Multi-stage coordinated robust var planning of wind penetrated power system based on voltage resilience indices

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**MULTI-STAGE COORDINATED ROBUST VAR
PLANNING OF WIND PENETRATED POWER SYSTEM
BASED ON VOLTAGE RESILIENCE INDICES**

CHI YUAN

School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2021

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Xu Yan

Authorship Attribution Statement

This thesis contains material from 4 papers published in the following peer-reviewed journals in which I am listed as an author.

Chapter 2 is published as Y. Chi and Y. Xu, Multi-stage coordinated dynamic VAR source placement for voltage stability enhancement of wind-energy power system, *IET Generation, Transmission & Distribution*, 14 (6), 1104-1113 (2020). DOI: 10.1049/iet-gtd.2019.0126

The contributions of the co-authors are as follows:

- Prof. Xu provided the initial direction and discussed the idea with me.
- I prepared the manuscript draft. Then it was revised by Prof Xu.
- I collected all the data and conducted all the simulations. Then Prof Xu and I discussed the results.
- When the paper was in revision, Prof. Xu provided suggestions and helped me to revise the response letter.

Chapter 3 is published as Y. Chi, Y. Xu, and T. Ding, Coordinated VAR Planning for Voltage Stability Enhancement of a Wind-Energy Power System considering Multiple Resilience Indices, in press, *IEEE Transactions on Sustainable Energy*, 11 (4), 2367-2379 (2020). DOI: 10.1109/TSTE.2019.2956733.

The contributions of the co-authors are as follows:

- Prof Xu suggested the general idea of the research topic.
- I wrote the drafts of the manuscript. Then it was revised together with Prof. Xu and Prof. Ding.
- I performed all the simulations and collected the data.
- Prof. Xu and Prof. Ding provided valuable comments on how to revise the manuscript in the first-round and the second-round revision.

Chapter 4 is published as Y. Chi and Y. Xu, Zoning-based candidate bus selection for dynamic VAR planning in power system towards voltage resilience, *IET Generation, Transmission & Distribution*, 14 (6), 1012-1020 (2019). DOI: 10.1049/iet-gtd.2019.1049.

The contributions of the co-authors are as follows:

- Prof. Xu discussed the initial idea with me and provided some suggestions.
- I prepared the manuscript draft. Then it was revised by Prof Xu.
- I collected all the data and conducted all the simulations. Then Prof Xu and I discussed the results.
- Prof. Xu provided me many suggestions on how to revise the manuscript in the first-round and the second-round revisions.

Chapter 5 is published as Y. Chi, Y. Xu and R. Zhang, Many-objective Robust Optimization for Dynamic VAR Planning to Enhance Voltage Stability of a Wind-Energy Power System, *IEEE Transactions on Power Delivery*, 36 (1), 30-42 (2021), DOI: 10.1109/TPWRD.2020.2982471.

The contributions of the co-authors are as follows:

- Prof Xu provided the general idea of the research topic.
- I wrote the drafts of the manuscript. Then it was revised together with Prof. Xu and Dr. Zhang.
- I performed all the simulations and collected the data.
- Prof. Xu and Dr. Zhang provided valuable comments on how to revise the manuscript in the first-round and the second-round revisions.

01-08-20

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Summary

Escalating environmental pressure leads to increasing grid integration of renewable energy resources, such as wind power, which in turn makes a significant impact on the energy profile of nations worldwide. However, the inertia of power systems is decreased remarkably due to the high penetration level of wind energy and the large-scale electric power system becomes vulnerable to voltage disturbance triggered by equipment failure or extreme weather conditions for following reasons: 1) large wind farms are usually installed far from load center and long-distance transmission would become a potential threat for voltage stability. 2) conventional static VAR source is not sufficient because of its relatively slow response against large voltage disturbance or frequent small disturbance. 3) increasing wind power penetration level leads to lower effective inertia of the system, exacerbating the situation of reactive power deficiency. 4) power system dynamics become complicated with growing number of power electronic interfaced devices. Besides, the growing industrial loads further deteriorate the post-contingency voltage performance of the system. Considering the stochasticity of these extreme accidents and the prosperous wind power generation, the insufficiency of fast response reactive power and their corresponding implications are expected to manifest themselves on a larger scale in the future.

Thus, dynamic VAR source, like Static Synchronous Compensator (STATCOM), is one of the effective methods to alleviate the short-term voltage stability issue mainly affected by load dynamics, such as induction motors, because of its fast response time (within milliseconds). Given the fact that the performance of STATCOMs, in terms of the voltage stability improvement, are largely determined by the installation sites and size, a multi-stage coordinated VAR planning model is proposed in this thesis, to address the voltage stability issues of a wind-penetrated power system (due to operational uncertainties, reactive power deficiency, and additional grid codes) and to improve the efficiency of VAR planning.

First, a multi-stage coordinated dynamic VAR source placement framework for both steady-state and short-term voltage stability improvement of the power system with a high-level wind power penetration is proposed. Both preventive controls (including wind curtailment and system re-dispatch) and corrective

control (load shedding) are coordinated with the installation of reactive power sources to enhance the voltage stability. Then, a set of novel voltage resilience metrics designed to evaluate not only the steady-state and short-term voltage stability but also the defensive and restorative performance of the system is proposed to comprehensively evaluate the voltage resilience performance before and after a contingency. Specifically, the trajectory-based voltage stability and resilience indices consider the extent of voltage deviation, the voltage deviation duration, time of post-contingency stabilization, and the post-contingency steady-state profile.

Next, considering the heavy computational burden, candidate buses for installations are selected before the capacity optimization of VAR sources to reduce the complexity of the problem. A comprehensive multi-objective zoning-based candidate bus selection approach is proposed based on the Fuzzy C-means clustering and Morris Screening methods, categorizing buses into different zones with capacity sensitivity analysis to avoid selecting redundant buses and improve the consistency when the selected candidate buses are subjected to different capacities.

To further improve the robustness of the proposed method when subjected to operational uncertainties, a novel robustness index is proposed to quantitatively evaluate the robustness of a Pareto optimal solution without a requirement for the presumed probability distributions of uncertainties, providing a trade-off between the robustness of VAR plan solution and the voltage stability performance of the solution. In the thesis, the wind power output and initial state of STATCOMs before a contingency are considered as uncertainties, but this robustness assessment method can be easily extended to incorporate other operational uncertainties such as load demand. Finally, the STATCOM planning model is formulated as a many-objective optimization problem. An Adaptive Non-dominated Sorting Genetic Algorithm-III based on Latin Hypercube Sampling (A-NSGA-III-LHS), which shows better performance, in terms of finding optimal solutions, and requires less computation time compared with the original NSGA-III, is proposed to solve this optimization problem. The proposed optimization formations are tested on the New England 39-bus system and Nordic 74-bus system with a composite load model, showing high robust optimality and computational efficiency over conventional methods.

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List of Acronyms

AAT	All-At-a-Time
AEMO	Australian Energy Market Operator
ASR	Acceptable Sensitivity Region
CBS	Candidate Bus Selection
CI	Crowdedness Index
CLOD	Complex Load Model
CP	Constant Power
DC	Defensive Control
DE	Differential Evolution
DFIG	Doubly-Fed Induction Generator
DL	Discharging Lighting Load
DR	Demand Response
EDLS	Event-driven Load Shedding
FACTS	Flexible AC Transmission System
FCM	Fuzzy C-Mean
FSR	Feasibility Sensitivity Region
FWCSR	Feasibility Worst Case Sensitivity Region
GSC	Grid-side Converter
HVRT	High Voltage Ride-Through
IBDR	Incentive Based Demand Response
ISGA	Integral Squared Generator Angle
LDC	Line-Drop Compensation
LHS	Latin Hypercube Sampling
LM	Large Motor
LVRT	Low Voltage Ride-Through
MOEA/D	Multi-Objective Evolutionary Algorithm based on Decomposition
NERC	North American Electric Reliability Corporation
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NSGA-III	Non-dominated Sorting Genetic Algorithm III
OLTC	On-load Tap Changer
OPF	Optimal Power Flow
PBDR	Price Based Demand Response
PDF	Probability Density Function
PF	Pareto Front
PS	Pareto Set
RC	Restorative Control
RDLS	Response-Driven Load Shedding
RI	Robustness Index

RMS	Root-Mean-Square
RSC	Rotor-side Converter
RVSI	Root-mean-squared Voltage-dip Severity Index
SBX	Simulated Binary Crossovers
SM	Small Motor
STATCOM	Static Synchronous Compensator
SVC	Static VAR Compensator
TEP	Transmission Expansion Planning
TOAT	Taguchi's Orthogonal Array Testing
TS	Transformer Saturation
TVDI	Transient Voltage Deviation Index
TVSI	Transient Voltage Severity Index
UVLS	Under-Voltage Load Shedding
VCPI	Voltage Collapse Proximity Indicator
VSC	Voltage Source Converter
WCSR	Worst Case Sensitivity Region
WT	Wind Turbine
WTVI	Transient Voltage Deviation Index for Wind Turbines

Nomenclature

The main notations used in this thesis are presented below separately for each chapter. It should be noted that some of the notations are used in different chapters, however, for the sake of consistency they are repeated in each chapter when they are being used. Besides, to present the same meaning, different chapters may use different symbols.

Chapter 2

Indices

d	Index for loads
D	Index for dynamic states
f	Index for objective functions
g, g'	Indices for generators
h	Index for control variables
i, j	Indices for buses
k	Index for contingencies
l	Index for lines
p	Index for solutions
S	Index for static states
s	Index for bus with STATCOMs
t	Index for the time
w	Index for wind turbines
o	Index for an original state

Sets

$\mathcal{B}$	Set of all buses
$\mathcal{B}_l$	Set of load buses
$\mathcal{B}_c$	Set of buses with STATCOMs
$\mathcal{G}$	Set of all the generators
$\mathcal{G}_s$	Set of synchronous generators
$\mathcal{G}_w$	Set of wind turbines
$\mathcal{H}$	Set of control variables
$\mathcal{L}$	Set of all the lines
$\mathcal{K}$	Set of contingencies
$\mathcal{T}$	Set of time

Variables

B_{ij}	Susceptance between i and j
----------	---------------------------------

cap_i	Capacity of STATCOM at bus i
$cap_w^{curtail}$	Curtailment of wind turbine w
f_f^{max}	Max/min of the f^{th} objective function
G_{ij}	Conductance between i and j
L_l	Apparent power flow on line l
P_d	Active power of load
P_d^{shed}	Active power of load shedding at bus d
P_l^r	Active power transferred to the receiving end through line l
P_g	Active output of generator g
$\widetilde{P}_w$	Uncertain active power output of wind turbine w
P_w^c	Curtailed active power of wind turbine w
Q_d	Reactive power of load at bus d
Q_d^{shed}	Reactive power of load shedding
Q_l^r	Reactive power transferred to the receiving end through line l
Q_g	Reactive output of generator g
$\widetilde{Q}_w$	Uncertain reactive power output of wind turbine w
Q_w^c	Curtailed reactive power of wind turbine w
Q_s^{stat}	Output of STATCOM
T_i^r	Time when voltage of bus i reaches a recovery voltage threshold
V_i, V_w	Voltage magnitude of bus i (or bus w)
$V_{i,t}, V_{i,0}$	Voltage magnitude of bus i at time t and 0
$V_i^{post}(t)$	Post-contingency voltage at bus i
V^s	Voltage magnitude at sending end
x^{ori}, u^{ori}	Original operating states
x^{opt}, u^{opt}	Optimal operating states
x_p	Pareto optimal solution
$x_{i,k}$	Amount of load shedding after contingency k at bus i
Z^s	line impedance
μ^p	Satisfactory degree
φ	Phase angle of load
θ	Phase angle of line impedance
$\Delta\delta_{gg'}^T$	Rotor angle deviation between generator g and generator g'

Parameters

a_g, b_g, c_g	Generation cost coefficients
$c^{curtail}$	Unit cost of wind power curtailment
c^{cap}	Unit capacity cost of STATCOM
c^{ls}	Unit cost of load shedding
$c_i^{install}$	Install cost of STATCOM at bus i
CP	Percentage of constant power loads in CLOD model

d_i	Priority assigned to the load at bus i
DL	Percentage of discharge lighting loads in CLOD model
K_p	Parameter for voltage-dependent real power load in CLOD model
$L_l^{max/min}$	Max and min power flow on line l
$LVRT/HVRT(t)$	Constraints for LVRT/HVRT
LM	Percentage of large motor loads in CLOD model
N^b	Number of buses
p_k	Probability of contingency k
$P_i^{ls,max}$	Maximum load shedding allowed at bus i
$P_g^{max/min}$	Max and min active power of generator g
$Q_g^{max/min}$	Max and min reactive power of generator g
$s, z, x_i^{threshold}$	Coefficients for Sigmoid cost function
SM	Percentage of small motor loads in CLOD model
t^a	Annual maximum load equivalent hours
t^c	Curtailment hours
T^c	Fault clearing time
T^{end}	End time of set $\mathcal{T}$
T^f	Fault time
T^{max}	Max time allowed under recovery voltage
TS	Percentage of transformer saturation loads in CLOD model
$u^{1st}, u^{2nd}, u^{3rd}$	1 st , 2 nd , 3 rd , load shedding stage
$V_i^{max/min}$	Max and min voltage at bus i
W^c	Curtailment ratio
ω	Rotor deviation in extreme conditions
δ	Maximum acceptable voltage deviation
Δcap	Small perturbation in capacity

Functions

C_i	Cost function of load shedding at bus i
$C_w^{curtail}$	Total curtailment cost of wind turbine w
C^{CC}	Total cost for corrective control
C^{gen}	Generation cost of all generators
C^{linear}	Linear load shedding cost model
C_i^{ls}	Load shedding cost at bus i
C^{invest}	Total investment cost
C_i^{invest}	Investment cost at bus i
C^{PC}	Total cost for preventive control
$C^{quartic}$	Quartic load shedding cost model
C^{re-dis}	Re-dispatch cost of the system
$C^{sigmoid}$	Sigmoid load shedding cost model

f_1, f_2, f_3	Objective functions
G	Equality constraints
H	Inequality constraints
$S_i(\cdot)$	Sensitivity function for candidate bus selection

Chapter 3

Indices

d	Index for loads
f	Index for objective functions
g, g'	Indices for generators
i, j, n	Indices for buses
k	Index for contingencies
l	Index for lines
m	Index for post-contingency hours (or LHS levels)
o	Index for an original state
t	Index for the time
w	Index for wind turbines

Sets

B	Set of all the buses
B_c	Set of capacitor bank buses
B_d	Set of load buses
B_s	Set of STATCOM buses
B_{DR}	Set of buses for demand response
B_{RDLS}	Set of buses for response-driven load shedding
B_{EDLS}	Set of buses for event-driven load shedding
G	Set of all generators
G_s	Set of synchronous generators
G_w	Set of wind turbines
K	Set of contingencies
L	Set of lines
M	Set of shift hours after the demand response
P	Set of Pareto optimal solutions
T	Set of time

Variables

B_{ij}	Susceptance between i and j
$c_{n,t}^{DR}$	Demand response price at bus n at time t
$cap_{i \text{ or } j}$	Reactive power source capacities at bus i or j
DR^{res}	Total amount of demand response

DR_m^{shift}	Violation index at m^{th} hour after DR
$EE_{i,m}$	Elementary effect of Δ_m change
G_{ij}	Conductance between i and j
I^r	Rotor current of DFIG
L_l	Apparent power flow on line l
P_d	Active power of load
$\widetilde{P}_w$	Active output of wind turbine w
P_w^{curt}	Active power curtailment of wind turbine w
P_i^{DR}, P_n^{DR}	Demand response of load at bus i (or at bus n)
P^{inv}	Inverter active power of DFIG
P^{peak}	Original load peak within the shifted hours
P_m^{pred}	Load peak at m^{th} hour after DR
P_l^r	Active power transferred to the receiving end through the line l
P^s	Stator active power of DFIG
Q_d	Reactive power of load
$\widetilde{Q}_w$	Reactive output of wind turbine w
$Q^{capacitor}$	Reactive power output of a capacitor
Q_w^{curt}	Reactive power curtailment of wind turbine w
Q^{inv}	Inverter reactive power of DFIG
Q_l^r	Reactive power transferred to receiving end through line l
Q^s	Stator reactive power of DFIG
Q^{stat}	Actual reactive power output of STATCOMs
$Q^{statrated}$	Rated reactive power output of STATCOMs
Q^w	Actual reactive power output of DFIG
s	Slip ratio
T_i^r	Time when V_i reaches a recovery threshold
U^s	Stator voltage of DFIG
V_i	Voltage magnitude of bus i
V^s	Voltage magnitude for VCPI calculation
x^{opt}, u^{opt}	Optimal steady-state operating state
x^{ori}, u^{ori}	Original steady-state operating state
$x_{i,k}, x_{j,k}$	Amount of EDLS and RDLS after contingency k at bus i and j
x_p	Pareto optimal solution
$\Delta\delta_{gg'}^T$	Rotor angle deviation between g and g'
Δ_m	Offset in Morris Screening Method
μ^p	Satisfactory degree for objective functions
μ_i^*	Mean of bus i for LHS
σ_i^*	Standard deviation of bus i for LHS
φ	Phase angles of load

θ Phase angles of line impedance

Parameters

a_g, b_g, c_g	Generation cost coefficients
c^{curt}	Unit wind power curtailment cost
c^{cap_c}	Unit capacity cost of capacitor bank
c^{cap_s}	Unit capacity cost of STATCOM
$c_i^{install}$	Installation cost of STATCOM at bus i
c^{ls}	Unit load shedding cost
$cap_{n,k}^{DR}$	Load participated in Demand Response program at bus n for contingency k
d_i	Priority assigned to loads at bus i
$HVRT(t)$	Time-varying constraints for HVRT
$LVRT(t)$	Time-varying constraints for LVRT
N^b	Number of total buses
N^c	Number of all potential candidate buses
N^m	Sample levels of Morris Screening
N^w	Number of wind turbines
p_k	Probability of contingency k
$p_n^{DR,max}$	Maximum DR allowed at bus n
$p_i^{LS,max}$	Maximum load shedding allowed at bus i
$q, z, x_i^{threshold}$	Coefficients for Sigmoid cost function
t^a	Annual maximum load equivalent hours
t^c	Wind power curtailment hours
t_n^{DR}	Demand response duration at bus n
T^c	Fault clearing time
T^{end}	End time of set $\mathcal{T}$
T^{max}	Max time allowed under recovery voltage
$u^{1st}, u^{2nd}, u^{3rd}$	First, second and third load shedding stage
v^r	Recovery voltage
W^c	Wind power curtailment ratio
X^m	Excitation reactance of DFIG
X^s	Stator reactance of DFIG
Δcap	Small perturbation in capacity
ϵ	Demand response rate
δ	Maximum acceptable voltage deviation
ω	Rotor deviation in extreme conditions
$\alpha_{1,2,3,4,5}$	Weighting factors for defensive capability indices
$\beta_{1,2,3,4}$	Weighting factors for restorative performance indices

Functions

C_i, C_j	Load shedding cost functions
C^{curt}	Total cost of wind power curtailment
C^{DC}	Total cost of defensive controls
C^{DR}	Total cost of DR
C^{EDLS}	Total cost of EDLS
C^{RDLS}	Total cost of RDLS
C^{gen}	Generation cost of all generators
C^{invest}	Total investment cost
C^{invest_c}	Cost of capacitor bank
C^{invest_s}	Cost of STATCOM
C^{re-dis}	Total cost of re-dispatch

Chapter 4

Indices

g	Index for generators
i	Index of buses
j	Index for voltage resilience indices
l	Index for lines
m	Index for LHS capacity
o	Index for an original state
t	Index for time

Sets

$\mathcal{B}$	Set of all buses
$\mathcal{B}_l$	Set of all load buses
$\mathcal{G}_s$	Set of synchronous generators
$\mathcal{L}$	Set of lines
$\mathcal{K}$	Set of contingencies
LHS	Set of LHS results
$\mathcal{Y}$	Set of clustering centers

Variables

D_{ri}	Square distance between the i^{th} example and the r^{th} clustering center
$EE_{i,m}$	Elementary effect of Δ_m change
M_i	Inertia of machine i
M^{TOT}	Total inertia of all machines
P_l^r	Active power transferred to the receiving end through the line l
Q_l^r	Reactive power transferred to the receiving end through the line l

t_i^s	Time when voltage of bus i enters an acceptable fluctuation boundary
$TVSI^r$	Time-constrained TVSI
$TVSI^s$	Steady-state TVSI
$\mathbf{U}$	Membership matrices
v_i	Voltage at bus i
v_i^d	Voltage deviation at bus i
v_i^o	Pre-contingency voltage at bus i
v_i^s	Post-contingency steady-state voltage at bus i
$x_{i,j,c}^o$	Evaluation result of bus i when index j is used with capacity c
y_r	r^{th} clustering center
μ^*	Mean of elementary effect
σ^*	Standard deviation of elementary effect
φ	Phase angle of load
θ	Phase angle of line impedance
δ_i	Rotor angle of machine i
δ^{COA}	Center of rotor angles
Δ_m	Offset in Morris Screening method

Parameters

F	Fuzziness of the clustering process
N^b	Number of buses
N^c	Number of all buses
N^{center}	Number of clustering centers
N^e	Number of examples
N^m	Number of capacity levels
p_k	Probability of contingency k
t^c	Fault clearing time
t^{dl}	Maximum voltage deviation time (lower)
t^{du}	Maximum voltage deviation time (upper)
t^{end}	End of time-domain simulation
t^f	Fault time
t^{l1}	End of voltage deviation time within t^{dl} (lower)
t^{l2}	End of voltage deviation time beyond t^{dl} (lower)
t^o	Start of time-domain simulation
$t_i^{s,th}$	Time threshold for t_i^s
t^{u1}	End of voltage deviation time within t^{du} (upper)
t^{u2}	End of voltage deviation time beyond t^{du} (upper)
v^{dl}	Lower voltage threshold
v^{du}	Upper voltage threshold
α^l	Penalty parameter for voltage violation (lower)

α^u	Penalty parameter for voltage violation (upper)
ϵ	Termination tolerance

Chapter 5

Indices

d	Index for individuals in a generation
g, g'	Index for generators
i, j	Indices of buses/objectives/constraints
k	Index for contingency
l	Index for lines
n	Index for uncertainties/generations in NSGA-III
o	Index for an original state
p	Index for Pareto solutions
t	Index for time

Sets

$\mathcal{B}$	Set of all buses
$\mathcal{B}_s$	Set of STATCOM buses
$\mathcal{B}_w$	Set of wind turbine buses
$\mathcal{G}$	Set of all generators
$\mathcal{G}_s$	Set of synchronous generators
$\mathcal{L}$	Set of lines
$\mathcal{K}$	Set of contingencies
$\mathcal{P}$	Set of Pareto optimal solution
$\mathcal{T}$	Set of time

Variables

B_{ij}	Susceptance between bus i and j
cap_i	Reactive power source capacities at bus i
CI_n	Crowdedness of the n^{th} generation (normalized)
CI_n^*	Crowdedness of the n^{th} generation (un-normalized)
G_{ij}	Conductance between bus i and j
L_l	Apparent power flow on line l
p_k	Probability of contingency k
p_m	Adaptive mutation rate
P_g	Active power output of generator g
P_l^r	Active power transferred to the receiving end through the line l
P_n	Parent population
$\widetilde{P}_w$	Active output of wind turbine w

Q_g	Reactive power output of generator g
Q_l^r	Reactive power transferred to the receiving end through the line l
Q^{stat}	Reactive power output of STATCOM
$\widetilde{Q}_w$	Reactive power output of wind turbine w
R^f	Radius of FWCSR
R^w	Radius of WCSR
s_1	Sensitive direction
s_2	Insensitive direction
S_n	Offspring population
$TVSI^r$	Time-constrained TVSI
$u_{d,n}$	Value of the fitness function of individual d in the n^{th} generation
u_n^{avg}	Average value of fitness functions in n^{th} generation
v^{dl}	Lower deviation threshold
v^{du}	Upper deviation threshold
$V_{i,t}$	Voltage magnitude of bus i at time t
$VCPI^p$	Prioritized VCPI of the whole system
$VCPI_l$	VCPI of line l
V^s	Annual maximum load equivalent hours
Z^s	Wind power curtailment hours
Δf_i	Variations of objective function i
$\Delta f_{0,i}$	Acceptable deviation of objective function i
$\Delta \widetilde{w}$	Variations of uncertainty
$\Delta \delta_{gg'}^T$	Rotor angle deviation between 2 generators
β_p	The p^{th} Pareto solution from a Pareto Front
φ	Phase angle of load
ψ	Phase angle of line impedance
θ_{ij}	Voltage angle difference between bus i and j
μ_i^p	Satisfactory degree for i^{th} objective function

Parameters

$c^{install}$	Installation cost of STATCOM
c^{cap}	Unit cost of STATCOM
CP	Percentage of constant power loads in CLOD model
DL	Percentage of discharging lighting loads in CLOD model
$HVRT(t)$	Time-varying voltage trajectory constraints for HVRT
K_p	Parameter for voltage-dependent real power load in CLOD model
LM	Percentage of large motor loads in CLOD model
$LVRT(t)$	Time-varying voltage trajectory constraints for LVRT
N	Number of an initial population

N^b	Number of total buses
N^f	Number of objective functions
N^g	Number of equality constraints
N^h	Number of inequality constraints
N^{ind}	Number of individual (in a generation)
N^l	Number of total power lines
N^u	Number of uncertainties
p	Parameter for L_p -norm
p_0	Mutation rate of the first generation
q_l	Priority of line l
R^{ref}	Reference robust radius
SM	Percentage of small motor loads in CLOD model
t^c	Fault clearing time
t^{dl}	Maximum voltage deviation time (lower)
t^{du}	Maximum voltage deviation time (upper)
t^{end}	End of time-domain simulation
t^f	Fault time
t^{l1}	End of voltage deviation time within t^{dl} (lower)
t^{l2}	End of voltage deviation time beyond t^{dl} (lower)
t^o	Start of time-domain simulation
t^{u1}	End of voltage deviation time within t^{du} (upper)
t^{u2}	End of voltage deviation time beyond t^{du} (upper)
TS	Percentage of transformer saturation loads in CLOD model
v^{dl}	Lower voltage threshold
v^{du}	Upper voltage threshold
α^l	Penalty parameter for voltage violation (lower)
α^u	Penalty parameter for voltage violation (upper)
τ_i^f	Tolerance for an acceptable deviation $\Delta f_{0,i}$
τ_i^g	Tolerance for constraint g_i
ω	Rotor deviation in an extreme condition

Functions

C^{invest}	Total investment cost
$f(\cdot)$	Sub-objective functions
F	Overall objective function
g_i	Equality constraint i
$\mathbf{G}$	Equality constraints
h_i	Inequality constraint i
$\mathbf{H}$	Inequality constraints

1.) Introduction

1.1 Background

1.1.1 Voltage stability

Power system stability plays an important role in a reliable and secure power system operation since the 1920s [1]. Initially, transient stability related problems have been the dominant stability problems and most of the studies focus on this area. As the growth of the interconnected power system and the evolution of new technologies, many other stability issues emerged, such as frequency stability, voltage stability, and inter-area oscillations. IEEE and CIGRE joint task force [2] provides a classification of power system stability as shown in Fig. 1.1.

Figure 1.1 Classification of power system stability

Based on the physical nature of the instability and the size of the disturbance, as well as the devices, the processes, and the time span, power system stability is categorized into five sub-groups: rotor angle stability, frequency stability, voltage stability, resonance stability, and converter-driven stability. Voltage stability is defined as the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition [2]. Generally, the voltage stability depends on the ability of the power systems to maintain (or restore to) an equilibrium between load and generation. Voltage instability may lead to tripping of transmission lines, loss of load [3] and even cascading outages like the one in reference [4]. According to the type of disturbance, the voltage stability problem can be

grouped into small disturbance voltage stability and large disturbance voltage stability as illustrated in Fig. 1.1.

From the perspective of the time scale, voltage stability problems may vary from seconds to minutes. The voltage stability problems can also be categorized into a long-term phenomenon group or a short-term phenomenon as shown in Figure 1.1. Short-term voltage stability is mainly affected by the dynamics of fast acting load components like induction motors, electronically controlled loads, and inverter-based generators. The time scale of the study is in the order of a few seconds. Differential equations of the systems are required for the analysis and accurate dynamic modeling of loads is also necessary. A typical example for the short-term voltage instability is the stalling of induction motors following a large disturbance [2].

As for the long-term voltage stability, it is mainly affected by equipment with slow response (like thermal loads and tap-changing transformers). The time scale of the study can extend to many minutes. The dynamic performance of the systems is analyzed through long-term simulations [5]. Usually, the stability issues are caused by an equipment failure/outage due to the disturbance, instead of the severity of the initiating disturbance. Specifically, these equipment failure/outages may lead to the loss of long-term equilibrium (such as reaching the transmission limits of the transmission lines) or unstable post-disturbance steady-state operating point [3, 6]. Static analysis [7, 8] are usually utilized for the estimation of stability margins, identification of factors influencing stability, and screening of system conditions and scenarios.

While the progressive voltage drop is the prevalent form of voltage instability, the risk of overvoltage instability cannot be ignored [2], which is related to the inability of the power system to operate below a minimum load consumption level [2].

1.1.2 Wind-penetrated power system with industrial loads

The technical advance and global warming crisis give an unprecedented boost to the renewable industries in recent years. Fig 1.2 illustrates the strong growth of wind energy in recent years and near future [9]. By 2040, wind energy

is expected to contribute 14% of global energy consumption and become the most important renewable energy. This rapid growth of wind energy is accompanied by significant changes in the energy profile: highly controllable conventional power generation is replaced by variable and less controllable wind power. Within the scope of my research topic, the major impacts of the growing integration of wind power on the power system are summarized as follows:

Figure 1.2 Renewables share of power generation by source [9]

1) *Operational uncertainty*

Conventional power systems are designed to operate with controllable power generators. However, the intermittent and stochastic nature of wind power complicate the operational uncertainty of the power systems. On the other hand, the conventional synchronous generators are exposed to higher fluctuations together with the reduced ramping capabilities [10]. Therefore, for a wind-penetrated power system, the flexible and adequate power supply is a challenging work [11].

2) *Reactive power deficiency*

The power system is expected to operate in a way that the voltages throughout the whole system stay within predetermined ranges. Accordingly, the protection devices are set based on these ranges in different circumstances.

Conventionally, the reactive power output of controllable generators is an important voltage regulation method. Since the potential of the reactive power output of wind turbines is generally smaller than that of the conventional generators [12], the growing penetration level of wind power is forcing the remaining conventional generators to take more portion of reactive power generation. Therefore, reactive power deficiency may occur occasionally in a wind-penetrated power system [13]. Furthermore, there are also concerns about long-distance reactive power transmission [14] since the load center are usually far away from the installation sites of the wind farms. Apart from causing potential voltage stability problems [4], the reactive power deficiency may also contribute to the rotor angle stability [15].

3) Additional grid codes (LVRT/HVRT)

Compared with conventional generators, wind turbines are inherently more sensitive to disturbance. Take the Doubly-Fed Induction Generator-based Wind Turbine (DFIGWT), which is the dominant WT technology, as an example. Its rotor-side converter (RSC) controls the maximum power capture through rotor speed control and its GSC controls the active and reactive powers delivered (also maintains constant DC-link voltage) [16]. During a voltage disturbance (a fault), the voltage might drop significantly (even as low as zero) and the active power generation is reduced. RSC will try to compensate for the active power decrease by increase the rotor current. Hence, the increased rotor voltage leads to overvoltage in the DC link. Then, the internal magnetization of DFIG is quickly lost and this demagnetization produces large outrush currents (greater than the ratings of the converter) on both stator and rotor circuits. Finally, this may result in tripping of wind turbines. In order to safely incorporate wind farms in power systems and avoid unnecessary tripping as much as possible, an additional Voltage Ride-through Standard (covering both Low Voltage Ride Through (LVRT) and High Voltage Ride Through (HVRT)) is required address the entire voltage excursion boundary of generating plants [17]. They should be strictly satisfied before and after a voltage disturbance.

Figure 1.3 Primary energy consumption by end-use sector (Ton of Oil Equivalent) [9]

On the other hand, the industrial sector (including the non-combusted use of fuels) accounts for nearly 50% of global energy as shown in Fig. 1.3 (unit is Billion Tonne of Oil Equivalent) [9] and will maintain the major share of global energy in the coming years. Industrial loads, such as large motors, will absorb a higher amount of reactive power in the post-contingency stage [2], which makes the large-scale wind-penetrated power system more susceptible and also complicates the time-varying voltage response of the system during the voltage recovery process.

1.1.3 Reactive power compensation device

For conventional VAR compensation devices (like capacitor banks), they are not adequate to alleviate short-term voltage stability issues because of their static nature and inability to response fast to a sudden disturbance. Flexible Alternating Current Transmission System (FACTS) devices, such as STATCOM, DVR, and SVC, which can respond within milliseconds, are promising candidates for mitigating short-term voltage stability problem caused by the growing penetration level of wind power and increasing industrial load levels. Apart from the fast response feature, STATCOM, which is with a higher transient margin and good overloading capability for short period during a

severe voltage dip, becomes the standard equipment required by some grid operators to install in wind farms [12, 18].

Generally, STATCOM is a Voltage Source Converters (VSC)-based power electronics device, consisting of VSC, DC bus with a capacitor or energy storage device, controller, and coupling interface transformer. It aims to improve the voltage profile of the installed bus by generating rapid and continuously variable VAR output. During a voltage disturbance (e.g., a short-circuit fault), STATCOMs can generate VAR output rapidly to support the bus voltages. Compared with another prevalent reactive power compensation device SVC, of which reactive power output decreases squarely with the bus voltage drop, the VAR output of the STATCOM decreases linearly. This feature makes the STATCOMs a better candidate for supporting the system voltage [19, 20]. The beneficial impact of STATCOMs is illustrated in Figure 1.4.

Figure 1.4 STATCOM reactive power output before and after a disturbance

Considering the high installation investment of STATCOMs, the sizes and locations should be determined optimally to enable an effective and efficient use of STATCOMs [21, 22], based on the economic concerns and voltage performance requirements.

1.1.4 Power system resilience

In recent years, extreme weather conditions and natural disasters bring unprecedented challenges to the electrical power system. In 2011, An earthquake hit Japan, leaving 4.4 million homes suffering prolonged outages

[23]. In 2012, 8 million people in 15 states of the United States experienced short of power supply due to Hurricane Sandy [24, 25]. The entire state of South Australia has been put into an overnight blackout after several rounds of violent storms and ruthless lightning strikes [26]. In 2016, the largest blackout in U.S. history is caused by the Category 4 Hurricane Maria. Three-quarters of residents in Puerto Rico are still without electricity, even 36 days after the landfall of the Hurricane [27].

Given the inherent uncertainty of these extreme incidents and their severity, it is impractical to maintain continuous power supply in all circumstances because of the prohibitive investment for the enhancement of infrastructures. Recently, many efforts are devoted to addressing the resilience of the electrical power system [28-31]. Power system resilience refers to the ability of a power system to recover quickly following a disaster or, more generally, to the ability of anticipating extraordinary and ‘high-impact, low-probability’ events, rapidly recovering from these disruptive events, and absorbing lessons for adapting its operation and structure to be better prepared for similar events in the future [32-34].

Figure 1.5 Evolution of the power system resilience after a contingency

Fig 1.5 illustrate different stages of the power system before and after a contingency, which is based on the conceptual resilience trapezoid proposed in [31]. R_0 and R_P indicate the original resilience level and the post-disturbance resilience level, respectively. Generally, there are 2 resilience categories: 1) operational resilience stage, including pre-disturbance state, degradation and coordination process, and post-contingency state, and 2) infrastructure resilience stage for infrastructure recovery and evaluation for future

enhancements. Instead of conventional measures such as the infrastructure enhancement (e.g. installation of reactive power sources, different countermeasures can be utilized in different stages. For instance, generation re-dispatch with VAR compensators can be used as a cost-effective measure to prepare the power system for the coming disturbance and the load shedding after a contingency can effectively mitigate the potential cascading events in a post-contingency stage.

1.2 Motivation

Although deficiency of reactive power after a contingency is one of the critical driven forces for instability and proper allocation of VAR sources in the power system is effective to improve the voltage stability, dynamic VAR source alone is still insufficient for the wind-penetrated power system with a high portion of industrial loads to survive a large voltage disturbance. There are still many challenges for the dynamic VAR planning for stability and resilience enhancement:

- 1) Formulation of the VAR sources placement problem as a single stage (planning stage) model will lead to relatively conservative planning decisions because of the lack of coordination between planning network enhancement measures and operational mitigation measures. South Australia 2016 blackout [4] is a vivid example that dynamic VAR sources (network enhancement) are necessary but not sufficient.

- 2) There is no comprehensive trajectory-based index for short-term voltage stability evaluation. As for the indices developed to evaluate the resilience of a power system, most of them focus on infrastructure resilience, and there is no metric for the evaluation of the resilience performance of wind-penetrated power system [35, 36]. The post-contingency voltage performance, including recovery speed, violation time, and post-contingency steady-state, should be evaluated, as well as the effectiveness of the operational mitigation measures.

- 3) Considering the computational complexity, candidate buses for reactive power compensation devices are usually determined before the capacity optimization of the devices. However, selection criteria based on a direct ranking

of the evaluation values will inevitably lead to excessive installation sites: the critical buses, which are efficient buses for reactive power compensation, and its adjacent buses, which are inefficient buses for reactive power compensation, will be selected due to the proximity of voltage dip. These redundant candidate buses adversely impact the optimality of the final solution.

4) The VAR planning problem for the enhancement of voltage stability is usually considered as a deterministic optimization problem. Operational uncertainties, including the initial status of STATCOM before a contingency and the output of wind power, that have a significant influence on voltage performance of the power system are neglected [37, 38], or not considered in a systematic way [40]. Other alternative approaches are based on probabilistic data [39] or scenarios [87, 124]. Therefore, the optimal solutions from these models are not robust enough to the uncertainties. Thus, large variations of uncertainties might make these solutions less effective and even impractical for a real-world application.

5) Although meta-heuristics algorithms are prevalent solution algorithms for this multi-objective VAR planning problem [22, 38, 41], there is still room for improvement, in terms of computation burden, diversity of the solutions, and the performance on a many-objective problem (with 4 or more objectives).

1.3 Objectives

To address the existing challenges for the dynamic VAR planning for enhancement of voltage stability, the research objectives of this thesis lie in the following aspects:

1) To formulate the dynamic VAR source placement problem as a multi-stage model, which coordinates network enhancement and operational mitigation measures. The coordinated model aims to avoid conservative planning decisions and redundant investment of the conventional single-stage approach.

2) To develop a set of voltage resilience indices for a comprehensive assessment of the voltage resilience of a wind-penetrated power system. Specifically, the post-contingency voltage performance is evaluated not only by

the extent of voltage deviation as the conventional metric, but also by recovery speed, violation time, and post-contingency steady-state.

3) To select the candidate buses for the installations through a zoning-based approach that categorizes the buses into different zones according to the similarity of voltage impacts on the power system. This zoning-based candidate bus selection method aims to avoid redundancy of bus selection and reduce planning cost without any deterioration of the voltage stability. To avoid inconsistency (when subjected to various capacities of VAR devices), the selection method also incorporates the capacity sensitivity analysis.

4) To quantitatively evaluate the robustness of a planning solution when subjected to operational uncertainties. A Robustness Index is developed to incorporate operational uncertainties as a sub-objective of the planning model, making the optimization of the robustness possible.

5) To improve the computation efficiency and diversity performance of meta-heuristics algorithms. An adaptive NSGA-III is developed to address the inherent diversity issues and the huge computation burden of original NSGA-III for a many-objective optimization problem.

1.4 Major contribution of the Thesis

This thesis investigates a robust many-objective Var planning model to enhance the voltage stability of the wind-penetrated power system. Its major contributions can be summarized as follows:

1) A coordinated multi-stage dynamic VAR source placement and operational mitigations model is proposed. Network enhancement (Var installation), preventive controls (including wind curtailment and generation re-dispatch) and corrective controls (load shedding) are coordinated to enhance voltage stability through objectives of the Var planning models, including: a) total cost, b) short-term voltage stability (or restorative performance), c) steady-state voltage stability (or defensive capability), d) robustness of the solution.

2) A set of new quantitative metrics are developed to evaluate the voltage stability and resilience performance at different stages comprehensively. They are categorized into two groups: defensive capability indices and restorative

performance indices. Specifically, the trajectory-based voltage stability and resilience indices consider the extent of voltage deviation, the voltage deviation duration, time of post-contingency stabilization, and the post-contingency steady-state profile.

3) A fuzzy clustering-based zoning approach is proposed to group the buses into different zones to avoid redundancy of candidate buses. Capacity sensitivity analysis is conducted to increase the consistency when the candidate buses are subjected to various capacities of VAR devices.

4) A robustness index is developed to quantitatively assess the robust optimality of the planning solutions according to the concept of Acceptable Sensitivity Region. So, the robustness of the planning decisions can be optimized as one of the objectives in the planning model. Furthermore, this quantitative evaluation of the robustness does not require any presumed probability distributions for operational uncertainties.

5) An Adaptive NSGA-III-LHS is developed to solve the many-objective VAR planning problem. The proposed algorithm has 3 improvements compared with the original NSGA-III: a) an adaptive mutation rate, b) Differential Evolution operator, and c) Latin Hypercube Sampling for an initial population generation.

Pre-assumptions, limitations and conditions of application of the proposed methods are summarized as follows:

- 1) an extreme weather condition can be forecasted, and additional cautiousness is required for a wind-penetrated power system with a high proportion of motor loads (40%).
- 2) the power system follows an area-based approach rather than taking the whole system as an undivided entity. To study the VAR planning problem in this area-based way can minimize the reactive power transmission between different areas and maximize the self-sufficiency of each area.
- 3) since only two operational uncertainties are considered in the case studies in Chapter 5, more operational uncertainties according to the practical needs of the decision-makers should be verified in this model before a real-world application.
- 4) the time horizon of the VAR planning is 5-10 years. The timing and

sequence of the placement of the reactive power sources is not considered in this thesis and should also be incorporated in future along with the transmission expansion planning.

- 5) exact shares of RES that should be regarded as “high” are different from system to system. In this thesis, the assumption is that for a test system with 40% induction motors loads and no dynamic reactive power source, 80% of the maximum wind power penetration level allowed (by specific grid codes) is considered as “high”.

1.5 Organization of the Thesis

This thesis is organized as follows:

Chapter 1 introduces the background, motivation, and contributions of this work.

Chapter 2 outlines the multi-stage coordinated VAR planning framework. Installation of dynamic VAR sources, preventive controls (including wind curtailment, and system re-dispatch), and corrective control (load shedding) are coordinated to enhance the voltage stability of the wind-penetrated power system. The steady-state and short-term voltage stability indices are used to evaluate the voltage stability of the power system before and after a contingency. To reflect the true load dynamics of the utility grid, an industry-standard composite load model is described and implemented, which is also applied in the case studies in other chapters. Furthermore, wind generation uncertainty and its Low/High Voltage Ride-Through capability are also modeled and analyzed. The following Chapters (Chapter 3, Chapter 4, and Chapter 5) are specific improvements based on this framework.

Chapter 3 proposes a set of novel quantitative indices to comprehensively evaluate the proposed preventive controls and corrective controls, as well as the voltage resilience of the system. Considering the different priorities in the planning and operational stages, the resilience is assessed from two perspectives after a feature analysis of different preventive controls and corrective controls: the defensive capability before a contingency and restorative performance after a contingency. Considering the significance of

short-term voltage stability, the corresponding indices are designed to comprehensively evaluate the whole voltage recovery process in terms of (a) extent of the deviation, (b) recovery speed, and (c) post-contingency steady state.

Chapter 4 aims to develop a zoning-based candidate bus selection scheme. Fuzzy C-means clustering and Morris Screening are utilized to group buses into different zones. A comprehensive multi-objective candidate bus selection scheme for voltage resilience enhancement is presented in detail. The advantages of the proposed scheme, avoiding redundant bus selection and improved robustness against different installation capacities, are analyzed, and demonstrated in the case studies.

Chapter 5 focuses on the robustness of the proposed VAR planning model and the solution algorithm for the many-objective optimization problem. After a detailed description of the Acceptable Sensitivity Region and the Most Sensitive Direction, a robustness index is developed to assess the robust optimality of the solutions quantitatively. Robust Pareto Front is introduced to replace the conventional Pareto Front as a set of trade-off solutions against 4 objectives: a) total cost, b) short-term voltage stability, c) steady-state voltage stability, and d) robust optimality. Finally, an adaptive NSGA-III-LHS is proposed with the 3 improvements compared with the original NSGA-III: a) adaptive mutation rates to improve the diversity of the solutions, b) Differential Operator to improve the ability to jump out of local optimality, and c) Latin Hypercube Sampling to alleviate the computational complexity. Case studies on the New England 39-bus system and Nordic 74-bus system demonstrate that both the computational efficiency and the robust optimality of the model outperform the conventional ones.

Chapter 6 gives the conclusion and discusses future works.

2.) Multi-stage Coordinated VAR Planning

As discussed in Chapter 1, the coordination of network enhancement, preventive controls, and corrective controls are usually neglected in the conventional VAR planning model considering the short-term voltage stability. This chapter deals with this issue and proposes a multi-stage coordinated VAR planning framework. Apart from the installation of dynamic VAR sources, preventive controls (wind curtailment, and system re-dispatch) and corrective control (load shedding) are coordinated to enhance the voltage stability of the wind-penetrated power system. A multi-stage coordinated model for voltage stability enhancement is proposed and it is followed by a detailed description of the mathematical form of the model. Finally, a case study on a modified New England 39-bus test system presented and discussed.

2.1 Introduction

There are 3 major challenges brought by the growing penetration level of wind power to the modern electric power system: 1) wind farms are usually far from areas with high load demand and the long-distance transmission requires more reactive power reserve of the system; 2) high penetration level brings down the effective inertia of the system while the reactive power capability of wind turbines is inferior compared with conventional synchronous generators; and 3) the power-electronic interfaced devices make dynamics of the power system more complicated. In addition, induction motor loads are increasing rapidly, which will consume a large amount of reactive power after a severe contingency. Due to the static nature and the fixed capacity, conventional VAR sources, such as a capacitor bank, are no longer effective mitigation to alleviate the short-term voltage instability. In 2016, South Australia experienced a state-wide electricity outage. The blackout is triggered by the tripping of several wind farms and the insufficient reactive power reserve is one of the major causes [4]. Considering the prosperous renewable energy industry and the inherent uncertainty of extreme weather conditions, the shortage of fast response reactive power sources and the corresponding consequences will present themselves on a much larger scale in the future.

Dynamic VAR sources, such as STATCOM which can respond within milliseconds, can be utilized as promising candidates to alleviate the short-term voltage stability issue. The performance of STATCOM is subjected to its installed capacity and its location [21, 22]. In earlier research, the steady-state stability [22, 42-44] and short-term voltage stability [20, 37, 41, 45] issues are studied separately. Therefore, the beneficiary impact of STATCOM on the electric power system is not fully revealed. In recent years, there are some studies focusing on the combination of the two perspectives [38, 46]. A multi-objective optimization model, of which objectives include total cost, steady-state voltage stability and short-term voltage stability, for STATCOM planning is proposed in [38]. This multi-objective model is further extended by incorporating the installation of STATCOM and the retirement of capacitor banks. Conventional VAR sources and FACTS devices are co-optimized in [47] to maximize the advantages of different compensation devices.

As discussed in Chapter 1, the post-contingency performance of wind turbines plays an important role in the overall stability of the power system. South Australia 2016 blackout [4] is a vivid example that VAR compensation devices are necessary but not sufficient to help the power system survive an extreme weather condition. Reduction of the wind power generation or a complete cut-off will not only break the generation-demand balance but also hold the potential of triggering cascading events. When the wind power is considered in a VAR source placement problem, the focus is usually LVRT/HVRT capability of the wind turbines [46] or the general voltage stability of a wind-penetrated power system [40]. Although the adjustment of wind power generation is important (since 40% of large blackouts events are caused by bad weather [48]), the curtailment of wind power, which is an effective preventive control for a better stability performance before a coming emergency, is not considered. Furthermore, the inherent stochasticity of wind power is not addressed in these studies.

Furthermore, other effective mitigations, including but not limited to reactive current compensation from synchronous generators [49], on-load tap changer [50], and the load shedding is rarely incorporated in existing studies related to VAR planning with considerations of short-term voltage stability. As a

dispatchable unit itself, STATCOM can also contribute to the system's steady-state voltage performance by participating in the generation dispatch. Since the cost of these operational mitigations is much less than the investment of dynamic VAR sources, the planning decisions from the models that do not consider the operational mitigations are conservative. Furthermore, the development of advance smart devices enables the operators to schedule the demand more flexibly and the impact of DR [51] on the power system planning should also be considered. For instance, DR is usually implemented in generation planning problems [52] and transmission planning problems [53], respectively, to cut down the peak load.

Therefore, for a power system with a large portion of induction motor load and high penetration level of wind power, STATCOM alone is not sufficient for the power system to survive large transient voltage disturbance. Prevalent single-stage multi-objective model [38, 41, 45, 46] for the VAR planning problem might generate arbitrary and conservative planning decisions due to the lack of coordination between planning of the compensation devices and operational mitigation measures (in both pre-contingency stage and post-contingency stage). To my best knowledge, only one study addresses this issue through a coordinated approach, which incorporates the load shedding as an operational control [54].

In this Chapter, to overcome the inadequacies of the previous works, including the neglect of coordination between network enhancement measures and operational mitigations, optimizing steady-state and short-term voltage stability separately, and without a consideration of wind power generation and composite loads simultaneously, a multi-stage coordinated dynamic VAR source placement framework is proposed for the power system with a high-level wind power penetration and a large portion of induction motor loads. Preventive controls (including dynamic VAR placement, wind curtailment, and system re-dispatch) and corrective control (load shedding) are coordinated to enhance voltage stability. Wind farm generation uncertainty and its LVRT/HVRT capability are modeled to increase the adaptability of the proposed framework in the face of transient disturbance. Both steady-state and short-term voltage stability criteria are considered to evaluate the voltage stability of the power

system with complex dynamic loads.

2.2 Multi-stage coordination framework for voltage stability enhancement

Conventionally, VAR planning is considered as an independent process. However, since different voltage stability mitigations have different features in terms of deployment time and cost as illustrated in Fig. 2.1, the conventional single-stage approach, which neglects the operational control measures, usually generate conservative planning decisions with a relatively high investment cost.

Figure 2.1 Different voltage stability mitigations comparison

In this chapter, different measures are employed in a multi-stage planning framework as illustrated in Fig. 2.2, aiming to coordinate the planning stage and the operation stage to enhance voltage stability optimally. Specifically, it includes planning stage and operation stage. For the operation stage, it has been divided into two sub-stages: pre-contingency stage and post-contingency stage. The multi-stage VAR planning framework as illustrated in Fig. 2.2 is further elaborated in Chapter 2.2 and the details of the mathematical formation will be presented in Chapter 2.3.

Figure 2.2 multi-stage coordinated var planning framework

2.2.1 Planning stage

In the planning stage, STATCOMs are deployed as a network hardening measure to improve both the static and short-term voltage stability of the wind-penetrated power system, which is similar to the conventional approach. Generally, given the heavy computational burden, candidate buses for VAR installations should be determined as inputs before the capacity optimization to reduce the complexity of the problem. The critical contingencies should be the most influential ones on the voltage stability.

In this stage, the inputs consist of: 1) network data (including network structure, generation information, and load information), 2) candidate buses for the installation of VAR sources, 3) selected critical contingencies, 4) specific grid codes for wind power generation (if any), and 5) forecasted peak load. It should be noted that, apart from STATCOM and other FACTS devices, conventional VAR compensation devices such as capacitor banks can also be considered in this stage since they are relatively cost-effective in improving the steady-state voltage stability of the power system.

2.2.2 Operation stage

The operation stage consists of two sub-stages: pre-contingency stage and post-contingency stage.

1) *Pre-contingency Stage*

In the pre-contingency stage, there are three preventive controls implemented to improve the capability of the system to withstand critical contingencies: a) generation re-dispatch with VAR compensators, b) reactive power compensation (by line drop compensation), and c) wind power curtailment. Firstly, the generation re-dispatch will optimize the power-sharing among the generators with the participation of STATCOMs. Then, line drop compensation will enhance the dynamic voltage response of the conventional generator in a contingency. Finally, with credible information about the weather condition (as an emergent contingency), wind power can be curtailed to improve the system's capability to withstand voltage disturbance.

2) *Post-contingency Stage*

In the post-contingency stage, response-driven load shedding (UVLS) is utilized as corrective control (CC) to help the power system restore back to a stable state. An appropriate and timely UVLS can effectively alleviate the detrimental impacts of the contingency and accelerate the voltage recovery process.

Economically speaking, the instantaneous costs for PCs and CCs (\$8/MWh for load shedding) are neglectable compared with the investment of VAR source deployment (\$1.5 million/unit for site installation and \$0.05million/MVar for unit capacity), but its aggregate cost over a long time is still considerable and cannot be ignored. For instance, the load shedding cost over 10 years is comparable to the investment of single VAR source deployment. On the other hand, investment of STATCOM is much higher [79], but it can provide immediate and direct reactive power support before and after a voltage disturbance, improving both the steady-state and short-term voltage stability of the wind-penetrated power system. However, South Australia 2016 blackout is a vivid example that dynamic VAR sources (network enhancement) are necessary but not sufficient. In practice, operational control measures will be used in certain scenarios (for instance, if there is a forecast of extreme weather condition, appropriate wind power curtailment is reasonable) no matter they are considered in the planning stage or not. Therefore, coordination of the very effective but expensive network enhancement measure and the less effective but more flexible and economic operational control measures will not only improve the voltage stability of the power system but also keep the total cost at an acceptable level and avoid unnecessary conservative investment.

2.3 Mathematical formation

2.3.1 Compact model

The compact mathematical model for this multi-objective VAR planning problem is as follows.

$$\min_{\mathbf{u}} \quad F[f_1(\mathbf{x}, \mathbf{u}, \tilde{\mathbf{w}}, \mathcal{K}), f_2(\mathbf{x}, \mathbf{u}, \tilde{\mathbf{w}}, \mathcal{K}), f_3(\mathbf{x}, \mathbf{u}, \tilde{\mathbf{w}}, \mathcal{K})] \quad (2.1)$$

$$\text{s.t.} \quad \mathbf{G}_0(\mathbf{y}_0, \mathbf{u}, \tilde{\mathbf{w}}) = 0 \quad (2.2)$$

$$\mathbf{H}_0^S(\mathbf{x}_0, \mathbf{y}_0, \mathbf{u}, \tilde{\mathbf{w}}) \leq 0 \quad (2.3)$$

$$\mathbf{G}_t(\mathbf{y}_t, \mathbf{u}, \tilde{\mathbf{w}}, \mathcal{K}) = 0 \quad (2.4)$$

$$\mathbf{H}_t^D(\mathbf{x}_t, \mathbf{y}_t, \mathbf{u}, \tilde{\mathbf{w}}, \mathcal{K}) \leq 0 \quad (2.5)$$

$$0 \leq u_h \leq u_h^{\max}, \quad \forall h \in \mathcal{H} \quad (2.6)$$

where F is the overall objective function, consisting of three sub-objectives: 1) total planning cost (f_1), including the investment cost and the operating cost, 2) short-term voltage stability index (f_2), and 3) static voltage stability index (f_3).

$\mathbf{x}$ denotes the power system's state and $\mathbf{y}$ denotes the algebraic variables during the transient period. $\mathbf{u}$ denotes the control variables and $\tilde{\mathbf{w}}$ indicates the uncertain variables. $\mathcal{K}$ denotes the critical contingencies. Constraints (2.2) are the steady-state power balance constraints and constraints (2.3) represent the steady-state operational limits. Constraints (2.4) are the post-contingency power balance constraint and constraints (2.5) represent the post-contingency rotor angle constraint, LVHT/HVRT constraint, voltage recovery constraint, and load shedding constraint. Constraints (2.6) are the bound constraints for control variables. This compact mathematical model will be expanded equation by equation in the following sub-chapters.

2.3.2 Total planning cost (f_1)

The 1st sub-objective function is the total monetary cost for network hardening measure (investment cost), PC, and CC. It can be calculated as follows:

$$f_1 = \underbrace{\sum_{i \in \mathcal{B}_c} C_i^{\text{invest}}}_{\text{investment cost}} + \underbrace{\sum_{w \in \mathcal{G}_w} C_w^{\text{curtail}} + C^{\text{re-dis}}}_{\text{preventive control}} + \underbrace{\sum_{i \in \mathcal{B}_l} C_i^{\text{ls}}}_{\text{corrective control}} \quad (2.7)$$

2.3.2.1 Investment cost

The overall investment cost for all STATCOMs and individual investment cost at each installation location are calculated as (2.8) and (2.9), respectively.

$$C^{invest} = \sum_{i \in \mathcal{B}_c} C_i^{invest} \quad (2.8)$$

$$C_i^{invest} = \begin{cases} c_i^{install} + c^{cap} \cdot cap_i, & \text{if } cap_i \neq 0 \\ 0, & \text{if } cap_i = 0 \end{cases} \quad (2.9)$$

2.3.2.2 Preventive Control Cost

Three PC actions are incorporated into the coordinated planning model:

- 1) *wind power curtailment*
- 2) *re-dispatch of synchronous generators and STATCOMs*
- 3) *reactive power compensation through LDC*

Conventional wind curtailment only sets an overall limit for a certain period [55], but the detailed curtailment for each wind farm is largely at the discretion of the operators based on their own experience and the corresponding grid codes. However, this practice fails to fully utilize the potential of wind curtailment for improving the voltage profile. Alternatively, when the system is subjected to a coming contingency such as the ones caused by extreme weather conditions, a well-calculated solution will be a better option. So, in this thesis, the curtailment for each wind turbine is determined optimally to avoid the conservative investment plan, as well as the unnecessary aggressive curtailment. The curtailment cost for the w^{th} wind farm is calculated as (2.10) with consideration of contingency probability, length of the curtailment.

$$C_w^{curtail} = \sum_{k \in \mathcal{K}} c^{curtail} \cdot cap_w^{curtail} \cdot t^c \cdot p_k, \forall w \in \mathcal{G}_w \quad (2.10)$$

Unlike the conventional capacitor banks (like switchable devices), STATCOM itself is a dispatchable reactive power source. So, it is possible to incorporate STATCOM into the generation re-dispatch (as the 2nd PC) to minimize the

power loss. Based on an optimized operating state and an original state, the re-dispatch cost can be calculated as follows:

$$C^{re-dis} = C^{gen}(x^o, u^o) - C^{gen}(x^{opt}, u^{opt}) \quad (2.11)$$

$$C^{gen} = \sum_{g \in \mathcal{G}_s} (a_g + b_g \cdot P_g + c_g \cdot P_g^2) \cdot t^a \quad (2.12)$$

The 3rd PC is line-drop compensation (LDC). It is available in most excitation systems of a synchronous machine as an effective compensation method [56]. If reactive output power increases, a rising voltage profile will be produced by LDC at generator terminals. LDC could be interpreted as the equivalent inner reactance of generators as (2.13), where V^T and I^T are terminal voltage and current, R^c and X^c are the resistive and reactive components of the compensation. The compensated voltage is generated by procesing the feedback signal V^{c1} through a first order system. As a cost-effective way to boost the utilization of generators' reactive capabilities, the cost of LDC is negligible compared to other preventive and corrective controls.

$$V^{c1} = |V^T + (R^c + jX^c)I^T| \quad (2.13)$$

However, existing studies on dynamic VAR source planning did not incorporate LDC and the default parameters are usually used. Given the detailed parameters of the LDC are usually based on specific simulation results, a stability verification of the system is necessary. In this thesis, different LDC levels will be verified under different contingencies and wind power scenarios to improve the flexibility of the setting of LDC.

The total cost of PCs is calculated based on (2.10) and (2.11) as follows, since the cost of the LDC is negligible compared with the other two PCs.

$$C^{PC} = \sum_{w \in \mathcal{G}_w} C_w^{curtail} + C^{re-dis} \quad (2.14)$$

2.3.2.3 Corrective Control Cost

In this thesis, Under Voltage Load Shedding (UVLS) is implemented as the corrective control measure. Specifically, in this chapter, the response-driven under voltage load shedding is utilized. So, the total corrective control cost can be written as (2.15).

$$C^{CC} = \sum_{i \in \mathcal{B}_l} C_i^{ls} = \sum_{i \in \mathcal{B}_l, k \in \mathcal{K}} C_i(x_{i,k}) \quad (2.15)$$

Conventionally, a linear function, like (2.16), is used as the load shedding model, where the priority factors are assigned to different load buses accordingly. A basic assumption for this approach is that the least amount of load shedding leads to the least load shedding cost [57]. This might be true for the residential loads, but the application on the industrial loads is an oversimplification because most of the loads in the industrial plant are actually dependent on each other. Therefore, considering priorities and characteristics of different loads, three different load shedding cost functions are used as $C_i(x_{i,k})$ in (2.15) to reflect the real practice and the distinctive impacts of loads on the dynamics of the system [57].

C^{linear} aims to describe the loads, usually residential loads, with a linear correlation between the amount and the cost of load shedding. $C^{quartic}$ is used to describe the loads, usually common industrial loads, with a quartically increasing load shedding cost. As for $C^{sigmoid}$, it is for important loads with a load threshold for fundamental electricity demand, such as an industrial plant requires different production lines for a working procedure. For these critical loads, the loss of any production lines (or certain equipment) will bring an immediate shutdown of the main production. A general illustration of these 3 load shedding functions is illustrated in Fig. 2.3. The sudden surge in (2.18) is a realistic description of the post-contingency scenario because the load shedding cost will increase significantly after a certain threshold due to the potential chain effect of load loss.

$$C^{linear}(x_{i,k}) = d_i \cdot x_{i,k} \cdot c^{ls}, \quad \forall i \in \mathcal{B}_l, k \in \mathcal{K} \quad (2.16)$$

$$C^{quartic}(x_{i,k}) = d_i \cdot x_{i,k}^4 \cdot c^{ls}, \quad \forall i \in \mathcal{B}_l, k \in \mathcal{K} \quad (2.17)$$

$$C^{sigmoid}(x_{i,k}) = \frac{z \cdot c^{ls}}{1 + e^{-s \cdot (x_{i,k} - x_i^{threshold})}}, \quad \forall i \in \mathcal{B}_l, k \in \mathcal{K} \quad (2.18)$$

Figure 2.3 Characteristics of load shedding cost functions

2.3.3 Short-term voltage stability evaluation (f_2)

Most of the industrial standards, such as the NERC criterion [58], only consider the extent and the duration of the voltage violation after contingencies as the evaluation criteria. Recently, as a respond to rapid expansion of renewable energy in Europe, a more detailed network code was published in April 2016 as Commission Regulation (EU) 2016/631 [123] aiming to bind EU wide harmonization of grid interconnection requirements. Instead of a quantitative and comparable evaluation result, these standards and guidelines only provide a binary judgment of the stability state, in terms of whether certain threshold is violated. A short-term voltage stability index called TVSI [37], which take both the magnitude and the duration of unacceptable voltage deviation into consideration and has been tested in several short-term voltage stability studies [38, 46, 72], is adopted in this chapter to evaluate the system's short-term voltage performance quantitatively and generate comparable evaluation results.

$$TVSI_k = \frac{\sum_{i \in \mathcal{B}} \sum_{t \in [T^c, T^{end}]} TVDI_{i,t,k}}{N^b} \quad (2.19)$$

where TVDI is defined as (2.20), based on the dynamic voltage trajectories after a disturbance (where $k \in \mathcal{K}$):

$$TVDI_{i,t,k} = \begin{cases} \frac{|V_{i,t} - V_{i,0}|}{V_{i,0}}, & \text{if } \frac{|V_{i,t} - V_{i,0}|}{V_{i,0}} \geq \delta, \forall t \in [T^c, T^{end}] \\ 0, & \text{otherwise} \end{cases} \quad (2.20)$$

A risk-based criterion for contingency analysis is adopted in this chapter to incorporate the impact of critical contingencies, with different probabilities, into the short-term voltage evaluation. So, the 2nd objective function is calculated as follows:

$$f_2 = Risk^{TVSI} = \sum_{k \in \mathcal{K}} TVSI_k \cdot p_k \quad (2.21)$$

2.3.4 Steady-state voltage stability evaluation (f_3)

The 3rd objective is the quantitative evaluation of the steady-state voltage stability. A line-based VCPI is employed in this chapter to assess the steady-state voltage stability [59]. As a line stability index, it is based on the concept of maximum power transferred through a line and can provide reliable information about the proximity to voltage collapse [59]. According to some comparison studies [59, 125], VCPI outperform steady-state voltage stability indices in terms of accuracy and robustness. Its mathematical expression can be written as (2.22), where $P_l^{r,max}$ and $Q_l^{r,max}$ are determined by (2.23). “VCPI (power)” in (2.22) indicates that the index is based on “power transferred in the line”.

$$VCPI(power)_l = \frac{P_l^r}{P_l^{r,max}} = \frac{Q_l^r}{Q_l^{r,max}} \quad (2.22)$$

$$\begin{cases} P_l^{r,max} = \frac{(V^s)^2}{Z^s} \cdot \frac{\cos \varphi}{4 \cos^2(\frac{\theta - \varphi}{2})} \\ Q_l^{r,max} = \frac{(V^s)^2}{Z^s} \cdot \frac{\sin \varphi}{4 \cos^2(\frac{\theta - \varphi}{2})} \end{cases} \quad (2.23)$$

Based on (2.22), the VCPI for the whole system (all the power lines) can be calculated as (2.24).

$$VCPI^T = \sum_{l \in \mathcal{L}} VCPI(power)_l \quad (2.24)$$

Similar to the risk-based criterion used in (2.21), the 3rd objective function is calculated as (2.25):

$$f_3 = Risk^{VCPI} = \sum_{k \in \mathcal{K}} VCPI_k^T \cdot p_k \quad (2.25)$$

2.3.5 Constraints

Pre-contingency constraints and post-contingency constraints are presented in the following sub-chapters. Specifically, the maximum capacity constraint for VAR sources is determined by the operator, based on the historical and forecasted information, including largest rated capacity of current VAR sources, expected load development, regulations on the wind farms reactive power regulations.

2.3.5.1 Pre-contingency Constraints

The pre-contingency constraints refer to steady-state constraints, including power flow balance and steady-state operational limits. The constraint for the active and reactive power equilibrium of each bus is written as (2.26), which the expansion of (2.2). Operational limits are represented by constraint (2.27), including voltage magnitude, line capacity, and generation output capacity. (2.27) is the expansion of (2.3).

$$\begin{cases} P_g + \widetilde{P}_w - P_d - P_w^c - V_i \sum_{j \in \mathcal{B}} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \\ Q_g + \widetilde{Q}_w + Q_s^{stat} - Q_d - Q_{w,i}^c - V_i \sum_{j \in \mathcal{B}} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \end{cases} \quad (2.26)$$

$$\begin{cases} V_i^{min} \leq V_i \leq V_i^{max} \\ L_l^{min} \leq L_l \leq L_l^{max} \\ P_g^{min} \leq P_g \leq P_g^{max} \\ Q_g^{min} \leq Q_g \leq Q_g^{max} \end{cases} \quad \begin{matrix} \forall i \in \mathcal{B} \\ \forall l \in \mathcal{L} \\ \forall g \in \mathcal{G} \end{matrix} \quad (2.27)$$

In the proposed planning model, the overall curtailment constraint of wind power is calculated based on the maximum curtailment allowed and the curtailment ratio. In practice, the maximum curtailment is usually stringent, but the operators still have the option to select an appropriate curtailment ratio, according to different operational conditions, to avoid the conservative wind power reduction.

$$0 \leq \sum_{w \in \mathcal{G}_w} cap_w^{curtail} \leq \sum_{w \in \mathcal{G}_w} \tilde{P}_w \cdot W^c, \forall W^c \in [0,1] \quad (2.28)$$

2.3.5.2 Post-contingency Constraints

Post-contingency constraints refer to the power balance constraint after a contingency, as well as dynamic voltage and stability constraints. First, the total power generation (including conventional synchronous generators, wind turbines, and STATCOMs), should match the load in the post-contingency stage, as expressed in (2.29).

$$\begin{cases} P_{g,k} + \tilde{P}_{w,k} + P_{d,k}^{shed} = P_d + P_{w,k}^c & \forall g \in \mathcal{G}_s, \forall w \in \mathcal{G}_w \\ Q_{g,k} + \tilde{Q}_{w,k} + Q_{d,k}^{shed} + Q_{s,k}^{stat} = Q_d + Q_{w,k}^c & \forall d \in \mathcal{B}_l, \forall k \in \mathcal{K} \end{cases} \quad (2.29)$$

Rotor angle is employed here as a transient stability constraint. As shown in (2.30), for any 2 generators (g and g') during a transient period of T after a contingency k , the maximum rotor angle deviation between them is ω . For instance, for an extreme condition, the threshold ω can be set to 180° [2].

$$[\max(\Delta\delta_{gg'}^T)]_k \leq \omega \quad \forall g, g' \in \mathcal{G}_s, \forall k \in \mathcal{K} \quad (2.30)$$

Once the fault has been cleared and the lower bound voltage violation is alleviated either by the load shedding or the reactive power support from STATCOMs, there might be a transient over-voltage, especially for a wind-

penetrated power system where the deployment of the dynamic VAR sources is relatively common. So, instead of focusing on low voltage dip and its detrimental impact on the wind turbines, both LVRT and HVRT constraints are incorporated in the proposed model. Voltage magnitude constraints for a time-varying LVHT/HVRT profile are modeled as (2.31), where $LVRT(t)/HVRT(t)$ denotes time-varying threshold for voltage magnitude after a contingency:

$$\begin{cases} V_i^{post}(t) - LVRT(t) \geq 0, \forall t \in \mathcal{T}, \forall i \in \mathcal{B} \\ V_i^{post}(t) - HVRT(t) \leq 0, \forall t \in \mathcal{T}, \forall i \in \mathcal{B} \end{cases} \quad (2.31)$$

Constraint (2.32) is for the voltage recovery speed. It aims to make sure that the duration of each bus under a lower voltage threshold, e.g., 0.9 p.u., is no more than the maximum allowed time, T^{max} .

$$T_i^r - T^C \leq T^{max}, \quad \forall i \in \mathcal{B} \quad (2.32)$$

Constraints (2.33) is for the load shedding in the post-contingency stage. The actual load shedding of each load bus should be smaller than the pre-determined maximum allowed amount.

$$x_{i,k} \leq P_i^{LS,max}, \quad \forall i \in \mathcal{B}_l, \forall k \in \mathcal{K} \quad (2.33)$$

2.3.6 Dynamic load modelling

Apart from the load demand level, load dynamics are also a critical factor for the dynamic voltage response of a power system, especially when it is subjected to large voltage disturbances. It is important and necessary to model the static and dynamic loads appropriately and fully reflect the diversity of the loads. In this thesis, an industry-standard composite load model "CLOD" [60] is employed (for all chapters) to model the complex load dynamics of the real-world power system as shown in Fig. 2.4. CLOD model consists of: 1) three-phase induction motor load (small motor and large motor, SM and LM), 2) discharge lighting load (DL), 3) saturation of distribution transformers, 4) static load, consisting of a constant MVA component (CP) and a load whose real component varies with

an exponent K_p and imaginary component varies with voltage squared. This dynamic load model can be defined by a 6-dimensional vector [LM, SM, DL, TS, CP, K_p]. The first 5 items represent the percentage value of large motors, small motors, discharge lighting, transformer exciting current, and constant power load, respectively. K_p is the exponent of voltage-dependent real power load as illustrated in Fig. 2.4. R^b is the branch resistance and X^b is the branch reactance.

Figure 2.4 Dynamic load model (CLOD)

2.3.7 Wind power uncertainty modelling

The output of wind turbine is stochastic by nature and difficult to predict. Although wind speed usually follows Weibull distribution, wind power output is a non-linear function of the wind speed. Therefore, the probability density function (PDF) of wind power output is much more complicated than Weibull distribution, and thus not easy to determine. Besides, for a long-term VAR planning problem (e.g. 10 years), such complicated PDF is even more difficult to obtain.

In this chapter, instead of using the PDF approach, we use the upper and lower bounds to model the stochastic wind power output. It is a more straightforward method and easier to implement for a long-term VAR planning problem. Specifically, TOAT [61], a robust parameter design technique, is used to decompose a large-scale stochastic programming problem into a series of deterministic problems. Generally, the decomposition is realized by approximating the whole uncertainty space with a smaller set of representative scenarios. For instance, if there are N stochastic variables, $\tilde{\mathbf{w}} = [\tilde{\mathbf{w}}_1, \tilde{\mathbf{w}}_2, \dots, \tilde{\mathbf{w}}_N]$ in an uncertainty space and M levels of values for each variable, the uncertainty space will have M^N combinations. It is of huge computation burden when N is large. TOAT is employed to reduce the number of scenarios that used to represent all the combinations. The relatively fewer scenarios are determined

by Orthogonal Arrays and its mathematical details can be found in [61]. In this chapter, there are two realistic assumptions for the application of TOAT on the wind power output uncertainty: 1) wind power prediction is given as a range with maximum value and minimum value, and 2) deviation of the actual output from its prediction follows the normal distribution.

Table 2.1 Decomposition of wind power scenarios

TOAT Library	Variable levels		
	$\tilde{w}_1$	$\tilde{w}_2$	$\tilde{w}_3$
Scenario 1	-	-	-
Scenario 2	-	+	+
Scenario 3	+	-	+
Scenario 4	+	+	-

For example, as listed in Table 2.1, each of three wind farms ($\tilde{w}_1, \tilde{w}_2, \tilde{w}_3$) has two levels (maximum and minimum values) of output predictions. So, the total number of scenarios is 2^3 . With the implementation of TOAT, the whole uncertainty space (8 scenarios) is decomposed as a TOAT library consisting of only four scenarios as the scenarios 1-4 in Table 2.1. The “+” indicates the maximum value of wind power outputs and “-” stands for the minimum value of wind power outputs.

2.3.8 Candidate bus selection

In order to reduce the computation burden of the planning problem, candidate bus selection is carried out before the capacity optimization of the capacity. It aims to find the most effective and efficient buses for voltage stability improvement. By excluding other buses in the optimization process, the problem size is reduced significantly. In this chapter, candidate bus is selected based on trajectory sensitivity analysis [38]. The sensitivity index S_i [38] is calculated as follows, where the 2nd objective (short-term voltage stability) and 3rd objective (steady-state voltage stability) are used to evaluate the effectiveness of the candidate buses.

$$S_i(f_2) = \frac{f_2(cap_i) - f_2(cap_i + \Delta cap)}{\Delta cap}, \forall i \in \mathcal{B}_c \quad (2.34)$$

$$S_i(f_3) = \frac{f_3(cap_i) - f_3(cap_i + \Delta cap)}{\Delta cap}, \forall i \in \mathcal{B}_c \quad (2.35)$$

A larger S_i means higher effectiveness for the objective f_i . Because a direct comparison of the two sensitivities indices is not available, a Pareto Front of the two indices is generated according to the Pareto optimality theory [62] (details will be explained in the following chapters). Finally, the candidate buses can be selected from this Pareto Front where none of the S_i can be improved in value without impairment in some of the other S_i .

2.4 Solution method

Considering the highly non-convex and non-linear property of the problem, NSGA-II is adopted the solving algorithm of this multi-objective optimization problem, providing a group of trade-off solutions, which is a balance or compromise achieved between two or three desirable but incompatible objectives, for decision-makers to choose from based on their practical needs (for instance, the preference for low investment over high short-term voltage stability).

2.4.1 Pareto optimality

Contrary to an optimization problem with only one objective, a multi-objective optimization problem has to deal with the conflicting objectives. For instance, in this chapter, it is the lower cost vs. higher voltage stability. There is no solution that can achieve a simultaneous minimization of all the objectives. Instead, a group of trade-off solutions is generated by NSGA-II. Pareto optimality theory [62] is a predominant concept to define trade-off solutions. Given the feasible decision space $\mathcal{X}$, a solution $x^* \in \mathcal{X}$ is called Pareto optimal (or non-dominated), if there is no another solution, $x \in \mathcal{X}$, such that $\mathbf{f}(x) \leq \mathbf{f}(x^*)$ and $f_i(x) \leq f_i(x^*)$ for at least one function. In other words, no further improvement in the value of objective functions can be achieved without impairment in some of the other

objective values. The Pareto optimal objective vector is defined as the vector of objective function values given by a Pareto optimal solution. And the set of all the Pareto optimal solutions is called the Pareto Set (PS) and the set of all the Pareto optimal objective vectors is the Pareto Front (PF). As illustrated in Fig. 2.5, blue circles are the non-dominated solutions (formulating the Pareto Front together) and the orange circles are dominated solutions. For instance, point C is not on the PF because it is dominated by both point A and point B while Points A and B are Pareto optimal because they are not dominated by any other solutions.

Figure 2.5 Illustration of Pareto Front

2.4.2 NSGA-II

Proposed by Deb in [63], NSGA-II has been proved to be an efficient algorithm for multi-objective benchmark optimization problems. One of the salient advantages of NSGA-II is Pareto optimal solutions from Pareto Front. Fig. 2.6 illustrates the general computation steps of NSGA-II, where P_t is the parent population, Q_t denotes the offspring population and R_t is the combined population. Firstly, the population is grouped after initialization based on non-domination levels into fronts. The first front consists of a set of non-dominant individuals. The individuals from the second front are only dominated by the ones from the first front and the following fronts follow the same pattern. Apart from the front ranking, the crowding distance is also computed for each

individual to measure how close an individual is to its neighbors. Larger average crowding distance indicates a more diversified population. Based on *Crowded-comparison Operator*, parents are from the population, following two general rules [63]:

- 1) *higher front ranking individual is always selected regardless of crowding distance;*
- 2) *for individuals in the same front, the one with a larger crowding distance is selected.*

After the operation of crossover and mutation operators, the parent population generates offspring. Then, the population is grouped again, and the best individuals are selected. Since all previous and current population members are included in R_t , elitism is ensured in the procedures.

Figure 2.6. Computation flowchart of NSGA-II

2.4.3 Coding rules

Conventionally, there are $2 \cdot H$ variables for H candidate buses for the installation and capacity decisions of STATCOMs, which leads to a relatively large number of decision variables and corresponding high computation time. A new planning cost function as (2.9) is adopted in this chapter and the installation decision is implicitly decided by the capacity which requires only H variables for H candidate buses as illustrated in Fig. 2.7. Besides, there are W wind power curtailment decisions for W wind farms, as illustrated in Fig. 2.7. So, the total number of the control variables is the sum of the number of candidate buses for STATCOMs and the number of wind farms. Specifically, the maximum capacity constraint for VAR sources is determined by the operator, based on the historical and forecasted information, including largest rated capacity of current VAR sources, expected load development, regulations on the wind farms reactive power regulations.

Figure 2.7 An individual coding structure

2.4.4 General computation steps

The computational flowchart is illustrated in Fig. 2.8. The details of the computation steps are described as follows.

1) Initialization

After the initialization of algorithms, candidate buses are selected based on the original network information and the method proposed in Chapter 2.3.8. The first generation of the population is generated, and each individual is with a number of control variables (in this chapter, they are decisions for STATCOM installation and wind power curtailment as illustrated in Fig. 2.7).

2) Evaluations of pre-contingency optimal power flow and steady-state voltage stability

Preventive controls will be implemented in this stage. Two OPF calculations are conducted. The 1st OPF is calculated without preventive controls and the 2nd one is updated with preventive controls and STATCOMs. VCPI is calculated for each scenario in this stage based on (2.24). Dispatch costs for two OPFs are also calculated and logged for the calculation of total cost in later steps.

3) *Time-domain simulation and evaluation of short-term voltage stability*

Time-domain simulation is conducted to verify the dynamic voltage performance of the system for each contingency. The corrective control, under-voltage load shedding, will be activated once the voltage thresholds are violated in the post-contingency stage. Each individual of a population generated by NSGA-II is also tested with different LDC parameters, wind farms output scenarios, and critical contingencies. TVSI for each scenario is calculated based on (2.19). After verifications of all the scenarios, corrective control cost is calculated. The cost is also saved to calculate the objective (f_1) in next stage.

4) *Calculation of objectives*

Total planning cost (f_1), short-term voltage stability evaluation result (f_2), and steady-state voltage stability evaluation result (f_3) are calculated based on (2.7), (2.21), and (2.25), respectively.

5) *Update of individuals:*

Individual is compared with each other. Then, the best Pareto solution is selected. The best individual in the current generation is updated with the solution.

6) *Break criteria*

the evaluation of individuals will be terminated if there is a violation of any dynamic constraint. The computation procedure will go to step 7) once the evaluation is terminated.

Figure 2.8 Computation flowchart

7) *Termination*

Two stopping criteria are adopted in this chapter, a) changes in fitness function is smaller than a specific tolerance, and b) the maximum iteration number is reached. If one of them is satisfied, the computation procedure will be terminated, and the final optimal solution will be presented as a Pareto Front.

8) *Generation of offspring*

If none of the stopping criteria is satisfied, new offspring of the current generation will be generated through mutation, recombination, and crossover [62]. Then, the main computation procedure will jump to step 2).

2.5 Numerical results and discussions

2.5.1 Test system and parameters

The New England 39-bus system is used to demonstrate the effectiveness of the proposed planning model. Synchronous generators originally installed at bus 30, bus 32, and bus 34 are replaced by Double-Fed Induction Generators (the generation capacity remained the same). These wind turbines are modeled in PSS®E 33.4 [60]: the generator model is WT3G2, the electrical model is WT3E1, the mechanical model is WT3T1, and the pitch control model is WT3P1. The dynamic setup for these models can be found in [66]. The compliance of these wind power plants is checked according to the technical regulation of the Australian Energy Market Operator (AEMO) [64] with one of the most stringent LVRT/HVRT regulations compared with other international wind power integration regulations [65]. As for the conventional synchronous generators, they are modelled by GENROU as generators, IEEEVC as compensators and ESDC1A as exciters.

SVSMO3U2 model is used for STATCOMs. Its block diagram is illustrated in Fig. 2.9 and the parameters used in this chapter is list in Table 2.2.

Figure 2.9 Block diagram of the SVSMO3 STATCOM model [66]

Table 2.2 SVSMO3U1 model parameters

Parameters	Definitions	Values
X_{c0}	Linear droop	0.01
T_{c1}	Voltage measurement lead time constant (sec)	0
T_{b1}	Voltage measurement lag time constant (sec)	0.1
K_p	Proportional gain	4
K_i	Integral gain	25
V_{emax}	maximum voltage error (p.u.)	0.5
V_{emin}	Minimum voltage error (p.u.)	-0.5
T_0	Firing sequence control delay (sec)	0.005
I_{max1}	Maximum continuous current rating (p.u. on STBASE)	10
dbd	Deadband range for voltage control (p.u.)	0
K_{dbd}	Ratio of outer to inner deadband	10
T_{dbd}	Deaband time (sec)	0.1
K_{pr}	Proportional gain for slow-reset control	0
K_{ir}	Integral gain for slow-reset control	0.001
I_{dbd}	Deadband range for slow-reset control (p.u. on STBASE)	0.01

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V_{rmax}	Maximum limit on slow-reset control output (p.u.)	0.1
V_{rmin}	Minimum limit on slow-reset control output (p.u.)	-0.1
I_{shrt}	Maximum short-term current rating multiplier of maximum continuous current	1.4
UV_1	Voltage at which STATCOM limit starts to be reduced linearly (p.u.)	0.5
UV_2	Voltage at which STATCOM is blocked (p.u.)	0.2
OV_1	Voltage above which STATCOM limit linearly drops (p.u.)	1.08
OV_2	Voltage above which STATCOM blocks (p.u.)	1.2
V_{trip}	Voltage above which STATCOM trips after time delay T_{delay2} (p.u.)	1.3
T_{delay1}	Short-term rating time (sec)	1
T_{delay2}	Trip time for $V > V_{trip}$ (sec)	0.08
V_{sched}	Voltage reference (p.u.)	1
V_{refmax}	Maximum limit on voltage reference (p.u.)	1.05
V_{refmin}	Minimum limit on voltage reference (p.u.)	0.95
T_{c2}	Lead time constant (sec)	0
T_{b2}	Lag time constant (sec)	0
I_{2t}	I_{2t} limit	0
$Reset$	Reset rate for I_{2t} limit	0
$hyst$	Width of hysteresis loop for I_{2t} limit	0
X_{c1}	Non-linear droop slope 1	0.01
X_{c2}	Non-linear droop slope 2	1
X_{c3}	Non-linear droop slope 3	0.01
V_1	Non-linear droop upper voltage (p.u.)	1.025
V_2	Non-linear droop lower voltage (p.u.)	0.975
T_{mssbrk}	Time for MSS breaker to operate (sec)	0.1
T_{out}	Time MSS should be out before switching back in (sec)	300
T_{delLC}	Time delay for switching MSSs (p.u. on STBASE)	0.5
I_{upr}	Upper threshold for switching MSSs (p.u. on STBASE)	0.3
I_{lwr}	lower threshold for switching MSSs (p.u. on STBASE)	-0.3

The CLOD model is used to represent the dynamic loads with parameters

listed in Table 2.3. The peak load is used as the load level to represent the worst case. Three critical contingencies are selected based on the methods used in [37, 38]. A brief explanation of the method is as follows: for each N-1 3-phase short-circuit contingency, the static and short-term voltage stability indices are respectively calculated according to equ. (2.19) and equ. (2.24); then, contingencies can be scattered in the distance space of the TVSI and the increment of VCPI (compared with the pre-contingency operating condition), similar to principle of Pareto Front. Finally, faults on line 2-3, line 6-7, and line 16-24 are selected since they are non-dominated ones on Pareto Front. On the other hand, these critical contingencies can be selected based on historical operational data and existing contingency tables in practice, such as critical transmission corridor of the system.

The case studies in this chapter are carried out under the assumption that an extreme weather condition is forecasted, and additional cautiousness is required for a wind-penetrated power system with a high proportion of motor loads (40%). Therefore, preventive controls and corrective controls described in the previous sub-chapter are all included. However, the final planning decision is at the discretion of decision-makers because a set of Pareto optimal planning solutions is provided, instead of only one deterministic solution. Table 2.3 lists the parameters for simulations. According to computation steps illustrated in Fig. 2.8, MATPOWER package [67] is used to solve OPF and PSS®E simulation package (through an interface in with Matlab) is employed to conduct the time-domain simulation.

Table 2.3 Parameters for simulation setting

Parameters	Value
$c_i^{install}$	\$1.5 million/unit
c^{cap}	\$0.05 million/MVar
u^{1st}	5% at 0.9 p.u.
u^{2nd}	5% at 0.85 p.u.
u^{3rd}	5% at 0.8 p.u.
W^c	10%
$c^{curtail}$	\$8/MWh
$P_i^{LS,max}$	20%
t^c	4 Hours
t^a	4500 Hours
ω	π
δ	0.1
NSGA II population and generation	100 and 15
NSGA II tolerance	1.0×10^{-3}
NSGA II mutation probability	0.25
NSGA II crossover rate	0.8
LM, SM, DL, CP, K_p	25%, 15%, 10%, 10%, 2
LDC levels	40%, 30%, 20%

Since three synchronous generators originally installed at bus 30, bus 32, and bus 34 are replaced by wind turbines, resulting in a low-inertia power system, and the system is with a high proportion of industrial motor loads, this modified New England 39-bus system is in need of additional dynamic reactive power sources after a critical voltage disturbance. Candidate buses of systems are selected based on two principles: 1) all the wind farm buses are candidate buses due to stringent voltage requirement and the potential danger of tripping offs (as the case in South Australia Blackout [4]); 2) candidate buses selected from load buses are based on Chapter 2.3.8. All seven selected candidate buses are marked with red triangles in Fig. 2.10.

Figure 2.10 New England 39-bus test system

2.5.2 Numerical results and compromise solution

The overall computation time is around 14 hours, which is acceptable for a long-term STATCOM planning problem. As illustrated in Fig. 2.11, A Pareto Front consisting of 42 Pareto optimal solutions is obtained. Compared with one deterministic optimized solution, these trade-off solutions are more practical and valuable since the decision-makers can make a more balanced and cost-effective decision according to their specific priorities and engineering practices. For the purpose of analysis and discussion on these results, fuzzy membership function [68] is adopted to select a compromise solution. For each Pareto optimal solution x_p , its satisfactory degree for objective function f_f can be calculated as (2.36). The satisfactory degrees for all objective functions can be calculated as (2.37).

$$\mu_f^p = \frac{f_f^{\max} - f_f(x_p)}{f_f^{\max} - f_f^{\min}} \quad (2.36)$$

$$\mu^p = \frac{\sum_{f \in [1,2,3]} \mu_f^p}{\sum_{p \in \mathcal{P}} \sum_{f \in [1,2,3]} \mu_f^p} \quad (2.37)$$

Figure 2.11 Pareto optimal solutions

Table 2.4 Installation decisions (in MVar)

Bus No.	15	16	24	27	30	32	34
Capacity	64.5	86.5	83.9	85.7	33.4	45.0	51.1

Table 2.5 Compromise solution

Objectives	Total Cost	TVSI	VCPI
Value	\$32.78m	0.7465	18.05

A compromise solution is the solution with the smallest μ^p . So, the compromise solution for this case study is selected by the fuzzy membership method as marked in Fig. 2.11. The corresponding installation plan of STATCOM is presented in Table 2.4. The wind curtailment scheme for wind farms at bus 30, bus 32, and bus 34 are 1.95%, 1.37%, and 6.29%, respectively. The total load shedding for the worst contingency is 49.5MW. The details of the compromise solution, namely the values of 3 objectives are listed in Table 2.5. It should be noted that the compromise solution is selected for the convenience of comparative study in the following sub-chapter. In practice, the proposed method provides the decision-makers the flexibility to choose any solution from the Pareto optimal solution according to their practical needs. For example, for a conservative decision-maker, a planning decision with more investment on the STATCOMs is favourable, while for a decision-maker with more economic concerns, a planning decision with more aggressive preventive controls will be selected.

2.5.3 Comparisons and discussions

The short-term and the steady-state voltage stability evaluation results (TVSI and VCPI) for the base case (i.e., no STATCOM installation) are 1.2509 and 19.24. With the installations of STATCOMs, there are 40.32% and 6.18% improvements on TVSI and VCPI, respectively. With enhanced dynamic voltage stability, even the wind power penetration level is as high as 30%, all the wind turbines in the system successfully satisfy the LVRT/HVRT requirements and the power factor limits (within 0.95 lagging and 0.95 leading). Besides, an appropriate amount of preventive wind curtailment is also effective in improving voltage stability during a specific credible contingency, e.g., before extreme weather conditions. To demonstrate the advantages of the proposed method, two other methods, as listed in Table 2.6 as method B and method C, are compared with the proposed method in Table 2.7. Both Method B and method C are with 35 Pareto optimal solutions.

Table 2.6 Methods for comparisons

Method	Details
A	the proposed method
B	the proposed method for STATCOM placement but without wind curtailment.
C	the proposed method for STATCOM placement but no PC nor CC is considered.

Table 2.7 Comparison results

Methods/ Objectives	Installed Capacity	Investment Cost	PC Cost	CC Cost	Total Cost	TVSI	VCPI
A	450MVar	\$32.99m	\$-0.22m	\$0.015m	\$32.78m	0.7465	18.05
B	525MVar	\$36.76m	\$-0.25m	\$0.016m	\$36.51m	0.7444	18.01
C	504MVar	\$35.59m	-	-	\$35.59m	0.7782	18.01
Base case	-	-	-	-	-	1.2509	19.24

Compared with method C that only considers the location and capacity of the STATCOM but ignores other operational mitigations, the proposed method successfully takes advantage of preventive and corrective controls. As shown in Table 2.7, the capital investment (method A) of STATCOM installations is

reduced without deteriorating the dynamic voltage performance of the system. Since method C is with a larger total capacity of STATCOM, its steady-state voltage stability evaluation result (VCPI) is slightly better than that of method A. However, this marginal improvement in VCPI significantly increase investments of method C, making method C less cost-efficient.

Fig. 2.12 shows the mean value of time-varying voltage trajectories of all the load buses under the same severe contingency for the base case and the case using method A, respectively. The voltage trajectory of method A recovers rapidly and maintains in a stable state after the fault is cleared, while there is voltage collapse after the fault is cleared for the base case. It demonstrates that, because of the relatively low inertia of the system (high-level wind power penetration) and the high portion of induction motor loads, the reactive power capability of the generators in the system cannot fully support the voltage and help the system recover to a new stable balance during a critical contingency. Thus, the installation of dynamic VAR compensators is necessary for the wind-penetrated system to survive such a severe voltage disturbance.

Fig. 2.13-2.15 show the reactive power generated by each wind farm after a contingency, with and without the implementation of method A (the proposed method), respectively. Although the power factor limits (within 0.95 lagging and 0.95 leading) is always satisfied for all the wind farms in both cases, the margins are very small for wind farms at bus 30 and 32 for the base case. As for method A, the need for additional reactive power in the post-contingency stage has been shared by STATCOMs. Therefore, the flexibility of wind farm operation is enhanced effectively.

Fig. 2.16 illustrates dynamic voltage response after the contingency at bus 24 with method A and method C, respectively. Obviously, the voltage response of method C is inferior to that of method A. Furthermore, for method A, the first round UVLS (5% at 0.9 p.u.) is triggered during the voltage recovery process. The UVLS successfully accelerates the voltage recovery and the overall under-voltage period is reduced accordingly, which proves the effectiveness of the coordination between STATCOMs deployment and corrective controls.

As one of the salient advantages of the proposed method, other Pareto optimal solutions can also be selected according to different practical needs. For instance, if the planner is more sensitive to the total cost than voltage stability issues, a more economical planning solution (denoted as method A*) could be selected as listed in Table 2.8. In this case, method C (with no PC and CC is considered) costs 19.97 % more total planning cost to achieve similar VCPI and TVSI of method A*. The coordination of STATCOM deployment, PC, and CC adopted in method A* effectively reduces the total planning cost without any degradation in voltage performance.

Figure 2.12 Mean value of time-series voltage magnitude profiles

Figure 2.13 Reactive power output of wind farms at bus 30

Figure 2.14 Reactive power output of wind farms at bus 32

Figure 2.15 Reactive power output of wind farms at bus 34

Figure 2.16 Post-contingency voltage response at bus 24

Table 2.8 Alternative solution comparison

Methods/ Objectives	Installed Capacity	Total Cost	TVSI	VCPI
A*	363MVar	\$28.48m	0.7719	18.21
C	504MVar	\$35.59m	0.7782	18.01

2.6 Conclusions

This chapter proposes a multi-stage multi-objective VAR source placement method for STATCOM deployment. This method aims to improve the steady-state and short-term voltage stability of the system simultaneously for a wind-penetrated power system. Furthermore, the LVRT/HVRT capabilities of wind turbines in a system with complex dynamic load models are also considered. Compared with conventional conservative methods focusing only on the capacity and location of the STATCOMs, the proposed method effectively coordinates STATCOMs deployment (planning stage), preventive controls (pre-contingency operation stage), and corrective controls (pre-contingency operation stage) to enhance the steady-state and short-term voltage stability. The complexity and computation burden of the model is mitigated by the selection of critical contingencies and candidate buses selection before the optimization of STATCOM capacity. Instead of providing only one deterministic planning solution, this method provides the decision-makers with a group of flexible Pareto optimal solutions. These solutions help them to achieve an optimal trade-off between planning cost and operation cost with the consideration of various practical factors that affect the overall performance of the system. Case studies on a modified New England 39-bus system demonstrate that the coordination of STATCOM planning decisions, PC, and CC can reduce the total planning cost effectively without any deterioration of the voltage stability performance.

3.) Resilience-oriented Voltage Stability Evaluation Indices

This chapter is a continuation of the research in Chapter 2. In the previous chapter, a coordinated multi-stage VAR planning framework is proposed for a wind-penetrated power system with a high portion (40%) of induction motor loads. The method considers the whole resilience process, from the time before the disturbance to the time a new equilibrium is achieved as illustrated in Fig. 2.2, with the introduction of various preventive and corrective controls. However, the general voltage performance related to the reactive power deficiency and stability issues are still evaluated with conventional steady-state and short-term voltage stability indices. Since different planning and operation measures have their pros and cons, the effectiveness of these mitigations cannot be fully assessed by TVSI and VCPI. Therefore, in this chapter, apart from TVSI and VCPI, a set of novel voltage resilience metrics are proposed to quantify the defensive capability and restorative performance of a wind-penetrated power system.

3.1 Introduction

As introduced in Chapter 2, modern power systems are exposed to technical challenges brought by large-scale wind power integration. Conventional reactive power compensation device such as capacitor banks is an economical solution, but it is not effective enough in mitigating transient voltage stability issues due to its relatively slow response. Thus, FACTS, such as STATCOM, is a promising candidate for this short-term voltage stability issue. Various studies have explored the potentials and effectiveness of FACTS devices, in terms of enhancing the steady-state [42-44] and short-term [38, 41, 45, 46] voltage stability of the power. Considering the prohibitive capital investment of STATCOMs, co-optimization of the conventional reactive power source and FACTS devices is also studied in [47]. However, these researches only focus on the voltage stability of the system through various steady-state or short-term stability indices and the issues of the voltage resilience and the general restoration process of the system are not fully discussed.

Resilience mainly refers to the ability of a power system to recover quickly

from “high impact, low probability” events [24, 25, 69]. Since most recent studies mainly concern about infrastructure resilience [31, 48], there is no holistic quantitative evaluation framework for the resilience performance of a power system [35]. In [70], four simplified quantitative indices are proposed: withstand capability, restoration speed, preparation capacity and adaptation capability. Ref. [30] proposes a probabilistic model to evaluate the resilience of power systems against hurricane using a set of conventional reliability metrics.

Extreme weather conditions are culprits of nearly 40% of large blackouts events [48], the performance of wind turbines plays a critical role in the overall voltage resilience of the system. However, these weather-sensitive generators are not evaluated directly in the previous voltage stability studies. Ref. [46] considers the LVRT/HVRT capability of DFIG as constraints for a VAR planning problem. In [40], the authors study the impact of reactive power capability of DFIG and its implications on the planning problem. However, these studies do not have a quantitative evaluation of the reactive power support from wind turbines. Besides, as an effective defensive measure to improve the dynamic voltage response of a wind-penetrated power system, the wind power curtailment, has not been considered.

As discussed in Chapter 2.3.2, neglect of the excitation system compensation (such as LDC) and the load shedding in a VAR planning problem might lead to conservative planning decisions because the operational countermeasures cost much less compared with the capital investment of FACTS devices. On the other hand, the development of advanced metering techniques and infrastructures provides operators with more flexible demand scheduling. The potential of DR [51], in terms of reducing the peak load, is explored in [52, 53] in generation and transmission planning problems, respectively.

Given different priorities in the planning and operational stages, as well as different characteristics of various operational mitigations, the resilience level is evaluated from different perspectives, instead of only focusing on the steady-state and short-term voltage stability performance.

To improve the inadequacies of the previous works, including the lack of

proper metrics for voltage resilience evaluation from different perspectives, neglect of the coordination between network enhancement measures and operational mitigations, optimizing steady-state and short-term voltage stability separately, and without a consideration of wind power generation and composite loads simultaneously, a multi-stage coordinated VAR planning method for voltage resilience enhancement of a wind-penetrated power system is proposed in this chapter. The key technical contributions of this method are as follows:

1) Since different planning and operation measures have their pros and cons, the effectiveness of these mitigations cannot be fully assessed by conventional stability indices alone. A set of novel quantitative resilience indices are developed to assess the voltage resilience performance before and after a contingency in a VAR planning problem, as well as evaluating the effectiveness and consequences of network enhancement and operation mitigations.

2) Compared with conventional methods, which are conservative for their neglect of operational countermeasures, network enhancement (VAR devices placement) and operational mitigations (defensive controls and restorative controls) are optimally coordinated in the planning framework for the enhancement of the voltage resilience of a power system and to avoid conservative planning decisions.

3) a multi-objective VAR planning optimization model is formulated. to optimally balance the tradeoff among three different aspects: a) monetary cost, including: planning cost and operation mitigations cost, b) defensive capability, and c) restorative performance.

3.2 Multi-stage coordination framework

In order to optimally coordinate both the planning and the operation stages to enhance voltage resilience, a multi-stage VAR planning framework is proposed in this chapter as shown in Fig. 3.1. It is quite similar to the multi-stage coordination framework proposed in Chapter 2.2, but with several improvements as explained below.

3.2.1 Planning resilience stage

Conventional capacitors and STATCOM are co-optimized to harden the network as a planning resilience improvement. They are mainly employed for steady-state and short-term voltage stability enhancement of the power system. Instead of only consider the fast-response STATCOM as Chapter 2, in this chapter, less effective but much more economical capacitor banks are also incorporated in the coordination framework.

The inputs consist of: 1) network data (including network structure, generation information, and load information), 2) candidate buses for the installation of VAR sources, 3) Demand response program, 4) load shedding setting, 5) selected critical contingencies, and 6) specific grid codes for wind power generation (if any). It should be noted that, apart from STATCOM and capacitor banks, other FACTS devices can also be considered based on the practical concerns, such as decision-makers' preference on the voltage stability performance or the total cost.

Figure 3.1 Multi-stage coordinated var planning framework for resilience

3.2.2 Operation resilience stage

To reduce the total investment and avoid conservative planning decisions, two sub-stages are introduced in the operation resilience stage in this chapter. The Defensive Control and the Restorative Control used in this chapter are similar to preventive control and corrective control used in Chapter 2, respectively. The different terminology used here is in compliance with the proposed resilience indices in this chapter.

3.2.2.1 Pre-contingency stage

In the pre-contingency stage, generation re-dispatch (including STATCOM), reactive power compensation strategy (such as LDC), wind power curtailment, and demand response are implemented as Defensive Control (DC) to increase the resilience level of the system before a contingency. The generation re-dispatch with the participation of STATCOM will optimize power flow and reduce the operating cost accordingly. LDC is utilized for a better voltage response during an emergency. Furthermore, with credible forecasting of weather conditions, wind power curtailment and DR can help the wind-penetrated power system survive the coming transient voltage disturbance. In this stage, the inputs include a set of critical contingencies and load forecast information.

3.2.2.2 Post-contingency stage

In the post-contingency stage, EDLS (event-driven load shedding) and RDLS (response-driven load shedding) are employed as Restorative Control (RC) to improve the capability of the system to restore to a new stable state after a voltage disturbance. Specifically, under voltage load shedding is triggered as an RDLS once the voltage is dropping below the lower threshold. On the other hand, since the RDLS is relatively slow, EDLS, which is activated instantly when a specific contingency occurs, is employed for a critical contingency with a serious detrimental impact on the voltage stability. The application of RDLS can compensate for the slow response of UVLS and improve the capability of the system to stop the potential propagation of instability or cascading events.

As discussed in Chapter 2, instantaneous costs for DCs and RCs are relatively low but its aggregate cost over a long time cannot be ignored. On the other hand, although the investment for STATCOM deployment is very high, the performance of STATCOMs is certainly better than that of other operation mitigations, in terms of both steady-state and dynamic voltage response. Therefore, coordination of planning and operation stages can reduce the overall investment while maintaining the voltage resilience of the system at a high level. Besides, DCs and RCs applied in the operation stage have much more flexible and short schedule/deployment time, compared with the long deployment time of STATCOMs.

Different planning and operation measures have their advantages and disadvantages. These measures are compared in the five aspects (in degrees from 1 to 5, the larger area indicates better performance in a specific aspect) as illustrated in Fig. 3.2: investment cost, deployment time, response time, steady-state, and short-term voltage stability improvement. Different characteristics of these measures bring challenges to the decision makers: a balance between the performance and the total capital investment. For instance, although STATCOM outperforms others in improving short-term voltage stability, its relatively long deployment time and high investment cost are not preferable. It will be very difficult to comprehensively evaluate the effectiveness of STATCOM installations, DCs, and RCs, due to different characteristics. On the other hand, conventional metrics, such as TVSI and VCPI used in Chapter 2, are usually designed for a generic voltage stability assessment and are no longer accurate enough if these different planning and operation measures are all implemented.

Figure 3.2 Comparison of characteristics of different measures

3.3 Voltage resilience indices

The different characteristics of these mitigations bring new a new challenge to the decision-makers: how to quantitatively evaluate the effectiveness of different mitigations and the overall performance of the wind-penetrated power system. So, in this chapter, a set of new voltage resilience indices is proposed in this chapter to assess the situation more accurately. Generally, considering

the different priorities in the planning and operation stages, the voltage resilience level is assessed from two perspectives: the defensive capability before a contingency and restorative performance after a contingency. All the indices are grouped based on the two perspectives and designed to be the smaller the better unless otherwise specified.

3.3.1 Defensive capability indices

3.3.1.1 Reactive power margin of DFIG

The maximum reactive power output of DFIG is usually modeled as a fixed value subject to the dynamic reactive power limits of the stator and the inverters of DFIG, as shown in Fig. 3.3.

Figure 3.3 Illustration of a general DFIG

For the stator, its reactive power regulation potential is mainly limited by the rotor current and the active power output [71], as illustrated in Fig. 3.4. Q_s^{max} is changing according to the active power output. For instance, the real-time reactive power capability of the stator, $Q_s^{s1,max}$, will decrease as the actual active power output (P^{s1}) approaching the maximum active power ($P^{s,max}$). The maximum and minimum stator reactive power can be calculated as in (3.1) and (3.2), respectively.

Figure 3.4 Active and reactive power limits of stator (DFIG)

$$Q^{s,max} = \frac{-3(U^s)^2}{X^s} + \sqrt{(3U^s \cdot X^m \cdot \frac{I_{r,max}}{X^s})^2 - (P^s)^2} \quad (3.1)$$

$$Q^{s,min} = -\frac{3(U^s)^2}{X^s} - \sqrt{(3U^s \cdot X^m \cdot \frac{I_{r,max}}{X^s})^2 - (P^s)^2} \quad (3.2)$$

As for the inverter, $Q^{inv,max}$ is mainly limited by the inverter capacity. It can be calculated as (3.3). As shown in Fig. 3.3, the maximum reactive power output of DFIG is determined by the stator side and grid side together. So, the maximum output can be calculated as the sum of $Q^{s,max}$ and $Q^{inv,max}$, as shown in (3.4). A larger margin of reactive power is favorable to the wind-penetrated power system when subjected to a voltage disturbance, as well as the wind turbine itself. Accordingly, an index RI^{margin} is proposed in this chapter as (3.5) to evaluate the reactive power margin of wind turbines quantitatively. It is calculated as the ratio of the difference between maximum possible reactive power output and the reactive power output before the contingency, and the maximum possible reactive power output. A larger margin to the maximum possible reactive power indicates a larger reactive power regulation capability while a smaller one means the reactive power regulation capability of a wind turbine is close to its maximum upper limit.

$$Q^{inv,max} = \sqrt{(P^{inv,max})^2 - (s \cdot P^s)^2} \quad (3.3)$$

$$Q^{w,max} = Q^{s,max} + Q^{inv,max} \quad (3.4)$$

$$RI^{margin} = \left(\sum_{w \in G_w} \frac{Q_w^{w,max}}{Q_w^{w,max} - Q_w^w} \right) / N^w \quad (3.5)$$

3.3.1.2 Wind power curtailment

Fig. 3.5 illustrates the impacts of an increasing wind power penetration level (installed wind power capacity as a percentage of total installed generation) on the voltage response after a contingency.

Figure 3.5 Impact of wind power penetration level on the voltage profile

When there is no wind power generation in the power system, the bus voltage can restore to a stable state quickly after the contingency. As the penetration level increases, the voltage response is becoming inferior and the recovery is slowing down. When the penetration level is increased to 45%, the bus voltage is unable to recover to a stable state after the contingency. So, an appropriate preventive wind curtailment is effective in enhancing voltage stability during a critical contingency. For instance, it can be implemented hours before the storms or other extreme weather conditions, since the forecast about these extreme weather conditions is usually with high credibility.

To quantitatively evaluate the effectiveness of the proactive wind power curtailment on helping the power system withstand a disturbance, a straightforward wind power curtailment index is proposed as (3.6).

$$RI^{curtail} = \frac{\sum_{w \in G_w} (\widetilde{P}_w - P_w^{curt})}{\sum_{w \in G_w} \widetilde{P}_w} \quad (3.6)$$

3.3.1.3 Dynamic var source margin

In this chapter, STATCOMs are also participating the generation dispatch as a reactive power source. So, the actual output of STATCOM is usually different from its rated capacity. Obviously, this capacity margin has its own impact on the voltage performance of the system during the voltage recovery process. RI^{dev} , calculated as the ratio of rated capacity to the capacity margin in (3.7), is proposed to assess this capacity margin. A smaller RI^{dev} indicates a higher potential for reactive power output after a contingency.

$$RI^{dev} = \sum_{i \in \mathcal{B}_s} \sum_{i \in \mathcal{B}_s} Q_i^{statrated} / (Q_i^{statrated} - Q_i^{stat}) \quad (3.7)$$

3.3.1.4 Load shifting due to DR program

After a critical contingency, an accurate forecast of the peak load is important since the power system is generally in a state of deficiency of active power and reactive power. On the other hand, the impact of load shifting after a demand response is rarely addressed. Since the responded loads will be restored later, there is a chance that the restoration will lead to a new peak load (larger than the original one), as illustrated in Fig. 3.6.

Figure 3.6 Impact of DR shifting on the peak load after a contingency

$RI^{DRshift}$ is proposed to quantitatively assess the potential peak load shifting in the recovery process after a contingency. It can be calculated as (3.8). A smaller $RI^{DRshift}$ is favorable since it indicates a lower possibility to create a higher peak load after the responded load is restored.

$$RI^{DRshift} = \sum_{k \in \mathcal{K}} \sum_{m \in \mathcal{M}} DR_{m,k}^{shift} \cdot p_k \quad (3.8)$$

$$DR_{m,k}^{shift} = \begin{cases} (DR_k^{res} + P_m^{pred})/P^{peak}, & DR_k^{res} + P_m^{pred} > P^{peak} \\ 0, & \text{otherwise} \end{cases} \quad (3.9)$$

$$DR_k^{res} = \sum_{i \in \mathcal{B}_{DR}} P_{i,k}^{DR} \cdot \epsilon \quad (3.10)$$

3.3.1.5 Steady-state voltage stability

A line based VCPI [59] used in Chapter 2 is also employed here to quantify the steady-state voltage stability of a power system. So, RI^{VCPI} is calculated based on (2.21) and (2.22) as a probability-weighted sum of VCPIs of all the lines as (3.11).

$$RI^{VCPI} = \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} VCPI(power)_l \cdot p_k \quad (3.11)$$

3.3.2 Restorative performance indices

3.3.2.1 Wind turbine voltage violation

As part of the protection mechanism, wind turbines will experience forced cut-off temporarily if there are several moderate low voltage dip incidents, even these voltage dips are actually above the LVHT threshold, within a short transient period after a voltage disturbance [4]. So, RI^{WV} is proposed in this chapter to assess this cut-off potential when the wind turbines are subjected to minor but more frequent voltage dips. It can be calculated as (3.12). WTVI is a transient voltage deviation index for buses with wind turbines (grid codes of these buses might be different from the buses without wind turbines), evaluating the extent of voltage violation after a contingency, based on voltage trajectories from time-domain simulation.

$$RI^{WV} = \sum_{k \in \mathcal{K}} \frac{\sum_{w \in \mathcal{G}_w} \sum_{t \in [T^c, T^{end}]} WTVI_{w,t}}{N^w} \cdot p_k \quad (3.12)$$

$$WTVI_{w,t} = \begin{cases} \frac{|V_{w,t} - V_{w,t0}|}{V_{w,t}}, & \frac{|V_{w,t} - V_{w,t0}|}{V_{w,t}} \geq \delta_w, \forall t \in [T^c, T^{end}], \forall w \in \mathcal{B}_w \\ 0, & \text{otherwise} \end{cases} \quad (3.13)$$

3.3.2.2 Short-term voltage stability

TVSI is proposed in [37] and also successfully used in Chapter 2 to assess the short-term voltage performance. However, since TVSI adopts a direct averaging method, it cannot fully reveal a slow voltage recovery of a specific bus if the recovery speed of others is relatively fast. To improve this shortcoming, A root-mean-square method [72] is used in this chapter to evaluate the voltage performance in a more accurate way as (3.14), with the consideration of probabilities of different contingencies. TVDI is defined as (3.15), which is similar to (2.19). Like TVSI, a smaller RI^{RVSI} is favorable since it indicates fewer voltage violation and faster voltage recovery.

$$RI^{RVSI} = \sum_{k \in \mathcal{K}} \sqrt{(\sum_{i \in \mathcal{B}} \sum_{t \in [T^c, T^{end}]} TVDI_{i,t})^2 / N^b \cdot p_k} \quad (3.14)$$

$$TVDI_{i,t} = \begin{cases} \frac{|V_{i,t} - V_{i,t0}|}{V_{i,t}}, & \frac{|V_{i,t} - V_{i,t0}|}{V_{i,t}} \geq \delta \\ 0, & \text{otherwise} \end{cases} \quad \forall t \in [T^c, T^{end}], \forall i \in \mathcal{B} \quad (3.15)$$

3.3.2.3 Rotor angle deviation

Conventionally, the rotor angle is considered as a constraint, such as (2.29). The constraint can only provide binary information about the transient stable state, while there is a huge difference between a very stable state and a marginal one. RI^{angle} , the ratio of maximum rotor angle deviation to the rotor angle threshold, is proposed to quantitatively evaluate the rotor angle deviation during a restoration, as calculated in (3.16). A smaller RI^{angle} is favorable because it indicates that there is a larger distance between the actual rotor angle deviation and the constraint.

$$RI^{angle} = \sum_{k \in \mathcal{K}} \max(\Delta\delta_{gg'}) \cdot p_k / \omega \quad (3.16)$$

3.3.2.4 Load loss

$RI^{loadloss}$ is used to indicate the total load loss, including RDLS, EDLS and demand response. Considering the probabilities of different contingencies, it can be calculated as (3.17). $RI^{loadloss}$ is helpful in coordinating DR, load shedding and other voltage stability countermeasures.

$$RI^{loadloss} = \sum_{k \in \mathcal{K}} (\sum_{i \in \mathcal{B}_{EDLS}} x_{i,k} + \sum_{i \in \mathcal{B}_{RDLS}} x_{j,k} + \sum_{i \in \mathcal{B}_{DR}} P_{i,k}^{DR} \cdot \epsilon) \cdot p_k \quad (3.17)$$

3.4 Mathematical formation

The compact mathematical model of this multi-objective VAR planning problem is similar to the proposed model in Chapter 2, (2.1-2.5). The details of

the model are expanded as follows. The modeling of dynamic loads and wind power uncertainty in this chapter follows the same principle described in Chapter 2.3. So, they won't be covered here.

3.4.1 Objective functions

3.4.1.1 Total planning cost (f_1)

Total planning cost f_1 is calculated as (3.18). It includes investment cost and operating cost. The operating cost consists of defensive control cost and restorative control cost.

$$f_1 = \underbrace{C^{invest}}_{\text{investment cost}} + \underbrace{C^{re-dis} + C_w^{curtail} + C^{DR}}_{\text{defensive control cost}} + \underbrace{C^{EDLS} + C^{RDLS}}_{\text{restorative control cost}} \quad (3.18)$$

1) Investment cost

The investment cost is calculated as (3.19) [J4], consisting of installation costs for fixed capacitor banks and STATCOMs. The installation decision at a specific candidate bus is implicitly determined by the installed capacity as (3.21).

$$C^{invest} = \sum_{i \in \mathcal{B}_s} C_i^{invest_s} + \sum_{j \in \mathcal{B}_c} C_j^{invest_c} \quad (3.19)$$

$$C_j^{invest_c} = c^{cap_c} \cdot cap_j \quad (3.20)$$

$$C_i^{invest_s} = \begin{cases} c_i^{install} + c^{cap_s} \cdot cap_i, & \text{if } cap_i \neq 0 \\ 0, & \text{if } cap_i = 0 \end{cases} \quad (3.21)$$

2) Defensive control cost

Four defensive controls are considered in this chapter. First, wind power curtailment before a critical contingency is optimized to avoid aggressive curtailment or a conservative one. The curtailment cost is calculated as (3.22) [J4].

$$C^{curt} = \sum_{w \in \mathcal{G}_w} C_w^{curt} = \sum_{w \in \mathcal{G}_w, k \in \mathcal{K}} C^{curt} \cdot P_w^{curt} \cdot t^c \cdot p_k \quad (3.22)$$

With curtailment decisions for each wind farm, synchronous generators will be re-dispatched along with the dispatchable STATCOMs. The corresponding cost is calculated as (3.23) [J4], which is the difference between the new operating state (optimized) and the original state.

$$C^{re-dis} = C^{gen}(x^{ori}, u^{ori}) - C^{gen}(x^{opt}, u^{opt}) \quad (3.23)$$

$$C^{gen} = \sum_{g \in \mathcal{G}_s} (a_g + b_g \cdot P_g + c_g \cdot P_g^2) \cdot t^a \quad (3.24)$$

The 3rd defensive control is Line Drop Compensation. It is also adopted in Chapter 2 and its cost is negligible compared to other mitigations.

The last defensive control is demand response. In this chapter, paper incentive-based DR [53] is employed because it has a relatively higher response rate compared with the price-based DR. This characteristic is advantageous when the operators of the system are expecting an extreme condition. The cost of DR is calculated as (3.25) [J4]:

$$C^{DR} = \sum_{n \in \mathcal{B}_{DR}, k \in \mathcal{K}} cap_{n,k}^{DR} \cdot t_n^{DR} \cdot c_{n,t}^{DR} \cdot \epsilon \cdot p_k \quad (3.25)$$

The total defensive control cost can be calculated as (3.26) [J4] since the cost of LDC is negligible compared with DR and generation re-dispatch.

$$C^{DC} = C^{curt} + C^{re-dis} + C^{DR} \quad (3.26)$$

3) Restorative control cost

Given the potential quick propagation of short-term voltage instability in a wind-penetrated power system with a high portion of induction motor loads, event-driven load shedding is used together with under voltage load shedding

to help the system restore to a stable state. Therefore, restorative control cost can be calculated as (3.27) [J4], where $C_{i,j}$ is the cost function for different load types. For a practical description of differentiated impacts of loads on the voltage response after a contingency, three load shedding cost functions (linear, quartic, and sigmoid) are used and their mathematical details can be found in Chapter 2.3.2.3.

$$C^{EDLS} + C^{RDLS} = \sum_{i \in \mathcal{B}_{EDLS}, k \in \mathcal{K}} C_i(x_{i,k}) \cdot p_k + \sum_{j \in \mathcal{B}_{RDLS}, k \in \mathcal{K}} C_j(x_{j,k}) \cdot p_k \quad (3.27)$$

3.4.1.2 Resilience indices of defensive capability (f_2)

The 2nd objective function is a weighted sum of the indices RI^{margin} , $RI^{curtail}$, RI^{dev} , $RI^{DRshift}$ and RI^{VCPI} as (3.28) [J4]. The determination of weighting factors will be explained in Chapter 3.4.1.4.

$$f_2 = RI^{margin} \cdot \alpha_1 + RI^{curtail} \cdot \alpha_2 + RI^{dev} \cdot \alpha_3 + RI^{DRshift} \cdot \alpha_4 + RI^{VCPI} \cdot \alpha_5 \quad (3.28)$$

3.4.1.3 Resilience indices of restorative performance (f_3)

The 3rd objective function is a weighted sum of the indices RI^{WV} , RI^{RVSI} , RI^{angle} and $RI^{loadloss}$ as (3.29) [J4]. The determination of weighting factors will be explained in Chapter 3.4.1.4.

$$f_3 = RI^{WV} \cdot \beta_1 + RI^{RVSI} \cdot \beta_2 + RI^{angle} \cdot \beta_3 + RI^{loadloss} \cdot \beta_4 \quad (3.29)$$

3.4.1.4 Determination of indices weighting parameters

In a practical application, the weighting factors α and β in (3.28) and (3.29) should be determined based on the following two aspects:

1) Empirical priorities of the indices in a practical planning problem. These priorities are usually determined according to the experts' judgment on their importance and the corresponding operational requirements.

2) Sensitivity analysis of the indices. It is used to figure out the range of

potential index variations when subjected to different scenarios and uncertainties.

The empirical priorities adopted in this chapter are illustrated in Fig. 3.7 (a larger area of the pie means a higher priority). Then, All-At-a-Time (AAT) method is used to carry out the sensitivity analysis. The output variations (numerical variation of indices) are obtained by changing all the inputs (the capacities of STATCOMs) simultaneously. By using AAT, both the direct impact of increasing capacity and joint impact of interactions among STATCOMs installed at different buses. Finally, with empirical priorities and the results of sensitivity analysis, α and β can be determined. A typical example is presented as follows:

1) Determine the priorities based on the empirical estimations of their importance and the corresponding operational requirements. RI^{margin} , $RI^{curtail}$, RI^{dev} , $RI^{DRshift}$, and RI^{VCPI} are assigned with priorities α_{1a} , α_{2a} , α_{3a} , α_{4a} , and α_{5a} , while RI^{RVSI} , RI^{wv} , RI^{angle} , and $RI^{loadloss}$ are assigned with β_{1a} , β_{2a} , β_{3a} , and β_{4a} . For instance, $\alpha_{1a} = 20\%$, $\alpha_{2a} = 15\%$, $\alpha_{3a} = 10\%$, $\alpha_{4a} = 15\%$, and $\alpha_{5a} = 40\%$; $\beta_{1a} = 50\%$, $\beta_{2a} = 20\%$, $\beta_{3a} = 20\%$, and $\beta_{4a} = 10\%$.

2) Increase the capacities of STATCOMs (2 MVAR a step) from 0 MVAR to 100 MVAR simultaneously.

3) Normalize the original evaluation results. Then, compute the variation range of each index with the priorities. For example, the variation range of " $RI^{RVSI} \cdot \beta_{1a}$ ".

4) Adjust the results obtained from step 3) by multiplying a group of parameters ($\alpha_{1b} \sim \alpha_{5b}$ and $\beta_{1b} \sim \beta_{5b}$). This is to avoid the situation that the values of f_2 and f_3 are largely determined by some very sensitive indices, even these indices are actually with relatively low priorities in step 1).

5) Calculate the α and β . For instance, $\alpha_1 = \alpha_{1a} \cdot \alpha_{1b}$, $\beta_1 = \beta_{1a} \cdot \beta_{1b}$.

Figure 3.7 Illustration of priorities assigned to different indices.

3.4.2 Constraints

Pre-contingency constraints are the power flow balance constraints as in (3.30) and steady-state operational constraints in (3.31). Constraint (3.32) is the wind curtailment constraint determined by the operators with a modified curtailment ratio.

$$\begin{cases} P_g + \widetilde{P}_w - P_w^{curt} - P_d - V_i \sum_{j \in \mathcal{B}} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \\ Q_g + \widetilde{Q}_w + Q^{capacitor} + Q^{stat} - Q_w^{curt} - Q_d - V_i \sum_{j \in \mathcal{B}} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \end{cases} \quad (3.30)$$

$$\begin{cases} V_i^{min} \leq V_i \leq V_i^{max} \\ L_l^{min} \leq L_l \leq L_l^{max} \\ P_g^{min} \leq P_g \leq P_g^{max} \\ Q_g^{min} \leq Q_g \leq Q_g^{max} \end{cases}, \forall i \in \mathcal{B}, \forall l \in \mathcal{L}, \forall g \in \mathcal{G} \quad (3.31)$$

$$\sum_{w \in \mathcal{G}_w} P_w^{curt} \leq \sum_{w \in \mathcal{G}_w} \widetilde{P}_w \cdot W^c, \quad \forall W^c \in [0,1] \quad (3.32)$$

Constraint (3.33) is the rotor angle stability constraint (transient stability). It is used to guarantee that the maximum rotor angle difference between any 2 generators during a transient period of T is no larger than ω . Constraints for LVHT/HVRT are modeled as (3.34). Constraint (3.35) is a constraint for voltage recovery speed, indicating that the time of a bus voltage under the voltage threshold (like 0.9 pu) should be no more than the maximum allowed time. Constraint (3.36) and (3.37) are constraints for event-driven load shedding and

response-driven load shedding, respectively. Constraint (3.38) is the demand response constraint, indicating that the responded loads before a contingency should be equal to the shifted loads after the contingency. Furthermore, the responded loads are also limited by the maximum loads participated in DR program as (3.39).

$$[\max(\Delta\delta_{gg'}^T)]_k \leq \omega \quad \forall g, g' \in \mathcal{G}_s, \forall k \in \mathcal{K} \quad (3.33)$$

$$\begin{cases} V_{i,t} - LVRT(t) \geq 0, & \forall t \in \mathcal{T}, \forall i \in \mathcal{B} \\ V_{i,t} - HVRT(t) \leq 0, & \forall t \in \mathcal{T}, \forall i \in \mathcal{B} \end{cases} \quad (3.34)$$

$$T_i^r - T^c \leq T^{max}, \quad \forall i \in \mathcal{B} \quad (3.35)$$

$$x_{i,k} + x_{j,k} \leq P_i^{LS,max}, \quad \forall i \in \mathcal{B}_{EDLS}, \forall j \in \mathcal{B}_{RDLS}, \forall k \in \mathcal{K} \quad (3.36)$$

$$x_{j,k} \leq P_j^{LS,max}, \quad \forall j \in \mathcal{B}_{RDLS}, \forall k \in \mathcal{K} \quad (3.37)$$

$$\sum_{n \in \mathcal{B}_{DR}} P_n^{DR} \cdot \epsilon = \sum_{n \in \mathcal{B}_{DR}} P_n^{DRshift} \quad (3.38)$$

$$P_n^{DR} \cdot \epsilon \leq P_n^{DR,max}, \quad \forall n \in \mathcal{B}_{DR} \quad (3.39)$$

3.4.3 Candidate buses selection

To reduce the computation burden of a VAR planning problem, candidate buses should be selected before capacity optimization. In this chapter, an LHS-based Morris Screening method is developed to select the most influential buses for STATCOMs installation, aiming to alleviate the computation complexity of the planning optimization problem. Morris Screening method [73] is originally proposed to identify the most influential parameters by creating a multi-dimensional semi-global trajectory within its search space. Compared with local trajectory analysis, it is more accurate [127]. On the other hand, it is also more time-efficient than the time-consuming global sensitivity analysis. Although LHS might not be so advantageous in high-dimensional problems, it is still effective for the studied VAR planning problem since this thesis adopts the

assumption of the area-based approach (as discussed in Chapter 1.4) for a VAR planning.

Firstly, LHS is used to generate random samples following the normal distribution. Compared with simple random sampling or uniform sampling, LHS is a better representative of the real variability. Then, one variable at a time will be changed at a step of Δ_m (the step is determined based on the LHS results). So, an elementary effect of a Δ_m change is calculated as (3.40).

$$EE_{i,m} = \frac{f(\alpha_{i,m} + \Delta_m) - f(\alpha_{i,m})}{\Delta_m}, \forall i \in \mathcal{B}_d, m = 1, \dots, N^m \quad (3.40)$$

$f(\alpha_{i,m})$ is an evaluation result when a STATCOM with a specific capacity ($\alpha_{i,m}$, determined by LHS) installed at a candidate bus. In this chapter, RI^{RVSI} is chosen as the criterion for STATCOM candidate bus selection since it is mainly responsible for the post-contingency voltage restoration and RI^{VCPI} is employed to select candidate bus for capacitors because capacitors only improve the steady-state voltage stability of the power system. Then, the mean (μ^*) of the elementary effects are calculated as (3.41). It represents the sensitivity strength between the input (different buses with different STATCOM/capacitor capacities) and the output (RI^{RVSI} or RI^{VCPI}). The standard deviation (σ_i^*), which is calculated as (3.42), represents the interaction between different variables.

$$\mu_i^* = \left(\sum_{m=1}^{N^m} |EE_{i,m}| \right) / N^c \quad (3.41)$$

$$\sigma_i^* = \sqrt{\left(\sum_{m=1}^{N^m} (|EE_{i,m}| - \mu_i^*)^2 \right) / N^c} \quad (3.42)$$

A smaller μ_i^* indicates that the deployment reactive power compensation devices at i^{th} bus has a relatively lower effect on the power system, in terms of RI^{RVSI} or RI^{VCPI} . On the other hand, a larger σ_i^* indicates a nonlinear effect on RI^{RVSI} or RI^{VCPI} and it has higher interactions with other buses. As shown in Fig. 3.8, there are four scenarios according to the values of the (μ_i^*, σ_i^*) pair:

Figure 3.8 mean and the standard deviation of the elementary effects

1) small values for both μ_i^* and σ_i^* imply that a deployment of reactive power source at i^{th} bus has a low and linear effect on the system (red squares).

2) a small value for μ_i^* and a large value for σ_i^* implies that a deployment of reactive power source at i^{th} bus has a low but nonlinear effect on the system (blue star).

3) a large value for μ_i^* and a small value for σ_i^* implies that a deployment of reactive power source at i^{th} bus has a high and linear effect on the system (green triangles).

4) large values for both μ_i^* and σ_i^* imply that a deployment of reactive power source at i^{th} bus has a high but non-linear effect on the system (yellow circles).

Therefore, the buses with high and linear impact are the best candidate buses. However, in practice, if the ideal candidate buses are insufficient or even no such bus at all, the high and non-linear impact can also be selected as candidate buses.

3.4.4 Contingency selection

To identify the critical contingencies, RI^{RVSI} or RI^{VCPI} are calculated for each contingency on a typical operation state. Pareto optimality theory [62] is employed here to find the trade-off solutions between RI^{RVSI} or ΔRI^{VCPI} (difference of RI^{VCPI} before and after a contingency). As discussed in Chapter

2, for a feasible solution space, a Pareto Optimal solution is a solution of which objective values (RI^{RVSI} or ΔRI^{VCPI}) cannot be improved without impairment of the other objective values. The Pareto front, consisting of a set of Pareto Optimal solutions, is illustrated in Fig. 3.9. For each N-1 3-phase short-circuit contingency, RI^{RVSI} or RI^{VCPI} are calculated according to equ. (3.11) and equ. (3.14), respectively. Then, contingencies can be scattered in the distance space of the RI^{RVSI} and the increment of RI^{VCPI} (ΔRI^{VCPI} , compared with the pre-contingency operating condition). Critical contingencies are non-dominated (blue) points as illustrated in Fig. 3.9 and they are more severe than dominated (black) ones.

Figure 3.9 Pareto Front for the contingency analysis

3.4.5 Coding rules

The coding rules adopted in this chapter is similar to the one used in Chapter 2. As illustrated in Fig. 3.10, control variables include installation decisions, wind power curtailment, and DR scheme.

Figure 3.10 An individual code structure

3.5 Solution method

Like Chapter 2, NSAG-II is also used in this Chapter to find the Pareto Front. Details of NSGA-II can be found in Chapter 2.4.2. Since “higher resilience

performance” always conflicts with “lower cost”, a group of trade-off solutions can be generated to satisfy the practical needs of the decision-makers. Fig. 3.11 shows the computation flowchart of the proposed method. Detailed computation steps are described as follows:

1) Initialization

after the algorithm parameters setting, candidate buses are selected according to Chapter 3.4.3. Then, the first generation of the population is generated. Each individual consists of decision variables for STATCOMs, capacitor banks, DR, and wind power curtailment, as illustrated in Fig. 3.10.

2) Pre-contingency OPF and defensive capability evaluation

Defensive controls are implemented in the pre-contingency stage. Two OPF calculations under different scenarios are carried out. The first one is without defensive controls and the second one is with both defensive controls and the dispatchable STATCOM. With the OPF results, RI^{margin} , $RI^{curtail}$, RI^{dev} , $RI^{DRshift}$, and RI^{VCP} are calculated. The defensive controls cost is also calculated for the total cost calculation.

3) Time-domain simulation, and resilience performance evaluation

time-domain simulations are conducted in this stage. Specifically, load shedding (restorative controls) is activated if: pre-determined voltage thresholds are violated (as under voltage load shedding), or one of the predetermined critical contingencies occurs (as event-driven load shedding). The individuals of the population generated by NSGA-II are verified under different LDC parameters, wind power generation scenarios, and critical contingencies. After all the scenarios are checked, RI^{RVSI} , RI^{wv} , RI^{angle} , and $RI^{loadloss}$ are calculated. Restorative control cost is also calculated for the calculation of total investment.

Figure 3.11 Computation flowchart

4) Objective calculations

The total investment and voltage resilience indices (including defensive capability indices and resilience performance indices) are calculated in a risk-based manner with different contingency probabilities.

5) Individual update

Find and update the best individual of the current generation.

6) Termination

If one of the following stopping criteria is satisfied, the main procedure will be terminated and a Pareto Front will be presented: a) reached the maximum iteration number, or b) variations in the fitness function is smaller than or equal to a pre-determined tolerance.

7) Offspring generation

If the stopping criteria are not satisfied, the new offspring of the current generation will be generated. Then, the computation procedure will go back to step 2. Typical operations for the offspring generation include mutation,

recombination, and crossover [62].

8) Break criteria

the evaluation of each individual will be terminated if any post-contingency constraint is violated and the cost objectives will be calculated with high penalty parameters. Then, the new offspring of the current generation will be generated, and the computation procedure will go back to step 2.

3.6 Numerical results and discussions

3.6.1 Test systems and parameter settings

Figure 3.12 New England 39 buses test system

The proposed method is tested on a modified New England 39-bus system as illustrated in Fig 3.12. It has the same modification adopted in Chapter 2.5.1 and the models for DFIG, STATCOM, and synchronous generators are also the same ones adopted in Chapter 2.5.1. The short-term load forecast data (used in (3.8-3.10) for $RI^{DRshift}$) is from reference [74]. In practice, load forecast data can be obtained from artificial neural network based methods, such as the one proposed in reference [75]. CLOD model is also used in this chapter. Other important parameters are listed in Table 3.1. Based on Chapter 3.4.4, faults on

line 2-3, line 6-7, and line 16-24 are selected as three critical contingencies. MATPOWER 6.0 [67] is used to solve OPF. The time-domain simulation is carried out using PSS®E 33.4 (through an interface with Matlab). NSGA-II is implemented in Matlab 2018b. The case studies are carried out on a laptop workstation, with Intel®Core™ i7-8750H CPU @ 4.6GHz and 32GB DDR4 2400MHz RAM.

Table 3.1 Parameters for simulation setting

Parameters	Value Settings
$c^{install}, c^{cap_s}$	1.5 million/unit, 0.05 million/Mvar
c^{cap_c}	1400 US dollar/Mvar
$u^{1st}, u^{2nd}, u^{3rd}$	5% each at 0.9 pu, 0.85 pu and 0.8 pu
W^c	15% of Original Load
$c^{curtail}$	8/MWh
t^c, t^a	4 Hours, 4500 Hours
ω, δ	$\pi, 0.1$
LHS levels	20 (0~100Mvar)
LM, SM, DL, CP, K_p	25%, 15%, 10%, 10%, 2
NSGA II population & generation	100 and 15
NSGA II tolerance	1.0×10^{-3}
NSGA II mutation probability	0.06
NSGA II crossover rate	0.8
Fault setup	3-phase short-circuit (cleared after 0.1s)

3.6.2 Simulation results and comparisons

The overall computation time is 62046s (17.235 hours), including 2912s for the candidate bus selection and 59134s for the main optimization process. In Fig. 3.12, buses with triangles marks are candidate buses for STATCOMs and buses with circle marks are candidate buses for capacitor banks. As illustrated in Fig. 3.13, the STATCOM candidate buses are selected because of their relatively high values of μ . As for the conventional sensitivity analysis method, it only considers the direct impact. In this case, if more candidate buses (for

instance, 5 buses) are required, it would be quite difficult to select one from the buses in the dashed square as illustrated in Fig. 3.13, since these buses are very close to each other on the x-axis. By using Morris Screening method, the four buses are distinguishable at the y-axis (σ) since their non-linearity is different. So, the 5th candidate bus (if needed) can be selected as the one at the bottom of the dashed square.

Figure 3.13 Candidate bus selection results for STATCOMs

A Pareto Front is obtained and shown in Fig. 3.14. These are 42 tradeoff solutions and these solutions are more valuable and practical than a single optimized result because they can support a cost-effective balanced decision.

Fuzzy membership function [68] is also used here like Chapter 2 to select a compromise solution. The compromise solution is marked in Fig. 3.14 and the installation plan of this solution is listed in Table 3.2. For each Pareto optimal solution x_p , its satisfactory degree for f^h objective function, and the satisfactory degrees for all objective functions can be expressed as (3.43) and (3.44). The solution with the largest μ^p (0.0159) is selected as the fuzzy membership result.

$$\mu_f^p = \frac{f_f^{max} - f_f(x_p)}{f_f^{max} - f_f^{min}} \quad (3.43)$$

$$\mu^p = \frac{\sum_{f \in [1,2,3]} \mu_f^p}{\sum_{p \in \mathcal{P}} \sum_{f \in [1,2,3]} \mu_f^p} \quad (3.44)$$

Figure 3.14 Pareto optimal solutions

Table 3.2 Installation decisions (MVAR, 11 candidate buses)

Bus	STATCOM							Capacitor Bank			
	16	21	23	24	30	32	34	1	3	8	15
Mvar	86.2	17.2	21.8	94.0	31.6	87.8	76.0	12.2	13.1	12.0	10.4

Table 3.3 Compromise solutions

Objectives	Total Cost (\$)	Defensive Capability	Restorative Performance
11-bus	32.35m	0.4650	1.062
15-bus	37.93m	0.4771	1.073

Table 3.4 Installation decisions (MVAR, 15 candidate buses)

Bus	STATCOM											Capacitor Bank			
	7	8	16	18	21	23	24	27	30	32	34	1	3	8	15
Mvar	9.4	4.2	85.3	4.8	27.7	33.1	72.3	8.3	39.3	72.2	70.5	17.0	10.0	11.9	12.6

The wind curtailment for wind farms at bus 30, bus 32, and bus 34 are 0.90%, 0.41%, and 5.16%, respectively. Table 3.3 shows the values of the three objectives. The defensive capability and restorative performance indices of the original system (base case) are 0.962 and 1.871. After the deployment of STTACOMs and the implementation of DCs and RCs, the 2 indices are improved by 51.6% and 43.2%, respectively.

To demonstrate the effectiveness of the candidate bus selection method proposed in this chapter, four more buses are selected (the buses in the dashed box in Fig.3.13) as additional candidate buses for a comparison. The compromise solution of this 15-bus case (11 buses + 4 additional buses) is listed in Table 3.3 and the corresponding installation plan is listed in Table 3.4. It can be concluded from the two tables that the additional 4 buses are redundant, because: 1) the performance of 15-bus case is inferior to that of the 11-bus case, and 2) the total cost of the 15-bus case is even higher than that of the 11-bus case. On the other hand, the optimized capacities of the additional buses (bus 7, 8, 18, and 27) are much smaller than that of buses in Table 3.2.

Table 3.5 Robust design comparison

Uncertainty Modeling	Defensive Capability	Restorative Performance	Total Numbers of Scenarios
TOAT	0.4650	1.062	4
Monte Carlo	0.4651	1.060	100

To demonstrate the advantages and the effectiveness of TOAT, which is also used in Chapter 2, the Monte Carlo method (100 wind power generation scenarios) is implemented as a comparison. The numerical results are in Table 3.5. These two methods have similar performance, in terms of defensive capability and restorative performance results. But the proposed method only uses 4 scenarios, which significantly alleviate the computation burden of the planning problem without any deterioration of the performance.

To further demonstrate the advantages of the proposed method, five methods and a base case are compared in Table 3.6.

1) **Method A:** The proposed method with the proposed resilience indices. The solution is a compromise solution.

2) **Method B:** The proposed method with conventional indices (*TVSI* & *VCPI*). The solution is also a compromise solution.

3) **Method C:** The proposed method with conventional indices (*TVSI* & *VCPI*). It is the same with Method B, but the solution is selected from the Pareto Front based on resilience performance.

4) **Method D:** The proposed method with the proposed resilience indices (same with method A). But the solution is selected from the Pareto Front based on investment cost.

5) **Method E:** It is the conventional method (considers only the deployment of STATCOMs and capacitor banks) based on the *TVSI* and *VCPI*. The solution is a compromise solution.

Table 3.6 Comparison results (MVAR, MW & Million)

Method	Total Capacity		Total LS (MW)	Total DR (MW)	Total Cost (million)	Defensive capability	Restorative performance
	Capacitor banks (MVAR)	STATCOM (MVAR)					
A	47.7	414.7	146.0	30.1	32.35	0.4650	1.062
B	88.2	445.6	141.7	31.0	33.93	0.5569	1.095
C	92.6	504.7	148.5	67.6	37.00	0.4741	1.094
D	45.7	411.5	146.5	30.0	31.34	0.5364	1.073
E	58.1	490.0	-	-	35.08	0.4922	1.099
Base	-	-	-	-	-	0.9615	1.871

As illustrated in Fig. 3.1, method E (conventional method) only considers the planning stage countermeasures (installation of STATCOMs). Its planning decisions are relatively conservative compared with the proposed method. As in Table 3.6, the total cost of method E is 8.44% higher than that of method A and at the same time both the defensive capability and restorative performance of method E are inferior to those of method A. On the other hand, even with the implementation of operational control measures, the conventional voltage metrics (*TVSI* and *VCPI*) are no longer adequate for a comprehensive evaluation of the voltage performance before and after a contingency. For instance, although DCs and RCs are implemented in method A and method B, method A still has better resilience results in terms of defensive capability and restorative performance, improved by 16.50% and 3.01%, respectively. At the same time, the total cost of method A is 1.58 million less than that of method B.

Another disadvantage of using the conventional *TVSI* and *VCPI* is that the load shedding and demand response is not directed evaluated, although they

are both implemented as the control measures to mitigate the reactive power deficiency after a voltage disturbance. This might make the load shedding and the demand response aggressive or conservative. For an aggressive scheme, although load shedding or demand response will be helpful in the voltage recovery process, the cost is too high. On the other hand, the installation capacity of STATCOMs will be large if the load shedding or demand response is too conservative. For instance, as listed in Table 3.6, the load shedding and DR of method C (the conventional metrics) is higher compared with those of method A (the proposed metrics), while the resilience evaluation results of method C are still inferior to that of method A.

Fig. 3.15 shows the voltage trajectory of bus 24 after a critical line contingency. It is clear method A has a faster voltage recovery than method B. Once the fault is cleared, method A experiences an acceleration of voltage recovery while the recovery speed of method B is relatively slow. Furthermore, two cross points of the two trajectories indicate that method A is with a smaller fluctuation after restoring to the acceptable voltage range. This voltage trajectories comparison is consistent with the performance results listed in Table 3.6. Two more critical contingencies are also compared in Fig. 3.16 (fault on line 2-3) and Fig. 3.17 (fault on line 6-7). Similar to the case in Fig. 3.15, method A outperforms method B under both contingencies.

Figure 3.15 Post-contingency voltage response (fault on line 16-24) at bus 24

Figure 3.16 Post-contingency voltage response (fault on line 2-3) at bus 24

Figure 3.17 Post-contingency voltage response (fault on line 6-7) at bus 24

Table 3.7 summarizes RI^{RVSI} results in different wind power generation scenarios for all critical contingencies. Compared with method B, method A has better results in all representative scenarios. On the other hand, the performance improvement of these three critical contingencies is relatively large (average improvement 2.914%) compared with other contingencies (average improvement 0.890%), which demonstrates that the contingencies selected are representative and adequate for the contingency analysis in this problem.

Fig. 3.18 further demonstrates that why TVSI and VCPI are insufficient for a comprehensive voltage resilience evaluation of the power system. When there is an $N-2$ contingency in the system (wind turbines at bus 30 and bus 32 are forced off-line), which is not included in the contingency analysis in both

methods, the voltage of bus 8 becomes unstable at 1.3s with method B and it still remains stable with method A. This is because method A has a better evaluation result of RI^{angle} (as listed in Table 3.8), which means there is a larger margin in terms of the distance away from the edge of rotor angle instability. On the other hand, Method A also outperform method B in $RI^{curtail}$, which indicates a lower penetration level during the voltage recovery stage.

Table 3.7 RI^{RCSI} results comparison

contingency/method		scenario 1	scenario 2	scenario 3	scenario 4
Line 16-24	Method A	0.343	0.388	0.371	0.375
	Method B	0.352	0.401	0.379	0.381
	improvement	2.62%	3.35%	2.16%	1.60%
Line 2-3	Method A	0.344	0.389	0.372	0.375
	Method B	0.352	0.402	0.379	0.382
	improvement	2.33%	3.34%	1.88%	1.87%
Line 6-7	Method A	0.334	0.377	0.361	0.363
	Method B	0.347	0.396	0.374	0.375
	improvement	3.89%	5.04%	1.93%	3.31%

Figure 3.18 Post-contingency (N-2) voltage response at bus 8

Table 3.8 Details of resilience evaluation results

Method	$RI^{curtail}$	$RI^{DRshift}$	RI^{VCPI}	RI^{angle}	RI^{RVSI}
A	0.1136	0.070	0.1236	0.0628	0.6455
B	0.1870	0.072	0.1125	0.0757	0.6713

3.6.3 Scalability and computation efficiency discussion

Due to the highly non-linear and non-convex features, as well as the time-consuming time-domain simulations, the VAR planning problem considering short-term voltage stability issues is naturally with high computational complexity. The total execution time T can be estimated based on the parameters listed in (3.45).

$$T \propto (N^c, N^{gen}, N^{pop}, N^{dec}, N^{TOAT}, T^{dts}, T^{OPF}) \quad (3.45)$$

where N^c is the number of contingencies considered in time-domain simulations. N^{gen} , N^{pop} , and N^{dec} are the number of generations, population size, and the number of decision variables for NSGAI, respectively. N^{TOAT} is the number of scenarios in TOAT library. T^{dts} and T^{OPF} represent the computation time for a single time-domain simulation and a single OPF run, respectively.

In this chapter, the computation complexity is alleviated through the contingency selection and the representative scenarios for wind power generation. When the size of the power system increases, the corresponding increase in computation time is relatively moderate since the number of candidate buses for a larger system is not necessary to increase proportionally. As listed in Table 3.9, when the proposed method is applied in a Nordic 74-bus test system [76], there is only a small increase in the total computation time, even the number of buses in this test system nearly doubled (from 39 buses to 74 buses). On the other hand, the long-term VAR planning is not a time-critical problem and the total computation time is around 17-18 hours for both test systems, which is fully acceptable in practice.

Table 3.9 Computation times for different test systems

Test System	Candidate Bus Selection	Main Optimization	Total Time
New England 39	2912s	59134s	62046s (17.24h)
Nordic 74	3057s	61820s	64877s (18.02h)

In practice, VAR planning of a large-scale power system is usually studied in an area-based way rather than in a way that takes the whole system as one entity. By employing the area-based method, the self-sufficiency of each area can be maximized and the reactive power transmission between different areas can be minimized [77]. Specifically, a large-scale power system can be divided into different areas and then the VAR planning can be conducted within one area at a time while the other areas are modeled as equivalent sub-systems. So, the proposed method in this chapter is applicable for a VAR planning of a real-world transmission network as long as the network can be divided into areas, which is also the operational practice for most of the utility corporations.

3.7 Conclusions

Compared with conventional methods, which are conservative because of the neglecting of operational controls, the proposed method in this chapter coordinates planning decisions, defensive controls, and restorative controls to enhance the resilience level of the wind-penetrated power with less investment cost. Furthermore, the novel resilience metrics gives a more comprehensive description of the system performance from the perspectives of defensive capability and restorative performance, including reactive power margin of wind turbines, wind power curtailment, reactive power source margin, load shifting due to DR program, steady-state voltage stability, wind turbine voltage violation, short-term voltage stability, rotor angle deviation, and load loss. It also increases the potential of candidate solutions to survive an extreme contingency, such as an N-2 contingency. The computational complexity is firstly mitigated by candidate buses selection based on the Morris Screening method and then reduced by the critical contingency identification. A group of flexible Pareto solutions provides the decision-makers to incorporate a variety of pragmatic

factors that affect the resilience performance of the system. Case studies on the New England 39-bus system and Nordic-74 system show that the coordination of planning decisions, DCs, and RCs can effectively reduce the total cost without any deterioration of the voltage resilience performance. Finally, the advantages of the proposed indices are also illustrated.

4.) Zoning-based Candidate Bus Selection for VAR Planning

In this chapter, a new candidate bus selection is proposed to reduce the computational complexity of the VAR planning problem and improve the optimality of the planning decisions. First, A set of novel indices focusing on an accurate evaluation of the post-contingency voltage resilience performance is proposed. Then, to avoid the selection of redundant buses, a fuzzy clustering-based zoning approach is developed to categorize buses into zones based on their impacts on the voltage resilience. Finally, a multi-objective candidate bus selection method is proposed for voltage resilience improvement of a wind-penetrated system with complex dynamic loads.

4.1 Introduction

Given its highly non-linear and non-convex features, the VAR planning problems considering short-term voltage stability issues are naturally with high computational complexity. To alleviate the computation burden of the planning problems, candidate buses for the reactive power source deployment can be determined before the optimization of the capacity. On the other hand, the candidate bus selection (CBS) is also a critical factor that influences the optimality of the final planning results. Generally, steady-state [43, 44, 78] and short-term [79-81] voltage stability metrics are prevalent in the assessment of the voltage performance of different buses and the evaluation results are usually used to rank the buses. Load margins of branches or voltage violations are often used as indicators to show the effectiveness of a specific reactive power source installation, as a steady-state evaluation. As for the assessment of short-term voltage stability, it is mainly based on post-contingency voltage responses (like time-varying voltage trajectories). However, the conventional metrics only consider the extent of the voltage violation but neglect the duration of the violation. There are also industrial standards [82-84] that can be utilized for the stability assessment, but their evaluation results are designed for the operational scenarios focusing on a binary judgment: stable or unstable. These binary assessment results cannot be used to rank the candidate buses.

In recent years, there are some new indices for short-term voltage stability

assessment [38, 41, 72, 85-88] are proposed. The recovery speed of voltage is incorporated in [41] and [85] as a new index to evaluate voltage response after a contingency. The recovery speed is calculated based on the duration between the first violation of a threshold and the first recovery to a threshold. In [86] and [38], the integration of the voltage deviation after a disturbance is cleared is employed to assess the voltage performance, with the considerations of the time of the violation and extent of the violation. A similar index aiming to quantitatively assess the voltage performance after a contingency is developed in [87]. However, the index is calculated only based on the largest voltage deviation and the overall voltage performance cannot be fully reflected. In [72], a root-mean-square approach is used to improve the accuracy of an averaging-based index proposed in [38], aiming to evaluate the slow voltage recovery of a certain bus accurately when other buses are experiencing a relatively fast recovery. A continuous index [88] is developed to calculate the margin of short-term voltage stability. The duration and extent of the voltage deviation are considered in [88], but they are only considered as constraints, instead of quantitative metrics that can be incorporated in an optimization model. All the indices mentioned above effectively evaluate the voltage stability according to their own priorities and successfully satisfy their specific research goals. Nonetheless, none of them are sufficient for the candidate bus selection for two reasons: 1) the steady-state and short-term voltage stability are usually evaluated in the literature separately; 2) there is no comprehensive evaluation for the voltage resilience and most of them only focus on one or two of the critical aspects of voltage performance including recovery speed, duration of the deviation, and post-contingency steady-state assessment. Although there are some widely accepted metrics for the evaluation of the power system resilience [31], they are mainly focusing on the resilience of the infrastructure and the indices are not suitable for CBS applications.

On the other hand, an accurate index is not the only concern of a CBS problem. The straightforward ranking method will inevitably lead to abundant candidate buses in the same area because for geographical adjacent weak buses they tend to have similar evaluation results in terms of voltage stability. If several adjacent buses are selected as candidate buses, the efficiency of the

compensation cannot be guaranteed. To avoid this redundancy, zoning-based candidate bus selection methods are proposed in [89, 90, 126] by categorizing the buses into different zones. The zoning-based approach is effective, but the existing studies either neglect the short-term voltage performance [89] or do not consider the capacity sensitivity of the reactive power source [90] or based on a preliminary estimation [126].

The conventional VAR planning problem is widely studied, but it is rarely discussed in the context of a wind-penetrated power system with a high portion of complex dynamic loads. After a harsh voltage disturbance, the wind turbines that exposed to voltage dips and voltage fluctuations are potential threats to the power system since their trip-offs or the generation reduction will not only lead to power imbalance but also potentially to cause cascading events due to loss of synchronism and frequency damping [4]. Besides, since LVRT/HVRT (Low/High Voltage Ride-Through) capability of wind turbines are usually considered only as constraints in VAR planning problems [46], the indices in previous studies are not designed to consider the features of wind turbines, such as their relatively high sensitivity to the extent and the length of voltage deviation. In a word, both the metrics and the candidate bus selection methods for VAR planning problems mentioned here are not designed for a wind-penetrated power system.

To overcome the inadequacies of the previous works, including lack of a metric accurately reflecting post-contingency voltage response, and neglect the capacity sensitivity analysis in the candidate bus selection stage, a new candidate bus selection method of dynamic VAR source for voltage resilience enhancement of a wind-penetrated power system is proposed in this chapter. The contributions are summarized as follows:

- 1) A set of trajectory-based indices are proposed to evaluate the voltage resilience performance in the post-contingency stage. Compared with conventional indices used for candidate bus selection, the performance is assessed more comprehensively from four aspects: the extent of voltage deviation, the voltage deviation duration, time of post-contingency stabilization, and the post-contingency steady-state voltage level.

2) A zoning approach based on fuzzy clustering is developed to categorize buses into different zones according to evaluation results. Compared with the conventional non-zoning based method, the proposed method effectively avoid selection of redundant buses. Compared with existing zoning methods, the proposed method can avoid the inconsistency problem through capacity sensitivity analysis.

4.2 General framework of candidate bus selection method

Generally, there are three typical procedures in a CBS (candidate bus selection) problem: 1) contingency selection, 2) performance evaluation, and 3) bus selection, as illustrated in Fig. 4.1. However, there are some inadequacies of the conventional method. First, conventional methods select contingencies based on historical data and past operational experience. The lack of a quantitative impact analysis might lead to an inaccurate assessment of the severity of the contingencies. Secondly, when the performance of the VAR sources is evaluated in each bus, conventional methods only focus on a specific part of the whole dynamic voltage evolution process, instead of a comprehensive assessment. Finally, a straightforward simple ranking is usually adopted by conventional methods in the bus selection stage. This strategy might lead to a selection of the adjacent buses in a relatively small area where the reactive power deficiency is high. Therefore, the concentrated candidate buses in a small region will significantly reduce the efficiency of the reactive power compensation.

Considering the drawbacks of conventional methods, a multi-objective CBS scheme based on fuzzy clustering for STATCOMs to improve the voltage resilience of the wind-penetrated power system is proposed in this chapter. The proposed method also adopts a conventional three-stage framework as illustrated in Fig. 4.1 and all three stages are improved to address the limitations of conventional methods. The advantages of the proposed method can be summarized in the following three aspects. First, instead of using historical data or empirical judgment, the severity of different contingencies is evaluated quantitatively based on three criteria, including steady-state voltage stability, short-term voltage stability, and rotor angle stability. Then, the general voltage

resilience of the system before and after different contingencies are evaluated on steady-state voltage stability, post-contingency voltage restoration performance, post-contingency steady-state and rotor angle deviations. To avoid the selection of redundant buses, the final stage of the proposed CBS scheme is divided into two steps: 1) categorizing the buses into zones based on their similarity of voltage impacts on the power system; 2) selecting the most effective bus from each zone. Specifically, the selection can be carried out once (one bus from each zone) or several times iteratively according to the practical needs.

1. contingency selection	2. performance evaluation	3. bus selection
conventional method operation experience & historical data	conventional method post-contingency voltage stability index	conventional method selection of top n buses based on (single- or two-objective)
×no quantitative analysis ×inaccurate severity estimation	×lack of evaluation throughout the whole restoration process	×inevitable selection of adjacent buses ×no capacity sensitivity analysis
proposed method severity assessment	proposed method comprehensive multi-objective assessment	proposed method zoning (fuzzy c-mean clustering) multi-objective bus selection
√quantitative severity analysis √voltage trajectories & rotor angles	√pre-contingency assessment (steady-state) √post-contingency assessment (voltage restoration and steady-state)	√avoid redundant buses √capacity sensitivity analysis (morris screening) √most efficient bus

Figure 4.1 Comparison between conventional method and the proposed method

4.3 Indices for voltage resilience evaluation

In this chapter, steady-state voltage stability is evaluated by the line-based VCPI (Voltage Collapse Proximity Indicator), voltage resilience performance after a contingency is evaluated by two improved TVSIs (Transient Voltage Stability Indices), $TVSI^r$ and $TVSI^s$, based on the voltage trajectories (the trajectories data can be obtained by time-domain simulation, or from PMU data). The rotor angle stability of the system is assessed by ISGA (Integral Squared Generator Angle).

4.3.1 $TVSI^r$ for voltage recovery stage assessment

In existing studies, short-term voltage stability indices are usually calculated based on the extent of post-contingency voltage violation subjected to a specific threshold. However, these indices ignore the time of voltage violation. In practice, not only the extent but also the duration of the voltage violation has a significant impact on LVRT/HVRT capability of wind turbines. Therefore, an improved index, $TVSI^r$, is proposed to evaluate the immediate voltage response of buses after a voltage disturbance. Specifically, it is defined by: 1) the extent of the deviation v^d (direct voltage deviation impact), 2) the corresponding acceptable maximum duration t^{dl} and t^{du} (voltage recovery speed). S_1 , S_2 , S_3 , and S_4 are used to represent different voltage violation areas formed by the time-varying voltage trajectory, upper and lower voltage limit (1.1 and 0.9 p.u. in this chapter), and pre-determined time spans (t^{du} and t^{dl}):

- 1) S_1 : voltage violation below lower voltage threshold within t^{dl}
- 2) S_2 : voltage violation below lower voltage threshold beyond t^{dl}
- 3) S_3 : voltage violation above upper voltage threshold within t^{du}
- 4) S_4 : voltage violation above upper voltage threshold beyond t^{du}

Based on S_1 , S_2 , S_3 , and S_4 , $TVSI_i^r$ for each bus is calculated as (4.1) [J2]. It consists of two parts: the evaluation for a normal voltage violation and the evaluation for a penalized voltage violation. Penalty parameters, α^l and α^u , are used to evaluate the impact of a delayed voltage recovery. The delayed voltage

recovery is usually ignored by the conventional index. Post-contingency voltage trajectories under three typical scenarios (named as A, B, and C) are shown in Fig. 4.2 to Fig. 4.4, respectively. It should be noted that $TVSI_i^r$ is zero when there is no voltage violation after a disturbance.

$$\begin{aligned}
 TVSI_i^r &= \overbrace{S_1 + S_3}^{\text{normal deviation}} + \overbrace{\alpha^l \cdot S_2 + \alpha^u \cdot S_4}^{\text{penalized deviation}} \\
 &= \int_{t^f}^{t^f+t^{dl}} (v_i^{dl} - v_i) dt + \alpha^l \cdot \int_{t^f+t^{dl}}^{t^{l2}} (v_i^{dl} - v_i) dt \\
 &\quad + \int_{t^{u1}}^{t^{u1}+t^{du}} (v_i - v_i^{du}) dt + \alpha^u \cdot \int_{t^{u1}+t^{du}}^{t^{u2}} (v_i - v_i^{du}) dt
 \end{aligned} \tag{4.1}$$

4.3.1.1 Typical scenario A

As shown in Fig. 4.2, Scenario A represents that only a lower voltage threshold is violated during the post-contingency stage and the voltage magnitude of the steady-state after a contingency is within the boundary. In this scenario, S_3 and S_4 in equation (4.1) are zero. So, $TVSI_i^r$ can be calculated as (4.2).

$$TVSI_i^r = S_1 + \alpha^l \cdot S_2 = \int_{t^f}^{t^f+t^{dl}} (v_i^{dl} - v_i) dt + \alpha^l \cdot \int_{t^f+t^{dl}}^{t^{l2}} (v_i^{dl} - v_i) dt \tag{4.2}$$

Figure 4.2 Illustration of typical scenario A

4.3.1.2 Typical scenario B

Scenario B is the case that both lower and upper voltage thresholds are violated, and the voltage magnitude of steady-state after a disturbance is within the boundary. In this scenario, $TVSI_i^r$ can be calculated as (4.3):

$$\begin{aligned}
 TVSI_i^r &= S_1 + \alpha^l \cdot S_2 + S_3 + \alpha^u \cdot S_4 \\
 &= \int_{t^f}^{t^f+t^{dl}} (v_i^{dl} - v_i) dt + \alpha^l \cdot \int_{t^f+t^{dl}}^{t^{l2}} (v_i^{dl} - v_i) dt \\
 &\quad + \int_{t^{u1}}^{t^{u1}+t^{du}} (v_i - v_i^{du}) dt + \alpha^u \cdot \int_{t^{u1}+t^{du}}^{t^{u2}} (v_i - v_i^{du}) dt
 \end{aligned} \tag{4.3}$$

Figure 4.3 Illustration of typical scenario B

4.3.1.3 Typical scenario C

Scenario C represents the case that only the lower voltage threshold is violated and the voltage magnitude of steady-state after a disturbance is out of the boundary. In this case, S_2 and S_3 are zero. So, $TVSI_i^r$ can be calculated as (4.4).

$$\begin{aligned}
 TVSI_i^r &= S_1 + \alpha^l \cdot S_2 \\
 &= \int_{t^f}^{t^f+t^{dl}} (v_i^{dl} - v_i) dt + \int_{t^{l1}}^{t^{l1}+t^{dl}} (v_i^{dl} - v_i) dt + \alpha^l \cdot \int_{t^{l1}+t^{dl}}^{t^{l2}} (v_i^{dl} - v_i) dt
 \end{aligned} \tag{4.4}$$

Figure 4.4 Illustration of typical scenario C

For the case that the post-contingency steady state is out of the upper limit boundary, the index can also be calculated according to (4.3) with t^{du} , v^{du} , t^{u1} , and t^{u2} .

4.3.1.4 Determination of weighting factors

The values of the weighting factors, α^l and α^u , are determined by the following two aspects:

1) Priorities of delayed upper/lower voltage recovery, which is based on the engineering empirical judgment of their importance and the specific operational requirements (for instance, wind turbines are highly sensitive to delayed voltage recovery. So, higher values of α^l and α^u are expected).

2) Sensitivity analysis against different capacities of STATCOMs. The sensitivity analysis for the weighting factors is mainly to minimize the unexpected surge in the evaluation results due to the non-linearity of the problem and also to avoid the situation that high priority components end up with little influence (for instance, they might be very insensitive to the capacity change) in the evaluation result. In this chapter, All-At-a-Time (AAT) method is used for the sensitivity analysis, of which output variations are induced by changing all the inputs (the capacities of all VAR compensation devices) at a time simultaneously. Therefore, both the direct impact of capacity variations and the joint impact due to interactions among different reactive power sources are considered. It should be pointed out that more advanced methods for the

sensitivity analysis, such as the Morris Screening method [91], can be employed to determine the weights.

4.3.1.5 Risk-based root-mean-square index

Like described in Chapter 3.3.2.2, this chapter also adopts a root-mean-squared approach to calculate the $TVSI^r$. Compared with the direct average approach used in the conventional method, the root-mean-squared method can fully reveal the performance change of a specific bus if other buses experience relatively minor ones. Specifically, if a large number of buses are considered, the direct averaging method cannot fully represent the voltage performance of the worst buses (they are usually minority) and it also makes the total $TVSI^r$ less sensitive to the performance improvement of a certain bus.

Therefore, first, the root-mean-squared method is used to calculate the $TVSI^r$ under a contingency and then the final risk-based $TVSI^r$ is calculated as (4.5) based on the critical contingency probabilities.

$$TVSI^r = \sum_{k \in \mathcal{K}} \sqrt{\frac{\sum_{i \in \mathcal{B}} (TVSI_i^r)^2}{N^b}} \cdot p_k \quad (4.5)$$

4.3.2 $TVSI^s$ for post-contingency steady-state assessment

$TVSI^s$ is proposed in this chapter to quantitatively assess the voltage stabilization process in the post-contingency stage. It not only describes the steady-state in the post-contingency stage but also evaluates the time that a particular bus voltage takes to restore to an acceptable voltage range. Generally, a stabilized voltage can be in one of the two post-contingency steady states: 1) stays within the voltage limit range, and 2) out of the voltage limit range. There are two critical variables for $TVSI^s$: t^s and v^s . Settling time t^s is calculated based on the acceptable voltage fluctuation range $[v^{fu}, v^{fl}]$ and it indicates how fast the steady state can be reached. v^s is the average value of voltage magnitude after the t^s . As for the unstable/unacceptable case, t^s is set to be $t^{s,th}$ and v^s is calculated based on the average voltage magnitude after the t^s .

A general definition of $TVSI_i^s$ is presented as (4.6) and two corresponding typical scenarios are illustrated in Fig. 4.5 and Fig. 4.6.

$$TVSI_i^s = \begin{cases} 1 - \frac{v_i^s - v^{dl}}{v_i^o - v^{dl}} \cdot \frac{t^s}{t^{s,th}}, & v^{dl} \leq v_i^s < v_i^o \\ 1 - \frac{v^{du} - v_i^s}{v^{du} - v_i^o} \cdot \frac{t^s}{t^{s,th}}, & v_i^o \leq v_i^s \leq v^{du} \\ 1 + \frac{v^{dl} - v_i^s}{v^{dl}} \cdot \frac{t_i^s}{t_i^{s,th}}, & 0 \leq v_i^s < v^{dl} \\ 1 + \frac{v_i^s - v^{du}}{v^{du}} \cdot \frac{t_i^s}{t_i^{s,th}}, & v^{du} < v_i^s \end{cases} \quad (4.6)$$

4.3.2.1 Typical scenario D

Figure 4.5 Illustration of typical scenario D

If there is sufficient reactive power support for a bus, its voltage can stay within the boundary after a short fluctuation, as illustrated in Fig. 4.5. Specifically, it stabilizes within the voltage range but lower than the original voltage value v^o . So, in this case, $TVSI_i^s$ is calculated as (4.6), with the condition that $v^{dl} \leq v_i^s < v_i^o$.

Similarly, when the voltage stabilizes within the voltage range but larger than the original value v^o , $TVSI_i^s$ is calculated as (4.6) with condition that $v_i^o \leq v_i^s \leq v^{du}$.

4.3.2.2 Typical scenario E

Contrary to typical scenario D, when the reactive power is deficient, the stabilized voltage might be inferior, as shown in Fig. 4.6. The stabilized voltage is smaller than the lower threshold. So, $TVSI_i^s$ is calculated as (4.6), with the condition that $0 \leq v_i^s < v^{dl}$. Similarly, when the stabilized voltage is above the upper voltage threshold, $TVSI_i^s$ is calculated as (4.6), with the condition that $v^{du} < v_i^s$.

Figure 4.6 Illustration of typical scenario E

Generally, a smaller $TVSI_i^s$ indicates a better steady-state voltage in the post-contingency stage. For instance, the range of $TVSI_i^s$ is $[0,1]$ for scenario D, and the range of $TVSI_i^s$ is $(1,2]$ for scenario E. Fig. 4.7 illustrates the relationship between $TVSI_i^s$ and v_i^s . $TVSI_i^s$ is designed to guarantee that any assessment of scenario E is always inferior to that of scenario D. So, an inferior voltage recovery of a specific bus can be identified clearly without further comparison with other buses. It is also a salient advantage of the proposed indicators not only for the candidate bus selection but also in cases like online operational monitoring. The distinctive difference can provide direct information about the stabilized voltage after a contingency to the operators clearly. On the contrary, this feature is usually ignored by most of the existing voltage stability indicators. In the literature, without comparison with others (either other bus voltage, or the same bus voltage before and after compensation), the evaluation result alone does not reveal any information about the inferiority or superiority.

Figure 4.7 Values of $TVSI_i^s$ against the varying v_i^s

4.3.2.3 Risk-based root-mean-square index

After assessment of each bus, a risk-based root-mean-square index is proposed to quantify the system-level post-contingency steady-state, with a set of critical contingency probabilities:

$$TVSI^s = \sum_{k \in \mathcal{K}} \sqrt{\frac{\sum_{i \in \mathcal{B}} (TVSI_i^s)^2}{N^b}} \cdot p_k \quad (4.7)$$

4.3.3 ISGA for rotor angle assessment

When there is a contingency in a power system, rotor angle stability and voltage stability are associated with each other. In this chapter, rotor angle stability is introduced as an indicator for the evaluation of the post-contingency resilience performance. Conventionally, the rotor angle is only considered as a binary constraint in VAR planning problems [38, 46]. However, this binary judgment abandons all the information about the extent of stability/instability. ISGA [92] is employed in this chapter to measure the cumulated deviation and relative severity of the incidents. ISGA is calculated and normalized as (4.8) based on a weighted center of inertia angle and the weighted center is calculated with generator inertia constants and rotor angles.

$$ISGA = \sum_{k \in \mathcal{K}} \frac{1}{M^{TOT}} \int_{t^0}^{t^{end}} \sum_{i \in \mathcal{G}_s} M_i (\delta_i - \delta^{COA})^2 dt \cdot p_k \quad (4.8)$$

$$M^{TOT} = \sum_{i \in \mathcal{G}_s} M_i \quad (4.9)$$

$$\delta^{COA} = \frac{\sum_{i \in \mathcal{G}_s} M_i \cdot \delta_i}{M^{TOT}} \quad (4.10)$$

4.3.4 VCPI for pre-contingency steady-state voltage stability assessment

A line based VCPI [59] used in Chapter 2 is also employed in this chapter to quantify the steady-state voltage stability of the wind-penetrated power system. So, $VCPI$ is calculated based on (2.21) and (2.22) as a probability-weighted sum of VCPIs of all the lines as (4.11). VCPI is used in chapter to quantitatively compare the steady-state voltage stability performance of different candidate bus selection results with different capacities installed, showing the extent of improvement or deterioration.

$$VCPI = \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{L}} VCPI(power)_l \cdot p_k \quad (4.11)$$

4.4 Proposed method for candidate bus selection

To address the inadequacy of a direct selection method based on the indices ranking and avoid selection of redundant candidate buses, a multi-objective zoning-based bus selection scheme based on the fuzzy clustering method is developed in this chapter. The method also considers the capacity sensitivity of STATCOMs through the Morris Screening method.

4.4.1 Capacity sensitivity analysis

In the literature, zoning-based CBS methods [89, 90] only use one pre-determined value of capacity in the whole candidate bus selection process. Consequently, the selected buses are most effective with capacity around this value, rather than an optimal capacity which is determined in the capacity optimization stage. Besides, in practice, empirical or arbitrary capacity used for these CBS methods might lead to inaccurate and inconsistent zoning results (for instance, different selected candidate buses for different capacity values

used). Although it is impossible to determine an optimal capacity before the candidate bus itself is determined, it is relatively easy to determine a reasonable capacity range. In this chapter, the capacity sensitivity analysis (using Morris Screening method) is carried out to alleviate the inconsistency problem of conventional methods. The mathematical details of the proposed LHS-based Morris Screening method are presented in Chapter 3.4.3.

4.4.2 Fuzzy C-mean (FCM) clustering

Because of the proximity of voltage dip, the conventional methods adopting a direct index ranking method will inevitably select the most critical bus and its geographically adjacent buses. Obviously, this selection will adversely impact the efficiency of the compensation in a later stage (capacity optimization stage), since concentrated compensation devices in a relatively small area will have a decreasing marginal contribution to the system when the installed capacity increases. An effective way to address this issue is to categorize the buses according to their similarity of dynamic voltage responses after a contingency into different zones. In this chapter, an iterative clustering method called FCM clustering algorithm [93] is used to categorize the buses. It is formulated to minimize the objective function with respect to the membership function and the center vector.

4.4.2.1 Formation of the initial matrices group

An $N^c \times M$ matrix (N^c buses and M indices as defined in Chapter 4.3), is formed for a specific capacity as (4.12) and (4.13).

$$\mathbf{X}_c^o = [x_{1,c}^o, x_{2,c}^o, \dots, x_{M,c}^o] \quad (4.12)$$

$$\mathbf{x}_{j,c}^o = [x_{1,j,c}^o, x_{2,j,c}^o, \dots, x_{N^c,j,c}^o]^T, \quad j = 1, 2, \dots, M \quad (4.13)$$

Figure 4.8 Structure of initial matrices group

The structure of the initial matrices is illustrated in Fig. 4.8, based on the result of LHS. Specifically, as part of the capacity sensitivity analysis, $[x_{1,j,c}^o, x_{2,j,c}^o, \dots, x_{N^c,j,c}^o]^T$ in the initial matrix for FCM is obtained from corresponding Morris Screening results μ^* for different indices. Then, they are unified to make all the items in the matrices are within $[0,1]$, as calculated in (4.14).

$$x_{i,j,c} = \frac{x_{i,j,c}^o - x_{i,c}^{o,min}}{x_{i,c}^{o,max} - x_{i,c}^{o,min}} \quad (4.14)$$

4.4.2.2 Mathematical Formulation

FCM algorithm is based on the minimization of an objective function [93] defined as (4.15).

$$\text{Min } J(\mathbf{U}, \mathbf{Y}) = \sum_{r=1}^{N^{center}} \sum_{i=1}^{N^e} (u_{ri})^F D_{ri}(x_i, y_r) \quad (4.15)$$

$$u_{ri} = \frac{D_{ri}(x_i, y_r)^{\frac{1}{1-F}}}{\sum_{j=1}^{N^{center}} D_{ji}(x_i, y_j)^{\frac{1}{1-F}}} \quad (4.16)$$

$$y_r = \frac{\sum_{j=1}^{N^e} (u_{rj})^F x_j}{\sum_{j=1}^{N^e} (u_{rj})^F} \quad (4.17)$$

$$D_{ri}^2 = \|x_i - y_r\|^2 \quad (4.18)$$

The constraints of FCM are described in (4.19) and (4.20):

$$\sum_{r=1}^{N^{center}} u_{ri} = 1 \quad (4.19)$$

$$0 < \sum_{i=1}^{N^e} u_{ri} < 1 \quad (4.20)$$

4.4.2.3 Solution steps

The following four steps will be iteratively processed until the termination criterion is satisfied or the max iteration number is reached.

1) Choose the number for the clusters. Determine the weighting exponent and a proper termination tolerance ϵ . Then, conduct the initialization of the membership matrix $U_{(0)}$.

2) Calculate the center vector $\mathbf{y}$ according to (4.17).

3) Update the membership matrix based on (4.16).

4) Go back to Step 2) until: a) $\|U_z - U_{z-1}\| < \epsilon$ is satisfied (where U_z is z^{th} membership matrix) or b) maximum iteration number is reached.

4.4.3 Computation steps

Fig. 4.9 illustrated the computational flowchart of the proposed candidate bus selection scheme. The details of each computation step are described as follows.

1) Contingency Selection

Contingency severity analysis is based on $TVSI^r$ and $ISGA$. Specifically, these two indicators are calculated according to voltage trajectories and rotor

angles obtained from the time-domain simulation results. Then, the critical contingencies will be selected according to the principles of the Pareto Front as discussed in Chapter 3.4.4.

2) *Performance Evaluation*

Random capacity samples following the normal distribution are generated based on LHS. Optimal Power Flow is conducted according to these samples for the calculation of $VCPIs$. Then, $TVSI^r$, $TVSI^s$ and $ISGA$ are calculated to assess the voltage performance for each critical contingency, with all capacity samples.

3) *Categorizing Buses*

initial matrices are formed with evaluation results obtained from step 2) for different capacity samples. Capacity analysis is conducted by the Morris Screening method. FCM is initialized with cluster numbers, weighting exponent and termination tolerance. Center set $\mathbf{y}$ is calculated according to (4.17) with a random generated initial $U_{(0)}$. Then, the membership matrix is updated with new $\mathbf{y}$ until the variations of membership matrix reaches tolerance or iterations reaches the maximum number. Finally, FCM results are obtained saved for the categorization of buses.

4) *Candidate Bus Selection*

bus zones with low impact on the system (not influential on the assessment results) are excluded. For cases without pre-determined candidate buses, the highest-ranking bus in each zone is selected iteratively. As for system with m pre-determined buses (e.g., the bus with wind turbines), m buses are selected firstly from zones with no pre-determined buses. Then, other $(n-2m)$ buses are selected based on the same principle as the case without pre-determined candidate buses.

5) *Termination*

the max number of candidate buses is reached.

Figure 4.9 Computation flowcharts of the proposed candidate bus selection method

4.5 Numerical results and discussions

4.5.1 Test system and parameter settings

The New England 39-bus test system, as illustrated in Fig. 4.10, is used to validate the effectiveness of the proposed method. Like previous chapters, the steady-state analysis is carried out in Matlab 2018b with MATPOWER 6.0 [67] and PSS®E 33.4 is employed for time-domain simulation.

Figure 4.10 New England 39-bus test system

For case study 1, the original New England 39-bus system is used. For case study 2, one wind farm replaces the synchronous generator at bus 30 and another two wind farms replace the synchronous generator at bus 32, with the same generation capacity as the original generators. The models for DFIG, STATCOM, and synchronous generators are the same ones used in Chapter 2.5.1. Two buses with wind farms are considered as the pre-determined installation sites for STATCOMs. The wind power uncertainty is modeled through TOAT as described in Chapter 2.3.7.

Table 4.1 Parameters for simulation setting

Parameters	Value
N^{center}	3
$t_i^{s,th}$	4.2s
t^{dl}/t^{du}	0.6s/0.6s
v^{dl}/v^{du}	0.9 pu/1.1 pu
α^l/α^u	2.0/2.0
unit capacity range	0~100 Mvar
LHS level (w/o wind power)	80 (from 0 to 100Mvar)
LHS level (with wind power)	20 (from 0 to 100Mvar)
LM, SM, DL, TS, CP, K_p	25%,15%,10%,10%,10%, 2
Fault setup	3-phase short-circuit (cleared after 0.1s)

The industry-standard composite load model "CLOD" [60], as illustrated in Fig. 2.4, used in previous chapters are also used here to simulate the load dynamics. Specifically, this load model can be defined by an 8-dimensional vector $[LM, SM, DL, TS, CP, K_p, R_b, X_b]$. The first five items stand for the proportions of different loads, respectively. The values of these parameters are shown in Table 4.1.

4.5.2 Simulation results and comparison study

There are two case studies in this chapter: case study 1 is without wind farms and case study 2 is with wind farms. The total computation time is 64 mins for case study 1 and is 67 mins for case study 2. The computation burden is manageable for a planning problem.

4.5.2.1 Case study 1 (without wind farms)

Fig. 4.11 shows the results of contingency severity analysis, where the analysis results are normalized. Four critical contingencies, which have relatively larger impacts on the dynamic response of the system, are selected: faults on lines 2-25, line 16-17, line 16-21, and line 21-22.

Figure 4.11 Contingency severity analysis results

Based on the membership matrix results, 18 load buses are categorized into 3 zones as illustrated in Fig. 4.10.

- Zone A: bus # 3, 4, 7, 8, 20;
- Zone B: bus # 12, 15, 16, 18, 21, 23, 24;
- Zone C: bus # 1, 25, 26, 27, 28, 29.

Figure 4.12 Evaluation results for each bus

Among them, as illustrated in Fig. 4.12, zone C (marked as red) has a limited impact on the dynamic performance of the system (voltage response and rotor angle dynamics). Therefore, candidate buses are only selected from zone A and zone B. Specifically, bus 8 and bus 20 from zone A are selected because they are the most influential buses in terms of $ISGA$ and $TVSI^S$; and bus 16 and bus 24 from zone B are selected because they are the highest-ranking buses for $VCPI$ and $TVSI^r$ results, respectively.

A comparison as listed in Table 4.2 with a conventional non-zoning method is carried out to show the effectiveness of the proposed method. Both the

proposed and conventional methods are with 210 MVAR STATCOM and the capacity is the same for each selected bus. For instance, the installed capacity for each of the 7 selected buses from the conventional method is 30 MVAR and the installed capacity for each of the 4 selected buses from the proposed method is 52 MVAR. Since there are fewer buses selected in the proposed method (only 4 buses), the overall installation cost is lower than that of the conventional method, even they are with the same total installed capacity. Furthermore, the performance evaluation of the proposed method is better than that of the conventional method, in terms of $TVSI^r$, $TVSI^s$, and $ISGA$. These three indicators are improved by 44.92%, 2.48%, and 2.74%, respectively. It should be noted that $TVSI^r$ of the proposed method is significantly improved compared with the conventional method. This is because the zoning approach avoids the redundancy of candidate bus selection in a nearby area and improves the efficiency of the reactive power compensation (achieving a better evaluation result, $TVSI^r$, with same total installed capacity).

Table 4.2 Simulation results for case study 1

method	Conventional (non-zoning)	Zone-based
Buses	8,15,12,16,20,21,24	8,16,20,24
VCPI	23.32	23.55
$TVSI^r$	0.9590	0.5282
$TVSI^s$	1.6575	1.6163
ISGA	2586.3	2515.9

4.5.2.2 Case Study 2 (with wind farms)

Like case study 1, four contingencies are selected as critical ones: faults on line 5-6, line 6-7, line 16-21, and line 21-22. Based on the membership matrix results, 18 load buses and 2 wind farms buses are categorized into 3 zones:

- Zone A: bus # 7, 23, 28;
- Zone B: bus # 1, 3, 4, 8, 20, 25, 26, 29, 30 (wind farm), 32 (wind farm);
- Zone C: bus # 12, 15, 16, 18, 20, 21, 24, 27.

Table 4. 3 Simulation results for case study 2

	Conventional (non-zoning)	Proposed (zone-based)	
		Four buses	Three buses
Buses	7,16,24,29	7,16,23,24	7,16,23
VCPI	23.48	23.41	23.45
TVSI ^r	1.0842	1.0241	1.0946
TVSI ^s	1.7205	1.6002	1.6568
ISGA	2728.1	2700.1	2710.4

For the conventional method, buses with the best evaluation results for different indicators are selected as candidate buses for STATCOM installation as listed in Table 4.3. Specifically, bus 7 is for $TVSI^r$, bus 16 is for $VCPI$, bus 29 is for $TVSI^s$, and bus 24 is for $ISGA$. However, since wind farm buses 30 and 32 are pre-determined candidate buses and they are all from zone B, there are 3 buses from zone B. This concentration is the cause of and inefficient compensation. As for the proposed method, bus 7, bus 16, bus 23, and bus 24 are selected as candidate buses. Instead of selecting bus 29, which is the best bus for $TVSI^s$ improvement, the proposed method selects the second best bus (bus 23) for $TVSI^s$ to avoid the concentration in zone B. So, there are 2 buses from each zone, which is more balanced than the conventional method without consideration of the redundancy in the same zone.

The superiority of the proposed method is also shown in Table 4.3. Although both methods are with the same total installed STATCOM capacity (210 MVar), $TVSI^r$ and $TVSI^s$ of the proposed method is better than that of the conventional method, improved by 5.43% and 6.99%, respectively. The proposed method is also with better evaluation results for $VCPI$ and $ISGA$, although the improvements are relatively small. On the other hand, if the post-contingency performance is the top priority and the planner is more sensitive to the total investment, the evaluation results of the conventional method can be obtained by the proposed method with only 3 candidate buses as listed in the last column of Table 4.3, which means a reduced installation cost.

Table 4.4 Capacity impact on zoning result of [89, 90]

Unit Capacity	Zones	Buses
20MVar	A	3,4,7,8,12, 18 ,26,27
	B	1,25,28,29,30, 32
	C	15,16, 20 ,21, 23 ,24
60MVar	A	3,4,7,8,12, 23 ,26,27, 32
	B	1,25,28,29,30
	C	15,16, 18 , 20 ,21,24
100MVar	A	3,4,7,8,12, 20 , 23 ,26,27, 32
	B	1,25,28,29,30
	C	15,16, 18 ,21,24

One of the salient advantages of the proposed method is the consideration of capacity sensitivity analysis. Conventional zoning-based CBS methods, such as methods developed in reference, only consider one specific capacity in the candidate bus selection. This simplification might lead to inconsistent results of the candidate bus selection. A comparison is listed in Table 4.4, showing the zoning results based on three typical STATCOM capacities. It is worth noting that bus 18, bus 20, bus 23, and bus 32 are grouped into different zones when different capacities are used for the candidate bus selection. Among them, bus 23 (second best bus for $TVSI^s$ improvement) and bus 32 (one of the only two buses with wind farms) play critical roles in the overall effectiveness of the VAR compensation. Since it is impossible to find an optimal capacity in candidate bus selection stage, the capacity used in reference [89] and [90] are arbitrary and the inconsistency of categorization results might lead to a sub-optimal capacity optimization results since the candidate buses would be considered as pre-determined inputs during the optimization of capacity.

Furthermore, to demonstrate the superiority of the proposed method, Fig. 4.13-4.16 compare the evaluation results between the proposed method and other zoning-based methods without consideration of capacity sensitivity. All the methods presented in the figures are evaluated with the same indices proposed in this paper. As listed in Table 4.3, bus 7, bus 16, bus 23, and bus 24 are

candidate buses from the proposed method. Bus 7, bus 16, bus 29, and bus 24 are for the other two zoning-based methods. It is obvious that the proposed method has fewer unexpected sudden surges/drops. Besides, it improves the dynamic voltage performance of the system more efficiently, in terms of all the metrics, except for $TVSI^s$ in two small capacities scenarios (namely 7 and 21 MVar).

Figure 4.13 Capacity sensitivity comparison of VCPI

Figure 4.14 Capacity sensitivity comparison of $TVSI^r$

Figure 4.15 Capacity sensitivity comparison of TVSI^s

Figure 4.16 Capacity sensitivity comparison of ISGA

Table 4.5 shows the advantage of the root-mean-square method (used in equ. 4.7) over the Direct Averaging method (used in original TVSI [38]).

Table 4.5 Comparison between Direct Averaging and RMS

TVSI results for each bus	System-level TVSI (Direct Average)		System-level TVSI (RMS)	
	value	improvement	value	improvement
Bus 1: 0.4; Bus 2-bus 39: 0.1	0.10769	0.00513 (4.76%)	0.11767	0.01390 (11.81%)
Bus 1: 0.2; Bus 2-bus 39: 0.1	0.10256		0.10377	

Originally, let us assume the evaluation results for each bus are as follows: bus 1 is 0.4, bus 2-39 are all 0.1. After a reactive power compensation, the compensated results are changed: bus 1 is improved to 0.2, bus 2-39 are all still 0.1. Although the improvement of TVSI for bus 1 is significant (50%), the

improvement of system-level TVSI is relatively small (4.76%) when the direct averaging approach is used, compared with the root-mean-square case (11.81%). So, the root-mean-square approach can make TVSI results more sensitive to reactive power compensation. In practice, there are usually only a few buses experiencing the large reactive power deficiency, while most of the buses in the system are with relatively minor voltage dips after a disturbance. But these few buses play much more important roles than other buses, in terms of voltage stability. Therefore, compared with the direct averaging approach that only focuses on the overall voltage performance of the system, the root-mean-square approach, which is more sensitive to the voltage response of the worst buses, can identify the most influential buses more efficiently in the capacity sensitivity analysis.

4.6 Conclusions

A novel zoning-based candidate bus selection scheme for a wind-penetrated power system is proposed in this chapter. It aims to select effective and efficient buses for STATCOM installation. Four metrics are developed to evaluate the steady-state voltage stability, short-term voltage stability, post-contingency voltage steady-state, and rotor angle stability. Case studies on an original New England 39-bus system and a modified New England 39-bus system demonstrate the effectiveness of the proposed method. The proposed indices, $TVSI^r$ and $TVSI^s$, can assess the whole voltage recovery process comprehensively in terms of the extent of the deviation, recovery speed, and post-contingency steady state, compared with the conventional voltage stability metrics based on post-contingency trajectories. The proposed method can avoid the selection of redundant buses and reduce installation costs without any deterioration of the voltage stability. Furthermore, compared with other zoning-based methods, the proposed method can improve the inconsistency problem by applying capacity sensitivity analysis and obtain a relatively better evaluation result. For the case of a higher wind power penetration level, since there are still the proximity of voltage dip problem and inconsistency issue for non-zoning method and the zoning method without the consideration of capacity sensitivity analysis, the proposed method is still a promising candidate bus selection

approach. However, the performance improvement brought by the proposed method might be less obvious.

5.) Many-objective Robust Optimization of VAR Planning

Although operational uncertainties (like wind power output) are considered in previous chapters, the uncertainty is not considered in a systematic way and the robustness of these planning decisions cannot be quantitatively evaluated. In this chapter, first, a robustness index is developed for the quantitative robustness assessment of the solutions for the VAR planning problem. Then, it is incorporated into a robust VAR planning model as an objective for the voltage stability enhancement of a wind penetrated power system under various operational uncertainties. Finally, as a many-objective problem, the robust VAR planning is solved by an improved NSGA-III.

5.1 Introduction

The VAR planning to enhance the voltage stability of the power system is usually formulated as a deterministic optimization problem. Different uncertainties, including but not limited to the wind power generation and the initial status of STATCOM before a contingency, that have influential impacts on the dynamic voltage response of the power system are usually neglected [20, 38, 46]. A significant change of the operating condition, compared with the condition used in the planning models, might decrease the robustness of the solutions. Recently, some researchers explore different approaches to improve the robustness of planning decisions. In the earlier stage of Var planning research, uncertainty of load level is usually considered [94, 95]. These works focus on the impacts of the load variations on their optimization objectives, such as the operational cost in [94] and the voltage stability in [95]. The robustness of the solutions is explicitly considered. In [37], the uncertainty of load models is considered. The impact of this operational uncertainty is studied in terms of voltage stability. A robust VAR planning model is proposed in [96, 97], considering the uncertainty of load level. However, these two studies are only focusing on steady-state voltage stability enhancement. A multi-objective VAR planning model is proposed in [39], considering several uncertainties simultaneously. PDF (Probability Distribution Function) of wind power output and the probability of load variations are needed in the model. The accuracy

and effectiveness of the method largely depend on the quality of these probability data. However, it is difficult to accurately obtain these data for a long-term planning problem. The wind power uncertainty is formulated as a multi-scenario generation resource in [40], but the probability data for the “load factor” and “capacity factor” are still needed. Scenarios-based method is another alternative to address the uncertainty issue [87, 124] and the main concern over this method is computation burden. In a word, previous VAR planning models fail to consider the operational uncertainties in a systematic way and are overdependent on the quality of probability data. Given these limitations, the planning solutions from these methods are not robust to operational uncertainties, such as load levels and wind power outputs. They would be less effective and even impractical when the operational uncertainties change significantly.

As for the solving algorithm, NSGA-II has been demonstrated to be one of the most effective algorithms on many benchmark problems [63] and it is also one of the most prevalent algorithms to solve the multi-objective VAR planning problem [37, 38, 46], as well as other power system planning problems [98-100]. Nonetheless, a direct implementation of the original NSGA-II on a VAR planning problem [46] has some limitations due to the inherent drawbacks of NSGA-II when applied on a complex problem, including premature convergence, poor solution diversity, and the large distance between the solutions. Besides, considering the increasing number of objectives when steady-state voltage stability, short-term voltage stability, investment cost, and the new robust metric proposed in this chapter is incorporated in VAR planning model, the algorithms, such as NSGA-II and MOEA/D [38, 46] used to solve the multi-objective optimization problem (2 or 3 objectives) is no longer sufficient. As reported in [101], for many-objective (4 or more objectives) optimization problems, the performance of NSGA-II is not satisfactory. The weighted-sum method is a prevalent approach to address this issue. However, the information will be lost by using the weighted-sum method to combine several objectives into one and it is also very difficult to determine the weight parameters for a practical engineering problem.

To address the inadequacies of the existing works, including lack of a

quantitative way to evaluate the robustness of a solution when subjected to different uncertainties, and the inability to optimize the robustness, a robust VAR planning method for the voltage stability enhancement (including steady-state and short-term) of a wind-penetrated power system towards many-objectives (i.e., 4 or more objectives) is proposed in this chapter. There are three major technical contributions as follows:

1) A novel robustness index is proposed to quantitatively assess the robust optimality of the planning solutions without a requirement for probability distributions of any uncertainty parameters. Then, the robustness of solutions can be optimized and compared in the VAR planning model as an objective.

2) A 4-objective VAR planning method is proposed and used to optimally balance the tradeoff among 4 different aspects: a) total planning cost, b) short-term voltage stability index, c) steady-state voltage stability index, and d) robustness of the solutions.

3) An adaptive NSGA-III-LHS is developed to solve this many-objective VAR planning problem. Compared with the original NSGA-III, the adaptive NSGA-III-LHS algorithm has three improvements for the implementation in the VAR planning problem: a) a fixed mutation rate is replaced by an adaptive one, b) Simulated Binary Crossover is replaced by Differential Evolution operator, and c) Latin Hypercube Sampling is used for the sampling of initial generation, instead of simple random sampling.

5.2 Voltage stability indices

Two metrics are used in this chapter to assess the steady-state and short-term voltage stability of a wind-penetrated power system, respectively. First, an improved VCPI is employed to evaluate the steady-state voltage stability. Then, $TVSI^r$ proposed in Chapter 4 is used to assess short-term voltage stability, considering the deviation extent and the deviation duration simultaneously.

5.2.1 Prioritized VCPI for steady-state assessment

Line-based VCPI [102] is an efficient indicator to assess the steady-state voltage stability with high accuracy and reliability. The details of its mathematical

description can be found in Chapter 2, equ. (2.21) and equ. (2.22). However, the original VCPI neglects the priority and impact of different lines on the power system since it simply calculates the sum of VCPIs of all the lines as the final result. In this chapter, a prioritized index based on original VCPI is developed as (5.1). $VCPI^p$ takes the priorities of lines into evaluation. In practice, the weighting factors for each line (q_l) are determined by three criteria: 1) the ratio of power flow over line capacity, and 2) the geographical location of lines, and 3) sensitivity analysis when subjected to different STATCOM capacities.

$$VCPI^p = \sum_{l \in \mathcal{L}} (q_l \cdot VCPI_l - \sum_{l \in \mathcal{L}} VCPI_l / N^l)^2 / N^l \quad (5.1)$$

5.2.2 Time-constrained TVSI for short-term assessment

As discussed in Chapter 4, prevalent voltage stability metrics are based on the voltage thresholds and the time-varying voltage trajectories. Given the increasing penetration level of wind power generation and its high sensitivity to not only the extent of the voltage deviation but also the time duration of the voltage deviation, $TVSI^r$ proposed in Chapter 4 is employed in this chapter to describe the dynamic voltage response of buses including the extent of the deviation and its corresponding maximum duration of deviation. The details of $TVSI^r$ can be found in Chapter 4.3.1

With the evaluation results for each bus in the system, the overall voltage evaluation result can be calculated in a root-mean-square way like previous chapters. As demonstrated in Chapter 4.5.2, the root-mean-square based metric can reveal the slow or delayed voltage recovery of a bus if other buses recover quickly after a contingency. $TVSI^r$ is calculated as (5.2).

$$TVSI^r = \sqrt{\sum_{i \in \mathcal{B}} (TVSI_i^r)^2 / N^b} \quad (5.2)$$

5.3 Many-objective robust optimization

For a many-objective (i.e., 4 or more objectives) problem with conflicting

objectives (such as lower total cost vs. higher stability performance), instead of one deterministic solution, a group of optimized trade-off solutions should be provided to decision-makers for their different practical needs. Like previous chapters, Pareto optimality theory [62] is also used in this chapter. However, the original Pareto Optimality does not consider the robustness of solutions.

As illustrated in Fig. 5.1, the variation of operational uncertainties might compromise the optimality of the solution. Compared with the operational status considered in VAR planning problems, the actual operational status, due to the inevitable variation of operational uncertainties, might lead to a lower steady-state voltage in post-contingency, or a delayed voltage recovery, or more severe voltage fluctuation. To address this inadequacy, the concept of Robust Optimality is proposed in this chapter. It is used to describe the robustness of the solutions. Furthermore, Sensitivity Region is employed to describe the sensitivity of these trade-off solutions and a robust many-objective optimization method is developed with a robustness index, which is also one of the objectives, that evaluates the robust optimality of the solutions quantitatively. Finally, a many-objective robust optimization problem is formulated.

Figure 5.1 Impact of variations of uncertainties on the voltage dynamics

5.3.1 Compact model

To further explain the concept of Robust Optimality and Sensitivity Region, a compact mathematical model of a multi-objective optimization problem is presented as (5.3-5.5), where in (5.3) F is the overall objective function and $f(\cdot)$ is the sub-objective function. x and $\tilde{w}$ indicate the power system's state and the uncertain variables, respectively. u denotes the decision variables. Constraints (5.4) are the steady-state power balance constraints and post-contingency

power balance constraint. Constraints (5.5) represent the steady-state operational limits, the post-contingency rotor angle constraint, LVHT/HVRT constraint. This compact mathematical model will be expanded equation by equation in the following sub-chapters.

$$\min_u \quad F[f_1(x, u, \tilde{w}), f_2(x, u, \tilde{w}), \dots, f_{Nf}(x, u, \tilde{w})] \quad (5.3)$$

$$\text{s.t.} \quad G(x, u, \tilde{w}) = 0 \quad (5.4)$$

$$H(x, u, \tilde{w}) \leq 0 \quad (5.5)$$

In this chapter, the capacity of STATCOM at each installation bus is the decision variable. Two operational uncertainties are incorporated for the robust VAR planning model: a) wind power generation, and b) the difference between the actual output of STATCOMs before a contingency and their rated capacity. It should be noted that other operational uncertainties, such as load levels can also be incorporated if needed.

5.3.2 Robust Optimality and Robustness Index

5.3.2.1 Acceptable Sensitivity Region (ASR)

As illustrated in Fig. 5.1, random variations of uncertain variables could lead to changes in the values of objective functions (namely, the evaluation results). A robust solution is a solution with objective functions whose values are insensitive or less sensitive to the uncertainty realizations. Given a solution u_0 that is analyzed for its robustness, ASR [103] can be formed in the space of objective function value around the nominal value $f_i(x_0, u_0, \tilde{w}_0)$, as shown in Fig. 2 (a). Subscript “0” of the variables in f_i stands for the original solution. ASR is the maximum acceptable variation of the objective function value when subjected to the variations of specific uncertain parameters ($\Delta\tilde{w}$). For a better elaboration, a case of two uncertainties ($\Delta\tilde{w}_1$ and $\Delta\tilde{w}_2$ in Fig. 2 (a)) and two objective functions (f_1 and f_2 in Fig. 2 (b)) are used as an example. Fig. 2 (a) shows the shape of ASR when the objective functions are subjected to uncertainties. Point A is the scenario when the variation of f_i , which is

represented as Δf_i , is smaller than the maximum acceptable variation Δf_i^{max} when subjected to specific uncertain parameter. Point B represents the scenario when Δf_i equals Δf_i^{max} ; point C represents the scenario when Δf_i is larger than Δf_i^{max} . Correspondingly, Fig. 2 (b) illustrates the range of Δf_i (marked as a dashed rectangle) due to $\Delta \tilde{w}_i$. The points A, B, and C in Fig. 3 (a) correspond to points A, B, and C of the Δf_i ranges (Fig. 3 (b)), respectively. The smaller the range of Δf_i is, the more robust the solution is, because it means that the same variation of uncertainties leads to a smaller change in the objective function.

Figure 5.2 Illustration of (a) Acceptable Sensitivity Region (ASR) and (b) its corresponding Δf_i

For a practical engineering problem, the shape of ASR is always asymmetrical and irregular. It is time-consuming to calculate the area of ASR directly. Therefore, the concept of Sensitive Direction is employed in this chapter to quantitatively estimate the ASR. For instance, as shown in Fig. 5.2 (a), the change rate of Δf_i is smallest in direction s_1 , which indicates that the objective function is the least sensitive to the variations of uncertainty in this direction. The change rate of Δf_i is largest in direction s_2 , which indicates that the

objective function is most sensitive to the variations of uncertainty in this direction.

5.3.2.2 Robust Optimality and Robust Pareto Front

In the conventional VAR planning model, the optimality of a solution is only achieved (or validated) under one or a group of specified operational conditions. Fig. 5.3 illustrates the impact of varying wind power output on the post-contingency voltage response. First, the voltage response of an optimal solution with a 10% wind power penetration level is considered as an original case. As the penetration level increases, the dynamic voltage response is getting worse. In this chapter, the concept of *Robust Optimality* is proposed to describe the phenomena and is incorporated in the VAR planning model to improve the robustness of the solutions.

Figure 5.3 Impact of wind power penetration level on the voltage dynamics

The Pareto front based on a fixed $\tilde{w}_0$ is defined as nominal Pareto front. Generally, a robust Pareto front is inferior to the nominal Pareto front [62], in terms of the objective functions. Fig. 5.4 illustrates three typical scenarios:

- 1) the nominal Pareto front is completely superior to the robust Pareto front;
- 2) there are one or several overlaps between the two Pareto fronts. The rest of the solution from robust Pareto front are sub-optimal, compared with the nominal Pareto front.

3) the robust Pareto front is a sub-set of the nominal Pareto front.

(a)

(b)

(c)

Figure 5.4 Comparison between nominal Pareto Front and Robust Pareto Front

Ideally, a perfect Pareto Front is the one that does not change when subjected to variations of uncertainties (to be the same as the nominal Pareto Front). However, in practice, it is always not the case. The robust Pareto set is generally inferior to the nominal Pareto set, but at same time, with a higher robustness. The purpose of introducing the idea of robust Pareto Front is for the selection of solutions more robust to variations of uncertainties. The robust optimality refers to the insensitivity of the optimal solutions when subjected to uncertainties. Although a robust solution might be a sub-optimal Pareto solution, the robust

optimality of the robust Pareto solution is improved when subjected to the variations of $\tilde{w}$. Besides, there is no probability distribution is needed in the proposed robust VAR planning model. Given the difficulty in reducing the detrimental impact of the uncertainties on a wind-penetrated power system, the robust Pareto front is an acceptable and practical trade-off.

5.3.2.3 Worst Case Sensitivity Region (WCSR)

Generally, the larger the area of ASR is, the more robust the original solution is. However, for a practical engineering problem, the shape of ASR might be extremely irregular. To calculate the area of ASR directly is time-consuming. On the other hand, the worst case is not fully reflected in the robustness analysis under this scenario. Therefore, based on the sensitive direction discussed in chapter 5.3.2.1 and Fig. 5.2, a concept of WCSR is used to quantitatively estimate the robustness of the solution under multiple uncertainties, with an acceptable computation complexity.

WCSR is defined as the largest n -dimension sphere within the ASR (n is the number of uncertainties). A 2-dimension case is illustrated in Fig. 5.5. Instead of calculating the area of ASR, the radius, R^w , of the symmetric WCSR is employed as an indicator of robustness against uncertainties. Specifically, R^w is calculated based on L_p -norm in (5.6), of which p can be 1, 2 or ∞ . Different L_p -norms are illustrated in Fig. 5.6

$$\min_{\Delta \tilde{w}} \quad R^w(\Delta \tilde{w}) = \left[\sum_n^{N^u} |\Delta \tilde{w}_n|^p \right]^{1/p} \quad (5.6)$$

$$\text{s.t.} \quad \max_{i=1,2,\dots,N^f} (|\Delta f_i - \Delta f_{0,i}|) \leq \tau_i^f \quad (5.7)$$

where $\Delta f_{0,i}$ indicates an acceptable deviation of objective function caused by $\Delta \tilde{w}$. Δf_i is defined as the difference between $f_i(x_0, u_0, \tilde{w}_0 + \Delta \tilde{w})$ and $f_i(x_0, u_0, \tilde{w}_0)$. Since the actual area of ASR can be estimated through the radius, the robustness of a solution can be estimated by R^w as (5.6).

Figure 5.5 Illustrations of WCSR

Figure 5.6 Illustrations of different L_p -norms

5.3.2.4 Feasibility Sensitivity Region (FSR)

Similar to WCSR, FSR is employed to evaluate the feasibility of the solution, in terms of the constraints. As illustrated in Fig. 5.7, any $\Delta\tilde{w}$ within Feasibility Worst Case Sensitivity Region (FWCSR) will not compromise the feasibility of the solutions. R^f , calculated as L_p -norms in (5.8), is used to evaluate the solution feasibility. The boundary of FWCSR is determined by (5.9) and (5.10).

Figure 5.7 Illustrations of FWCSR

$$\min_{\Delta \tilde{w}} \quad R^f(\Delta \tilde{w}) = \left[\sum_n^{N^u} |\Delta \tilde{w}_n|^p \right]^{1/p} \quad (5.8)$$

$$\text{s.t.} \quad \max_{i=1,2,\dots,N^h} [h_i(x_0, u_0, \tilde{w}_0 + \Delta \tilde{w})] \leq 0 \quad (5.9)$$

$$\max_{i=1,2,\dots,N^g} [|g_i(x_0, u_0, \tilde{w}_0 + \Delta \tilde{w})|] \leq \tau_i^g \quad (5.10)$$

5.3.3 Objective functions

A many-objective robust optimization problem is proposed in this chapter, consisting of four sub-objectives: 1) total planning cost, 2) $TVSIR^r$, 3) $VCPI^p$, and 4) Robust Index (RI).

5.3.3.1 Total planning cost (f_1)

The first objective function is for the total planning cost. It is calculated as (5.11).

$$f_1 = C^{invest} = \sum_{i \in \mathcal{B}_s} C_i^{invest} \quad (5.11)$$

$$C_i^{invest} = \begin{cases} c_i^{install} + c^{cap} \cdot cap_i, & \text{if } cap_i \neq 0 \\ 0, & \text{if } cap_i = 0 \end{cases} \quad (5.12)$$

5.3.3.2 Time-constrained TVSI (f_2)

The second objective function is for short-term voltage stability evaluation. It is calculated as (5.13). Like previous chapters, a risk-based approach is used in this chapter for the contingency analysis, considering their probabilities and diverse impacts on the voltage performance of the system. $TVSI_k^r$ is calculated based on (5.2).

$$f_2 = \sum_{k \in \mathcal{K}} TVSI_k^r \cdot p_k \quad (5.13)$$

5.3.3.3 Prioritized VCPI (f_3)

The third objective function is for steady-state voltage stability assessment. A risk-based criterion is also used here as (5.14), where the $VCPI_k^p$ is calculated using (5.1).

$$f_3 = \sum_{k \in \mathcal{K}} VCPI_k^p \cdot p_k \quad (5.14)$$

5.3.3.4 Robustness Index (f_4)

For a practical engineering problem, R^w and R^f can be calculated for each solution and the solutions can be compared. However, with R^w and R^f alone, the decision-makers still cannot tell if this decision is robust or not. To address this inadequacy, a Robustness Index based on WCSR and FWCSR is proposed as (5.15). R^{ref} is a reference robust radius that is determined by an acceptable uncertainty vector $\Delta\tilde{w}$. By introducing the reference, not only the robustness of a solution can be optimized with other objectives, but also it can be judged without comparison with other solutions: it is considered as a robust solution if f_4 is smaller than 1 and it is not robust if f_4 is larger than 1.

$$f_4 = R^{ref} / \min(R^w, R^f) \quad (5.15)$$

5.3.4 Constraints

Constraints (5.16) are active and reactive power flow balance. The steady-state operational constraints, including voltage magnitude, line capacity, and generation output capacity are expressed in constraints (5.17).

$$\begin{cases} P_g + \widetilde{P}_w - P_d - V_i \sum_{j \in \mathcal{B}} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \\ Q_g + \widetilde{Q}_w + Q^{stat} - Q_d - V_i \sum_{j \in \mathcal{B}} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0 \end{cases} \quad (5.16)$$

$$\begin{cases} V_i^{min} \leq V_i \leq V_i^{max} \\ L_l^{min} \leq L_l \leq L_l^{max} \\ P_g^{min} \leq P_g \leq P_g^{max} \\ Q_g^{min} \leq Q_g \leq Q_g^{max} \end{cases}, \forall i \in \mathcal{B}, \forall l \in \mathcal{L}, \forall g \in \mathcal{G} \quad (5.17)$$

Constraint (5.18) serves as a transient stability constraint, which means that the maximum allowed rotor angle difference between any two generators ($\Delta \delta_{gg'}^T$) during a transient period of T of a contingency k should be smaller than or equal to ω . This constraint is used to check the transient rotor angle stability for each contingency. Constraints (5.19) are for LVRT and HVRT profile. $V_{i,t}$ is used to present the time-varying voltage trajectory.

$$[\max(\Delta \delta_{gg'}^T)]_k \leq \omega \quad \forall g, g' \in \mathcal{G}_s, \forall k \in \mathcal{K} \quad (5.18)$$

$$\begin{cases} V_{i,t} - LVRT(t) \geq 0, \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{B}_w \\ V_{i,t} - HVRT(t) \leq 0, \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{B}_w \end{cases} \quad (5.19)$$

5.4 Solution method

5.4.1 Non-dominated Sorting Genetic Algorithm-III (NSGA-III)

A reference point based many-objective evolutionary algorithm, called NSGA-III, is proposed by Deb and Jain in [104]. Generally, the framework of

NSGA-III is quite similar to that of NSGA-II [63]. However, NSGA-III has a better performance in solving many-objective problems because of an improved selection mechanism of the offspring. The diversity of individuals in a population is maintained by adaptively supplying and updating well-distributed reference points. The main body of NSGA-III is described as follows:

Algorithm 1 NSGA-III

1. Classify the population
 2. Calculate the number of reference points (H) to place on the normalized hyper-plane.
 3. Realize the non-dominated sorting.
 4. **for** $t=1$ *Stopping criteria* **do**
 5. Select P_1 and P_2 through tournament method
 6. Perform crossover between P_1 and P_2 (with probability P_c)
 7. Realize the non-dominated sorting
 8. Normalize the population members
 9. Associate population members with the reference points
 10. Apply the niche preservation
 11. Keep the niche obtained solution for the next generation
 12. **end for**
-
-

1) Classification of Population

For a parent population (of size N) at the t^{th} generation (P_t), the offspring population (Q_t) with N members, is obtained by the recombination and the mutation of P_t . The combination of the offspring population and parent population, namely C_t , is sorted to different non-dominant levels ($F_1, F_2, \dots, F_l$) in order to preserve elite members. So, a new population S_t is constructed by selecting individuals of each non-dominant levels until the size of $S_t \geq N$ (starting from the 1st non-dominant level). For $S_t = N$, no further action is needed, and the next generation starts with $P_{t+1} = S_t$. For $S_t > N$, since members from one to the

second last front are already selected, the remaining population members are selected from the last front.

2) *Determination of reference points*

Das's systematic approach [105] is employed to place points on a normalized hyper-plane that equally inclined to all objective axes and has an intercept of one on each axis. If p divisions are considered with each objective, the total number of reference points (H) in a G -objective problem is defined by (5.20).

$$H = \binom{G + p - 1}{p} \quad (5.20)$$

3) *Normalization of the population members*

The normalization of objective values is carried out according to (5.21-5.23). The ideal point of S_t is determined by identification of the minimum value (z_m^{min}) for each objective function ($m=1,2,\dots,M$), and by the construction of the ideal point $\bar{z} = (z_1^{min}, z_2^{min}, \dots, z_m^{min})$. $f'_m(x)$ is the translated objective function. $ASF(x, \omega)$ is the extreme point value in each objective axis and $f_m^n(x)$ is the normalized objective function. ω_m denotes the weight vector of each objective and a_m denotes the intercept of the m^{th} objective axis.

$$f'_m(x) = f_m(x) - z_m^{min} \quad (5.21)$$

$$ASF(x, \omega) = \max_{m=1}^M f'_m(x) / \omega_m \quad (5.22)$$

$$f_m^n(x) = f'_m(x) / (a_m - z_m^{min}) \quad (5.23)$$

4) *Association among reference points & solutions*

After normalization, a reference point will be associated with each population member. A reference line corresponding to each reference point on the hyper-plane is defined by joining the reference point with the origin. The shortest perpendicular distance between each individual of S_t and each reference line is calculated. If the reference line of a reference point is closest to a population member in the normalized objective space, it is considered to be associated with

the population member.

5) *Niche preservation operation*

After the association operation, “niche preservation” operation is carried out to select individuals (of i^{th} level) that are associated with each reference point. Details of the niche preservation procedures can be found in [104].

6) *Generation of offspring*

After the formation of P_{t+1} , Q_{t+1} can be generated by applying the usual crossover and mutation operator by randomly choose parents from P_{t+1} .

5.4.2 Adaptive NSGA-III

Although NSGA-III has been implemented to solve engineering problems successfully [106, 107], there are still some shortcomings when NSGA-III is employed to solve complex many-objective engineering problems.

1) *Fixed mutation rate*

Although a smaller mutation rate is favorable for the 1st generation because of the relatively good diversity, a larger mutation rate is better to improve the diversity when the diversity of later generations becomes poor. Since NSGA-III uses a fixed mutation rate for all generations, it would be difficult to select a suitable mutation rate.

2) *Random Sampling*

The sampling method adopted in NSGA-III is the simple random sampling. When it generates a new sample point, it does not take previously generated sample points into consideration. This pure randomness might lead to an inferior generation: some sampling points clustered closely, while some intervals in the space have no samples at all.

3) *Simulated Binary Crossovers (SBX)*

SBX used in the original NSGA-III has a strong local search ability. However, it prefers offspring near the parents than offspring away from parents. This preference increases the possibility of local optimality, especially for a complex practical engineering problem.

To address the aforementioned disadvantages and improve the original NSGA-III for a practical engineering application, an Adaptive NSGA-III-LHS is proposed in this chapter with the following three improvements.

5.4.2.1 An adaptive mutation rate

An adaptive strategy is developed as (5.26) to adaptively adjust the mutation rate based on not only the generation number but also the crowdedness of a generation. Firstly, a Crowdedness Index (CI) is defined in (5.24). Then, it is unified in (5.25) to make sure that the CI s of the n^{th} generation are in the range of $[0,1]$.

$$CI_n^* = \sum_{d=1}^{N^{ind}} (u_{d,n} - u_n^{avg}) / (u_n^{max} - u_n^{min}) \quad (5.24)$$

$$CI_n = \frac{CI_n^* - CI_n^{min}}{CI_n^{max} - CI_n^{min}} \quad (5.25)$$

Based on CI , an adaptive mutation rate p_m can be calculated as (5.26):

$$p_m = p_0 + \frac{CI_n \cdot (1 - p_0) \cdot (n - 1)}{n^{max} - 1} \quad (5.26)$$

where n and n^{max} are the current and maximum generation, respectively.

The improvements of the adaptive mutation rate are twofold: 1) for the first few generations, the result of $(1 - p_0) \cdot (n - 1) / (n^{max} - 1)$ is relatively small, and as the optimization proceeds, the result of $(1 - p_0) \cdot (n - 1) / (n^{max} - 1)$ increases gradually; 2) since CI_n completely depends the crowdedness of a population, p_m will be also modified as the crowdedness of the population changes. By applying (5.26), instead of being a fixed value like the original NSGA-III or blindly increasing proportionally as the number of generations increases, the mutation rate becomes more adaptive.

5.4.2.2 Latin Hypercube Sampling (LHS)

NSGA-III and most of the genetic algorithms use a simple random sampling approach to generate the 1st generation. Since the simple random sampling does not consider the previous samples when generating new ones, it will bring a non-uniform sampling problem as discussed at the beginning of chapter 5.4.2. So, dozens of repeated experiments are required to obtain an averaging result to cancel out this non-uniform problem. However, considering the high computation burden of a practical engineering problem, these repeated experiments are time-consuming and unacceptable, especially for a VAR planning problem considering short-term voltage stability and various operational uncertainties. Therefore, LHS, an experimental design method first proposed in [108], is adopted in this chapter to generate the first generation. Generally, the samples generated by LHS can represent the real variability in a sampling space (in this chapter, it is the range of potential STATCOM capacity) more accurately than the simple random sampling.

If a random input vector $\mathbf{X}$ has m dimensions $\mathbf{X} = (X_1, \dots, X_m)$ and each X_j is independent of the others ($j=1, \dots, m$). An LHS set can be generated as (5.27):

$$X_{i,j} = F^{-1} \left(\frac{\pi_j(i) - U_{i,j}}{n} \right), i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (5.27)$$

where n is the total number of samples and $\pi_j(1), \dots, \pi_j(n)$ are random permutations of $[1, \dots, n]$. $U_{i,j}$ is a random variable from a standard uniform distribution. The LHS approach is characterized by a segmentation of the assumed probability distribution into a number of randomly sampled and non-overlapping intervals with equal probability.

5.4.2.3 Differential Evolution (DE) Operator

DE operator, which has a good global search ability [109], is used in this chapter instead of the original SBX. It utilizes the differences between randomly selected individuals as evolutionary dynamics. Unlike the preference of SBX over nearer offspring, DE operator uses a “jump in neighborhood search” approach (adding weighted vectors to the target vector properly) to control the

evolutionary variation. Procedures of DE operator are as follows:

- 1) *Input*: Population size and the population P_n
- 2) *Random Selection*: Select three individuals $x_{r_1,n} \neq x_{r_2,n} \neq x_{r_3,n}$. They do not dominate each other from P_n .
- 3) *Mutation Operator*: Generate mutant vector $v_{i,n+1} = [v_{i,1}, v_{i,2}, \dots, v_{i,j}, \dots, v_{i,D}]$ (D represents the dimension of a problem and K is the scale factor).

$$v_{i,n+1} = x_{r_1,n} + K \cdot (x_{r_2,n} - x_{r_3,n}) \quad (5.28)$$

- 4) *Cross Operator*: Generate a trial vector $u_{i,n+1} = [u_{i,1}, u_{i,2}, \dots, u_{i,j}, \dots, u_{i,D}]$ by exchanging the components between the x_i and v_i . Usually there are 2 crossover methods used in DE: binomial and exponential. In this chapter, the binomial crossover method is employed as (5.29).

$$u_{i,1} = \begin{cases} v_{i,1}, & \text{if } \text{rand}(0,1) \leq CR \text{ or } j = j^{rand} \\ x_{i,n}, & \text{if } \text{rand}(0,1) \leq CR \text{ or } j = j^{rand} \end{cases} \quad (5.29)$$

where CR is a crossover rate, and j^{rand} is a number randomly selected from $[1, 2, \dots, D]$.

5.4.3 Computation steps

The computational flowchart is illustrated in Fig. 5.8 and the computation steps are described as follows:

1) Initialization

After algorithm parameters setting, the candidate bus is selected based on the method used in Chapter 3 or the new proposed method in Chapter 5. The individuals of the 1st generation are generated based on LHS.

2) Steady-state Voltage Stability and Robustness Evaluation

Steady-state voltage stability is evaluated with the different priorities of buses. The evaluation result for the base case, $f_3(x_0, u_0, \tilde{w}_0)$, is used to calculate the uncertainty sensitivity region and feasibility sensitivity region.

3) Short-term Voltage Stability and Robustness Evaluation

Voltage performance of the system in the post-contingency stage is evaluated based on the voltage trajectories that obtained from the time-domain simulations. The evaluation result for the base case, $f_2(x_0, u_0, \tilde{w}_0)$, is used to calculate the uncertainty sensitivity region and feasibility sensitivity region.

4) Calculations of Objectives

Four objectives are calculated in a risk-based approach, including total planning cost, evaluation result for steady-state voltage stability, evaluation result for short-term voltage stability, and Robustness Index (RI).

Figure 5.8 General computation flowchart of the proposed method

5) Individuals updating

Find the best individual of the current generation and then update it as the

best individual of the generation. The update further contains two steps: a) comparison between each individual, and b) selection of the best Pareto solution.

6) *Termination*

Two stopping criteria are adopted in this chapter: a) changes in fitness function is smaller than a specific tolerance, and b) the maximum iteration number is reached. If one of them is satisfied, the computation procedure will be terminated, and the final optimization result will be presented as a Pareto Front.

7) *Mutation update and Offspring generation*

If the stopping criteria are not satisfied, the mutation rate will be modified as (5.26). Then, the computation procedure will go to step 2 after new offspring are generated.

8) *Break criteria*

if any post-contingency constraints are violated, the assessment of the individual will be terminated. The objective functions will be calculated accordingly with high penalty parameters. Then, the computation procedure will go to step 4.

5.5 Numerical results and discussions

5.5.1 Test system and parameters

The effectiveness and efficiency of the proposed method are validated on the New England 39-bus test system with several modifications, as illustrated in Fig. 5.9. Compared with the original test system, synchronous generators at bus 30, bus 32, and bus 34 are replaced by wind farms. All the wind turbines are modeled as Double-Fed Induction Generators in PSS®E 33.4 [60]. Specifically, the generator model, the mechanical model, the electrical model, and the pitch control model are the same ones used in Chapter 2.5. The STATCOM model is SVSMO3 as illustrated in Fig. 2.9. An industry-standard complex load model "CLOD" [60] is adopted to simulate the time-varying load dynamics. The details

of the load model can be found in Chapter 2.3.6 with a simplified illustration (Fig. 2.4). Major parameters for case studies are listed in Table 5.1. In a real-world application, the parameters for the CLOD model can be determined based on historical load data.

Figure 5.9 New England 39-bus test system

Contingency analysis is based on the method used in reference [37, 38]. Faults on line 2-3, line 6-7, and line 16-24 are selected as three critical contingencies. Two operational uncertainties are considered in the case studies: 1) the initial state of STATCOMs (0.6p.u.~1.0p.u.) before the contingency, 2) and wind power generation (20%~30% penetration level). The peak load level is selected in the case studies because the dynamics of loads has a more profound impact on the short-term voltage stability of the system than load levels [110]. $p=2$ (namely, *Euclidean* norm) is used in (5.6) and (5.8) for the calculation of Robustness Index. The steady-state analysis is carried out in Matlab 2018b with MATPOWER 6.0 and the time-domain simulation is carried out in PSS®E 33.4.

Table 5.1 Parameters for simulation setting

Parameters	Value
$c^{install}, c^{cap}$	1.5 million/unit, 0.05 million/MVar
p_0	0.15
ω	π
t^{dl}/t^{du}	0.5s/0.5s
v^{dl}/v^{du}	0.9 pu/1.1 pu
penalty parameter (α^l & α^u)	2.0
LHS levels	20 (0~100MVar)
LM, SM, DL, TS, CP, K_p	25%, 15%, 10%, 10%, 10%, 2
Fault setup	3-phase short-circuit (cleared after 0.1s)

5.5.2 Simulation results and comparison study

The overall simulation time is 220790 seconds. The computation burden is acceptable for a long-term VAR planning problem. Fig. 5.10 shows a Pareto Front with 56 robust Pareto optimal solutions (as the planning decisions). As a four-dimension illustration, Robustness Index (f_4) is shown in different colors.

Figure 5.10 Pareto optimal solutions of the proposed method**Table 5.2 Installation decisions (in MVar)**

Bus No.	7	16	24	30	32	34
Capacity	96.3	97.2	100	29.7	98.5	47.7

Like previous chapters, the fuzzy membership function [68] is used to select the final compromise solution from the robust Pareto Front for further comparison and analysis. The mathematical details of the fuzzy membership function can be found in Chapter 2.5.2. A compromise solution is also marked in Fig. 5.10. The installation plans of the solution for each candidate bus are listed in Table 5.2.

Two additional methods (method B and method C) are compared in Table 5.3 to show the advantages of the proposed method.

1) **Method A:** It is the proposed method (with four objectives) based on the voltage stability indices introduced in this chapter. The proposed Adaptive NSGA-III-LHS is used to solve the problem. The solution used for the comparison and analysis is a compromise solution selected from the robust Pareto Front based on the fuzzy membership function [68].

2) **Method B:** It is the conventional method (with only three objectives, robust optimality is not considered) based on the voltage stability indices introduced in this chapter. NSGA-II is employed to solve the problem. The solution used for the comparison and analysis is a compromise solution selected from the normal Pareto Front based on the fuzzy membership function.

3) **Method C:** It is the proposed method (with four objectives) based on the voltage stability indices introduced in this chapter. The original NSGA-III is utilized to solve the problem. Two solutions are selected from the robust Pareto Front based on two different criteria, respectively. The first solution (marked as “avg.” in Table 5.3) is a mean value of compromise solutions from 10 simulation runs (in Table 5.3, computation time is the total time for 10 runs). Repeated simulations are conducted to offset the problem caused by the simple random sampling, as discussed in chapter 5.4.2. The second solution (marked as “best” in Table 5.3) is a compromise solution selected from the robust Pareto Front based on the fuzzy membership function.

Table 5.3 Simulation results

Methods	Total Cost (f_1)	Improved TVSI (f_2)	Improved VCPI (f_3)	Robustness Index (f_4)	Computation Time
A	32.47	3.825	1.539	0.7589	220790s
B	32.64	3.834	1.492	1.0707	25036s
C (avg.)	32.93	3.845	1.568	0.8289	2322498s [*]
C (best)	33.03	3.831	1.545	0.7956	227696s

Figure 5.11 Voltage trajectories comparison between method A and method B

For all the evaluation results, a smaller value indicates better voltage stability or higher robustness, as listed in Table 5.3. The voltage stability performance of method A (the proposed method) is close to that of method B (conventional method). Method B even has better steady-state voltage stability (VCPI) compared with method A. However, the robust optimality of the solution from method B is much worse than that of the solution from method A. Although method B does not consider the robustness of the solution, the Robustness Index can still be calculated for method B based on Chapter 5.3.2, which is 41.1% worse than that of method A. Figure. 5.11 compares the voltage trajectories of bus 16 between method A and method B under the worst scenario: the wind power penetration level is 30% and the output of STATCOMs before the contingency is at the rated capacity. Once the fault is cleared, method A has a fast voltage recovery while method B experiences a relatively slow voltage recovery.

Fig. 5.12 shows two Pareto Fronts of method A and method B. The Robustness Index of all Pareto optimal solutions of method B are calculated based on Chapter 5.3.2. Most of the solutions of method B have worse robustness (marked as diamonds) compared with the solutions of method A (marked as circles). On the other hand, some solutions of method B are better than those from method A, in terms of voltage stability and total cost. This is exactly the scenario presented in the robust analysis in Chapter 5.3.2.2, Fig. 5.4 (b).

Figure 5.12. Pareto optimal solutions comparison of method A and method B

Compared with solutions of method C (mean value of 10 simulation runs), solutions of method A not only have better evaluation results for steady-state and short-term voltage stability, but also cost less. Besides, the computation burden of method A is much lighter (90.5% reduction) than that of method B. When compared with the best compromise solution from all the solutions generated by the 10 simulation runs, namely method C (best) in Table 5.3, method A still outperforms method C in all aspects, including voltage stability, robust optimality, total cost, and computation time. It demonstrates that the proposed Adaptive NSGA-III-LHS effectively avoids the drawbacks of the original NSGA-III.

Fig. 5.13 shows the advantage of the time-constrained TVSI. It is the post-contingency voltage trajectory of bus 34. For a clearer illustration of the voltage deviation, the installation plan for STATCOMs used here is not the compromise solution of the proposed method. Based on the definition of original TVSI, which

does not differentiate the common voltage deviations (within the required time window) and the delayed voltage recovery, the evaluation result (0.2828 after normalized) for short-term voltage stability is calculated by integrating all the voltage deviations. However, since the prolonged voltage deviation after 6s contributes little to the final evaluation result, these minor but frequent voltage violation is not effectively reflected in the evaluation result. On the other hand, given the protection mechanism of wind turbines, they will be in danger of automatically triggering because of minor but frequent voltage deviations (after the 4s). These dangers cannot be fully revealed in the original TVSI. By using the proposed time-constrained TVSI, these prolonged voltage deviations are penalized. So, a significant 64.63% increase in the evaluation result (0.4656 after normalized) can clearly reveal the potential danger imposed on wind turbines. Furthermore, a larger variation can also make the Adaptive NSGA-III-LHS more efficient in finding optimal solutions.

Figure 5.13 Illustration of the un-penalized and penalized voltage deviations

5.5.3 Scalability and computation efficiency discussion

When the short-term voltage stability is considered, it is time-consuming to solve the VAR planning problem due to its highly non-convex and non-linear properties, as well as the complicated time-domain simulations. Specifically, for this robust VAR planning problem, the total time cost T is generally proportional to the following parameters.

$$T \propto (N^c, N^{gen}, N^{pop}, N^{dec}, N^{unc}, T^{dts}, T^{OPF}) \quad (5.30)$$

where N^c is the number of critical contingencies verified in time-domain simulations. N^{gen} , N^{pop} , and N^{dec} are the number of generations, population size, and the number of decision variables for the evolutionary algorithm, respectively. N^{unc} is the number of the uncertainties considered in the problem. T^{dts} denotes computation time for a single time-domain simulation. T^{OPF} is the computation time for a single OPF run.

As the studied network becomes larger, the corresponding increase in computation cost is relatively moderate when compared with the increase of total buses. This is partly because the number of candidate buses, which determines the number of decision variables of the problem, needed for a larger system is not necessary to increase proportionally with the number of the total bus. Another case study carried out on a Nordic 74-bus system [76] is used for comparison, as in Table 5.4. Although the number of total buses increases from 39 to 74 (89.7% increase), the computation time only slightly increases from 220790s to 246583s (10.5%).

Table 5.4 Computation costs for different test systems

Test system	Total computation time
New England 39-bus	220790s
Nordic 74-bus	246583s

On the other hand, VAR planning of a large-scale power system usually follows an area-based approach rather than taking the whole system as an undivided entity [77] in practice. To study the VAR planning problem in this area-based way can minimize the reactive power transmission between different areas and maximize the self-sufficiency of each area. Besides, it is also a long-standing industrial standard and engineering practice in countries like China [111, 112]. Therefore, it is practical to divide a large power system into areas and then study the VAR planning problem within each area while other areas can be modeled as one or several equivalent sub-systems. On the other hand, a distributed computing platform [113] can also be developed for PSS®E-based

power system analysis. For a control center of a utility grid, parallel computing is prevalent. Although there is a concern over the communication efficiency between different processors and control centers, the computational burden of the proposed method can be significantly reduced by assigning tasks of contingency verifications and operation scenario verification using parallel computation techniques [113]. So, the computation burden is manageable for a real-world application.

5.6 Conclusions

In this chapter, a many-objective robust dynamic VAR planning method for a wind-penetrated power system is proposed to enhance the steady-state and short-term voltage stability based on two voltage stability indices and a novel robustness index without a requirement for the presumed probability distributions of uncertainties. An Adaptive NSGA-III-LHS, which has a better performance over the original NSGA-III and reduces the computation time significantly, is proposed to solve the planning problem. Case studies on the modified IEEE 39-bus system and Nordic 74-bus system show the effectiveness of the proposed method. The robustness of a Pareto optimal solution can be effectively evaluated by the proposed robustness index. The robust Pareto optimal solutions from the proposed method are less sensitive to two operational uncertainties (the initial state of STATCOMs before the contingency and variations of wind power generation), compared with the solutions of the conventional method. Compared with the conventional short-term voltage stability index TVSI, the proposed time-constrained TVSI can clearly reveal the impact of the minor but prolonged voltage deviations on the wind-penetrated power system.

6.) Conclusion and recommendations

6.1 Conclusions

In this thesis, a robust multi-stage VAR planning model for voltage stability enhancement is developed to deal with the voltage stability issue and the lack of fast-response reactive power source in a wind-penetrated power system, based on a set of improved voltage resilience indices and a robustness index. The main conclusions are summarized as follows:

In Chapter 2, a multi-stage coordinated VAR planning framework is proposed for a wind-penetrated power system. Network enhancement measures (installation of STATCOM) and operational measures (preventive controls and corrective control) are coordinated to enhance the voltage stability of the wind-penetrated power system. Compared with conventional methods focusing only on the capacity and location of the STATCOMs, the proposed method effectively coordinates STATCOMs deployment (planning stage), preventive controls (pre-contingency operation stage), and corrective controls (pre-contingency operation stage) to enhance the steady-state and short-term voltage stability. Case studies on a modified New England 39-bus system demonstrate that the coordination of countermeasures in different stages can reduce the total planning cost effectively without any deterioration of the voltage stability performance. The research objective 1 defined in Chapter 1, a coordinated model aims to avoid conservative planning decisions and redundant investment of the conventional single-stage approach, has been achieved. The corresponding work has been published in [J1] in Author's Publications.

Chapter 3, Chapter 4, and Chapter 5 are specific improvements based on the framework proposed in Chapter 2. In Chapter 3, a set of novel quantitative indices is proposed to comprehensively assess evaluate the network enhancement measure and the operational measures, as well as the voltage resilience of the system as a whole, from two perspectives: the defensive capability before a contingency and restorative performance after a contingency. Compared with the conventional voltage stability index, the novel resilience metrics describe the voltage performance more comprehensively and

increase the potential of candidate solutions to survive an extreme contingency. The research objective 2 defined in Chapter 1, to develop a set of voltage resilience indices for a more comprehensive assessment of the voltage resilience of a wind-penetrated power system, has been achieved. The corresponding work has been published in [J2] in Author's Publications.

Chapter 4 deals with the candidate bus selection issue. Conventional short-term voltage stability is improved to evaluate the whole voltage recovery process. The proposed indices can assess the whole voltage recovery process comprehensively in terms of the extent of the deviation, recovery speed, and post-contingency steady state, compared with the conventional voltage stability metrics based on post-contingency trajectories. The proposed method can avoid the selection of redundant buses and reduce installation costs without any deterioration of the voltage stability. Case studies demonstrate that the proposed method can effectively avoid the selection of redundant buses and improve the inconsistency problem of conventional candidate bus selection by applying capacity sensitivity analysis. The research objective 3 defined in Chapter 1, to avoid redundancy of bus selection and to avoid inconsistency issue of other existing zoning-based approaches, has been achieved. The corresponding work has been published in [J3] in Author's Publications. For the case of a higher wind power penetration level, since there are still the proximity of voltage dip problem and inconsistency issue for non-zoning method and the zoning method without the consideration of capacity sensitivity analysis, the proposed method is still a promising candidate bus selection approach. However, the performance improvement brought by the proposed method might be less obvious.

Chapter 5 aims to improve the robustness of the VAR planning decisions by incorporating a novel robustness index as an objective to be optimized and improve the performance of the solution algorithm for a many-objective optimization problem with less computation complexity. Case studies on two prevalent test systems demonstrate the effectiveness of the proposed robustness index in the assessment of the robust optimality of a Pareto optimal solution, as well as the superiority of the proposed adaptive NSGA-III-LHS over the original NSGA-III. The robust Pareto optimal solutions from the proposed

method are less sensitive to two operational uncertainties (the initial state of STATCOMs before the contingency and variations of wind power generation), compared with the solutions of the conventional method. The research objective 4 defined in Chapter 1, to quantitatively evaluate the robustness of decision plans (with a robustness index) when subjected to operational uncertainties, has been achieved. The research objective 5 defined in Chapter 1, to improve performance of the original NSGA-III, has been achieved. The corresponding work has been published in [J4] in Author's Publications.

As for the limitations and conditions of application of the proposed methods, the methods proposed for a VAR planning of a large-scale power system based on an assumption that this power system follows an area-based approach rather than taking the whole system as an undivided entity. To study the VAR planning problem in this area-based way can minimize the reactive power transmission between different areas and maximize the self-sufficiency of each area. On the other hand, since only two operational uncertainties are considered in the case studies in Chapter 5, more operational uncertainties according to the practical needs of the decision-makers should be verified in this model before a real-world application. Lastly, timing and sequence of the placement of the reactive power sources is not considered in this thesis and should also be incorporated in future along with the transmission expansion planning.

6.2 Recommendations for future research

In addition to the work presented in this thesis, there are some research topics that are worthy to be explored in the future, as listed below:

1) *Impacts of correlated operational uncertainties*

Although different uncertainties are considered in this thesis, they are regarded as independent inputs for the VAR planning problem. In practice, there is always a certain level of stochastic correlation that exists between different operational uncertainties. For instance, loads and wind power generation are dependent, and their correlation is nonlinear and non-Gaussian [114]. Conventional random sampling methods, such as the Monte Carlo method with independent distribution, only consider the operational uncertainties in a

separate approach. Even for a method with a consideration of a joint distribution of wind power and loads [115], the linear correlation may not be accurate enough to reveal the dependence between uncertainties. Currently, there are some literatures, although not directly used in a VAR planning problem, employing Copula theory [116] to represent dependence between the operational uncertainties [114, 117, 118]. However, the selection of an appropriate copula family for different correlations largely depends on a case-by-case trial and error method. The efficiency and accuracy of different copula families should be further verified. On the other hand, copula families should be also selected systematically. Therefore, the research on the impacts of correlated operational uncertainties on the wind-penetrated power systems is a very promising area that should be explored in the future.

2) Coordination of VAR planning and Transmission Expansion Planning

Generally, VAR planning is carried out after the Transmission Expansion Planning (TEP) is completed. In other words, the network structure at the end of the planning horizon is considered and the topological uncertainty of the network is largely ignored by researchers in this area. However, since VAR planning is long-term (5 years or even 10 years), changes or expansion of the network structure should be considered in the planning framework. Otherwise, the planning decisions made based on this static model will lead to an overcapacity of STATCOMs since the ultimate capacity is not needed until the end of the planning horizon.

On the other hand, many studies have explored the coordination of generation and transmission expansion planning [119, 120] using a dynamic approach. The dynamic model enables planners to adjust to changes in network structure throughout the whole planning horizon. There are also few studies [121, 122] working on the coordination of VAR planning and TEP. However, these studies only focus on steady-state analysis. The computation burden of these methods would be unacceptable if the short-term voltage stability issues are considered. Therefore, a dynamic coordinated planning model of the reactive power source and transmission expansion throughout the whole planning horizon should be developed in the future to address the overcapacity issue with a manageable computation complexity.

Author's publications

Journal publications

- [J1] **Y. Chi** and Y. Xu, "Zoning-based candidate bus selection for dynamic VAR planning in power system towards voltage resilience," *IET Generation, Transmission & Distribution*, vol. 14, no. 6, pp. 1012-1020, Mar. 2020.
- [J2] **Y. Chi** and Y. Xu, "Multi-stage coordinated dynamic VAR source placement for voltage stability enhancement of wind-energy power system," *IET Generation, Transmission & Distribution*, vol. 14, no. 6, pp. 1104-1113, Mar. 2020.
- [J3] **Y. Chi**, Y. Xu and T. Ding, "Coordinated VAR planning for voltage stability enhancement of a wind-energy power system considering multiple resilience indices," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 4, pp. 2367-2379, Oct. 2020.
- [J4] **Y. Chi** and Y. Xu, "Multi-objective robust tuning of STATCOM controller parameters for stability enhancement of stochastic wind-penetrated power systems," *IET Generation, Transmission & Distribution*, vol. 14, no. 21, pp. 4805-4814, Nov. 2020.
- [J5] **Y. Chi**, Y. Xu and R. Zhang, "Candidate bus selection for dynamic VAR planning towards voltage stability enhancement considering copula-based correlation of wind and load uncertainties," *IET Generation, Transmission & Distribution*, vol. 15, no. 4, pp. 780-791, Dec. 2020.
- [J6] **Y. Chi**, Y. Xu and R. Zhang, "Many-objective robust optimization for dynamic var planning to enhance voltage stability of a wind-energy power system," *IEEE Transactions on Power Delivery*, vol. 36, no. 1, pp. 30-42, Feb. 2021.

Conference publications

- [C1] **Y. Chi**, Y. Xu, C. Hu and S. Feng, "A State-of-the-Art Literature Survey of Power Distribution System Resilience Assessment," *2018 IEEE Power & Energy Society General Meeting (PESGM)*, Portland, OR, 2018, pp. 1-5.
- [C2] **Y. Chi** and Y. Xu, "Resilience-oriented microgrids: A comprehensive literature review," *2017 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, Auckland, 2017, pp. 1-6.
- [C3] J. Liu, Z. Dong, Y. Xu and **Y. Chi**, "Sensitivity Analysis of Composite Dynamic Load on Power System Short-Term Voltage Stability," *2019 9th International Conference on Power and Energy Systems (ICPES)*, Perth, Australia, 2019, pp. 1-6.

Bibliography

- [1] C. P. Steinmetz, "Power control and stability of electric generating stations," *Trans. Am. Inst. Electr. Eng.*, vol. XXXIX, no. 2, pp. 1215-1287, Jul. 1920.
- [2] Stability definitions and characterization of dynamic behavior in systems with high penetration of power electronic interfaced technologies, IEEE Power and Energy Society, Tech. Rep. PES-TR77, May 2020. (available on-line: https://resourcecenter.ieee-pes.org/technical-publications/technical-reports/PES_TP_TR77_PSDP_stability_051320.html)
- [3] T. Van Cutsem and C. Vournas, *Voltage stability of electric power systems*. New York: Springer, 2008.
- [4] AEMO, "2016 South Australia separation event - Final report," Australian Energy Market Operator Limited, Brisbane, Australia, 2016.
- [5] T. Van Cutsem, "Voltage instability: phenomena, countermeasures, and analysis methods," *Proc. IEEE*, vol. 88, no. 2, pp. 208–227, Feb. 2000.
- [6] C. W. Taylor, N. J. Balu, and D. Maratukulam, *Power system voltage stability*. New York: McGraw-Hill, 1994.
- [7] B. Gao, G. K. Morison, and P. Kundur, "Toward the development of a systematic approach for voltage stability assessment of large-scale power systems," *IEEE Trans. Power Syst.*, vol. 11, pp. 1314-1324, Aug. 1996.
- [8] P. A. Lof, T. Smed, G. Andersson, and D. J. Hill, "Fast calculation of a voltage stability index," *IEEE Trans. Power Syst.*, vol. 7, pp. 54-64, Feb. 1992.
- [9] British Petroleum, "BP Energy Outlook 2019 edition," Feb. 2013. [Online]. Available: <https://www.bp.com/en/global/corporate/energy-economics/energy-outlook.html>
- [10] N. Troy, E. Denny, and M. O'Malley, "Base-load cycling on a system with significant wind penetration," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1088-1097, May 2010.
- [11] E. Lannoye, D. Flynn, and M. O'Malley, "Transmission, variable generation, and power system flexibility," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 57-66, Jan. 2015.
- [12] AEMO, "Wind turbine plant capabilities report," Australian Energy Market Operator Limited, Brisbane, Australia, 2013.
- [13] P. Cuffe, P. Smith and A. Keane, "Transmission system impact of wind energy harvesting networks," *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 643-651, Oct. 2012.
- [14] Y. Chi and Y. Xu, "Multi-stage coordinated dynamic VAR source placement for voltage stability enhancement of wind-energy power system," *IET Gener. Transm. Distrib.*, vol. 14, no. 6, pp. 1104-1113, Mar. 2020.
- [15] E. Vittal, "The impact of reactive power from wind generation on power system stability," PhD dissertation, School of Electrical, Electronic and Mechanical Engineering, University College Dublin, 2011.

- [16] V. F. Mendes, C. V. de Sousa, S. R. Silva, B. C. Rabelo, and W. Hofmann, "Modeling and ride-through control of doubly fed induction generators during symmetrical voltage sags," *IEEE Trans. Energy Convers.*, vol. 26, no. 4, pp. 1161-1171, Dec. 2011.
- [17] WECC, "The technical basis for the new WECC voltage ride-through (VRT) standard," Western Electricity Coordinating Council, US, June 2007.
- [18] H. Geng, L. Liu, and R. Li, "Synchronization and reactive current support of pmsg-based wind farm during severe grid fault," *IEEE Trans. Sustain. Energy*, vol. 9, no. 4, pp. 1596-1604, Oct. 2018.
- [19] J. A. Diaz de Leon and C. W. Taylor, "Understanding and solving short-term voltage stability problems," *2002 IEEE Power Engineering Society Summer Meeting, Chicago, IL, USA, 2002*, vol. 2, pp. 745-752.
- [20] B. Sapkota and V. Vittal, "Dynamic VAR planning in a large power system using trajectory sensitivities," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 461-469, Feb. 2010.
- [21] W. Huang, K. Sun, J. Qi, and J. Ning, "Optimal allocation of dynamic var sources using the voronoi diagram method integrating linear programming," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4644-4655, Nov. 2017.
- [22] S. Gerbex, R. Cherkaoui, and A. J. Germond, "Optimal location of multi-type FACTS devices in a power system by means of genetic algorithms," *IEEE Trans. Power Syst.*, vol. 16, no. 3, pp. 537-544, Aug. 2001.
- [23] Y. Ishikawa, "Summary of the 2011 off the Pacific coast of Tohoku Earthquake," *GEOINFORMATICS*, vol. 22, no. 3, pp. 143-147, 2011.
- [24] U.S. Department of Energy, "Economic benefits of increasing electric grid resilience to weather outages," Aug. 2013. [Online]. Available: [http://energy.gov/sites/prod/files/2013/08/f2/Grid Resiliency Report FINAL.pdf](http://energy.gov/sites/prod/files/2013/08/f2/Grid%20Resiliency%20Report%20FINAL.pdf)
- [25] The GridWise Alliance, "Improving electric grid reliability and resilience: Lessons learned from Superstorm Sandy and other extreme events," Jun. 2013. [Online]. Available: http://www.gridwise.org/documents/ImprovingElectricGridReliabilityandResilience_6_6_13webFINAL.pdf
- [26] The Atlantic, "The Australian state without power," Sep. 2016. [Online]. Available: <https://www.theatlantic.com/news/archive/2016/09/southaustralia-power-outage/501992/>
- [27] The Weather Channel, "Puerto Rico is now largest blackout in U.S. history, report says," Oct. 2017. [Online]. Available: <https://weather.com/news/news/2017-10-26-puerto-rico-day-36-largestblackout-united-states-history>
- [28] S. McManus, E. Seville, D. Brunsdon, and J. Vargo, "Resilience management: A framework for assessing and improving the resilience of organisations," *Resilient Organ. Res. Rep.*, vol. 1, pp. 1-79, 2007.
- [29] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao and Z. Bie, "Microgrids for enhancing the power grid resilience in extreme conditions," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 589-597, March 2017.

- [30] M. Ouyang, L. Dueñas-Osorio, "Multi-dimensional hurricane resilience assessment of electric power systems," *Structural Safety*, vol. 48, pp. 15-24, 2014.
- [31] M. Panteli, D. Trakas, P. Mancarella and N. Hatziaargyriou, "Power systems resilience assessment: hardening and smart operational enhancement strategies," *Proceedings of the IEEE*, vol. 105, no. 7, pp. 1202-1213, July 2017.
- [32] U.K., Cabinet Office, *Keeping the Country Running: Natural Hazards and Infrastructure*, London: Cabinet Office, 2011.
- [33] USA, National Infrastructure Advisory Council, *A framework for establishing critical infrastructure resilience goals*, Washington, D.C.: National Infrastructure Advisory Council, 2010.
- [34] F. D. Petit, R. E. Fisher, and S. N. Veselka, "Resilience measurement index: an indicator of critical infrastructure resilience," Argonne National Laboratory, USA, Tech. Rep. ANL/DIS-13-01, 2013.
- [35] Y. Chi, Y. Xu, C. Hu, and S. Feng, "A state-of-the-art literature survey of power distribution system resilience assessment," *2018 IEEE Power & Energy Society General Meeting (PESGM)*, Portland, OR, 2018, pp. 1-5.
- [36] Y. Chi and Y. Xu, "Resilience-oriented microgrids: a comprehensive literature review," *2017 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, Auckland, 2017, pp. 1-6.
- [37] Y. Xu, Z. Y. Dong, K. Meng, W. F. Yao, R. Zhang and K. P. Wong, "Multi-objective dynamic var planning against short-term voltage instability using a decomposition-based evolutionary algorithm," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2813-2822, Nov. 2014.
- [38] Y. Xu, R. Zhang, Z. Y. Dong, K. P. Wong, and C. Xiao, "Optimal placement of static compensators for multi-objective voltage stability enhancement of power systems," *IET Gener. Transm. Distrib.*, vol. 9, no. 15, pp. 2144-2151, 2015.
- [39] T. Han, Y. Chen and J. Ma, "Multi-objective robust dynamic VAR planning in power transmission grids for improving short-term voltage stability under uncertainties," *IET Gener. Transm. Distrib.*, vol. 12, no. 8, pp. 1929-1940, Apr. 2018.
- [40] R. Azim, F. Li, Y. Wei, Y. Xu, and X. Fang, "Reactive power planning under high penetration of wind energy using Benders decomposition," *IET Gener. Transm. Distrib.*, vol. 9, no. 14, pp. 1835-1844, Nov. 2015.
- [41] T. Han, Y. Chen, J. Ma, Y. Zhao, and Y. Chi, "Surrogate modeling-based multi-objective dynamic var planning considering short-term voltage stability and transient stability," *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 622-633, Jan. 2018.
- [42] N. Yorino, E. E. El-Araby, H. Sasaki, and S. Harada, "A new formulation for facts allocation for security enhancement against voltage collapse," *IEEE Trans. Power Syst.*, vol. 18, no. 1, pp. 3-10, Feb. 2003.
- [43] A. Sode-Yome, N. Mithulananthan, and K. Y. Lee, "A maximum loading margin method for static voltage stability in power systems," *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 799-808, May 2006.

- [44] E. Ghahremani and I. Kamwa, "Optimal placement of multiple-type FACTS devices to maximize power system loadability using a generic graphical user interface," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 764-778, May 2013.
- [45] A. Tiwari and V. Ajjarapu, "Optimal allocation of dynamic var support using mixed integer dynamic optimization," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 305-314, Feb. 2011.
- [46] J. Liu, Y. Xu, Z. Y. Dong, and K. P. Wong, "Retirement-driven dynamic var planning for voltage stability enhancement of power systems with high-level wind power," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2282-2291, Mar. 2018.
- [47] F. Ugranli and E. Karatepe, "Coordinated TCSC allocation and network reinforcements planning with wind power," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1694-1705, Oct. 2017.
- [48] Y. Wang, C. Chen, J. Wang, and R. Baldick, "Research on resilience of power systems under natural disasters - a review," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1604-1613, Mar. 2016.
- [49] D. Kosterev, "Design, installation, and initial operating experience with line drop compensation at John Day powerhouse," *IEEE Trans. Power Syst.*, vol. 16, no. 2, pp. 261-265, May 2001.
- [50] N. Daratha, B. Das, and J. Sharma, "Coordination between OLTC and SVC for voltage regulation in unbalanced distribution system distributed generation," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 289-299, Jan. 2014.
- [51] US Department of Energy, "Benefits of demand response in electricity markets and recommendations for achieving them," Report to the United States Congress, Feb. 2006.
- [52] M. Samadi, M. H. Javidi, and M. S. Ghazizadeh, "Modeling the effects of demand response on generation expansion planning in restructured power systems," *J. Zhejiang Univ. - Sci. C*, vol. 14, no. 12, pp. 966-976, Dec. 2013.
- [53] F. Luo, Z. Dong, G. Chen, J. Liu, and C. Li, "Flexible transmission expansion planning associated with large-scale wind farms integration considering demand response," *IET Gener. Transm. Distrib.*, vol. 9, no. 15, pp. 2276-2283, Nov. 2015.
- [54] J. López, J. R. S. Mantovani, and J. Contreras, "Reactive power planning under conditional-value-at-risk assessment using chance-constrained optimisation," *IET Gener. Transm. Distrib.*, vol. 9, no. 3, pp. 231-240, Feb. 2015.
- [55] M. Joos and I. Staffell, "Short-term integration costs of variable renewable energy: Wind curtailment and balancing in Britain and Germany," *Renew. Sust. Energ. Rev.*, vol. 86, pp. 45-65, Apr. 2018.
- [56] *IEEE recommended practice for excitation system models for power system stability studies*. New York: IEEE, 2016.
- [57] M. Ruppert, V. Bertsch, and W. Fichtner, "Optimal load shedding in distributed networks with sigmoid cost functions," *2015 International Symposium on Smart Electric Distribution Systems and Technologies (EDST)*, Vienna, Austria, Sep. 2015, pp. 159-164.
- [58] Voltage and reactive control, VAR-001-4.2, NERC, Atlanta, 2017.

- [59] M. Cupelli, C. Doig Cardet and A. Monti, "Comparison of line voltage stability indices using dynamic real time simulation," *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*, Berlin, 2012, pp. 1-8.
- [60] Siemens Power Technologies International, "PSS®E 33.4 Model Library," Mar. 2013.
- [61] G. S. Peace, *Taguchi Methods: A Hand on Approach*. Reading, MA: Addison Wesley, 1993.
- [62] K. Miettinen, *Nonlinear Multiobjective Optimization*, vol. 12. Boston, MA: Springer US, 1998.
- [63] K. Deb, A. Pratap, S. Agarwal and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182-197, April 2002.
- [64] National electricity rules version 110, A. E. M. Commission, Sydney, July 2018.
- [65] H. T. Mokui, M. A. S. Masoum, and M. Mohseni, "Review on Australian grid codes for wind power integration in comparison with international standards," *in 2014 Australasian Universities Power Engineering Conference (AUPEC)*, Perth, Australia, Sep. 2014, pp. 1-6.
- [66] Siemens Power Technologies International, "PSS®E 33.4 Program Application Guide Volume 2," Mar. 2013.
- [67] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, "MATPOWER: steady-state operations, planning, and analysis tools for power systems research and education," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 12-19, Feb. 2011.
- [68] S. Agrawal, B. K. Panigrahi, and M. K. Tiwari, "Multiobjective particle swarm algorithm with fuzzy clustering for electrical power dispatch," *IEEE Trans. Evol. Computat.*, vol. 12, no. 5, pp. 529-541, Oct. 2008.
- [69] North American Electric Reliability Corporation (NERC), "High-impact low-frequency event risk to the north american bulk power system," North American Electric Reliability Corporation, Jun. 2010.
- [70] A. Kwasinski, "Quantitative model and metrics of electrical grids' resilience evaluated at a power distribution level," *Energies*, vol. 9, no. 2, p. 93, Feb. 2016.
- [71] S. Wang, G. Li, and M. Zhou, "The reactive power adjusting mechanism and control strategy of Double Fed induction Generator," *Proceedings of the CSEE*, vol. 34, no. 16, pp. 2714-2720, June 2014.
- [72] Y. Zhang, Y. Xu, Z. Y. Dong and R. Zhang, "A hierarchical self-adaptive data-analytics method for power system short-term voltage stability assessment," *IEEE Trans. Ind. Informat.*, vol. 15, no. 1, pp. 74-84, Jan. 2019.
- [73] B. Iooss and P. Lemaître, *A Review on Global Sensitivity Analysis Methods*. New York, NY, USA: Springer, 2015.
- [74] New York Independent System Operator, "Open Access Same-time Information System: Load Data/ISO load forecast data," New York Independent System Operator, 2018, [Online], Available: http://mis.nyiso.com/public/csv/pal/20180601pal_csv.zip. [Accessed: Aug. 10, 2018].

- [75] R. Zhang, Z.Y. Dong, Y. Xu, K. Meng, and K.P. Wong, "Short-term load forecasting of Australian National Electricity Market by an ensemble model of extreme learning machine," *IET Gener. Transm. Distrib.*, vol. 7, no. 4, pp. 391-397, Apr. 2013.
- [76] T. Cutsem, "Test systems for voltage stability analysis and security assessment," *IEEE Power System Dynamic Performance Committee*, New York, USA, Tech. Report. PES-TR19, 7 Aug. 2015.
- [77] Y. Lee and H. Song, "A reactive power compensation strategy for voltage stability challenges in the Korean power system with dynamic loads," *Sustainability*, vol. 11, no. 326, pp. 1-19, Jan. 2019.
- [78] L. Aolaritei, S. Bolognani, and F. Dorfler, "Hierarchical and distributed monitoring of voltage stability in distribution networks," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6705–6714, Nov. 2018.
- [79] M. Paramasivam, A. Salloum, V. Ajjarapu, V. Vittal, N. B. Bhatt, and S. Liu, "Dynamic optimization based reactive power planning to mitigate slow voltage recovery and short term voltage instability," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3865-3873, Nov. 2013.
- [80] A. Chowdhury, H. Liu, J. D. McCalley, and V. Krishnan, "Optimal planning of static and dynamic reactive power resources," *IET Gener. Transm. Distrib.*, vol. 8, no. 12, pp. 1916-1927, Dec. 2014.
- [81] Z. H. Rather, Z. Chen, P. Thogersen, and P. Lund, "Dynamic reactive power compensation of large-scale wind integrated power system," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2516-2526, Sep. 2015.
- [82] Security and stability of the national grid computing specification, Q/GDW 404-2010, State Grid Corporation of China, Beijing, Dec. 2010.
- [83] D. J. Shoup, J. J. Paserba and C. W. Taylor, "A survey of current practices for transient voltage dip/sag criteria related to power system stability," *IEEE PES Power Systems Conference and Exposition, 2004.*, New York, NY, 2004, vol.2, pp. 1140-1147.
- [84] Transmission System Planning Performance Requirements, TPL-001-4, NERC, Atlanta, Nov. 2010.
- [85] Z. Deng, M. Liu, Y. Ouyang, S. Lin, and M. Xie, "Multi-objective mixed-integer dynamic optimization method applied to optimal allocation of dynamic var sources of power systems," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1683-1697, Mar. 2018.
- [86] S. Wildenhues, J. L. Rueda, and I. Erlich, "Optimal allocation and sizing of dynamic var sources using heuristic optimization," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2538-2546, Sep. 2015.
- [87] A. M. Tahboub, M. S. El Moursi, W. L. Woon, and J. L. Kirtley, "Multiobjective dynamic var planning strategy with different shunt compensation technologies," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 2429-2439, May 2018.
- [88] W. Zhao, Q. Guo, H. Sun, H. Ge, and H. Li, "Practical short-term voltage stability index based on voltage curves: definition, verification and case studies," *IET Gener. Transm. Distrib.*, vol. 12, no. 19, pp. 4292-4300, Oct. 2018.

- [89] Y. Wang, F. Li, Q. Wan, and H. Chen, "Reactive power planning based on fuzzy clustering, gray code, and simulated annealing," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2246-2255, Nov. 2011.
- [90] L. Guan, L. Wu, F. Li, and Q. Zhao, "Heuristic planning for dynamic VAR compensation using zoning approach," *IET Gener. Transm. Distrib.*, vol. 11, no. 11, pp. 2852-2861, Aug. 2017.
- [91] M. D. Morris, "Factorial sampling plans for preliminary computational experiments," *Technometrics*, vol. 33, no. 2, pp. 161-174, May 1991.
- [92] G. Li and S. M. Rovnyak, "Integral Square Generator Angle Index for Stability Ranking and Control," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 926-934, May 2005.
- [93] R. J. Hathaway, J. C. Bezdek, and Yingkang Hu, "Generalized fuzzy c-means clustering strategies using Lp norm distances," *IEEE Trans. Fuzzy Syst.*, vol. 8, no. 5, pp. 576-582, Oct. 2000.
- [94] M. Eghbal, N. Yorino, E. E. El-Araby, and Y. Zoka, "Multi-load level reactive power planning considering slow and fast VAR devices by means of particle swarm optimisation," *IET Gener. Transm. Distrib.*, vol. 2, no. 5, p. 743, 2008.
- [95] M. M. Farsangi, H. Nezamabadi-pour, Y.-H. Song, and K. Y. Lee, "Placement of SVCs and selection of stabilizing signals in power systems," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1061-1071, Aug. 2007.
- [96] J. López, D. Pozo, J. Contreras and J. R. S. Mantovani, "A multiobjective minimax regret robust var planning model," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 1761-1771, May 2017.
- [97] S. O. Faried, R. Billinton and S. Aboreshaid, "Probabilistic technique for sizing FACTS devices for steady-state voltage profile enhancement," *IET Gener. Transm. Distrib.*, vol. 3, no. 4, pp. 385-392, April 2009.
- [98] S. M. Mazhari, H. Monsef and R. Romero, "A multi-objective distribution system expansion planning incorporating customer choices on reliability," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1330-1340, March 2016.
- [99] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali and M. Moeini-Aghaie, "A multi-objective transmission expansion planning framework in deregulated power systems with wind generation," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 3003-3011, Nov. 2014.
- [100] S. Roy Ghatak, S. Sannigrahi and P. Acharjee, "Optimised planning of distribution network with photovoltaic system, battery storage, and DSTATCOM," *IET Renew. Power Gener.*, vol. 12, no. 15, pp. 1823-1832, Nov. 2018.
- [101] M. Köppen and K. Yoshida, "Substitute distance assignments in NSGA-II for handling many-objective optimization problems", *Proc. 2007 Int. Conf. Evolutionary Multi-criterion Optimization*, pp. 727-741, 2007.
- [102] M. Moghavvemi and O. Faruque, "Real-time contingency evaluation and ranking technique," *IEE Proc. Gener. Transm. Distrib.*, vol. 145, no. 5, pp. 517-524, Sept. 1998.

- [103] S. Gunawan and S. Azarm, "Non-gradient based parameter sensitivity estimation for single objective robust design optimization," *J. Mech. Des.*, vol. 126, no. 3, p. 395, 2004.
- [104] K. Deb and H. Jain, "An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints," *IEEE Trans. Evol. Comput.*, vol. 18, no. 4, pp. 577-601, Aug. 2014.
- [105] I. Das and J. E. Dennis, "Normal-boundary intersection: a new method for generating the pare-to surface in nonlinear multicriteria optimization problems," *SIAM J. Optimiz.*, vol. 8, no. 3, pp. 631-657, Aug. 1998.
- [106] F. Chen, J. Zhou, C. Wang, C. Li, and P. Lu, "A modified gravitational search algorithm based on a non-dominated sorting genetic approach for hydro-thermal-wind economic emission dispatching," *Energy*, vol. 121, pp. 276-291, Feb. 2017.
- [107] X. Wu, J. Li, X. Shen, and N. Zhao, "NSGA-III for solving dynamic flexible job shop scheduling problem considering deterioration effect," *IET Collaborative Intelligent Manufacturing*, vol. 2, no. 1, pp. 22-33, Mar. 2020.
- [108] M. D. McKay, R. J. Beckman, and W. J. Conover, "A comparison of three methods for selecting values of input variables in the analysis of output from a computer code," *Technometrics*, vol. 21, no. 2, p. 239, May 1979.
- [109] Musrrat. Ali, P. Siarry, and Millie. Pant, "An efficient Differential Evolution based algorithm for solving multi-objective optimization problems," *Eur. J. Oper. Res.*, vol. 217, no. 2, pp. 404-416, March 2012.
- [110] R. Zhang, Y. Xu, Z. Y. Dong and K. P. Wong, "Measurement-based dynamic load modelling using time-domain simulation and parallel-evolutionary search," *IET Gener. Transm. Distrib.*, vol. 10, no. 15, pp. 3893-3900, Nov. 2016.
- [111] Technical Guidelines on Voltage and Reactive Power of the Power System, National Energy Administration of China, SD325-1989, 1989.
- [112] Technical Principles on Reactive Power Compensation of the Power System, State Grid Corporation of China, Q/GDW 212-2008, 2008.
- [113] K. Meng, Z. Y. Dong, K. P. Wong, Y. Xu and F. J. Luo, "Speed-up the computing efficiency of power system simulator for engineering-based power system transient stability simulations," *IET Gener. Transm. Distrib.*, vol. 4, no. 5, pp. 652-661, May 2010.
- [114] K. N. Hasan and R. Preece, "Influence of stochastic dependence on small disturbance stability and ranking uncertainties," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3227-3235, May 2018.
- [115] P. Li, X. Guan, J. Wu, and X. Zhou, "Modeling *Dynamic Spatial Correlations of Geographically Distributed Wind Farms and Constructing Ellipsoidal Uncertainty Sets for Optimization-Based Generation Scheduling*," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1594-1605, Oct. 2015.
- [116] H. Joe, *Dependence modeling with copulas*. Boca Raton: CRC Press, Taylor & Francis Group, 2015.

- [117] X. Xu, Z. Yan, M. Shahidehpour, H. Wang, and S. Chen, "Power system voltage stability evaluation considering renewable energy with correlated variabilities," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3236-3245, May 2018.
- [118] H. Park, R. Baldick, and D. P. Morton, "A stochastic transmission planning model with dependent load and wind forecasts," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3003-3011, Nov. 2015.
- [119] J. Aghaei, N. Amjady, A. Baharvandi, and M. Akbari, "Generation and transmission expansion planning: MILP-based probabilistic model," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1592-1601, Jul. 2014.
- [120] M. Mehrtash and A. Kargarian, "Risk-based dynamic generation and transmission expansion planning with propagating effects of contingencies," *Int. J. Electr. Power Energy Syst.*, vol. 118, p. 105762, Jun. 2020.
- [121] H. Zhang, H. Cheng, L. Liu, S. Zhang, Q. Zhou, and L. Jiang, "Coordination of generation, transmission and reactive power sources expansion planning with high penetration of wind power," *Int. J. Electr. Power Energy Syst.*, vol. 108, pp. 191-203, Jun. 2019.
- [122] C. V. Montes, J. F. Franco, M. J. Rider, L. H. Macedo, and R. Romero, "MILP branch flow model for concurrent AC multistage transmission expansion and reactive power planning with security constraints," *IET Gener. Transm. Distrib.*, vol. 10, no. 12, pp. 3023-3032, Sep. 2016.
- [123] Commission Regulation (EU) 2016/631 of 14 April 2016 establishing a network code on requirements for grid connection of generators (Text with EEA relevance) C/2016/2001, OJ L 112, 27.4.2016, p. 1-68, http://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:JOL_2016_112_R_0001
- [124] L. Wu and L. Guan, "Integer quadratic programming model for dynamic VAR compensation considering short-term voltage stability," *IET Gener. Transm. Distrib.*, vol. 13, no. 5, pp. 652-661, Mar. 2019.
- [125] N. A. M. Ismail, A. A. M. Zin, A. Khairuddin and S. Khokhar, "A comparison of voltage stability indices," 2014 *IEEE 8th International Power Engineering and Optimization Conference* (PEOCO2014), Langkawi, 2014, pp. 30-34.
- [126] X. Mao, W. Zhu, L. Wu, and B. Zhou, "Optimal allocation of dynamic VAR sources using zoning-based distributed optimization algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 113, pp. 952-962, Dec. 2019.
- [127] B. Qi, K. N. Hasan and J. V. Milanović, "Identification of Critical Parameters Affecting Voltage and Angular Stability Considering Load-Renewable Generation Correlations," *IEEE Trans. Power Syst.*, vol. 34, no. 4, pp. 2859-2869, July 2019.