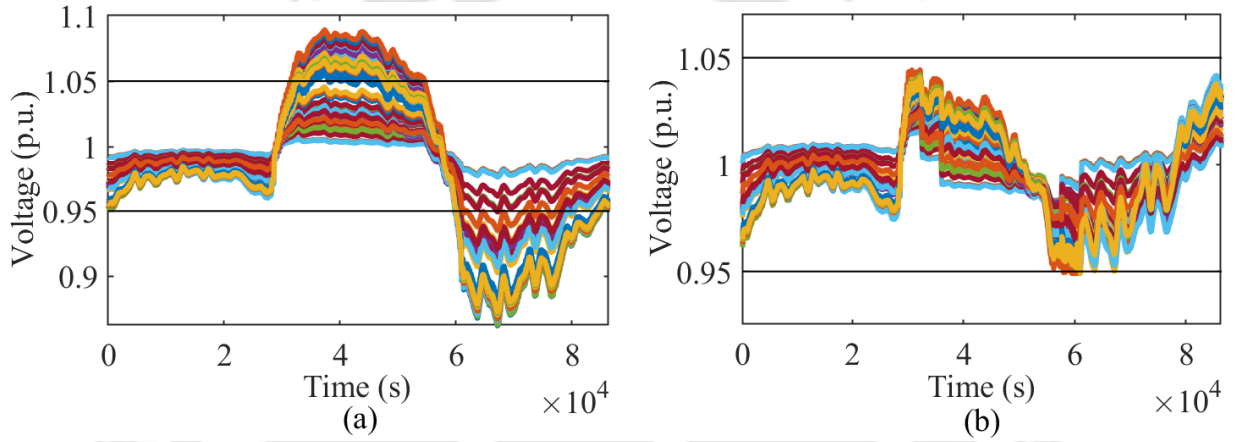


Fig. 6.13: Voltage profiles of IEEE 123-bus system over 24 hours: (a) under no control action (b) under distributed coordination of IDCs.

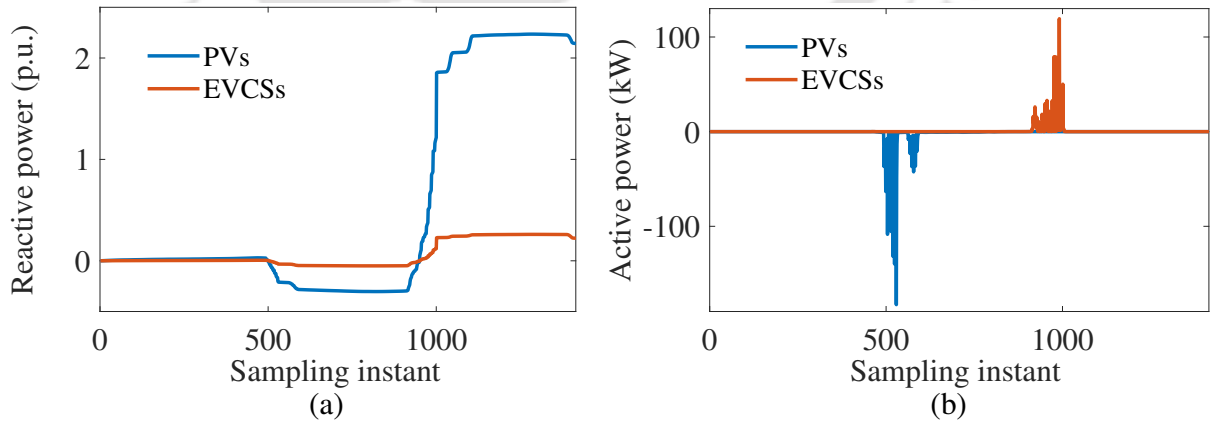


Fig. 6.14: Net power exchange of PVs and EVCSs, with sampling rate of 1-minute: (a) reactive power exchange (b) active power exchange.

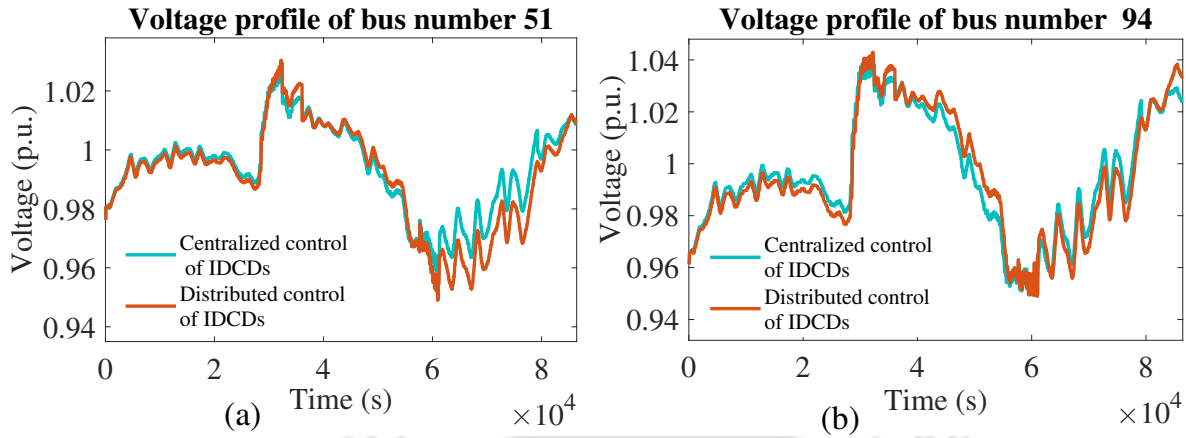


Fig. 6.15: Comparative voltage profiles of bus 30 of 123-bus network obtained with centralized and distributed coordination of IDCs.

6.6.2 Simulations on IEEE 123-Bus Distribution Network

To study the scalability of the proposed approach, simulations are also carried on the modified IEEE-123 bus network. The net connected active and reactive demands across the network are 3.49 MW and 1.92 MVar, respectively. The network is connected via a 4.16 kV substation, with a base voltage and base power of 4.16 kV and 1 MVA, respectively. Residential EV chargers are assumed in every low-voltage (LV) network connected to the network nodes, with a total of 140 Level 1 and 560 Level 2 chargers. The PVs and EVCSs are distributionally placed as shown in Fig. 6.4, with all other details and ratings given in [133]. The network is optimally partitioned into 11 clusters having distributed controllers. The pilot nodes identified for centralized control of OLTC are assumed to have bidirectional communication with the substation, as shown in Fig. 6.4. An initial time-domain simulation depicts a severe voltage violation over extended hours, with significant under-voltages during the evening hours, as shown in Fig. 6.13(a). Using the proposed hybrid control approach, it can be seen from Fig. 6.13(b) that all the severe voltage violations are eliminated and the voltages remain within the normal operation limits. The net active and reactive power exchange of the control devices is shown in Table 6.5, and the reactive power exchange profile is shown in Fig. 6.14(a). The active power is employed under only severe over-voltage or under-voltage conditions, heavy weight on active power exchange, as evident from Fig. 6.14(b). Only 5 tap operations are observed throughout the simulation period of 24 hours, as shown in Fig. 6.10(b), and it can be seen that the tap operations in distributed coordination

of IDCs closely follow as in centralized coordination. The efficacy of the voltage control using the distributed coordination of IDCs is further compared with the centralized coordination of IDCs. For this purpose, the voltage profile of bus 94 {Fig. 6.15(a)} and bus 51 {Fig. 6.15(b)} are compared. It can be seen that the voltage profile using distributed control closely follows that of the centralized coordination of IDCs, with the mean deviation and standard deviation of bus 51 as 0.0037 p.u. and 0.0035 p.u., respectively, and the mean deviation and standard deviation for bus 94 as 0.0051 p.u. and 0.0025 p.u., respectively.

6.7 Conclusion

In this study, a multi-stage MPC-driven hybrid voltage control strategy has been developed for ADNs with high renewable penetration. The voltage deviations are minimized while optimizing the operation of various control resources. The operation of OLTC carried out at STS leverages a sparse-communication-based centralized control structure, with a reduced number of required measurements. The IDCs are coordinated at FTS by employing MPC and ADMM-based decomposition coordination, enabling parallel optimization while reducing the measurement and communication overhead significantly. An improved network partitioning is achieved using the improved modularity index, considering cluster diameter uniformity. Compared to partitioning based on the existing modularity indices, the improved modularity index gives higher values, with a reduced maximum diameter of clusters and standard deviation in the cluster diameters. The simulation results on the IEEE 123-bus network and 33-bus distribution network with the proposed control framework, utilizing the improved network partitioning and comparison with the centralized control scheme, depict the high coordination capability of the proposed control framework. A small mean and standard deviation of 0.0048 p.u. and 0.0064 in the 33-bus network, and 0.0051 and 0.0025 p.u. in the IEEE 123-bus network, respectively, are seen in voltage profiles, at the critical nodes, in comparison to the centralized control structure. Compared to centralized or fully distributed voltage control approaches, the proposed hybrid control framework coordinates OLTC and IDCs at multiple time scales, utilizing both centralized and distributed control paradigms. Thus, the proposed scheme provides a balanced solution considering coordi-

nation efficacy and communication burden. The incorporation of improved network partitioning and multi-time scale coordination enables efficient voltage regulation and enhanced scalability, compared to the existing schemes.



Chapter 7

A centralized-distributed hybrid control framework using CC-MPC for voltage control and energy loss minimization in ADNs with nodal power uncertainties

This chapter proposes a centralized-distributed hybrid control structure for ADNs, considering nodal power uncertainties in ADNs, for voltage control and energy loss minimization. The work presented in Chapter 6, employing deterministic MPC, is extended in this work to contain power uncertainties using chance-constrained model predictive control. The presented framework is based on a hierarchical voltage control framework for ADNs employing a hybrid control framework. The control framework deploys OLTC using centralized control with a reduced measurement infrastructure, while the IDCDs are controlled by ADMM-based distributed coordination.

7.1 Introduction

The stochastic behavior of renewable energy sources (RESs) and electric vehicle (EV) charging loads leads to nodal power uncertainties, thereby causing rapid and uncertain voltage fluctuations in active distribution networks (ADNs) [128]. The voltage deviations exceeding permissible thresholds of the network (e.g., 5% of the nominal value as per ANSI Standard C84.1-2016 [9]) may hinder the large-scale renewable DG integration or may even necessitate their disconnection [8]. Since conventional voltage regulation devices are often inadequate to mitigate these uncertain voltage fluctuations due to their slow, discrete control mechanism and limited life-span. The rapid response inverter-based control devices (IDCDs) provide a viable solution with continuous voltage support using their available active/reactive power capabilities compliant with the IEEE 1547 standard [17].

The voltage control in ADNs is extensively investigated through various optimization frameworks, including optimal power flow based [75] and model predictive control (MPC) based [76, 133, 137] centralized strategies. Multi-time scale optimization approaches coordinating OLTC and PVs [75, 76], along with EV charging stations (EVCSS) using vehicle-to-grid (V2G) paradigm [57, 118] have been utilized for coordinated voltage control (CVC). The uncertainties in renewable power and EV demand, coupled with varying temporal characteristics of control devices, render day-ahead optimization-based schemes insecure. Thus, multi-stage and real-time MPC-driven optimization models [57, 118] have gained prominence due to advancements in short-term forecasting, availability of extensive data logs, and known system models. Although multi-stage real-time approaches [57, 118] effectively enhance the network voltage control; however, due to the deterministic nature of the MPC, the detailed uncertainties in node power exchanges are not studied. To account for uncertainties, a single-stage robust optimization framework considering load and EV uncertainties is proposed in [74], and a two-stage optimization model with a scenario-based chance-constrained approach is proposed in [75], considering load and PV uncertainties. Nevertheless, OLTC operation and PV uncertainties are not considered in [74]. The model in [75] does not consider the real-time control with an advanced and fast responsive measuring infrastructure.

In contrast, authors in [76] have proposed a real-time stochastic MPC framework with renewable

generation uncertainties via chance-constrained affine-disturbance feedback control. However, the EV uncertainties remain unaddressed. A real-time, multi-stage chance-constrained model predictive control (CC-MPC) based CVC model is proposed in [133], considering uncertainties in PVs, EVs, and conventional loads, utilizing a scenario-based solution approach for solving the problem deterministically.

The scalability of centralized control approaches [76, 133] is restrained by the demand for extensive communication and measurement infrastructure, as network size and the number of control resources increase. Moreover, centralized schemes bring up privacy concerns among various stakeholders [112], and they are susceptible to cyber-physical threats, wherein a single point of failure can compromise the entire network control [87]. Thus, distributed control strategies have been leveraged, with optimization-based methods, such as ADMM, for distributed coordination using tractable sub-problems. Authors in [60] present an MPC-based control framework, utilizing V2G reactive power support from EVs, while overlooking the control capabilities of PV inverters and legacy devices like OLTC. A distributed framework leveraging multi-agent system-based coordination is proposed in [89] for multi-storage systems, using back-and-forth communication. However, the intractable uncertainties in PV, EV, and load powers are not considered in [60] and [89]. A machine-learning (ML) assisted distributed control method is proposed in [136], using long short-term memory (LSTM), for improved convergence of ADMM. However, the nodal power uncertainties are not taken into account, and the network partitioning is rule-based. A decentralized MPC framework is proposed in [99], employing modified modularity index-based network clustering. However, the multi-time scale coordination with OLTC and uncertainties in the intermittent renewable generation, EV loads, and conventional loads are not considered. A distributed framework is proposed in [87] with multi-time scale ADMM-based coordination. The stochastic CVC framework is used for uncertainties in DG and load; however, the control capabilities of EVs are not taken into account. Furthermore, the network partitioning is based on observational heuristics, which may lead to sub-optimal solutions. Thus, existing distributed control frameworks, despite leveraging advanced coordination mechanisms such as ADMM, MPC, and multi-agent coordination using deterministic formulations, largely overlook the nodal power uncertainties inherent in ADNs. The lack of rigorous treatment of uncertainties within these

frameworks constrains their robustness and adaptability to practical ADNs. The existing research gaps can be briefly summarized as follows:

- Several studies exist in centralized control with uncertainties in PVs and load [75, 76], EVs [74], and PVs, EVs, and conventional loads [133]. However, uncertainty consideration is largely ignored in distributed control paradigms. To the best of our knowledge, no existing study on distributed control comprehensively considered the uncertainties in nodal power injection/ absorption due to PVs, EVCSs, and conventional loads.
- Existing distributed control studies predominantly adopt single-time scale approaches, or overlook the control capabilities of EVCSs using V2G support. The control capabilities of devices with slow temporal characteristics, such as OLTC, in conjunction with IDCs, have not been studied within a multi-time scale control. Furthermore, the realistic trial data of EVs are not considered in the existing studies.
- Network clustering in existing literature predominantly uses observational heuristics or pre-defined partitioning rules. Only limited studies have considered the partitioning considering electrical coupling between the nodes, for improved zonal coordination and voltage control.

This study presents a real-time CC-MPC-based distributed control framework with detailed nodal power uncertainties using the scenario-based solution approach, while considering realistic domestic EV data sets. Monte-Carlo simulation is employed for scenario generation corresponding to the probability distribution of the uncertainty parameter, and backward scenario reduction is used for improved computational efficiency. The proposed control approach employs a hybrid control strategy, wherein centralized control is leveraged at the first stage for OLTC, using sparse measurements from strategically chosen pilot nodes. At the second stage, MPC-based distributed coordination framework is leveraged for the control of IDCs, utilizing reactive as well as active power exchange. A hierarchical community detection algorithm is employed to optimally cluster the network into electrically coupled zones, based on an improved modularity index. For distributed coordination, an ADMM-driven distributed optimization strategy is implemented, enabling parallelized and localized decision-making, reducing communication overhead, and enhancing computational efficiency and scalability. The main contributions of this work can be

enumerated as follows:

1. A novel CC-MPC-based real-time and multi-stage CVC control framework is proposed for voltage control and energy loss minimization using PV inverters, EV inverters, and OLTC.
2. The nodal power uncertainties in the conventional loads, EV loads, and PVs are considered with varying levels of uncertainties using a scenario-based solution approach for the CC-MPC-based CVC problem.
3. The confidence in uncertainty consideration in the solution is preserved with sufficient scenario generation using Monte-Carlo simulation, pertaining to a predefined confidence parameter.
4. An ADMM-enabled distributed optimization is used for reduced information exchange and communication overhead, while providing near-optimal zonal coordination. Furthermore, a modified clustering modularity index is introduced, which incorporates cluster diameter, in addition to average voltage sensitivity, and devices' regulation capacity, for improved uniform network clustering.

In the rest of this chapter, Section 7.2 provides an MPC framework for ADNs with nodal power uncertainties, Section 7.3 entails the chance-constrained problem formulation, Section 7.4 discusses the two-stage control framework with centralized control architecture for OLTC, and ADMM-based distributed coordination of IDCs. Section 7.5 provides detailed simulation results, and Section 7.6 provides the conclusion of the chapter.

7.2 MPC Framework for ADNs with Nodal Power Uncertainties

The model Predictive Control framework enables real-time control for ADNs through predictive multi-step optimization, leveraging the network model. A linearized distribution network model is considered for the linear discrete state space formulation of MPC. Consider the set $\mathcal{N} \cup \{0\} := \{0, 1, 2, 3, \dots, N\}$ denotes the network nodes (including substation node 0), and $\mathcal{E} := \{(m, n)\} \subset (N + 1) \times (N + 1)$ denotes the distribution lines with impedances $r_{mn} + jx_{mn}$, and complex power flows $\bar{S}_{mn} = P_{mn} + jQ_{mn}$, where (m, n) represents the terminal nodes of the

line. The network state is governed by the net nodal power injection $\bar{s}_n = p_n + jq_n, \forall n \in \mathcal{N}$. The intermittency in PVs and EVs renders the ADN susceptible to nodal power uncertainty. Consider that the parameter ζ represents the uncertain power, then $p_n = p_n^{pv} + p_n^{ev} + p_n^l = \hat{p}_n + \zeta$, where $p_n^{pv}, p_n^{ev}, p_n^l$ represent PV power, EV power, and load power, respectively. At any time instant t , we have,

$$p_n^{pv}(t) = \hat{p}_n^{pv}(t) + \zeta_n^{pv}(t), \forall n \in \mathcal{N}^{PV}, \zeta_n^{pv} \in B(0, \sigma^{pv}) \quad (7.1)$$

$$p_n^{ev}(t) = \hat{p}_n^{ev}(t) + \zeta_n^{ev}(t), \forall n \in \mathcal{N}^{EV}, \zeta_n^{ev} \in N(0, \sigma^{ev}) \quad (7.2)$$

$$p_n^l(t) = \hat{p}_n^l(t) + \zeta_n^l(t), \forall n \in \mathcal{N}, \zeta_n^l \in N(0, \sigma^l) \quad (7.3)$$

Sets $\mathcal{N}^{PV}$ and $\mathcal{N}^{EV}$ represent nodes with PVs and EVs, and N and B represent normal and beta distribution, respectively [76]. Detailed discussion on the linear distribution network model with uncertainties is given in Chapters 2 and 4. If $\mathbf{V} \in \mathbb{R}^{N \times 1}$, $\mathbf{I} \in \mathbb{R}^{N \times 1}$ represent the vectors of node voltages and lines currents, and vectors $\mathbf{P}$ and $\mathbf{Q}$ represent the active and reactive power flows in lines, respectively, corresponding to the vector of nodal active power injection ($\mathbf{p}$) and reactive power injection $\mathbf{q}$, then the compact matrix representation of the Distflow model is expressed as,

$$\begin{bmatrix} \mathbf{p}^\top & \mathbf{q}^\top \end{bmatrix}^\top = \begin{bmatrix} \mathbf{P}^\top \mathbb{A}^\top & \mathbf{Q}^\top \mathbb{A}^\top \end{bmatrix}^\top \quad (7.4)$$

$$\begin{bmatrix} \tilde{\mathbb{A}} \end{bmatrix}^\top \begin{bmatrix} \mathbf{V}_0 & \mathbf{V}^\top \end{bmatrix}^\top = \mathbf{R}_l \mathbf{P} + \mathbf{X}_l \mathbf{Q} \quad (7.5)$$

where $\tilde{\mathbb{A}} = [a_0, \mathbb{A}^\top]^\top$ corresponds to the bus incidence matrix, capturing the network topology. Expanding Eq. (7.5) and substituting Eq. (7.4), the vector of voltages ($\mathbf{V}$) at any instant κ is given by,

$$\mathbf{V}(\kappa) = (\mathbb{A}^{-1} \mathbf{R}_l \mathbb{A}^{-1}) \mathbf{p}(\kappa) + (\mathbb{A}^{-1} \mathbf{X}_l \mathbb{A}^{-1}) \mathbf{q}(\kappa) + (-\mathbb{A}^{-1} a_0) \mathbf{V}_0(\kappa) \quad (7.6)$$

Consider matrices $\mathbf{S}_v^p$, $\mathbf{S}_v^q$, and $\mathbf{S}_v^{\text{tap}}$ represent the voltage sensitivity coefficients corresponding to the nodal active power exchange, reactive power exchange and OLTC tap change, respectively, then $\mathbf{S}_v^p = \mathbb{A}^{-1} \mathbf{R}_l \mathbb{A}^{-1}$, $\mathbf{S}_v^q = \mathbb{A}^{-1} \mathbf{X}_l \mathbb{A}^{-1}$, and $\mathbf{S}_v^{\text{tap}} = -\mathbb{A}^{-1} \mathbf{a}_0$. Considering the nodal power injections as controllable quantities, the updated voltages at time step $\kappa + 1$ due to the change in

nodal active power $\Delta \mathbf{p}(\kappa) = \mathbf{p}(\kappa + 1) - \mathbf{p}(\kappa)$ and reactive power $\Delta \mathbf{q}(\kappa) = \mathbf{q}(\kappa + 1) - \mathbf{q}(\kappa)$, then using Eq. (7.6) the updated voltages at time $\kappa + 1$ are given by,

$$\mathbf{V}(\kappa + 1) = \mathbf{V}(\kappa) + \mathbf{S}_v^p \Delta \mathbf{p}(\kappa) + \mathbf{S}_v^q \Delta \mathbf{q}(\kappa) + \mathbf{S}_v^{\text{tap}} \Delta \mathbf{V}_0(\kappa) \quad (7.7)$$

Similarly, as discussed in Chapter 4, the dependence of network power losses and line currents on the nodal power exchange is given by the relations,

$$\mathbf{L}(\kappa + 1) = \mathbf{L}(\kappa) + \mathbf{S}_l^p \Delta \mathbf{p}(\kappa) + \mathbf{S}_l^q \Delta \mathbf{q}(\kappa) + \mathbf{S}_l^{\text{tap}} \Delta \mathbf{V}_0(\kappa) \quad (7.8)$$

$$\mathbf{I}(\kappa + 1) = \mathbf{I}(\kappa) + \mathbf{S}_i^p \Delta \mathbf{p}(\kappa) + \mathbf{S}_i^q \Delta \mathbf{q}(\kappa) + \mathbf{S}_i^{\text{tap}} \Delta \mathbf{V}_0(\kappa) \quad (7.9)$$

The matrices $\mathbf{S}_l^p$, $\mathbf{S}_l^q$, and $\mathbf{S}_l^{\text{tap}}$ represent the loss sensitivity coefficients, with respect to active power, reactive power, and OLTC tap change, respectively. Similarly, the matrices $\mathbf{S}_i^p$, $\mathbf{S}_i^q$, and $\mathbf{S}_i^{\text{tap}}$ represent the current sensitivity coefficients. Based on the linear model given in Eq. (7.7) and Eq. (7.8), the general form discrete state-space MPC model [133] is expressed as,

$$\boldsymbol{\xi}(\kappa + 1) = \hat{\mathbf{A}} \boldsymbol{\xi}(\kappa) + \hat{\mathbf{B}} \Delta \mathbf{u}(\kappa) + \hat{\mathbf{D}} \Delta \boldsymbol{\omega}(\kappa) \quad (7.10)$$

$$\mathbf{y}_p(\kappa) = \hat{\mathbf{C}} \boldsymbol{\xi}(\kappa) \quad (7.11)$$

$\Delta \boldsymbol{\omega} = \boldsymbol{\zeta}$ incorporates the nodal active power uncertainties at each node, where $\boldsymbol{\zeta} = \boldsymbol{\zeta}^{pv} + \boldsymbol{\zeta}^{ev} + \boldsymbol{\zeta}^l$, and $\boldsymbol{\zeta}^{pv}, \boldsymbol{\zeta}^{ev}, \boldsymbol{\zeta}^l \in \mathbb{R}^{N \times 1}$. The value of k^{th} element in $\boldsymbol{\zeta}^{pv}$ and $\boldsymbol{\zeta}^{ev}$ is 0 if $k \in \mathcal{N} \setminus \mathcal{N}^{PV}$ and $k \in \mathcal{N} \setminus \mathcal{N}^{EV}$, respectively. Consider the prediction horizon and control horizon of the MPC controller as N_p and N_c , respectively, the matrix form representation of the system output over N_p can be expressed as,

$$\mathbf{Y}_p = \boldsymbol{\chi} \boldsymbol{\xi}(\kappa) + \boldsymbol{\psi} \Delta \mathbf{U} + \boldsymbol{\Sigma} \Delta \boldsymbol{\Omega} \quad (7.12)$$

The MPC model (7.12) involves changes in control input, therefore, the actual inputs for time horizon N_c can be expressed as,

$$\mathbf{U}(\kappa) = \hat{\mathbf{G}} \mathbf{u}(\kappa - 1) + \hat{\mathbf{H}} \Delta \mathbf{U} \quad (7.13)$$

Matrices χ , ψ , Σ , $\hat{\mathbf{G}}$ are developed using matrices $\hat{\mathbf{A}}$, $\hat{\mathbf{B}}$, and $\hat{\mathbf{C}}$, and detailed derivations are given in Chapter 2. The voltage, loss, and current sensitivity coefficients embedded within the input matrix ψ are evaluated using the Z-bus based method, discussed in Chapter 4.

7.3 Problem Formulation

The proposed strategy employs a hierarchical two-stage optimization framework, integrating centralized control of OLTC at a slower time scale of 1 hour and distributed control of IDCDs at a faster time scale of 2 minutes. The objective function is structured as a quadratic programming (QP) problem, aiming to minimize voltage deviations, line currents, changes in control inputs, and line losses. The nodal power uncertainties are considered using a chance-constrained formulation, which is solved deterministically using a scenario-based solution approach.

7.3.1 Chance-constrained Problem Formulation for MPC

Considering these objectives in the CVC framework, the QP chance-constrained optimization problem can be expressed as,

$$\min \sum_{i=1}^{N_p} \left(\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\mathbf{I}(\kappa + i)\|_{\mathbf{w}_i}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{P}_l\|_{\mathbf{w}_l}^2 \right) + \sum_{i=1}^{N_c} (\|\Delta \mathbf{u}(\kappa + i)\|_{\mathbf{w}_u}^2) \quad (7.14)$$

subjected to the constraints,

$$\underline{\underline{\Delta \mathbf{u}}} \leq \Delta \mathbf{u} \leq \overline{\overline{\Delta \mathbf{u}}} \quad (7.15a)$$

$$\underline{\underline{\mathbf{u}}} \leq \mathbf{u} \leq \overline{\overline{\mathbf{u}}} \quad (7.15b)$$

$$\mathbb{P}(\underline{\underline{V_i}} \leq V_i \leq \overline{\overline{V_i}}) = 1 - \epsilon, \quad \forall i \in \mathcal{N} \quad (7.15c)$$

$$\mathbb{P}(0 \leq I_{ij} \leq \overline{\overline{I_{ij}}}) = 1 - \epsilon, \quad \forall (i, j) \in \mathcal{E} \quad (7.15d)$$

The control input vector $\Delta \mathbf{u} = \Delta \mathbf{V}_{\text{tap}}$ for the operation of OLTC at slow time scale, while as $\Delta \mathbf{u} = [\Delta \mathbf{Q}_{\text{PV}}; \Delta \mathbf{Q}_{\text{EV}}; \Delta \mathbf{P}_{\text{PV}}; \Delta \mathbf{P}_{\text{EV}}]$ for the operation of IDCDs at a faster time scale. The weights of matrices $\mathbf{w}_v$, $\mathbf{w}_u$, $\mathbf{w}_s$, $\mathbf{w}_l$, and $\mathbf{w}_i$ are empirically determined through repeated simulations to find a suitable trade-off between different objectives. These are dynamically adjusted

under different voltage levels, using adaptive if-then-else rules, to prioritize favored objectives with changing network states. The solution to the chance-constrained problem given in Eqs. (7.14), (7.15a)-(7.15d) is said to be ε -level robustly feasible [75]. Thus, corresponding to the power uncertainty parameter (ζ), the above formulation upholds security constraints with a predefined probability threshold of $(1 - \varepsilon)$. The solution to the above chance-constrained formulation requires the known probability spaces associated with chance constraints (7.15c), (7.15d). However, the exact evaluation of probability spaces associated with these constraints is difficult, thereby making a direct approach intractable. Therefore, a scenario-based methodology is employed, which reformulates probabilistic constraints as deterministic hard constraints. As discussed in [122], if the constraints are enforced to satisfy a set of randomly selected samples with N_s scenarios, wherein ζ is sampled within its probability space, the resulting solution guarantees feasibility of the original problem with a predetermined confidence level. The performance is guaranteed if the deterministic reformulation of the formulation is convex, or the problem is a mixed-integer convex program [75]. The scenario-based approach preserves the original chance-constrained problem structure and remains applicable to any probability distribution. With a large number of control variables, the computational burden of the scenario-based optimization increases. To enhance the computational efficiency, the backward scenario reduction method discussed in chapter 4 is employed. The reduced scenario set retains only the minimum representative scenarios, thereby maintaining the solution accuracy. The scenario-based problem is solved deterministically by transforming the chance constraints given by Eqs. (7.15c), (7.15d) into hard constraints, as explained in [133]. The QP deterministic reformulation of the chance-constrained problem is given as,

$$\min \sum_{s=1}^{N^R} p^s \left(\sum_{i=1}^{N_p} (\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + i)\|_{\mathbf{w}_v}^2 + \|\mathbf{I}(\kappa + i)\|_{\mathbf{w}_i}^2 + \|\sigma\|_{\mathbf{w}_s}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_l}^2) + \sum_{i=1}^{N_c} \|\Delta \mathbf{u}(\kappa + i)\|_{\mathbf{w}_u}^2 \right) \quad (7.16)$$

where p^s denotes the scenario probability of each scenario in the representative set. The standard QP reformulation of the CC-MPC problem is given in detail in Chapter 4.

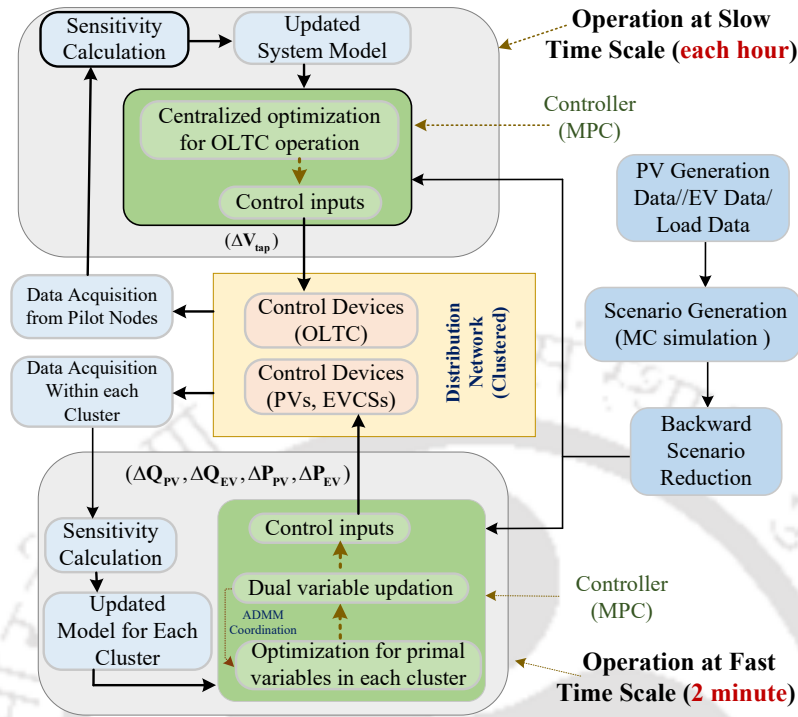


Fig. 7.1: Schematic of the two-stage voltage control architecture for ADNs.

7.4 Two-stage Control Scheme under Nodal Power Uncertainties

The proposed scheme employs a centralized control structure for OLTC operation, and a distributed coordination scheme for IDCs using ADMM. The detailed schematic of the proposed two-stage control scheme is depicted in Fig. 7.1.

7.4.1 Centralized Control of On-Load Tap Changer (OLTC)

The framework determines an optimal sequence of control input through multi-time step optimization problem given as,

$$\min \sum_{i=1}^{N_p} \left(\|\tilde{\mathbf{V}} - \mathbf{V}(\kappa + 1)\|_{\mathbf{w}_v}^2 + \|\mathbf{I}(\kappa + i)\|_{\mathbf{w}_i}^2 + \|\mathbf{p}_l\|_{\mathbf{w}_1}^2 + \|\boldsymbol{\sigma}\|_{\mathbf{w}_s}^2 \right) + \sum_{i=1}^{N_c} \|\Delta \mathbf{V}_{\text{tap}}(\kappa + i)\|_{\mathbf{w}_{\text{tap}}}^2 \quad (7.17)$$

subject to the following constraints,

$$\underline{\underline{\Delta \mathbf{V}_{\text{tap}}}} \leq \Delta \mathbf{V}_{\text{tap}}(\kappa + i) \leq \overline{\overline{\Delta \mathbf{V}_{\text{tap}}}} \quad (7.18a)$$

$$\underline{\underline{\mathbf{V}_{\text{tap}}}} \leq \mathbf{V}_{\text{tap}}(\kappa + i) \leq \overline{\overline{\mathbf{V}_{\text{tap}}}} \quad (7.18b)$$

$$-\sigma_1 \mathbf{1} + \underline{\underline{\mathbf{V}}} \leq \mathbf{V}(\kappa + i) \leq \overline{\overline{\mathbf{V}}} + \sigma_2 \mathbf{1} \quad (7.18c)$$

OLTC control leverages data from a limited number of pilot nodes, thus using sparse communication. These pilot nodes are strategically selected by identifying the centroid node within each cluster, determined using the proximity index, as discussed in the previous chapter.

7.4.2 Distributed Coordination of IDCs using ADMM

The scenario-based centralized QP model in Eq. (7.16) being convex can be equivalently transformed into a distributed framework, without loss of generality. Leveraging distributed computation, the centralized problem is systematically decomposed into tractable sub-problems, assigned to the individual distributed controllers (agents) within the clusters. It is to be noted that the distributed solution closer to the centralized one is more effective in terms of voltage control, as well as control cost reduction.

If $f(\Delta \mathbf{u})$ represents the objective function of the centralized control model given in (7.16), the distributed coordination of distributed controllers in different clusters is achieved using the decomposition coordination of sub-problems of $f(\Delta \mathbf{u})$. The sub-problem for cluster c is given by,

$$\min \sum_{c \in \mathcal{C}^*} f_c(\Delta \mathbf{u}_c) \quad (7.19)$$

subject to,

$$\Delta \mathbf{u}_c \in \Delta \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (7.20a)$$

$$\mathbf{u}_c \in \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (7.20b)$$

$$\mathbf{a}_c = \mathbf{g}_c, \quad \forall c \in \mathcal{C}^* \quad (7.20c)$$

where, $\mathcal{U}_c$ and $\Delta \mathcal{U}_c$ in constraint Eqs. (7.20a) and (7.20b) correspond to the feasibility regions of the decision/control variables. Auxiliary variables represented by vector $\mathbf{a}_c$ are assigned corresponding to the boundary nodes of each cluster $c \in \mathcal{C}^*$. Thus, the constraint in Eq. (7.20c) enforces the equality conditions on node voltage deviations at boundary nodes, using global variables

represented by vector $\mathbf{g}_c$. The constraint in Eq. (7.20c) acts as a consensus constraint enforcing,

$$a_c = a_d = g_c = g_d; \quad a_c \in \mathbf{a}_c \text{ \& } a_d \in \mathbf{a}_d \quad (7.21)$$

where, $a_c \in \mathbf{a}_c$ and $a_d \in \mathbf{a}_d$ are auxiliary variables corresponding to nodes in the set of boundary nodes $\mathcal{B}_{c,d}$, $\forall c, d \in \mathcal{C}^*$. The ADMM-based solution process initially computes the primal variables (control inputs) by minimizing the augmented Lagrangian ($\mathcal{L}_c$) for each subproblem. The dual variables and auxiliary variables are updated subsequently through an iterative process, till the convergence criterion is satisfied. The augmented Lagrangian of (7.19) is given by,

$$\min \mathcal{L}_a(\Delta \mathbf{u}, \boldsymbol{\lambda}, \mathbf{a}, \mathbf{g}) = \sum_{c \in \mathcal{C}^*} \mathcal{L}_c(\Delta \mathbf{u}_c, \boldsymbol{\lambda}_c, \mathbf{a}_c, \mathbf{g}_c) \quad (7.22)$$

subjected to,

$$\Delta \mathbf{u}_c \in \Delta \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (7.23a)$$

$$\mathbf{u}_c \in \mathcal{U}_c, \quad \forall c \in \mathcal{C}^* \quad (7.23b)$$

where,

$$\mathcal{L}_c = f_c(\Delta \mathbf{u}_c) + \boldsymbol{\lambda}_c^\top (\mathbf{a}_c - \mathbf{g}_c) + \frac{\rho}{2} \|\mathbf{a}_c - \mathbf{g}_c\|_2^2 \quad (7.24)$$

It should be noted that the function $f_c(\Delta \mathbf{u}_c)$ corresponds to the chance-constrained problem (7.16) for each subproblem. In other words, the MPC output variables as well as the input variables of $f_c(\Delta \mathbf{u}_c)$ correspond to the network nodes within the cluster c . In this work, the auxiliary variables vector ($\mathbf{a}_c$) corresponds to the node voltage deviations at the boundary nodes of the cluster c . Thus, the ADMM iterative process proceeds with the update of the primal and dual variables. The detailed update of these variables in the iterative process is discussed in the previous chapter (Chapter 6).

Decomposition coordination is facilitated by the optimal clustering of the network into controllable voltage zones. The Louvain algorithm [138], discussed in Chapter 6, is used for clustering in this study as well. The algorithm considers each node as an independent cluster at the beginning, and progressively merges the network nodes to maximize the improved modularity index at

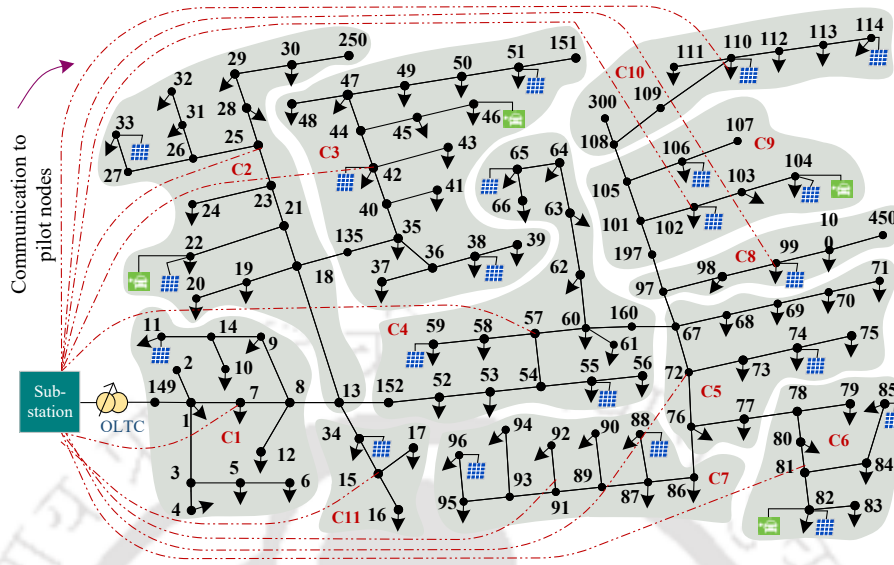


Fig. 7.2: Modified IEEE 123-bus distribution network with clustering.

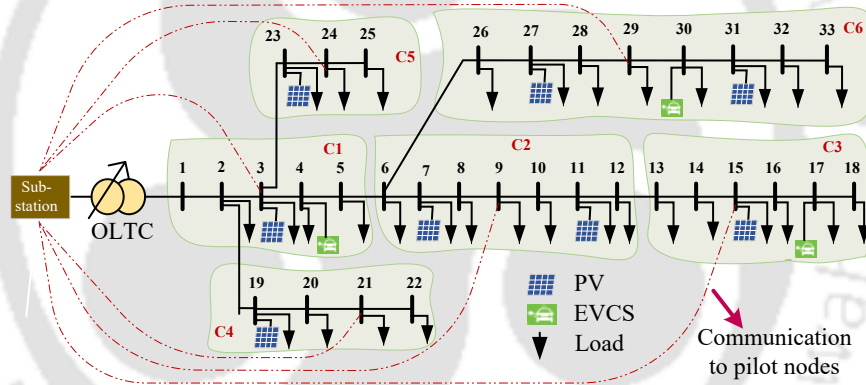


Fig. 7.3: 33-bus distribution network with clustering.

each clustering stage.

7.5 Simulation Results and Discussion

This study again leverages realistic and empirical data from 461 residential EVs under the Electric Nation project (UK) [124]. Residential charging behavior is characterized through key parameters, including charging duration, plug-in time and frequency, and charger capacity. The binary ON/OFF states of EV chargers are governed by temporal characteristics, while actual power consumption is determined by charger ratings. Two commercially available chargers; Level 1 (3.68 kW) and Level 2 (7.36 kW) are considered for battery electric vehicles (BEVs), plug-in

hybrid electric vehicles (PHEVs), and range-extended PEVs (REX-PEVs) with battery capacities spanning 6–100 kWh [124]. Detailed discussion on EV data, as well as the share of different battery capacities, is given in Chapter 4. EVCSs are integrated at locations shown in Fig. 7.2 and Fig. 7.3. While domestic chargers are treated as uncontrolled loads due to limited communication infrastructure, the EVCSs are distributionally coordinated, utilizing inverters for V2G operation. To study the network impact assessment within medium-voltage ADNs, an aggregate EV modeling approach is employed, wherein a group of EVs is represented as equivalent loads. The PV inverters are marginally overrated by 10% to facilitate at least 44% reactive power during peak power injections. Furthermore, EVs start charging at their rated power immediately upon connection. The inherent stochasticity associated with uncontrolled domestic EV charging as well as the charging at EVCSs, is modeled using the normal distribution.

Initially, stochastic scenarios are generated with MC simulation. The load and EV demand uncertainties are assumed to follow a normal distribution [75], while PVs follow a beta distribution, with shape parameters given in [63]. The standard deviation (σ^{ev}) for EV demand is set at 10%, and 5% for conventional loads (σ^l) and PV generation (σ^{pv}). Using the backward reduction method, only representative scenarios are retained. Simulations for sensitivity analysis of varying reduced scenario sets are carried out in chapter 4 to determine the feasible scenario set ($\mathcal{S}^R$). Comprehensive voltage deviation index (σ_{CVD}) [60] is used to determine the quality of reduced scenario set, providing $N_s = 50$ feasible representative scenarios, while ensuring a high solution accuracy.

7.5.1 Simulations on IEEE 123-Bus Distribution Network

Simulations are performed on the modified IEEE-123 bus network with a base voltage of 4.16 kV and a base power of 1 MVA. Residential EV chargers are integrated within each low-voltage network linked to the nodes, with a 50% penetration level, comprising 116 Level 1 and 464 Level 2 chargers. The spatial distributions of PV systems and EVCSs are depicted in Fig. 7.2, with detailed specifications and ratings given in [133]. For efficient control, the network is partitioned into 11 optimal clusters, each with a distributed controller, using the proposed enhanced modularity index. The evolution of the improved index with the number of clusters is shown in Fig. 7.4(a).

Table 7.1: Comparison of different clustering metrics.

Attribute	Modularity metric			
	ρ [Standard]	ρ_{im} [82]	ρ_{mod} [99]	ρ_{mod}^d [proposed]
Structural modularity	0.7677	0.7648	0.6618	0.8004
Maximum diameter	9.2915	13.9537	14.3297	9.2915
Std. deviation in diameters	3.4920	4.2456	4.1695	3.0988
Number of clusters	12	11	12	11

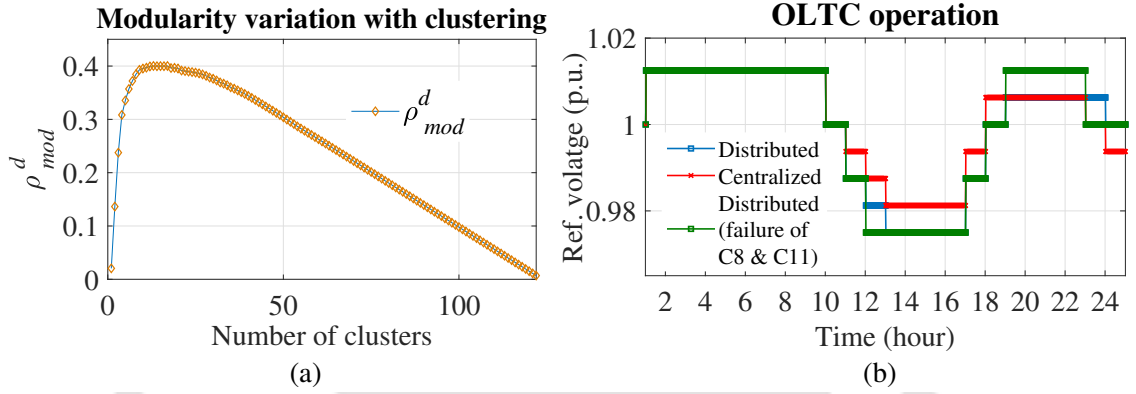


Fig. 7.4: OLTC reference voltage corresponding to centralized and distributed control of IDCs in IEEE 123-bus network.

The effectiveness of the proposed improved index is compared with existing indices using different parameters, as given in Table 7.1. Additionally, pilot nodes are identified for centralized control of OLTC, with bidirectional communication links to the substation (Fig. 7.2), using the proximity index. Time domain simulation under no control actions shows significant over-voltages due to increased PV generation with a maximum voltage of 1.0895 p.u., as shown in Fig. 7.5. Conversely, substantial under-voltage conditions prevail between 5 p.m. and 11 p.m., driven by peak evening and EV charging demands with a minimum voltage of 0.8661 p.u., and a net energy loss of 6.4762 MWh. Using the proposed two-stage distributed control employing IDCs and OLTC, the voltages are restricted within the permissible operational limits of [0.95,1.05] p.u., as shown in Fig. 7.6. The minimum and maximum voltages over the whole simulation period are seen to be 0.95 p.u. and 1.0462 p.u., respectively. It is seen that due to severe under-voltages as compared to the over-voltage conditions in the uncontrolled case, the reactive power injection from IDCs is quite significant that the reactive power absorption, as shown in Fig. 7.8. However, due to the

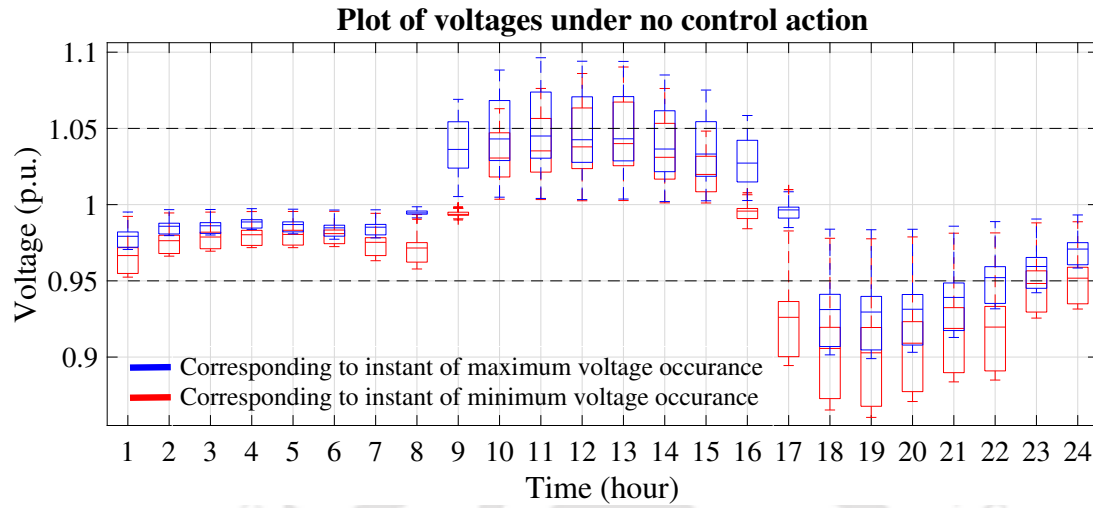


Fig. 7.5: Plot of voltages of modified IEEE-123 bus network corresponding to the instant of the occurrence of the minimum and maximum voltages in each hour, under no control action.

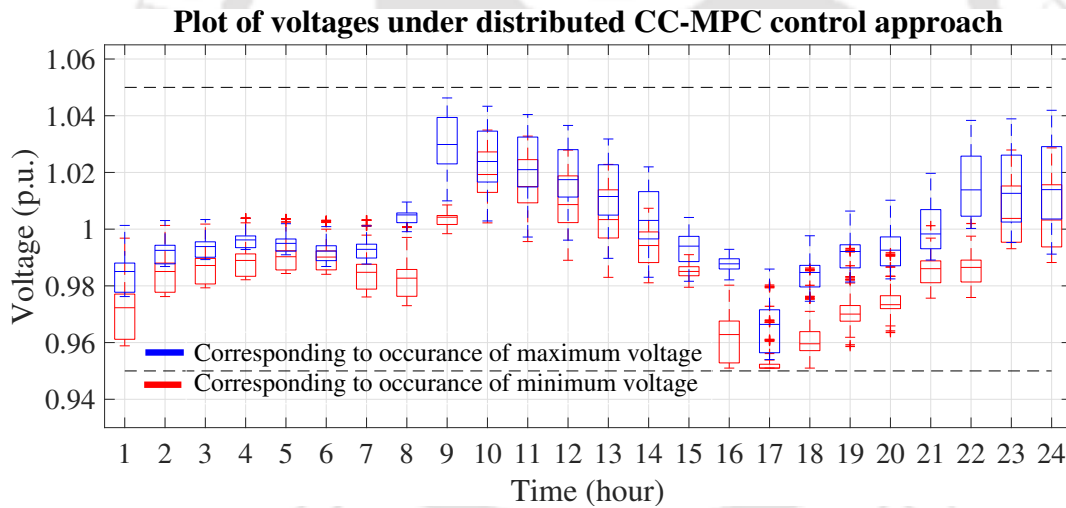


Fig. 7.6: Plot of voltages of IEEE-123 bus network corresponding to the instant of the occurrence of minimum and maximum voltages in each hour, under distributed CC-MPC control approach.

heavy penalization of active power exchange, the PV curtailment and V2G active power exchange from the EVCSs are quite less, exchanging only 58.555 kWh and 37.821 kWh, respectively. The reactive power exchange by PV inverters and EVCSs, along with total active power curtailment over the whole simulation period of 24 hours is given in Table 7.2. The net energy loss under the distributed CC-MPC approach is seen to be 5.320 MWh with a net reduction of 17.85%, as compared to the uncompensated case study. The two-stage operation with OTC control at a slower

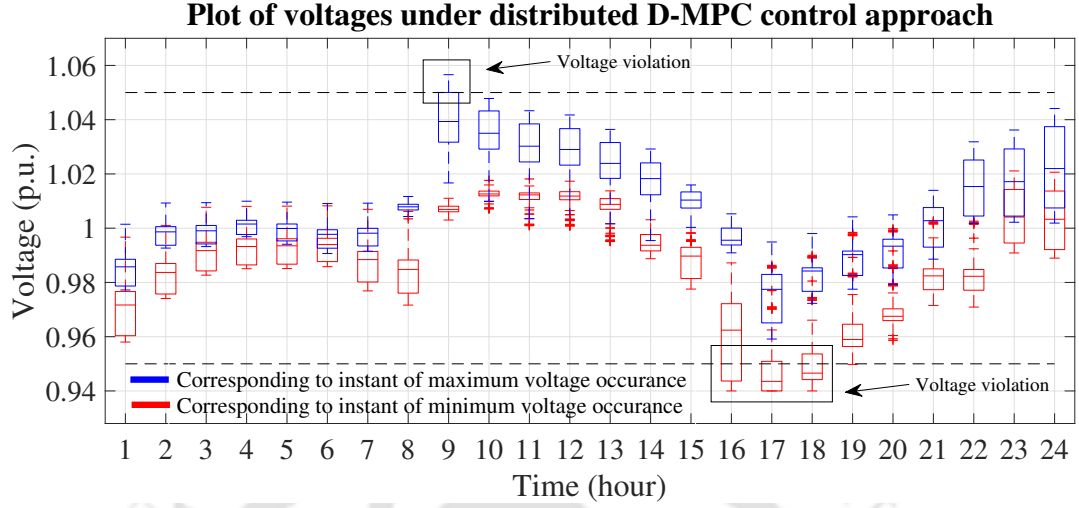


Fig. 7.7: Plot of voltages of IEEE-123 bus network corresponding to the instant of the occurrence of minimum and maximum voltages in each hour, under distributed D-MPC control approach.

Table 7.2: Numerical results of the IEEE 123-bus network using CC-MPC-based distributed control of IDCs.

Q_{PV} exchange (MVarh)	18.345	Min./ max. voltage (p.u.)	0.95/1.046
Q_{EV} exchange (MVarh)	3.567	Net energy losses (MWh)	5.320
Net APC of PVs (kWh)	58.555	Net V2G injection (kWh)	37.821

Table 7.3: Quantitative comparison between distributed and centralized coordination of IDCs.

Control scheme	Average time per optimization	$\sigma_{CVD}(\times 10^{-4})$ p.u.		Voltage deviation	
		Without OLTC	With OLTC	μ	σ
Centralized	0.0470 s	216	191	0.0024	0.0018
Distributed	0.0310 s	242	200		

time scale improves the voltage profile and reduces the net energy loss of the network. The effect of OLTC operation at a slow time scale is quantified using the comprehensive voltage deviation index (σ_{CVD}) [60,133]. It can be seen from Table 7.3 that the value of σ_{CVD} is lower when OLTC is deployed at a slow time scale and the energy losses are reduced by 4.45%, as compared to the case when only IDCs are deployed for control.

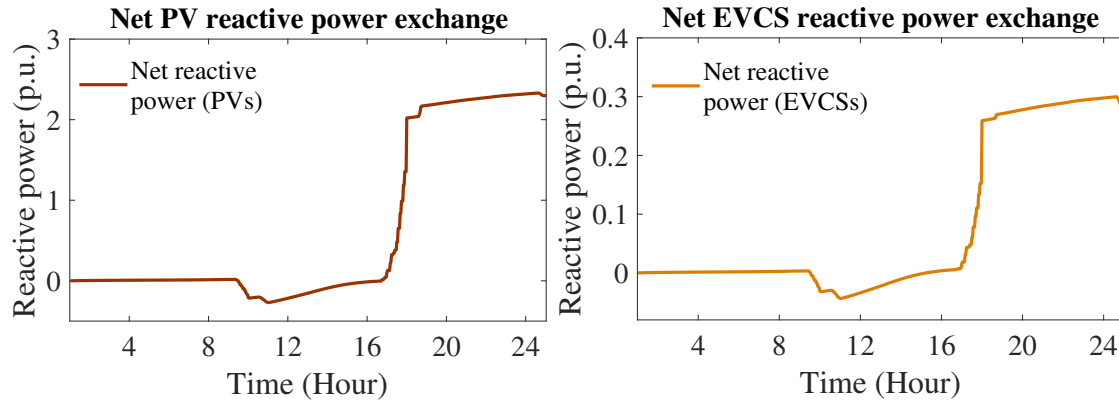


Fig. 7.8: Net reactive power exchange of IDCs: (a) PV inverters (b) EVCS inverters.

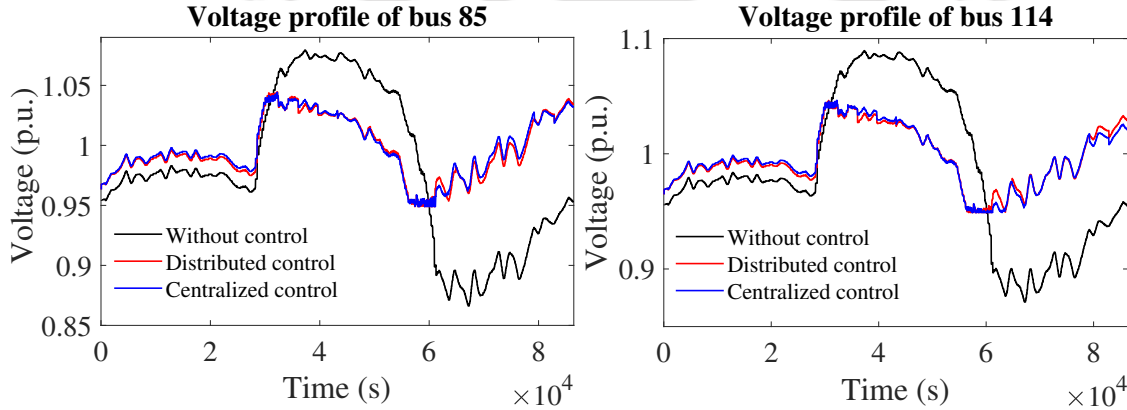


Fig. 7.9: Comparison of voltage profiles of critical buses in IEEE 123-bus network with centralized and distributed coordination of IDCs.

7.5.1.1 Comparison with the Centralized CC-MPC Framework

The proposed distributed framework is further compared with centralized dispatching of IDCs to assess the ADM-based control coordination. For this purpose, the demand profiles are incorporated with Gaussian noise, and the PV profile is incorporated with random uncertainty using a beta distribution, within the uncertainty levels discussed in Section 4.6. While centralized control generally requires network-wide observability with data from all network nodes, distributed coordination requires only limited inter-cluster data exchange, reducing communication burden and enhancing privacy. For comparison purposes, the voltage profiles of the critical buses 85 and 114 are chosen, and it can be seen from Fig. 7.9 that the voltage profile with the proposed distributionally coordinated control closely matches that of centralized coordination, with a mean deviation of 0.0023 p.u. and a standard deviation of 0.0032 p.u. Furthermore, it

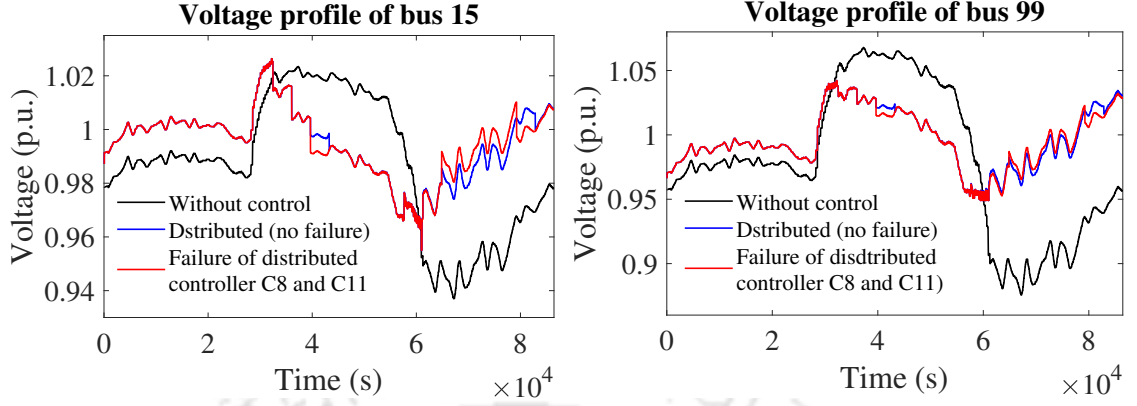


Fig. 7.10: Voltage profile of pilot buses 15 and 99 in the IEEE 123-bus network considering the failure of distributed controllers in clusters C8 and C11.

is observed that the OLTC operation is similar in distributed coordination as well as centralized coordination of IDCs; however, in the proposed scheme, only limited pilot nodes are utilized for real-time measurements {Fig. 7.4(b)}.

7.5.1.2 Scalability, Data Privacy, and Reliability in the Distributed Coordination

The decomposition-coordination framework, enabled with parallel computation of localized sub-problems, substantially alleviates the computational burden on individual controllers, thereby enhancing ADN scalability (Table 7.3). Moreover, the localized control processing architecture leverages limited inter-cluster communication and minimal data exchange, effectively preserving data privacy while optimizing bandwidth utilization and mitigating communication overhead. Furthermore, the distributed control paradigm enhances system reliability by mitigating the vulnerability associated with the single point failure, inherent in centralized systems. To evaluate the robustness and reliability under distributed controller failure, simulations are conducted with the failure of distributed controllers C8 and C11 at 13:10 hours. The resultant voltage profiles of the pilot nodes 15 and 99, corresponding to the clusters with the failed controllers, are depicted in Fig 7.10. The results show that the voltages are maintained within the permissible limits due to the compensatory response of the remaining functional distributed controllers.

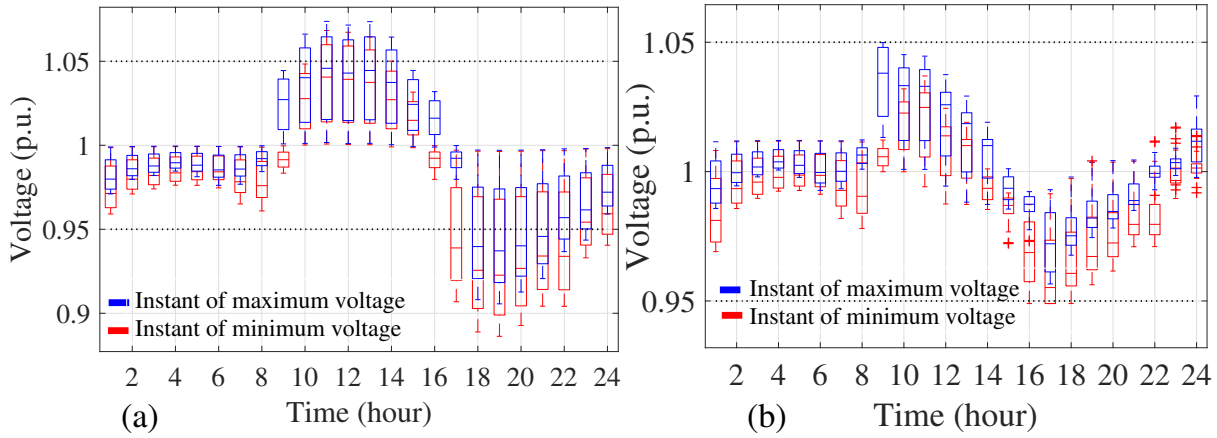


Fig. 7.11: Plot of voltages of 33-bus network corresponding to the instant of the occurrence of minimum and maximum voltages in each hour: (a) Under no control action (b) Under the distributed coordination of IDCDs using CC-MPC control approach.

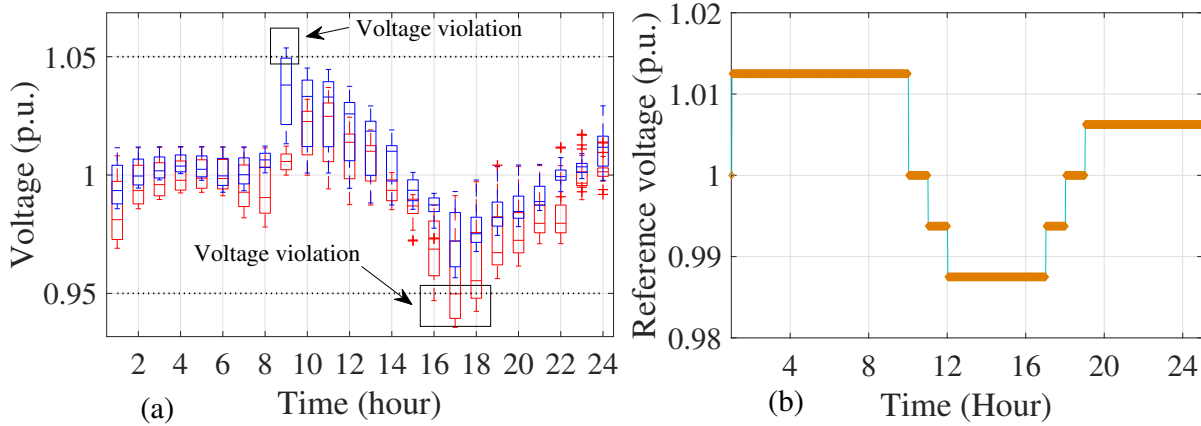


Fig. 7.12: Plot of voltages of 33-bus network corresponding to the occurrence of minimum and maximum voltages under D-MPC control approach.

7.5.2 Simulations on 33-Bus Distribution Network

The simulations are further carried out on the 33-bus distribution network shown in Fig. 7.3. The detailed system description is given in Chapter 4. Time domain simulations under no control action show significant voltage violations, as shown in Fig. 7.11(a), with minimum and maximum voltages as 0.886 p.u. and 1.074 p.u., respectively, and energy loss of 2.6315 MWh. Using the proposed control approach, the voltages are maintained within the normal operation range, as shown in Fig. 7.11(b), with minimum/maximum voltages as 0.95 p.u. and 1.049 p.u., respectively.

The net energy losses are seen to be 2.02 MWh with 23.24% reduction, as compared to the base

case. However, certain voltage violations are seen under the deterministic distributed solution approach when using stochastic PV, EV, and load data, as shown in Fig. 7.12(a).

7.6 Conclusion

In this chapter, a CC-MPC-driven hybrid voltage control architecture has been developed for voltage control and loss minimization in highly penetrated ADNs. A two-stage control framework has been developed, wherein OLTC operation using a sparse measurement-based centralized structure is performed at the first stage. At the second stage, IDCs are controlled utilizing an ADMM-based decomposition coordination framework, enabling parallelized operation for tractable sub-problems corresponding to each cluster. The improved modularity metric, incorporating cluster diameter, is deployed for optimal and uniform clustering. Simulations on the modified IEEE 123-bus and 33-bus networks depict a superior solution as compared to the centralized solution in terms of data privacy, computational efficiency, and communication overhead, as well as compared to the deterministic distributed solutions in terms of uncertainty handling. Compared to the D-MPC-based solution approach, wherein voltage violations are observed under uncertain nodal powers, the proposed scenario-based solution to the chance-constrained problem effectively eliminates these violations. Moreover, the integration of OLTC control at a slow time scale (using two-stage optimization) effectively enhances the voltage regulation with $\sigma_{CVD} = 200 \times 10^{-4}$ p.u., as compared to 216×10^{-4} p.u. using single-stage coordination of only IDCs, in the IEEE 123-bus network. Furthermore, energy losses are reduced by 17.85% as compared to the case when no control is used, and 4.45% as compared to the single-stage optimization of IDCs. Compared to the existing fully distributed control strategies, which do not consider nodal power uncertainties, the proposed control approach can effectively handle these uncertainties while coordinating the IDCs in a distributed manner.

Chapter 8

Conclusions and Future Scope

The significant integration of distributed energy resources (DERs), notably renewable energy sources and electric vehicles (EVs), has transformed electric distribution networks into active distribution networks (ADNs). While DERs enhance reliability and sustainability, the large-scale integration of renewable DG units with temporal uncertainties causes frequent voltage variations, leading to over/under voltage events, thermal limit violations, stability issues, etc. Existing networks also lack infrastructure for topological changes from extensive DERs and EV charging stations (EVCS), necessitating active network management (ANM), which employs advanced control and fast-acting power electronic devices. Voltage control in ADNs constitutes one of the primary challenges, as frequent violations may cause serious issues to voltage-sensitive loads and restrict the integration of renewable DG units if not addressed. Future power distribution networks (PDNs) will see massive growth of plug-in electric vehicles (PEVs), whose uncertain charging/discharging patterns, state-of-charge, and random driving behaviors can cause significant voltage violations, increased power losses, and localized overloading if uncoordinated. Research in ADN voltage control has focused on schemes to maintain voltages within acceptable limits using devices such as OLTC, shunt capacitors, and smart inverters of DG units, EV charging station inverters, and custom power devices, such as distribution static synchronous compensators (DSTATCOMs), and soft-open-points (SOPs). Advanced centralized and distributed coordinated control approaches are optimization-based, offering superior performance in optimal operation,

control resource utilization, energy loss reduction, and voltage regulation. The work carried out in this thesis employs various multi-time-scale coordinated voltage control strategies in centralized as well as distributed control paradigms. The major conclusions of the thesis are provided in the following section.

8.1 Conclusions of the Thesis

The chapter-wise conclusions of the work carried out in this thesis are as follows:

- In chapter 1, the voltage fluctuation problem in ADNs has been explained, along with a detailed discussion on the control characteristics of the conventional as well as power electronic-based advanced control devices used for voltage control. A detailed classification of the control strategies used in ADN voltage control has been provided based on the recent literature. The research gaps in the existing literature have been identified, and based on them, the objectives carried out in the thesis have been discussed.
- In chapter 2, a two-time-scale deterministic MPC-based reduced-order model centralized control strategy has been proposed for voltage regulation in ADNs, wherein OLTC is optimally operated at a slower time-scale, and inverter-driven control devices (IDCDs), such as PVs and EVCSs, are optimally coordinated at a faster time-scale. The control framework utilizes a minimal set of available control resources to mitigate the need for system-wide communication, measuring infrastructure, and computation time. Unlike the full-order system model, the observation and control nodes have been modeled only by using the linear model for the MPC framework. Furthermore, the controllable nodes and critical observation nodes have been assumed to have the necessary measuring infrastructure for real-time control. The minimal set of control resources has been identified by ranking the system nodes with control resources, corresponding to critical observation nodes. This is achieved using numerical voltage sensitivity analysis-based novel index called the ranking index. The efficacy of the proposed reduced-order model control strategy has been verified on the 33-bus network and the IEEE 123-bus distribution network. Compared to the full-order model, the mean and standard deviation of the voltages over the whole simulation period of 24

hours, at the critical bus, are seen to be 0.0034 p.u. and 0.0043 p.u., respectively, IEEE 123-bus network. Furthermore, the computation time per sample is seen to be reduced by 40.38% and 63.73%, for the 33-bus network and IEEE 123-bus network, respectively. The comparative results with the existing full-order model approaches show that the net energy losses are slightly increased in the proposed approach by around 4% in the 123-bus network; however, there is a reduction in the net reactive power exchange by the control resources by 13.3%, while the network voltages are maintained well within the normal operation limits of $[0.95, 1.05]$ p.u. Thus, the proposed reduced-order model approach suitably performs well for PV and EV penetrated distributed networks.

- In chapter 3, the dual-stage deterministic MPC-based reduced-order control model proposed in chapter 2 has been extended to incorporate network energy loss minimization, in addition to the minimization of voltage deviations and control resource utilization. The line currents are considered to be additional state variables to ensure operation within the thermal limits. The detailed quadratic formulation of the problem has been discussed, and the proposed reduced model performance has been compared to the full order model and other state-of-the-art deterministic MPC-based centralized control methods. The validation of the proposed model on the 33-bus network shows that the mean deviation (μ) and standard deviation (σ) of the voltages at the most critical node, with respect to the full-order model of the network, are merely 0.0038 p.u. and 0.0059 p.u., respectively. The network net energy losses are seen to be reduced by 23.24% in the 33-bus network, and 4% in the IEEE 123-bus network, when the power loss minimization is also considered along with voltage regulation, as compared to the case when power loss minimization is not incorporated, as in chapter 2 of the thesis. Moreover, it is seen that the energy losses slightly increase by 4% and 0.5%, for the 33-bus network and IEEE 123-bus network, when EV charging stations are incorporated; however, the voltage profile is improved, due to additional control provision of EV charger inverters. Furthermore, due to the reduced dimensionality of the model, the computation time is seen to be improved, with a reduction in computation time per sampling instant by 53% and 51%, for the 33-bus network and IEEE 123-bus network, respectively, as

compared to the full order model. Thus, the proposed reduced-order model can effectively be employed for voltage control in PV and EV penetrated distribution networks, along with energy loss minimization, and efficient control resource utilization.

- In chapter 4, a real-time chance-constrained model predictive control (CC-MPC) based control approach has been proposed for coordinated voltage control and energy loss minimization in active distribution networks. Since the nodal power uncertainties, mainly due to renewable DG units and EV loads, may lead to the violation of network voltage constraints, or even thermal limit violations of lines in ADNs, if not taken into account. The proposed model effectively considers inherent uncertainties in conventional loads, EV loads, and PVs, quantifying them individually to account for varying levels of uncertainty. The uncertainties are modelled using the known probability distributions, such as the beta distribution and normal distribution for PVs and conventional loads, respectively. A scenario-based approach (using Monte-Carlo simulation) has been leveraged to reformulate the chance-constrained (CC) problem as a deterministic counterpart while maintaining computational efficiency using the backward scenario reduction technique. The proposed approach considers the nodal power uncertainties, unlike the other existing deterministic model predictive control (D-MPC) based approaches, under varying degrees of uncertainties and EV penetration levels. The simulations have been performed on the 33-bus network and the IEEE-123 bus network to validate the performance in uncertainty handling. The proposed approach maintains the voltages within the limits for all domestic EV penetration levels considered, in both the test networks. The net energy losses in the 33-bus network increase by 19.179%, 22.483%, 44.063%, and 45.628% for domestic EV penetration levels of 70%, 80%, 90%, and 100%, respectively, compared to the base case EV penetration level of 60%. Moreover, an increase in control resource utilization is seen due to the controller action to counter possible voltage violations due to uncertainties. For the 33-bus network, the net increase in reactive power exchange and energy losses in the CC-MPC approach with power uncertainties is seen to be 513 kVarh and 403 kW, respectively, as compared to the D-MPC approach with nodal power uncertainties. For the IEEE 123-bus network, the net increase

in reactive power is seen to be 623.4 kVarh. However, in both the test networks, the voltages are maintained well within the predefined normal operation limits ($[0.95, 1.05]$ p.u.), using the proposed CC-MPC framework, unlike the D-MPC approach under uncertainties, wherein multiple violations of the voltage constraints are seen. Thus, the proposed real-time solution approach can effectively be used for uncertainty handling in ADNs with high renewable penetration and uncertainties in nodal power injection, at the cost of increased (but acceptable) control resource utilization and energy loss.

- In chapter 5, the uncertainties in real-time measurements have also been considered, in addition to the nodal power uncertainties, using a distributionally robust CC-MPC framework. The proposed framework explicitly addresses nodal power and measurement uncertainties by employing a hierarchical voltage control with OLTC, fast-acting PV inverters, EVCS inverters, and DSTATCOM via a multi-step receding horizon optimization. A fast-acting local control layer is incorporated to mitigate rapid voltage fluctuations and complement the centralized coordination mechanism. Unlike the scenario-based solution approach to the chance-constrained formulation, requiring pre-defined probability distributions of uncertain parameters, this study provides a scenario-independent tractable solution approach to the chance-constrained problem. The solution leverages only partially available information of uncertainties, such as first and second order moments, and does not require pre-defined probability distributions, thus providing a distributionally robust solution approach to the system with uncertainties. Moreover, the control capabilities of the DSTATCOM are utilized in coordination with other control devices. Comparative analysis with the deterministic solution approach shows that the voltage constraints are successfully restrained within the normal operation limits of 0.95 p.u. and 1.05 p.u., respectively, thus enhancing network security. Although the local control layer alleviates some of the voltage violations, its limited spatial scope due to localized actions prevents comprehensive mitigation, allowing some voltage violations to persist within the network. The voltage violations caused by the uncertainties are successfully eliminated with the proposed approach, at the cost of an increase in reactive power control and a slight, but acceptable increase in power losses.

Compared to the deterministic case study, the energy loss, as well as the aggregate reactive power exchange, increase by 112 kWh and 1.08 MVar, respectively, for the 33-bus system. However, the APC and V2G injection by EVCSs are reduced using the proposed control approach, employing the addition of a risk-adjusted safety margin to the chance constraints. The APC and V2G active power of EVs are reduced by 23.08 kWh and 21.21 kWh, respectively. This occurs due to the slightly conservative control actions through reactive power control, over the simulation period, waiving off the costly actions pertaining to the active power exchange. Furthermore, the proposed approach closely matches the scenario-based solution approach, with a small increase in control cost and an increase in net energy loss by 1.7%, due to the consideration of the worst cumulative distribution function of uncertainties. Thus, the proposed scenario-independent solution approach can effectively be employed for voltage control and energy minimization in ADNs having uncertainties with unknown probability distributions. While the control resource utilization and energy losses are seen to be slightly more than the scenario-based solution approach, the proposed approach is computationally efficient and more secure due to the consideration of the worst-case cumulative distribution of uncertainties.

- In chapter 6, a multi-stage MPC-driven centralized-distributed hybrid control structure has been developed for ADNs with high renewable penetration, employing centralized and distributed control paradigms. The proposed hybrid control scheme has been developed mainly to address certain issues of centralized control, such as privacy concerns, reliability, communication and computational complexity, and scalability in very large distribution networks with a large number of decision variables. In the proposed control framework, the voltage deviations have been minimized while optimizing the operation of control equipment for minimum control resource utilization. The operation of OLTC has been carried out at a slow time scale (STS), leveraging a sparse-communication-based centralized control structure, with a reduced number of required real-time measurements from strategically selected pilot buses. The inverter-driven control devices (IDCDs) have been coordinated at a fast time scale (FTS) to optimize both reactive and active power support by em-

playing ADMM-based decomposition coordination. The distributed coordination employed enhances privacy preservation, control reliability, and reduces communication overhead, notably in large networks. A modified modularity metric has been used, incorporating cluster diameter uniformity, in addition to the device regulation capacities, and average voltage sensitivities within the cluster, for effective partitioning, in order to achieve efficient distributed control. Compared to partitioning based on existing modularity indices, the improved modularity index provides a higher modularity value of the clustering result, with reduced maximum diameter and standard deviation in the cluster diameters. The simulation results on the IEEE 123-bus network and 33-bus distribution network with the proposed control framework, utilizing the improved network partitioning and comparison with the centralized control scheme, depict the high coordination capability of the proposed control framework. A small mean and standard deviation of 0.0048 p.u. and 0.0064 in the 33-bus network, and 0.0051 and 0.0025 p.u. in the IEEE 123-bus network, respectively, are seen in voltage profiles, at the critical nodes, in comparison to the centralized control structure. Thus, the proposed method can effectively be utilized in large-scale distribution networks with a mix of control resources.

- In chapter 7, the hybrid control framework presented in chapter 6 is extended to consider nodal power uncertainties, using a chance-constrained MPC-based control architecture. Assuming the known probability distributions of the nodal power uncertainties, the scenario-based control approach discussed is employed, while considering the distributed coordination of IDCs. Simulations on the modified IEEE 123-bus network and 33-bus distribution network depict a superior solution, as compared to the centralized solution, in terms of data privacy, computational efficiency, and communication overhead, as well as compared to the deterministic distributed solutions in terms of uncertainty handling. Compared to the D-MPC-based solution approach, wherein voltage violations are observed under uncertain nodal powers, the proposed scenario-based solution to the chance-constrained problem effectively eliminates these violations. Moreover, the integration of OLTC control at a slow time scale (using two-stage optimization) effectively enhances the voltage regulation with

$\sigma_{CVD} = 200 \times 10^{-4}$ p.u., as compared to 216×10^{-4} p.u. using single-stage coordination of only IDCs, for the IEEE 123-bus network. Furthermore, energy losses in the IEEE 123-bus network are reduced by 17.85%, as compared to the case when no control is used, and 4.45% as compared to the single-stage optimization of IDCs. Thus, the proposed hybrid control strategy can be effectively utilized for voltage control and energy loss minimization in large-scale distribution networks with high PV and EV integration.

Thus, in summary, the work carried out in this considers multi-time scale MPC-based coordinated voltage control and energy loss minimization in ADNs with high PV and EV penetration levels. The work mainly focuses on:

- Reducing the measurement and communication infrastructure in MPC-based centralized control schemes for small and medium-sized distribution networks.
- Consideration of nodal power and measurement uncertainties in ADNs in centralized and distributed control paradigms.
- Hybrid control architecture with distributed coordination of IDCs, to address certain issues of fully centralized control schemes in large-scale distribution networks.

All the simulations have been performed on a system equipped with a 12th Gen Intel Core i5-12500 processor (3.00 GHz) and 16.0 GB of RAM. The time-domain simulations have been performed using the Power System Analysis (PSAT) toolbox in MATLAB, and all the optimizations have been carried out using IBM ILOG CPLEX software with MATLAB interface.

8.2 Future Research Directions

The existing research on real-time voltage control in ADNs and the work in this thesis can be further enhanced and extended in various aspects mentioned below:

- *Consideration of real-time voltage control with optimal charging strategy:* The real-time voltage control frameworks in this work can be extended to incorporate detailed EV modelling and an optimal charging strategy, considering active participation of EV owners in

local energy markets. The customer perspective of EVs, considering range anxiety issues and real-time pricing structures, needs to be integrated and studied in detail.

- *Consideration of a model-free real-time control approach:* The work carried out in this thesis assumes a known model of the distribution network. In practical situations, however, the network model may not be precisely known. Hence, the work can be extended to develop a model-free approach, wherein real-time control is achieved without requiring precise knowledge of the network model.
- *Consideration of voltage control under dynamically changing network topology:* The work carried out in this thesis assumes a fixed network topology without considering network reconfiguration. In practice, however, distribution networks often undergo reconfiguration to improve operational flexibility, reliability, or minimize energy losses. Thus, the work can be extended to account for varying topologies and to develop control strategies capable of operating effectively under network reconfiguration.
- *Consideration of coordinated control scheme for multi-voltage level ADNs:* The control frameworks developed in this thesis consider the medium voltage (MV) test networks. The distributed agents in low-voltage (LV) networks can exhibit application prospects if low LV networks are integrated in the coordinated control scheme. Thus, the work can be extended for a joint coordinated voltage control architecture across multi-voltage-level ADNs.

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Appendix A

The detailed datasets of the benchmark test distribution networks employed in simulations are provided in this Appendix. The dataset encompasses bus data and line data of the test networks. Bus data includes base voltage (kVA), base power (MVA), active power demand (kW), and reactive power demand (kW) of the network. The line data comprises electrical topology through bus interconnections along with the corresponding line impedances (resistance and reactance).

A.1 Dataset of the 33-Bus Distribution Network

The 33-bus radial distribution system consists of a single feeder connected to a substation at bus 1, as depicted in Fig. A.1. The simulation data for this network is sourced from [141]. The network is fed through a substation at bus 1, and all the remaining buses are load buses. The system base voltage and base power are considered as 12.66 kV and 10 MVA, respectively, for all the case studies in this thesis. Table A.1 provides the bus data and line data of the system, wherein the active and reactive power demands correspond to the connected load at the buses.

A.2 Dataset of the IEEE 123-Bus Distribution Network

The IEEE 123-bus distribution system is also a single feeder connected to a substation, as depicted in Fig. A.2. The simulation data for this network is taken from [106]. The network is fed through a substation at bus number 149, connected through an OLTC, and all the remaining buses are load buses. The system base voltage and base power are considered as 4.16 kV and 1 MVA, respectively. Table A.2 provides the bus data and line data of the system.

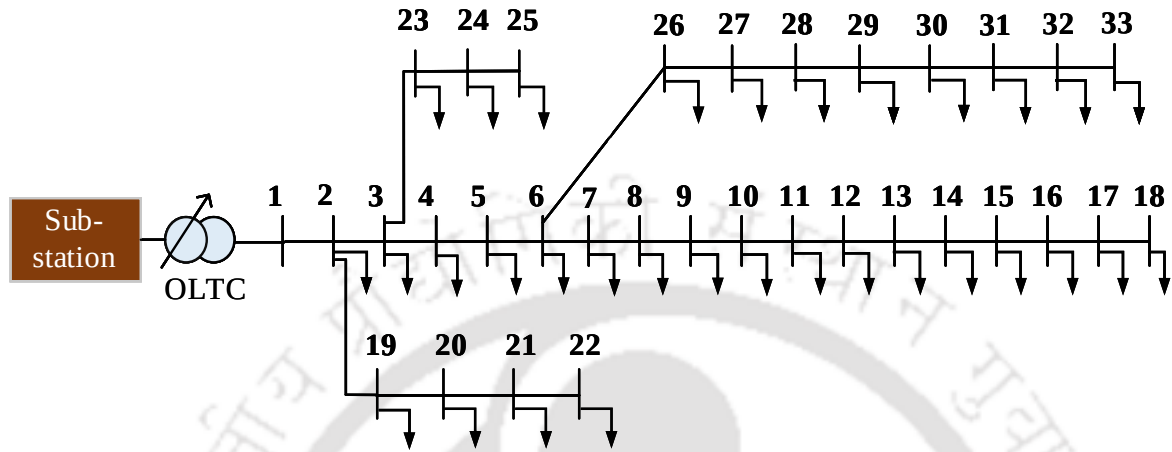


Fig. A.1: Single line diagram of the 33-bus radial distribution network.

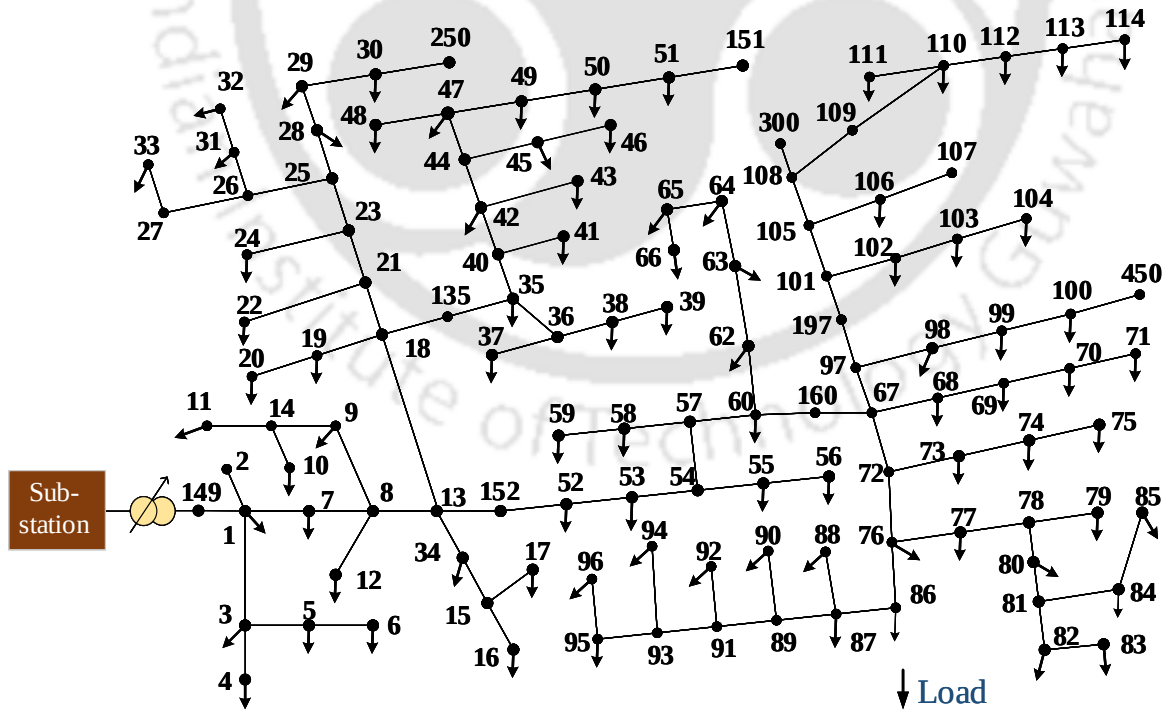


Fig. A.2: Single line diagram of the IEEE 123-bus distribution network.

Table A.1: Load data and line data of 33-bus radial distribution network.

Load Data			Line Data				
Bus No.	Active Power (kW)	Reactive Power (kVAr)	Branch No.	From Bus	To Bus	R (Ω)	X (Ω)
1	0	0	1	1	2	0.0922	0.0470
2	100	60	2	2	3	0.4930	0.2511
3	90	40	3	3	4	0.3660	0.1864
4	120	80	4	4	5	0.3811	0.1941
5	60	30	5	5	6	0.8190	0.7070
6	60	20	6	6	7	0.1872	0.6188
7	200	100	7	7	8	0.7114	0.2351
8	200	100	8	8	9	1.0300	0.7400
9	60	20	9	9	10	1.0440	0.7400
10	60	20	10	10	11	0.1966	0.0630
11	45	30	11	11	12	0.3744	0.1238
12	60	35	12	12	13	1.4680	1.1550
13	60	35	13	13	14	0.5416	0.7129
14	120	80	14	14	15	0.5910	0.5260
15	60	10	15	15	16	0.7463	0.5450
16	60	20	16	16	17	1.2890	1.7210
17	60	20	17	17	18	0.7320	0.5740
18	90	40	18	18	19	0.1640	0.1565
19	90	40	19	19	20	1.5042	1.3554
20	90	40	20	20	21	0.4095	0.4784
21	90	40	21	21	22	0.7089	0.9373
22	90	40	22	22	23	0.4512	0.3083
23	90	50	23	23	24	0.8980	0.7091
24	420	200	24	24	25	0.8960	0.7011
25	420	200	25	25	26	0.2030	0.1034
26	60	25	26	26	27	0.2842	0.1447
27	60	25	27	27	28	1.0590	0.9337
28	60	20	28	28	29	0.8042	0.7006
29	120	70	29	29	30	0.5075	0.2585
30	200	600	30	30	31	0.9774	0.9683
31	150	70	31	31	32	0.3105	0.3619
32	210	100	32	32	33	0.3410	0.5302
33	60	40	—	—	—	—	—

Table A.2: Load data and line data of the IEEE 123-bus distribution network.

Load Data			Line Data				
Bus No.	Active Power (kW)	Reactive Power (kVAr)	Branch No.	From Bus	To Bus	R (Ω)	X (Ω)
1	40	20	1	1	2	0.0025	0.0026
2	20	10	2	1	3	0.0036	0.0037
3	0	0	3	1	7	0.0015	0.0035
4	40	20	4	3	4	0.0029	0.0029
5	20	10	5	3	5	0.0047	0.0048
6	40	20	6	5	6	0.0036	0.0037
7	20	10	7	7	8	0.0010	0.0024
8	0	0	8	8	12	0.0033	0.0033
9	40	20	9	8	9	0.0033	0.0033
10	20	10	10	8	13	0.0015	0.0035
11	40	20	11	9	14	0.0062	0.0063
12	20	10	12	13	34	0.0022	0.0022
13	0	0	13	13	18	0.0042	0.0095
14	0	0	14	14	11	0.0036	0.0037
15	0	0	15	14	10	0.0036	0.0037
16	40	20	16	15	16	0.0055	0.0055
17	20	10	17	15	17	0.0051	0.0052
18	0	0	18	18	19	0.0036	0.0037
19	40	20	19	18	21	0.0015	0.0034
20	40	20	20	19	20	0.0047	0.0048
21	0	0	21	21	22	0.0076	0.0077
22	40	20	22	21	23	0.0013	0.0029
23	0	0	23	23	24	0.0080	0.0081
24	40	20	24	23	25	0.0014	0.0032
25	0	0	25	25	26	0.0018	0.0041
26	0	0	26	25	28	0.0010	0.0023
27	0	0	27	26	27	0.0014	0.0032
28	40	20	28	26	31	0.0033	0.0033
29	40	20	29	27	33	0.0073	0.0074
30	40	20	30	28	29	0.0015	0.0034
31	20	10	31	29	30	0.0018	0.0040
32	20	10	32	31	32	0.0044	0.0044
33	40	20	33	34	15	0.0015	0.0015
34	40	20	34	35	36	0.0033	0.0077
35	40	20	35	35	40	0.0013	0.0029
36	0	0	36	36	37	0.0044	0.0044
37	40	20	37	36	38	0.0036	0.0037
38	20	10	38	38	39	0.0047	0.0048
39	20	10	39	40	41	0.0047	0.0048

Load Data			Line Data				
Bus No.	Active Power (kW)	Reactive Power (kVAr)	Branch No.	From Bus	To Bus	R (Ω)	X (Ω)
40	0	0	40	40	42	0.0013	0.0029
41	20	10	41	42	43	0.0073	0.0074
42	20	10	42	42	44	0.0010	0.0024
43	40	20	43	44	45	0.0029	0.0029
44	0	0	44	44	47	0.0013	0.0029
45	20	10	45	45	46	0.0044	0.0044
46	20	10	46	47	48	0.0008	0.0017
47	105	75	47	47	49	0.0013	0.0029
48	210	150	48	49	50	0.0013	0.0029
49	140	95	49	50	51	0.0013	0.0029
50	40	20	50	52	53	0.0010	0.0024
51	20	10	51	53	54	0.0006	0.0015
52	40	20	52	54	55	0.0014	0.0032
53	40	20	53	54	57	0.0018	0.0041
54	0	0	54	55	56	0.0014	0.0032
55	20	10	55	57	58	0.0036	0.0037
56	20	10	56	57	60	0.0038	0.0087
57	0	0	57	58	59	0.0036	0.0037
58	20	10	58	60	61	0.0042	0.0021
59	20	10	59	60	62	0.0042	0.0021
60	20	10	60	62	63	0.0029	0.0014
61	20	10	61	63	64	0.0058	0.0029
62	40	20	62	64	65	0.0071	0.0035
63	40	20	63	65	66	0.0054	0.0027
64	75	35	64	67	68	0.0029	0.0029
65	140	100	65	67	72	0.0014	0.0032
66	75	35	66	67	97	0.0013	0.0029
67	0	0	67	68	69	0.0040	0.0041
68	20	10	68	69	70	0.0047	0.0048
69	40	20	69	70	71	0.0040	0.0041
70	20	10	70	72	73	0.0040	0.0041
71	40	20	71	72	76	0.0010	0.0023
72	0	0	72	73	74	0.0051	0.0052
73	40	20	73	74	75	0.0058	0.0059
74	40	20	74	76	77	0.0020	0.0047
75	40	20	75	76	86	0.0035	0.0082
76	245	180	76	77	78	0.0005	0.0012
77	40	20	77	78	79	0.0011	0.0027
78	0	0	78	78	80	0.0024	0.0056

Load Data			Line Data				
Bus No.	Active Power (kW)	Reactive Power (kVAr)	Branch No.	From Bus	To Bus	R (Ω)	X (Ω)
79	40	20	79	80	81	0.0024	0.0056
80	40	20	80	81	82	0.0013	0.0029
81	0	0	81	81	84	0.0098	0.0100
82	40	20	82	82	83	0.0013	0.0029
83	20	10	83	84	85	0.0069	0.0070
84	20	10	84	86	87	0.0023	0.0053
85	40	20	85	87	88	0.0025	0.0026
86	20	10	86	87	89	0.0014	0.0032
87	40	20	87	89	90	0.0033	0.0033
88	40	20	88	89	91	0.0011	0.0027
89	0	0	89	91	92	0.0044	0.0044
90	40	20	90	91	93	0.0011	0.0027
91	0	0	91	93	94	0.0040	0.0041
92	40	20	92	93	95	0.0015	0.0035
93	0	0	93	95	96	0.0029	0.0029
94	40	20	94	97	98	0.0014	0.0032
95	20	10	95	98	99	0.0028	0.0064
96	20	10	96	99	100	0.0015	0.0035
97	0	0	97	101	102	0.0033	0.0033
98	40	20	98	101	105	0.0014	0.0032
99	40	20	99	102	103	0.0047	0.0048
100	40	20	100	103	104	0.0102	0.0103
101	0	0	101	105	106	0.0033	0.0033
102	20	10	102	105	108	0.0016	0.0038
103	40	20	103	106	107	0.0084	0.0085
104	40	20	104	108	109	0.0065	0.0066
105	0	0	105	109	110	0.0044	0.0044
106	40	20	106	110	111	0.0084	0.0085
107	40	20	107	110	112	0.0018	0.0018
108	0	0	108	112	113	0.0076	0.0077
109	40	20	109	113	114	0.0047	0.0048
110	0	0	110	18	135	0.0000	0.0000
111	20	10	111	135	35	0.0019	0.0044
112	20	10	112	149	1	0.0020	0.0047
113	40	20	113	13	152	0.0000	0.0000
114	0	0	114	152	52	0.0020	0.0047
300	0	0	115	60	160	0.0000	0.0000
250	0	0	116	160	67	0.0018	0.0041
450	0	0	117	97	197	0.0000	0.0000

Load Data			Line Data				
Bus No.	Active Power (kW)	Reactive Power (kVAr)	Branch No.	From Bus	To Bus	R (Ω)	X (Ω)
151	0	0	118	197	101	0.0013	0.0029
135	0	0	119	108	300	0.0051	0.0117
160	0	0	120	100	450	0.0040	0.0093
152	0	0	121	30	250	0.0010	0.0023
149	0	0	122	51	151	0.0025	0.0058
197	0	0	—	—	—	—	—



List of Publications

Journal Publications

1. M. R. Dar and S. Ganguly, "Voltage Regulation and Loss Minimization of Active Distribution Networks With Uncertainties Using Chance-Constrained Model Predictive Control," *IEEE Transactions on Power Systems*, vol. 40, no. 3, pp. 2737-2749, May 2025.
2. M. R. Dar and S. Ganguly, "A Distributionally Robust Chance Constrained MPC-based Coordinated Voltage Control of Active Distribution Networks with Uncertainties under High Photovoltaic Penetration," in *IEEE Transactions on Industry Applications*, (Early access available), doi: 10.1109/TIA.2025.3621566.
3. M. R. Dar and S. Ganguly, "Dual-Stage Model Predictive Control Based Reduced Model Framework for Voltage Control in Active Distribution Networks," *Journal of Modern Power Systems and Clean Energy (IEEE Explore)*, vol. 12, no. 6, pp. 1880-1892, November 2024.
4. M. R. Dar and S. Ganguly, "Voltage regulation and energy loss minimization for distribution networks with high photovoltaic penetration and EV charging stations using dual-stage model predictive control," *Sustainable Energy, Grids and Networks (Elsevier)*, vol. 40, Art. no. 101529, December 2024.
5. M. R. Dar and S. Ganguly, "A Centralized-Distributed Hybrid Control Scheme for Voltage Control in Active Distribution Networks with High Renewable Penetration," *IEEE Systems Journal* (Provisionally accepted, subject to minor revision).

Book Chapters

1. M. R. Dar and S. Ganguly, "Voltage control of EV enabled future power distribution networks," in *E-Mobility in Electrical Energy Systems for Sustainability*, IGI Global, ISBN: 9798369326114, 9798369346020, pp. 156-198, 2024.

Conferences

1. M. R. Dar and S. Ganguly, "A review of voltage control strategies in active distribution networks," *2022 IEEE Calcutta Conference (CALCON)*, Kolkata, India, pp. 145-149, 2022.
2. M. R. Dar and S. Ganguly, "A Hybrid Control Scheme for Voltage Regulation and Energy Loss Minimization in Active Distribution Networks Based on Model Predictive Control," *2024 IEEE PES Innovative Smart Grid Technologies - Asia (ISGT Asia)*, Bengaluru, India, pp. 1-6, 2024.
3. M. R. Dar and S. Ganguly, "Voltage Control of Active Distribution Networks with Photovoltaic Systems and Residential Electric Vehicle Charger Penetration Using Model Predictive Control," *2024 23rd National Power Systems Conference (NPSC)*, Indore, India, pp. 1-6, 2024.
4. M. R. Dar and S. Ganguly, "A Hybrid Scheme for Voltage Control and Energy Loss Minimization in Active Distribution Networks with Uncertainties Using Chance-Constrained MPC," *2025 IEEE Kiel PowerTech*, Kiel, Germany, 2025, pp. 1-6.

Journal Papers Under Review

1. M. R. Dar and S. Ganguly, "A Chance-constrained MPC-based Hybrid Voltage Control Scheme in Active Distribution Networks with Uncertainties," in *IEEE Transactions on Industrial Informatics*, (**under Review**).

Author's Biography

Mudaser Rahman Dar received the Bachelor of Technology degree in electrical engineering from the Islamic University of Science and Technology, Kashmir, India, in 2017, and the Master of Technology degree in electrical power and energy systems from the National Institute of Technology, Srinagar, India, in 2020. He is currently working toward the Ph.D. degree with the Department of Electronics and Electrical Engineering, Indian Institute of Technology Guwahati, Guwahati, India. His research interests include distribution system optimization, voltage control and stability in active distribution networks, and EV integration in power distribution networks.