SOME INVESTIGATIONS ON DISTRIBUTION SYSTEM PERFORMANCE IMPROVEMENT

Ph.D. Thesis

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This thesis is submitted as a partial
fulfillment of the requirements for the degree of
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by

Neeraj Kanwar
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Under the Supervision of

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I, Neeraj Kanwar (I.D. No. 2012REE9017) declare that this thesis titled, "***Some Investigations on Distribution System Performance Improvement***" and work presented in it are my own, under the supervision of Dr. Nikhil Gupta and Prof. K.R. Niazi, Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur (Rajasthan), India. I confirm that:

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CERTIFICATE

This is to certify that the thesis entitled, "***Some Investigations on Distribution System Performance Improvement***", submitted by ***Neeraj Kanwar*** (I.D. No. 2012 REE 9017) to Malaviya National Institute of Technology Jaipur for the award of the degree of ***Doctor of Philosophy*** in Electrical Engineering is a bonafide record of original research work carried out by her under our supervision.

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ii. Ms. Neeraj Kanwar has fulfilled the requirement for the submission of this thesis.

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It is further certified that:

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iv. I, Neeraj Kanwar Institute ID: 2012REE9017 have fulfilled the requirements for the submission of this thesis.

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This is to certify that ***Ms. Neeraj Kanwar*** (I.D. No. 2012 REE 9017) has worked under our supervision for the award of the degree ***Doctor of Philosophy in Electrical Engineering*** on the topic entitled, "***Some Investigations on Distribution System Performance Improvement***". She has successfully defended her thesis work in viva-voce examination in front of the Oral Defense Committee and satisfactorily incorporated the changes suggested by the examiners in this revised version of the thesis.

The Thesis was examined and has been recommended for the award of the degree of ***Doctor of Philosophy in Electrical Engineering.***

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DEDICATIONS

*This thesis is dedicated to my parents **Mr. Shriram Singh & Mrs. Manoj Kanwar** who taught me the virtues of discipline, honesty and sincerity.*

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For any glitches or inadequacies that may remain in this work, the responsibility is entirely my own.

(Neeraj Kanwar)

TABLE OF CONTENTS

ABSTRACT

Existing distribution systems are moving toward smart distribution systems to achieve larger socio economic and other non-tangible benefits such as lesser carbon foot prints, better asset utilization, improved energy efficiency, reliability, security and power quality, etc. The construction of next generation active distribution networks requires the exploitation of existing infrastructure, use of new technologies of generation and changes in operational practices. The integration of distributed generations (DGs) and shunt capacitors (SCs), and network reconfiguration (NR) are the key technologies for realizing smart distribution systems. These key technologies may be coordinated together to get better solutions so that distribution systems can achieve optimum performance. The passive distribution systems will be gradually transformed into active distribution systems having wide spread deployment of distributed resources (DRs). Though, this transition requires a paradigm shift in both planning and operations of distribution systems. However, ground realities of distribution systems should be considered with a good degree of accuracy otherwise counterproductive results so obtained may jeopardize the planning and operation of distribution systems.

This thesis addresses the simultaneous optimal allocation of DRs such as DGs and SCs in the view of NR to reduce annual energy losses and to enhance node voltage profiles of distribution systems. More practical formulations for these optimization problems are suggested while considering realistic operational issues and realities of modern distribution systems. These concerns include characteristic load patterns of distribution buses, intermittency of renewable DGs, stochastic nature of load demand, environmental concerns, etc. With these concerns, the DR allocation problem of distribution systems assumes different dimension and thus requires different treatment. The DR allocation and NR problems are formulated while duly addressing these concerns in a stepwise manner. The effectiveness of DR tuning and NR is thoroughly investigated for distribution systems having adequate DRs to extract better operational strategy for distribution network operators. The uncertainty and variability pertaining to load demand and power generation among distribution buses are efficiently handled by introducing new deterministic approach to provide more realistic solutions for long-term DR planning and operation. Moreover, the impact of interaction among diverse time-variant energy resources and stochastic load demand is investigated and presented. The complexity of the DR allocation problem raised by many folds in the context of modern distribution systems. Therefore, improved variants

of five existing metaheuristics have been developed to successfully solve such complex large-scale optimization problem accurately and efficiently. In addition, a heuristic intelligent search algorithm (ISA) is suggested to enhance the overall performance of these techniques. Proposed methods are applied to standard as well as real distribution systems. The application results obtained reveal the importance of proposed methods to enhance the performance of distribution systems under more realistic scenarios. The developed algorithms are also thoroughly investigated on standard and real distribution systems. The results of study are investigated and presented.

LIST OF TABLES

LIST OF TABLES (continued…)

LIST OF FIGURES

LIST OF FIGURES (continued…)

LIST OF FIGURES (continued…)

NOMENCLATURE

A_b	Pulse loudness for the *b*-th bat
$< A_b(t) >$	Average loudness of bats at the *t*-th iteration
C_{rev}	Cost of revenue collection from grid and/or customer ($)
C_{inv}	Capital investment cost of DRs ($)
$C_{o\&m}$	Cost incurred in the operation and maintenance of DRs ($)
C_{fl}	Fuel cost incurred in total energy generated by MTs ($/kWh)
C_{emi}	Emission cost incurred in total energy generated by MTs ($/kg)
$C_{inv}^{SPV,WT,MT}$	Capital investment cost of SPV/ WT/ MT ($/kW)
C_{inv}^{SC}	Capital investment cost of shunt capacitors ($/kVAr)
C_y^{sg}	Cost of selling electricity to utility grid in *y*-th year ($/kWh)
C_y^{bg}	Cost of buying electricity from utility grid in *y*-th year ($/kWh)
C_y^{sc}	Cost of selling electricity to customers in *y*-th year ($/kWh)
C_y^{fl}	Fuel cost incurred in total energy generated by MTs in *y*-th year ($/kWh)
C_y^{emi}	Emission cost incurred in total energy generated by MTs in *y*-th year ($/kg)
c, c_1, c_2	Acceleration coefficients
D	Total number of design variables
D_s	Number of days in the *s*-th season
$D_{y,m}$	Number of days in *m*-th month of *y*-th year
d	Each dimension of selected individual ($1 \leq d \leq D$)
dr	Discount rate (%)
E_{Loss}^{base}	Annual energy losses without DR placement (kWh)
E_{Loss}^{DR}	Annual energy losses with DR placement (kWh)
f_b	Pulse frequency of the *b*-th bat
$f_{\max}$/ $f_{\min}$	Maximum/ minimum pulse frequency of a bat
gbest	Best particle position based on overall swarm experience
$H_{j,s}$	Load duration for *j*-th load level of the *s*-th season (hrs)
H_j	Load duration at *j*-th load level (hrs)
$H_{y,m,t}^{SPV,WT,MT}$	Total operation hours of SPV/WT/MT in *m*-th month of *y*-th year for *t*-th state (h)
$H_{y,m,t}^{SC}$	Total operation hours of SCs in *m*-th month of *y*-th year for *t*-th state (h)
IR_C	Yearly increasing rate of different costs (%)
IR_L	Yearly increasing rate of load (%)
$IC_n^{SPV,WT,MT,SC}$	Installation cost of SPV/ WT/ MT/ SC at *n*-th node ($/kWp)

$I_n^{\max}$	Maximum current of *n*-th branch (p.u.)
$I_{n,j}$	Current of *n*th branch at *j*-th load level (p.u.)
$I_{y,m,n}$	Current of *n*-th branch in *m*-th month of *y*-th year (p.u)
itr	Current iteration
itr_{max}	Maximum iteration count
K_b	Number of capacitor banks
K_d	Number of discrete dispatches of DG
K_{md}	Number of discrete tapings available in capacitor banks
L	Set of load levels
loc^{SC}/loc^{DG}	Candidate nodes for SC/DG placement
loc	Total number of candidate location for SC/DG placement
ldr	*r*-th residential node
ldi	*i*-th industrial node
ldc	*c*-th commercial node
$loc_{N_{DG}}^{SPV,WT,MT}$	Candidate nodes for SPV/WT/MT placement
$loc_{N_{SC}}^{SC}$	Candidate nodes for SC placement
M	Total number of months
M_c	Number of copies of a bat
$Mean_{d,k}$	Mean of the learners at *d*-th dimension for *k*th iteration
$MC_y^{SPV,WT,MT}$	Operation and maintenance cost for SPV/ WT/ MT in *y*-th year ($/kWh)
MC_y^{SC}	Operation and maintenance cost for SC in *y*-th year ($/kVArh)
$\Delta Mean_{d,k}$	Difference mean of the learners at *d*-th dimension for *k*-th iteration
mc	Mutation count
N	Set of system nodes
N_L	Total number of load levels
N_{SC}/N_{DG}	Total number of candidate locations for SC/DG placement
$N_r/\ N_i/\ N_c$	Set of nodes on residential/ industrial/ commercial feeders
N_b	Population size of bats
N_s	Total number of seasons
N_d	Total number of data
nsc	Maximum number of candidate SC banks at a node
ndg	Maximum number of discrete dispatches of DG at a node
n	Branch/sending node
P	Population size
$PLoss_{bj}$	Power loss without DRs at *j*-th load level (kWh)
$PLoss_{aj}$	Power loss with DRs at *j*-th load level (kW)
$PLoss$	Feeder power loss (kW)
$P_{r,j,s}/\ Q_{r,j,s}$	Active/reactive power flow in *r*-th residential feeders at *j*-th load level of the *s*-th season (kW/kVAr)

$P_{i,j,s}$/ $Q_{i,j,s}$	Active/reactive power flow in *i*-th industrial feeders at *j*-th load level of the *s*-th season (kW/kVAr)
$P_{c,j,s}$/ $Q_{c,j,s}$	Active/reactive power flow in *c*-th commercial feeders at *j*-th load level of the *s*-th season (kW/kVAr)
P_r, P_i, P_c	Active power flow from *r*-th/ *i*-th/ *c*-th branch of residential/ industrial/ commercial feeders (kW)
$P_{y,m,n}$	Active power flow from *n*-th node in *m*-th month of *y*-th year (kW)
$P_{y,m,n}^{loss}$	Real power loss for *n*-th node in *m*-th month of *y*-th year (kW)
P_d	Unit size of DG (kW)
$P_{n,j}/Q_{n,j}$	Real/ reactive power for sending end of *n*th branch at *j*th load level (kW/kVAr)
p_{ins}^{SC}	Installed capacities of SCs (MVAr)
$p_{y,m,n}^{SPV,WT,MT}$	Active power generation from SPV, WT and MT at the *n*-th node in *m*-th month of *y*-th year (kW)
$p_{N_{DG}}^{SPV,WT,MT}$	Active power generation from SPV, WT and MT at the N_{DG} candidate node (kW)
$p_{n,\min}^{SPV,WT,MT}$	Minimum active compensation provided by SPV, WT and MT at the *n*-th node (kW)
$p_{n,\max}^{SPV,WT,MT}$	Maximum active compensation provided by SPV, WT and MT at the *n*-th node (kW)
$p_{y,m,t,n}^{suplus}$	Power surplus of *n*-th branch in *m*-th month of *y*-th year at *t*-th state (MW)
$p_{y,m,t,n}^{deficient}$	Power deficiency of *n*-th branch in *m*-th month of *y*-th year at *t*-th state (MW)
$p_{y,m,t,n}^{ldr,ldi,ldc}$	Active power demand at *r*-th residential, *i*-th industrial and *c*-th commercial node of the system in *m*-th month of *y*-th year for state *t* (MW)
p_{st}^{suplus}	Power Surplus of state *st* (MW)
$p_{st}^{deficient}$	Power deficiency of state *st* (MW)
$p_{st}^{ldr,ldi,ldc}$	Active power demand at *r*-th residential, *i*-th industrial and *c*-th commercial node of the system in state *st* (MW)
$p_{st}^{SPV,WT,MT}$	Active power generation from SPV, WT and MT at state *st* (kW)
p_{ins}^{MT}	Installed capacities of MTs (MW)
$p_{\min}^{DG}$ / $p_{\max}^{DG}$	Minimum/maximum limits of DG penetration at a node (kW)
p_n^{DG}	DG power generation at the *n*-th node (kW)
p_n^L / q_n^L	Nominal active/reactive power demand of the system at the *n*-th node (kVAr/kW)
p_{best}	The own's best move of the cat
p_{pred}	Preceding movement of the cat
$pbest_p$	Best position of *p*th particle achieved based on its own experience
ΔP	Minimum discrete dispatch of DG (kW)

Q_r, Q_i, Q_c	Reactive power flow from *r*-th/ *i*-th/ *c*-th branch of residential/ industrial/ commercial feeders (kVAr)
Q_b	Size of capacitor bank (kVAr)
$Q_{y,m,n}$	Reactive power flow from *n*-th node in *m*-th month of *y*-th year (kVAr)
$Q_{y,m,n}^{loss}$	Reactive power loss for *n*-th node in *m*-th month of *y*-th year (kVAr)
q_n^{SC}	Reactive power injection by SCs at the *n*-th node (kVAr)
$q_{\min}^{\mathrm{SC}}$ / $q_{\max}^{\mathrm{SC}}$	Minimum/maximum reactive compensation provided by SCs at the *n*-th node (kVAr)
q_D/p_D	Nominal reactive/active power demand of the system (kVAr/kW)
$q_{N_{SC}}^{SC}$	Reactive power generation from SC at the N_{SC} candidate node (kVAr)
q_{st}^{SC}	Reactive power generation from SC at state *st* (kVAr)
$q_{n,\min}^{\mathrm{SC}}$	Minimum reactive compensation provided by SCs at the *n*-th node (kVAr)
$q_{n,\max}^{\mathrm{SC}}$	Maximum reactive compensation provided by SCs at the *n*-th node (kVAr)
$q_{y,m,n}^{\mathrm{SC}}$	Reactive power generation from SC at the *n*-th node in *m*-th month of *y*-th year (kVAr)
$q_{y,m,n+1}^{ldr,ldi,ldc}$	Reactive power demand at *r*-th residential, *i*-th industrial and *c*-th commercial node of the system in *m*-th month of *y*-th year (kVAr)
Δq	Tapping size of SC banks (kVAr)
R/X	Line resistance/ reactance (Ω)
R_n	Line resistance of the *n*-th branch (Ω)
R_r/ R_i/ R_c	Line resistance of the *r*-th/ *i*-th/ *c*-th branch of residential/ industrial/ commercial feeders (Ω)
rand	Random number in the range [0, 1]
$r_b(0)$	Initial pulse emission rate for the *b*-th bat
r_b	Pulse emission rate for the *b*-th bat
$r()$, $r_1()$, $r_2()$	Random numbers in the range [0, 1]
$S_{y,m,n}^{loss}$	Total loss for *n*-th node in *m*-th month of *y*-th year (kVA)
s_p^k / s_p^{k+1}	Position of *p*th particle at *k*-th/(*k*+1)-th iteration
T	Total number of states
$TF_{d,k}$	Teaching factor at *d*-th dimension for *k*-th iteration
$Teacher_{d,k}$	Position of the teacher at *d*-th dimension for *k*-th iteration
t_s	Predefined iteration count
Δt	Time step (s)
V_{max}/ V_{min}	Maximum/minimum permissible node voltage (p.u.)
$V_{r,j,s}$	Voltage at *r*-th residential node at *j*-th load level of the *s*-th season (p.u.)
$V_{i,j,s}$	Voltage at *i*-th industrial node at *j*-th load level of the *s*-th season (p.u.)
$V_{c,j,s}$	Voltage at *c*-th commercial node at *j*-th load level of the *s*-th season (p.u.)
V_{minS}	Minimum specified node voltage (p.u.)
$V_{n,j}$	Voltage of *n*-th node at *j*-th load level (p.u.)

V_r, V_i, V_c	Voltage at *r*-th/ *i*-th/ *c*-th node of residential/ industrial/ commercial feeder (p.u.)
$V_{y,m,n}$	Voltage at *n*-th node in *m*-th month of *y*-th year (p.u.)
$\Delta V_{r,j,s}$	Maximum node voltage deviation at *r*-th residential node at *j*-th load level of the *s*-th season (p.u.)
$\Delta V_{i,j,s}$	Maximum node voltage deviation at *i*-th industrial node at *j*-th load level of the *s*-th season (p.u.)
$\Delta V_{c,j,s}$	Maximum node voltage deviation at *c*-th commercial node at *j*-th load level of the *s*-th season (p.u.)
v_b	Velocity of the *b*-th bat
v_p^k / v_p^{k+1}	Velocity of *p*-th particle at *k*-th/(*k*+1)-th iteration
v_q/ v_{q+1}	Velocity of *q*-th/(*q*+1)-th cat
$W_{y,m,t}^{ldr,ldi,ldc,SPV,WT}$	Uncertainty set for load consumption, solar power and wind power at the *n*-th node in *m*-th month of *y*-th year
$\omega_{n,y,m,t}^{ldr,ldi,ldc,SPV,WT}$	Uncertain data of load consumption, power output from solar and wind at the *n*-th node in *m*-th month of *y*-th year for state *t*
$\underline{\omega}_{n,y,m,t}^{ldr,ldi,ldc,SPV,WT}$	Lower bound of uncertain data of load consumption, power output from solar and wind at the *n*-th node in *m*-th month of *y*-th year for state *t*
$\overline{\omega}_{n,y,m,t}^{ldr,ldi,ldc,SPV,WT}$	Upper bound of uncertain data of load consumption, power output from solar and wind at the *n*-th node in *m*-th month of *y*-th year for state *t*
$\hat{\omega}_{n,y,m}^{ldr,ldi,ldc,SPV,WT}$	Mean of the hourly mean of the forecasted data of month *m*
w	Inertia weight
w_{max}/ w_{min}	Maximum/minimum value of inertia weight
$Xnew$	New solution of learner
$Xold$	Existing solution of learner
X_r, X_i, X_c	Line reactance of the *r*-th/ *i*-th/ *c*-th branch of residential/ industrial/ commercial feeders (Ω)
X_n	Line reactance of the *n*-th branch (Ω)
$\chi_{n,y,m,t}^{ldr,ldi,ldc,SPV,WT}$	Generated synthetic data for load consumption, solar power and wind power at the *n*-th node in *m*-th month of *y*-th year
$\hat{\chi}_{n,y,m}^{ldr,ldi,ldc,SPV,WT}$	Mean of the generated synthetic data for load consumption, solar power and wind power at the *n*-th node in *m*-th month of *y*-th year
x_{best}	Position of the cat who has the best fitness value
x_q/ x_{q+1}	Position of *q*-th/(*q*+1)-th cat
x^*	Position of the current best bat
x_b	Position of the *b*-th bat
$x_{new,b}$	New position of the *b*-th bat
$x_{old,b}$	Existing position of the *b*-th bat
Y	Planning horizon
y_i	*i*th value of the data

y_b	best value of the data
$\sigma_{n,y,m,t}^{ldr,ldi,ldc,SPV,WT}$	SD of the hourly load demand of *n*-th residential, industrial and commercial node, SPV and WT generation over the month *m* of *y*-th year for state *t*
$\hat{\sigma}_{n,y,m}^{ldr,ldi,ldc,SPV,WT}$	Mean SD of the hourly load demand of *n*-th residential, industrial and commercial node, SPV and WT generation over the month *m* of *y*-th year for state *t*
α, γ	Design constants for BA
β	Random vector drawn from a uniform distribution [0, 1]
ε	Scaling factor in the range [–1,1]
λ	Node voltage deviation penalty function
Φ_j	Closed loop at *j*-th load level
ε	Emission factor for MT ($kg/kWh)
γ_y	Present worth factor of the cost in *y*-th year

ABBREVIATIONS

ABC	Artificial Bee Colony
AES	Alternative Energy Sources
AI	Artificial Intelligence
AM	Acquiescent Mutation
BA	Bat Algorithm
BFC	Brute Force Crossover
BOU	Budget of Uncertainty
CDC	Count of Dimensions to Change
CFE	Conditional Fitness Evaluation
CHA	Constraint Handling Algorithm
CI	Confidence Interval
COV	Coefficient of Variation
CR	Crossover Rate
CSO	Cat Swarm Optimization
DG	Distributed Generation
DGO	DG Operator
DisCo	Distribution Company
DL	Diversified Learning
DN	Distribution Network
DNA	Deoxyribonucleic Acid
DNO	Distribution Network Operator
DR	Distributed Resource
DS	Data Spread
EFB	Error from the Best
GA	Genetic Algorithm
HBO	Honey Bee Optimization
ICA	Imperialist Competitive Algorithm
ILRW	Improved Local Random Walk
ISA	Intelligent Search Algorithm
IWU	Inertia Weight Update
LEA	Local Escape Algorithm
LRW	Local Random Walk
MCS	Monte Carlo Simulation
MR	Mutation Rate
MT	Micro Turbines
MxR	Mixture Ratio
NPL	Node Priority List
NPV	Net Present Value
NR	Network Reconfiguration

PER	Pulse Emission Rate
PSO	Particle Swarm Optimization
QS	Quality of Solution
RES	Renewable Energy Sources
RW	Random Walk
RWS	Roulette-Wheel Selection
SAL	Self-Adaptive Learning
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SC	Shunt Capacitor
SD	Standard Deviation
SLP	Self-Learning Phase
SMP	Seeking Memory Pool
SPER	Self-Adapted PER
SPV	Solar Photovoltaic
SRD	Seeking Range of Selected Dimension
TC	Total Capacity
TD	Total Dispatch
TL	Teacher's Learning
TLBO	Teaching Learning Based Optimization
TS	Tabu Search
WT	Wind Turbine

CHAPTER 1

INTRODUCTION

THE electric power industries have witnessed many reforms in recent years. The existing distribution systems are moving toward smart distribution systems to achieve larger socio economic and other non-tangible benefits [1]. The potential promise of the smart grid includes environmental benefits, reduction in transmission congestion, peak load shaving, better asset utilization along with increased energy efficiency, reliability, security and power quality, etc. The rise of smart grid is a boon not only to society as a whole but to all who are involved in the electric power industry, its customers, and its stakeholders [1]. The integration of distributed resources (DRs) like distributed generations (DGs) and shunt capacitors (SCs) is one of the key technology areas for realization of smart distribution systems to improve the performance of distribution systems. In future massive deployment of renewable based DGs is expected to occur in electric distribution systems. To facilitate the integration of DGs and for other reasons, there will be large scale deployment of SCs to provide necessary reactive support. Gradually there will be transformation of the passive (legacy) distribution systems into active distribution systems having wide spread deployment of DRs. This transition from legacy distribution systems to smart distribution system requires a paradigm shift in both planning and operations. The distribution network reconfiguration (NR) is an effective operational method to improve the multiple performance objectives of contemporary distribution systems such as loss minimization, voltage profile improvement, congestion management, etc. The NR is a well-known operational strategy of modern distribution systems that alters the topological structure of the network by changing the open/close status of sectionalizing and tie-switches of distribution lines. The sectionalizing-switches and tie-switches are integral part of distribution system infrastructure. Besides distribution system performance improvement, the NR has an effective role to achieve the self-healing objective of future distribution systems.

The construction of next generation active distribution systems requires exploitation of existing infrastructure, use of new technologies of generation and changes in operational practices [2]. This originates new dimensions to the planning and operation of distribution systems. The smart grid initiatives require integrated solutions to well-formulated problems that reflect facts on the ground where all such devices/ infrastructure are to coexist to achieve smart grid goals of efficiency through loss minimization and high-quality power delivered to the ultimate user [1]. The integration of DGs and SCs along with NR can be effectively coordinated together to achieve some major objectives of smart grids. Therefore, this thesis addresses the problem of DR allocation in distribution system which takes into account the ground operational realities of distribution network infrastructure and devices.

The optimal DR allocation problem involves the determination of their optimal number, size and sites in distribution network whereas NR problem involves the determination of most optimal radial topology of distribution network while satisfying several network and operational constraints. However, improper sizing or improper placement of DRs may cause over voltages, excessive power losses and stability issues [3]. Therefore, such coordinated approach should be suitably tailored by duly addressing the realities of distribution systems otherwise the optimal solution so obtained may jeopardize the planning and operation of distribution systems. The problem of optimal allocation of DRs and optimal NR, each characterized as a highly complex combinatorial optimization problem. The complexity of the problem is further increased when more realistic operational issues of modern distribution systems have been taken into consideration in order to obtain more realistic solution. The existing optimization techniques therefore need further improvement to solve such complex optimization problems efficiently. In fact, the recent evolution toward modern active distribution systems imposes challenges against the modelling and solution techniques suitable for DR planning and operation of distribution systems.

In the present work, the problem of simultaneous allocation of DRs has been addressed in the view of NR to improve the performance of distribution systems. More practical formulation for these optimization problems is developed keeping in view of realistic operational issues and realities of modern distribution systems. Improved variants of some of the existing metaheuristics have been developed to successfully solve such complex combinatorial optimization problems. The applicability of developed methods has been thoroughly investigated on standard as well as real distribution systems. The results of the study are investigated and presented.

There is a wealth of literature dealing with optimal sizing and siting of SCs/ DGs and optimal NR, being treated separately, by considering a variety of techno-economic objectives. The problem is solved using various analytical, mathematical or heuristic techniques. Only few attempts have been made to coordinate any two of these approaches together. However, these attempts have not considered realities of distribution systems regarding the type of customers, their strategic locations within the network and their characteristic load patterns which may have seasonal variations. With these issues, certain load diversity exists among distribution buses, the consideration of which is very crucial in deciding the annual load profile as well as node voltage profiles of the system. These issues must be addressed while attempting any distribution system optimization problem otherwise it may prove to be counterproductive. Furthermore, SCs and DGs can independently act and control the power flow in distribution network [4], but the optimal allocation of these components is not independent; the presence of one may affect the optimal allocation of the other and vice-versa. Similarly, NR and the allocation of these DRs are not independent. Therefore, simultaneous allocation strategy of DRs is to be investigated with the consideration of NR. Furthermore, the time varying nature of load demand requires DR power control and frequent NR to achieve optimum objectives, but this introduces additional complexities in distribution system operation. Therefore, the relative effectiveness of these two operational strategies needs thorough investigations.

The roadmap of future distribution envisions widespread deployment of renewable energy sources (RESs) such as solar photovoltaics (SPVs), wind turbines (WTs) in distribution systems. These energy resources are seemed to be the only option to a sustainable energy supply infrastructure since they are neither exhaustible nor polluting [5]. However, these renewable energy-based DGs are mostly harvesting natural resources so produce clean emission-free electricity, but having intermittent power output so are non-dispatchable. Therefore, mix DG model has gained more popularity in recent DG planning of distribution systems. The mix DG model includes alternative energy sources (AESs) such as micro turbines (MTs) which are high speed and mechanically simple devices fired by natural gas or biogas, so are fully controllable. Moreover, the solar irradiations and wind speeds are complementary to each other in terms of power generation. Therefore hybridization of SPVs, WTs and MTs units seems to be a good idea for mix DG model [6]. However, there are certain economic, technical and environmental issues that need to be considered when selecting this DG model as they can limit their installation and restrict the associated economic and environmental benefits [7]. Furthermore, the mix DG model poses additional challenges on account of the interactions of diverse time-variant energy sources and stochastic load demand. Therefore, benefits associated with DGs depend not only on their sites and sizing, but also on the complex relationship between generation and load demand. Consequently, the optimal integration of such DGs must determine not only the optimal number, size and location, but also evaluate the stochastic impacts of DGs [7].

This approach has revolutionized the frame work of optimal DG allocation problems and thus intended to use some efficient optimization methods in probabilistic modelling of stochastic load and generation. With these concerns, the DR allocation problem of distribution systems assume different dimension and thus requires different treatment.

The optimal DR allocation problem has been solved using analytical, numerical, exhaustive search, meta-heuristic techniques, etc. Analytical methods are easy to implement and fast to execute, but their solutions are sub-optimal. Numerical methods are efficient, but some of them needs linearized modelling whereas exhaustive search methods suffer from the curse of dimensionality, so are not suitable for large-scale systems. On the other hand meta-heuristic techniques are robust and guarantee global or near global solutions even for large-scale optimization problem, but are computationally demanding. However, this limitation is not necessarily critical in DR allocation applications [8]. The actual challenge behind the application of these techniques is their parameter tuning, otherwise the performance may suffer adversely. Indeed, care should be taken to avoid premature or slow convergence, particularly when are applied to solve large-scale optimization problems. This leads to probably the most discussed disadvantage of metaheuristics. For example, genetic algorithm (GA) suffers from high processing time and premature convergence [9], particle swarm optimization (PSO) usually trapped into local optima [10], bat algorithm (BA) converges to suboptimal solution owing to weak exploration potential [11], cat swarm optimization (CSO) is computationally demanding [12] and teaching-learning based optimization (TLBO) has extremely slow convergence rate when deals with higher dimension problems [13], etc. These metaheuristics therefore require further reinforcement in order to extract their optimum potential. This probably could be achieved by overcoming inherent limitations associated with the standard models of these techniques.

Chapter 3 of the thesis deals with the development and investigation of improved variants of well-established metaheuristics, *i.e.* GA and PSO, and recently developed metaheuristics, namely BA, CSO and TLBO. Several algorithm specific modifications are proposed in each of their standard forms to enhance the convergence, accuracy and efficiency of these algorithms. In addition, a heuristic intelligent search algorithm (ISA) is suggested which can efficiently reduce the enormous problem search space offered to meta-heuristics, so further enhances their overall performance. The chapter also proposes a method for the simultaneous placement of DGs and SCs in distribution systems. The proposed method optimally allocates these DRs under piecewise multi-level annual load profile of the system with the objectives of annual energy loss reduction and node voltage profile enhancement. The DR allocation problem is solved for standard test distribution system by proposing improved GA (IGA), improved PSO (IPSO), improved BA (IBA), improved CSO (ICSO) and improved TLBO (ITLBO) algorithms. The application results show that a significant improvement can be achieved in system performance using proposed method. A thorough investigation has been carried to observe the performance of developed metaheuristics.

In chapter 4, the DR allocation problem is dealt with the consideration of NR while giving due concern to the load diversity that exists among dedicated distribution feeders on account of various types of customers and seasonal variations in their load demand. The objectives considered are the annual energy loss reduction and node voltage profile enhancement. A soft node voltage constraint is introduced using a penalty factor approach that considers NR while allocating DRs and also facilitates the application of metaheuristics to solve complex DR allocation problems of real distribution systems. The proposed method is applied on standard as well as real distribution systems using IGA, IPSO, IBA, ICSO and ITLBO techniques developed in chapter 3. The application results reveal that a significant improvement in objectives can be achieved using proposed coordinated solution for DR allocation and NR. In addition, the relative impact of DR tuning and NR is thoroughly investigated which may be beneficial for distribution network operators (DNOs).

In chapter 5, a new methodology is proposed for the optimal planning and operation of mix DR model consists of SPV, WT, MT units and SCs while considering intermittency in power generation from RESs and stochastic nature of load demand of various classes of customers. The DR planning model composed of several parameters pertaining to the capital and O&M costs of DRs, load growth, market prices, fuel price, revenue collection, effluent emission costs etc. whereas the operation model provides optimal tuning of MT units and SCs, and optimal radial topology of distribution network for each system states. The optimum sizing and siting problem of DRs is first solved to maximize the net present value (NPV) based profit over the long-term planning horizon. Thereafter, the DR operation problem is solved to optimize day-ahead scheduling of MT units, SCs and corresponding optimal network topologies of distribution network. The stochastic model for load demand and power generation from system buses is developed by proposing new deterministic polyhedral uncertainty set which is designed to have self-adaptive feature to deal with the diversity in load/generation among distribution buses. The problem is optimized using proposed ITLBO. The proposed method is investigated on the benchmark IEEE 33-bus test distribution system and the results of study are investigated and presented.

Chapter 6 summarizes the conclusions, major contributions and future research scope out of this thesis work. A comprehensive literature survey in the area of optimal allocation of DRs in distribution systems and NR is presented in the chapter 2. On the basis of critical reviews, the objectives of the thesis are framed.

CHAPTER 2
LITERATURE SURVEY

The origin of many power system issues are typically based on the electrical distribution systems as they are the tail ends of electric power systems. In the present competitive deregulated environment, the power distribution utilities are facing stressed operating conditions. The utilities have to optimize their annual profits by enhancing energy efficiencies of distribution systems and also have to supply reliable and quality power to customers. The optimal placement of shunt capacitors (SCs), distributed generations (DGs) and network reconfiguration (NR) are the three key strategies to enhance the performance of distribution systems. Whatever embedded in distribution systems, its impact percolates in the whole power system. A lot of research has been conducted during the past decades to address the NR and optimal allocation of these DRs by considering a variety of objectives while considering different types of DRs and their mode of power generations or the type of system load profile by employing several joint or simultaneous strategies using various analytical, numerical, heuristic and meta-heuristic techniques. In this chapter a brief literature review about these research areas is presented to identify the issues and concerns of current research directions for modern distribution systems. The research gaps pertaining to the current research directions are identified and presented in the critical reviews. The research objectives of this thesis work are then framed on the basis of critical reviews.

2.1 OPTIMAL ALLOCATION OF DISTRIBUTED ENERGY RESOURCES

The passive distribution networks are now being transforming into active distribution networks by integrating more and more DGs to achieve the objectives of smart distribution systems. DRs such as DGs and SCs can independently regulate active and reactive power flow among distribution feeders. Therefore, feeder power losses and node voltage profiles of distribution systems can be effectively regulated when they placed at strategic locations in distribution networks. From long back, researchers attracted towards the optimal allocation of SCs for power factor correction, however in the present scenarios they are still important as the performance of modern distribution systems can be enhanced by adopting suitable strategy of placing several types of DRs. A brief literature review about the optimal allocation of DRs is presented in the following sections.

2.1.1 OPTIMAL PLACEMENT OF SHUNT CAPACITORS

Reactive power compensation in distribution systems using SCs is typically an old classical problem of power systems. The capacitors must be allocating optimally otherwise line losses may increase and develop over voltages during light load hours. The optimal capacitor placement problem involves the determination of their optimal number, sizing and siting. Some pioneer works reported may include classical techniques [14-17], mathematical programming techniques [18-21], analytical methods [22-28] and numerical programming methods [29-33]. Many researchers attracted toward heuristic methods [34-38] which are simple, fast and easy to understand but usually converge to suboptimal solution. The evolutionary and swarm based intelligence techniques become the centre of attraction for researcher with the beginning of this century as their performance does not depend upon the type and shape of objective function, or the number of objectives or problem constraints employed, and are potentially very strong to get global or near global solution. Some salient works for optimal capacitor placement using a variety of objectives, constraints, as listed in Table 2.1, by employing various artificial intelligence (AI) techniques are listed in Table A.1.

TABLE 2.1
OBJECTIVES AND CONSTRAINTS FOR OPTIMAL CAPACITOR PLACEMENT

Objectives	Constraints
1. Peak active power loss reduction/ Line loss reduction/ cost of power loss 2. Reduce capacitor cost 3. Minimize energy loss cost 4. Capacity release in the expansion of network or avoid cost due to investment deferral in the expansion of the network/ release system capacity/ maximize the margin loading of feeders 5. Minimization of deviation of nodes voltage/ improve the voltage profile/ enhance voltage stability 6. Minimize the cost of reliability 7. Minimize number of switching operations 8. Minimize the total harmonic distortion	1. Active and reactive power flow balance equations /Power balance constraints 2. Voltage limit constraints 3. Reactive compensation limit 4. Maximum total compensation 5. Overall system power factor 6. Number and size of shunt capacitors 7. Total harmonic distortion of voltage 8. Total active power loss on all branches 9. Branch active power limit/ power source limit/ apparent power flow limit 10. Determination of type of capacitors 11. Selection of a unique bank per node/ impossibility to locate capacitors at certain nodes 12. Maximum limit of branch current/ line current/ line capacity limit 13. Maximum unbalance factor/ distortion indices 14. Capacitor switching transients

Distributed or dispersed generations (DGs) are becoming very common in distribution systems to achieve several techno-economic as well as social objectives. A wealth of literature is available to discuss optimal placement of DGs in distribution systems which is briefly described in the following section.

2.1.2 Optimal Placement of DGs

The potential promises of the smart grid include improved reliability and power quality, reduction in peak demand, reduction in transmission congestion costs, increased energy efficiency, better asset utilization, ability to accommodate more renewable energy, etc. [1]. Further, in a distribution system with specified structure, the value of active component of losses cannot be reduced by the use of the SCs alone, because the active power of loads connected to the system should be provided by the swing bus [102]. Therefore, to supply active loads of the distribution system, local generation should be privileged by DGs. DGs refer to small generating units typically connected to the utility grid in parallel near load centres and can satisfy these objectives. The penetration level of DGs in power system has been increased during the last few years due to the significant advances in several generation technologies, deregulation of power systems, environmental impacts and construction issues related to new transmission lines, etc. [103].

The DG allocation problem also involves the determination of optimal number, sizing and siting of DG units to achieve certain objectives under specified constraints. It is widely acknowledged that strategically placed and operated DG units can yield several benefits, while on the other hand, improper placement and operations of DG units in some circumstances may reduce benefits and even jeopardize the existing systems [104]. A lot of research work is available to solve optimal DG allocation problem by considering various technical, economical or techno-economic objectives while considering different constraints as presented in Table 2.2. The problem is solved using a variety of solution techniques which can be briefly mentioned here. Among classical methods, the most efficient are the nonlinear programming [5, 105-109], the sequential quadratic programming [110] and the ordinal optimization methods [111]. On the other hand the exhaustive search methods like brute force technique and dynamic programming [112] guarantee to find the global optimum, but they have the curse of dimensionality so are unfit for modern distribution systems. Several mathematical optimization techniques such as gradient search [113], Hereford ranch algorithm [114], decision theory approach [115], sequential quadratic programing [110], linear programming [116], primal-dual interior-point method [117], mixed-integer nonlinear programming [109], etc. have been addressed to solve this problem. However, major difficulty with these methods is that they provide only one solution which may not be feasible for DG placement owing to strategic location, political reasons, etc. Analytical methods [118-124] are easy to implement and fast to execute but they may provide impractical solution as they are based on certain unrealistic assumptions. Though population based metaheuristics suffer from high computational effort, but this limitation is not necessarily critical in DG placement applications [8]. Therefore, the swarm and evolutionary based meta-heuristic techniques have gained more attention of researchers to solve DG allocation problem efficiently. A brief comparison of solving DG allocation problem by considering various objectives and constraints using different solution techniques is presented in Table A.2.

TABLE 2.2
OBJECTIVES AND CONSTRAINTS FOR DG PENETRATION

Objectives	Constraints
1. Minimization of the total/ real power loss of the system	1. Power flow equality constraints/ P and Q mismatch equations
2. Minimization of energy loss or energy loss cost/ Maximize the apparent power exported from the substation (energy export)	2. Bus voltage or voltage drop limits
3. Minimization of system average interruption duration index (SAIDI) and frequency index (SAIFI)/ Minimize cost of interruption in distribution system/ Minimize the cost of reliability	3. Line or Transformer overloading or capacity limit
4. Minimization of cost of DG (investment, operation and maintenance cost)/ Reinforcement cost of the distribution network	4. Total harmonic voltage distortion limit / Individual harmonic distortion limits
5. Improve voltage stability margin	5. Reliability constraints eg. Max. SAIDI
6. Maximize the network investment deferrel incentives	6. Distribution substation capacity limit
7. Maximization of profit/ Maximize Benefit/Cost ratio	7. Power generation limits of DG
8. Maximize capacity adequacy cost in the planning period/ Identify the spare capacity in the network for accommodating DG	8. Protection coordination limits
9. Maximization of voltage limit loadability/ Enhance line loadability	9. DG with constant power factor/ power factor limit of DG/ power factor regulation for a DG site
10. Minimize system upgrade cost/ Line capacity release	10. DG annual operation time limit
11. Maximize the DG penetration level/ Maximize the rating of DG/ DG capacity maximization	11. Only one DG can be installed in one installation position
12. Improve voltage profile	12. Discrete size of DG units
13. Minimize total harmonic distortion in voltage	13. DG loss constraints/ active power losses of branches
14. Minimize the cost of purchased energy from the grid/ electricity market	14. Number and size of DG units/ Total installed DG capacity at each node/ Reactive power flow flowing back to source
15. Maximize the security margin of the distribution system/ Minimize the short-circuit current	15. Feeder capacity limit/ Line current constraints/ Branch current limit/ Thermal capacity limits of the network feeder lines
16. Minimize the number of DG units	16. Short circuit level/ Fault current limit/ Short circuit limitations
17. Minimization of load distributed/ Minimize the total load curtailed	17. The right of the way buses are excluded
18. Minimize Environmental cost	18. Constraints related to existing generator buses
	19. Branch flow limits (P and Q)/ Power source limit constraints
	20. Penetration level of DGs

2.1.3 SIMULTANEOUS ALLOCATION OF SCS AND DGS

In existing distribution systems, there is certain limit for DG penetration as most of the existing DGs operate at unity power factor control mode. This limit could be increased if sufficient and coordinated reactive support is available by deploying SCs. The optimal generation of active and reactive power from these devices reduces power import from the substation and thus regulates feeder power flows. Optimal capacitor placement achieves this goal by regulating reactive power flow, whereas optimal DG placement does the same by regulating active power flow in the system. In fact SCs and DGs can independently act and control the power flow, but the allocation of these components is not independent; the presence of one component may affect the optimal allocation of the other and vice-versa. Moreover, they also facilitate more effective utilization and life extension of existing distribution system infrastructure [1] and also contribute in creating self-sustained micro-grids. In this view, the simultaneous allocation of these DRs needs an investigation in order to extract optimum benefits and also to avoid counterproductive consequences. Recently, some researchers [102, 151, 192-202] addressed the simultaneous allocation of SCs and DGs in distribution systems using different approaches and shown fruitful mutual impact of these components on the network performance. The problem was solved to optimize one or more objectives related to power or energy loss minimization or voltage profile enhancement, etc. and is solved using analytical, mathematical or heuristic optimization techniques. But, the variation in annual load profile is not duly addressed in most of the above references [151, 192-197, 199-200, 202]. In fact, power losses can be studied in passive networks considering peak load scenarios—as is traditionally done—distribution networks with DG plants require the assessment of energy losses [203]. Though a multi-level annual load profile is considered in [102, 198] to minimize annual energy loss, but the benefits that could be achieved by employing the optimal dispatches of DRs under different load conditions are not taken into account. However, it is imperative to vary the power injections from DRs with system load demand otherwise the feeder losses may increase under light and moderate load conditions. Ref. [201] considered uncertainty in load demand using fuzzy data theory. But, they have not considered the specific load pattern associated with different buses of the system. This is crucial as some load diversity may exist among different system buses which decide not only the shape of load profile but also peak demand on the station. Unrealistic load profile may lead to unrealistic solutions and thereby erroneous benefits.

2.2 OPTIMAL DR ALLOCATION AND NETWORK RECONFIGURATION

Smart grid initiatives require integrated solutions for optimal allocation of DRs and NR that reflect coexistence of these strategies to achieve higher energy efficiency and good quality power supply [1]. Such co-ordinated efforts can provide maximum benefits for the network owner and/or the network users. Moreover, it can evaluate the feasibility of DG investment versus other traditional planning options, assuming that investment in DG is allowed by local regulation [8]. NR is another well-known operational strategy that is used to achieve high performance of distribution systems, so it may also employed in conjunction with optimal allocation of DRs.

NR is a process that modifies the states of the sectionalizing switches (normally close switches) and tie switches (normally open switches) to isolate a fault in the network or to meet given optimal requirements such as minimizing power loss of the network, maintaining the power balance and reducing the load of the transformers [204]. Merlin and Back [205] were the first who proposed the idea of NR in 1975. Since then, extensive research work has been carried over the past several decades to address reconfiguration problem using several objectives like loss minimization, voltage profile enhancement, reliability enhancement, etc. using diverse optimization techniques, viz. exhaustive algorithms, heuristic algorithms, mathematical programming, analytical methods, AI techniques, hybrid approaches, etc.

In Ref. [104, 173, 182, 206-218] NR is employed in conjunction with the optimal allocation of DRs, and it has been acknowledged that this strategy is very useful to improve the performance of distribution systems. Whereas, some researchers [173, 182, 206, 208, 209, 211, 214, 215, 218] employed joint optimization for DR allocation and NR. However, this approach is not seemed to be realistic as the solution obtained can demand an alteration in both network topology and sites of DRs with the variation in load demand. In practice, the network topology can be altered with the variation in load demand, but not the locations of DRs. Hung *et al*. [104] employed several combinatorial strategies for DR allocation and NR. According to their proposed strategy, NR should be carried out before DR addition. But, distribution system planning problem should be dealt before optimizing any operational strategies, so distribution network should be reconfigured after optimally placing DGs.

2.3 DR Allocation under Realistic Load and Generation Scenario

The load demand of the power system is a major source of uncertainty in power system planning [109], and its modelling is crucial for distribution system planners. Several researchers have attempted the modelling of load profile using aggregate multi-level hourly variations for the daily load profile [219], time varying loads along the feeder with specific line loading patterns [119], probabilistic-based hourly variations around a definite percentage of the peak loading [109] or estimating the uncertainty of the load using fuzzy data theory [201]. However, they have not considered the specific load pattern associated with different buses of the system. In practical situations, loads are mixtures of different load types, depending on the nature of the area being supplied, therefore, a load class mix of residential, industrial, and commercial loads is to be investigated too, in which every bus of the system has a different type of load connected to it [150]. Distribution system planners usually provide dedicated feeders to different class of customers. So, definite load diversity exists among distribution feeders which plays key role in deciding the annual load profile of the system. Ref. [112, 150] consider practical voltage-dependent load class mix model for different class of customers, but dedicated distribution feeders are not considered. Moreover, the load diversity attributed with hourly and seasonal variations in the load demand are also not taken into account. It has been concluded in [150] that the load models for different class of customers can significantly affect the optimal location and sizing of DG resources in distribution systems. Therefore, the modelling of annual load profile should consider these realities of distribution systems while dealing with any distribution system optimization problem.

On account of technology improvements and governmental incentives for the use of green energies, renewable energy sources (RESs) appears to be a promising approach for electricity generation, as RESs become a larger and larger portion of the generation mix, many aspects of the distribution systems operation and planning has changed [220]. Nowadays, several renewable and non-renewable DG technologies such as SPVs, WTs, MTs, fuel cells, combined heat and power, and combustion gas turbines are economically available in the market. Among these, the integration of SPVs and WTs are becoming more popular in distribution systems with the philosophy of smart grid initiatives and strict environmental laws. However, these DGs are characterized by intermittent power generations. In Ref. [108], the authors concluded that the optimal accommodation and sizing of DG units where the time-varying characteristics of demand are neglected is very likely to lead to sub-optimal results. Therefore, the stochastic nature of load demand has also to be considered while dealing with renewable DGs. The uncertainties in load and power generations not only increase complexities of DG allocation problem but also demands special treatment to handle uncertain data efficiently. Moreover, the consideration of intermittency in power generation and load model increases system states considerably, thus CPU time incurred by solution techniques also increases by many folds. But, this is necessary as the correlation between load and renewable resources has been nullified by dividing the study period into several segments and treating each segment independently [171]. With these issues, it is challenging to incorporate these complexities into an optimization framework for DG allocation problem as it considers the actual metrics used by distribution network operators (DNOs).

Several interesting approaches [5, 10, 108, 115,119, 136, 150, 152, 160, 179, 181, 190, 201, 220-225] have been addressed for DG allocation in such uncertain environment using various methods such as decision theory [115], probabilistic planning method [5, 109, 160, 171], point estimation method (PEM) [10, 220, 221], chance-constrained programming (CCP) [152], Monte Carlo simulation (MCS) [152, 225], fuzzy data theory [201] by considering one or more objectives such as to minimize power loss [119, 136], minimize energy loss [5, 108, 109, 179], maximize energy export to grid [136], profit maximization [223], voltage stability margin [181], maximizes the energy delivered from DG [226], etc. However, rare attempt [220] has been addressed to deal with the simultaneous capacitor and DG allocation where the authors have suggested day ahead scheduling of disapatchable DRs. In Ref. [179], a mix DG model is suggested and the authors' concluded that dispatchable DG unit has a more positive impact on energy loss minimization and voltage profile enhancement than non-dispatchable DG unit. A deterministic approach is employed in [223] to deal with the probabilistic nature of DG unit outputs and load consumption by suggesting column and constraint generation (CCG) frame-work. The merit of this approach is that it fully considers the system uncertainties yet only requires a deterministic uncertainty set, rather than a probability distribution of uncertain data which is difficult to obtain.

While comparing uncertainty handling methods, MCS generates different random values for uncertain input variables, but it requires a great number of simulations to attain convergence that makes it computationally demanding [190]. Analytical methods are more effective than MCS but are based on some unrealistic mathematical assumptions. On the other hand, probabilistic methods eliminate the need of time-series data, but dynamic changing performance of the system cannot be represented using these methods. Unlike the MCS method, the PEM is generally simpler and more flexible to deal with complex models [10]. However, it is computationally demanding when several load levels are considered [86]. Therefore, the use of PEM is impractical for realistic power systems having large number of input random variables. Although each of above mentioned methods is a useful tool to handle the uncertainty effects, but the process of modelling uncertainty in these methods is based either on the known statistical data or on the known probability distribution function of input variables, however, in some situations, none of the above two cases may be available [227]. Therefore, a suitable approach is required that involves less number of statistical information and a probability density function with a finite number of moments.

Several optimization techniques such as mathematical programming [5, 222, 226], analytical methods [119, 179] or heuristic method [115] used to optimize the problem. Many researchers have trusted upon metaheuristics though they are well-known to be computationally demanding. Among metaheuristics, the non-dominated sorting genetic algorithm (NSGA) [136, 224], GA and immune-genetic algorithm (IGA) [221, 152], PSO and its modified variant [10, 150, 160, 201, 228], evolutionary programming (EP) [171], modified shuffled frog leaping algorithm (MSFLA) [220] are preferred than other algorithms owing to their ability to obtain global or near global solution. However, the complexity of DR allocation problem urged to improve existing metaheuristics so that a better solution can be determined. A brief literature review about the strengths and limitations of some of the existing potential meta-heuristic techniques is presented in the following section.

2.4 META-HEURISTIC TECHNIQUES

With the advent of fast computational facilities, a large number of evolutionary or swarm-based AI techniques have attained the centre of attraction for researchers to solve complex combinatorial power system optimization problems. However, these techniques have their own merits and demerits. GA is simple, robust and flexible method, but it suffers from high processing time and premature convergence [9]. Particle swarm optimization (PSO) can generate a high-quality solution and stable convergence characteristic within a shorter calculation time [150], but it may experience inappropriate convergence and fall in local minima [10]. Bat algorithm (BA) [229] is simple, robust, easy to implement and significantly faster than other optimization techniques. The algorithm obtained good results when dealing with lower-dimensional optimization problems, but may become problematic for higher-dimensional problems because it tends to converge very fast initially [11]. The unique property of cat swarm optimization (CSO) is that it provides local as well as global search capability simultaneously [230], but is computationally more demanding [12]. Teaching learning based optimization (TLBO) [231] is another recently established optimizing technique which is free from algorithm specific parameters that makes it class apart than other techniques. Despite of its simplicity, easy implementation and lower computational complexity, the weak communication in the learner phase may lead to local trapping [232]. Another disadvantage of TLBO is that the convergence rate gets even worse when deals with higher dimension problems and hence some mechanism has to be incorporated to achieve the highest performance [13].

Most of metaheuristics are sensitive to variation in their control parameters that can affect their accuracy, unless tuned properly which needs several experimentations so are excessive computationally demanding. This imposes real challenge while solving large-scale optimization problems [203] like optimal allocation of DRs. Another typical feature of metaheuristics is that they offer enormous problem search space. Therefore, the search for the best combination amongst the various possible combinations is computationally arduous even when subjected for a small distribution system [171]. This adversely affects the accuracy, efficiency and CPU time of these techniques when applied to solve large-scale optimization problems. However, the overall performance of techniques can be improved by restricting the problem search space. But, the search space reduction should be accurate otherwise the global or near global optima may remain left outside the restricted search space. As a result, the algorithm converges to local optima, as in [74, 87, 89, 90, 92, 97, 171, 182, 192, 195, 233], where the problem search space being restricted using some unreliable sensitivity based approaches.

2.5 CRITICAL REVIEW

In the present deregulated environment, annual energy losses and node voltage profiles of distribution systems are very important issues for DNOs so may be called as two vital indices to check the performance of distribution systems. With this view, the performance of distribution systems can be enhanced by regulating and managing distribution line flows. This could be achieved by local generation of active and reactive power using DGs and SCs provided that these components should be optimally allocated with regard to their number, size and sites, otherwise system performance may deteriorate. An enormous literature is available to efficiently solve the optimal allocation problem of SCs alone or DGs alone. Although SCs and DGs can independently act and control the power flow among distribution feeders, yet the optimal allocation of these DRs are not independent. The presence of one component affects the optimal allocation of other component and vice-versa. Thus, the simultaneous optimal allocation strategy of these components is seemed to be more fruitful. Further, the NR is another well-known and effective operational strategy used to reduce feeder power losses and node voltage deviations in modern automated radial distribution systems. However, NR and DR allocation are also not independent. Therefore, NR is another resource that should be investigated in conjunction with simultaneous allocation of DRs to further enhance the performance of distribution systems.

Distribution planners usually provide dedicated feeders to serve particular class of customers e.g. residential, commercial, industrial, etc., each has its characteristic load pattern. This causes definite load diversity among distribution buses. Moreover, the seasonal variations in load demand must be considered while determining annual load profile of the system. Therefore, while dealing with distribution system optimization problems, these issues of power distribution must be duly addressed, in the lack of which, either an unrealistic solution would be obtained or the expected optimum benefits could not be achieved.

Recently, the mix DG model has gained more popularity on account of environmental and other techno-economic concerns. This DG model consists of controllable DGs with little emissions and renewable DGs with zero emissions. However, these renewable DGs like SPVs and WTs are characterized by intermittent power generations. While considering randomness of power generation from DGs, the stochastic nature of load demand has also to be taken into account. These concerns impose most challenging and complex task for distribution system optimization problem framework. Therefore, in the present scenario, the DR allocation problem of distribution systems needs reframing by considering the stochastic nature of load and local generations from RESs. This however requires specialized treatment to handle uncertain data. In addition to it, the realities of distribution networks like load diversity among distribution buses should be duly addressed in the problem formulation. With these considerations, the DR allocation problem becomes highly complex combinatorial exercise. Therefore, old classical methods are not suitable to solve such problems due to non-differentiability of the objective function. Whereas, the solution obtained using mathematical approaches may suffer from linearizing the problem. On the other hand, metaheuristics such as GA, PSO, DE, SA, etc. are independent from the type, shape and number of objective functions, and can also cater mixed integer problems, like DR allocation and NR, efficiently. These powerful techniques have shown their potential to obtain global or near global optima for complex engineering optimization problems and also provide a close set of solutions which is extremely useful for distribution planning engineers. However, the actual challenge with these techniques is related with their parameter tuning which is highly computationally demanding. Indeed, care has to be taken to avoid premature or slow convergence, particularly when are applied to large-scale applications. It probably happens due to certain inherent limitations in their internal mechanisms. Thus, there is stringent need to overcome such limitations of these metaheuristics and thus make them suitable to solve complex large-scale optimization problems.

2.6 RESEARCH OBJECTIVES OF THE THESIS

On the basis of above critical review, following objectives have been formulated for the research work.

1. To develop improved variants of existing meta-heuristic techniques to solve complex DR allocation problems of distribution systems accurately and efficiently.
2. To investigate the effectiveness of developed meta-heuristic techniques and to present an exhaustive comparative analysis for the same.
3. To develop a suitable mathematical modelling for the simultaneous allocation of DRs such as DGs and SCs in distribution systems to minimize annual energy losses and to enhance node voltage profiles under piecewise multi-level load profile. Solve the problem using developed improved meta-heuristic techniques and also to investigate the effectiveness of these techniques.
4. To propose mathematical modelling for the simultaneous allocation of DRs in distribution systems by considering realities of load diversity among distribution buses and seasonal variations in load demand and solve the problem using developed techniques. Also investigate the impact of load diversity, DR tuning and NR on the performance of distribution systems.
5. To develop a new method for mix DG allocation in distribution systems by considering stochastic nature of load demand and intermittent power generation from renewable DGs. Also develop suitable method to handle uncertain data efficiently.
6. To investigate the impact of the interaction between diverse time-variant energy resources and stochastic load demand on the operation of distribution system.

The organization of the thesis is as follows. Chapter 1 presented a brief introduction of thesis and a detailed literature survey is presented in Chapter 2. Chapter 3 deals with simultaneous allocation of DRs using improved variants of five different existing evolutionary or swarm based algorithms, and an integrated approach for the simultaneous allocation of DRs and NR considering realities of load diversity among dedicated distribution feeders allocated to different classes of customers is presented in Chapter 4. Chapter 5 introduces a new methodology for the optimal allocation of DRs considering uncertainty in hourly load demand of various categories of customers and hourly generation from renewable sources. Finally, the conclusions and future research scope from this thesis are presented in Chapter 6.

CHAPTER 3

DISTRIBUTED RESOURCE ALLOCATION USING META-HEURISTIC TECHNIQUES

With the advancement of technical and economic feasibility, the integration of DGs has taken wider acceptance for present and future active distribution systems. The roadmap of future distribution envisions widespread deployment of DRs such as SCs and DGs in the near future. DGs are installed primarily to tap available renewable energy and to supply local demand so that the power demand from the grid is reduced. On the other hand, SCs are primarily installed to meet the reactive power demand of the distribution systems. Besides their primary objectives, the integration of these components (DGs and SCs) into the distribution system reduces power and energy losses, defers major system upgrade and improves the reliability and quality of power supply. Moreover, they also facilitate more effective utilization and life extension of existing distribution system infrastructure [1]. Therefore, optimal placement and sizing of these devices are the important issues to extract optimum benefits. However, the amount of benefits achieved chiefly depends upon how optimally they have been placed in distribution network; a wrong placement may be counterproductive. It is important to note that DGs and SCs can independently set and control the real and reactive power flow in distribution networks [4]. But, the presence of DGs in distribution systems can cause a voltage drop or an over voltage that depends on power supplied by generators and their locations [234]. SCs can improve these power quality parameters by injecting the reactive power into distribution systems and also contributes to reduce feeder power losses. Extensive research has been carried for the placement of DGs and SCs independently in distribution systems with multiple objectives. However, future distribution systems require integrated and coordinated solutions for the optimal placement of these DRs that reflect coexistence of these devices to obtain more realistic and more efficient placement strategy. Therefore, by simultaneously determining the optimal number, sizing and siting of DGs and SCs, optimum benefits can be achieved at reduced rating of these components. Several references [102, 151, 192-202] have attempted this simultaneous allocation problem of DRs considering power losses as one of the major objective. However, distribution networks with DG plants require the assessment of annual energy losses [203]. In order to assess annual energy losses, the annual load profile of the distribution system needs to be considered. The load demand of distribution system varies with time, therefore many references [74, 87, 90, 95, 198, etc.] have considered multi-level piece-wise linearized modeling to represent annual load profile of the system. This leads to the consideration of all load levels simultaneously while optimizing DR allocation problem. With the optimal sizing of DRs so obtained, their power dispatches should be determined optimally for each load level to achieve optimum benefits.

The simultaneous DR allocation problem of distribution systems is a non-linear, mixed integer, complex combinatorial optimization problem and cannot be solved using classical optimization techniques. Its solution requires the application of modern heuristic techniques, i.e. meta-heuristic techniques. Meta-heuristic techniques initiated with a definite population size, called tentative solutions, being randomly spread over the problem search space. Each individual is characterized by its fitness value, decided by the objective function evaluation, which is being upgraded in due course of time by virtue of its strategic movement governed by the control equations of the algorithm. The best individual obtained after predefined iterations, i.e. maximum iterations, is treated as the optimal solution. The unique feature of these techniques is their independency on the type and nature of the objective function to be optimized. Further, they exhibit full potential to obtain global or near global optima while applied to solve diverse engineering optimization problems. However, the actual challenge while using these techniques is the tuning of control parameters that guide the optimization process. Indeed, care should be taken to avoid premature or slow convergence, particularly in large-scale applications [203] as they offer enormous problem search space to these techniques. In fact, the full potential of these techniques can be extracted by suitably regulating their internal mechanisms to achieve self-sustainable healing against their intrinsic flaws. Moreover, the overall performance of meta-heuristic techniques can be further enhanced by suitably employing search space reduction using engineering knowledge base of the concerned problem.

The critical review of the literature also shows that to solve simultaneous allocation problem of DRs, meta-heuristic techniques such as GA, PSO, ICA, HBO, TS etc. have been used. Out of these, GA and PSO have been widely used. However, these techniques are not deterministic and there is always a scope of improvement. Therefore, efforts should be made to further enhance the performance of these techniques when applied to solve such complex DR allocation problems. From the critical review it is also observed that no efforts or limited efforts have been made to apply relatively new meta-heuristic techniques such as BA, CSO and TLBO to solve such problems. Therefore, efforts should be made to make them suitable to solve complex DR allocation problems efficiently.

In this chapter, the simultaneous allocation problem of DGs and SCs in distribution systems is formulated to reduce annual energy losses and to maintain better node voltage profiles while considering a piece-wise multi-level annual load profile. The proposed methodology assumes controllable DRs so desired power output can be dispatched under varying load conditions to further optimize the objectives. Improved version of GA, PSO, BA, CSO and TLBO techniques have been developed to solve simultaneous allocation problem of DGs and SCs in distribution systems. Several algorithm specific modifications are suggested to improve the computational efficiency and convergence characteristic of the algorithms to make them suitable for simultaneous allocation problem of DRs. Moreover, a heuristic intelligent search algorithm (ISA) is also suggested for search space reduction of all meta-heuristic techniques. In order to investigate the effectiveness of the developed methods, they are applied on the benchmark IEEE 33-bus test distribution system to solve the optimal DR allocation problem and the application results obtained are presented. An exhaustive comparative analysis for the developed meta-heuristic techniques is also investigated and presented.

In the presence of DRs, the power flow equations of distribution systems are modified, therefore existing load flow methods cannot be as such used. In the following section a brief discussion on network power flow equations with integrated DRs is presented.

3.1 DISTRIBUTION NETWORK POWER FLOW EQUATIONS WITH INTEGRATED DRS

The sum of the power supplied from the utility grid and the total power generated by DRs integrated in the distribution system must be balanced by the local load demand and the power losses in the lines. A sample two bus radial system with installed DG and SC is shown in Fig. 3.1. The figure shows a branch connected between sending node n and the receiving node n+1. The real and reactive power flow through the branch is represented by P_{n+1} and Q_{n+1}, and the terminating node n+1 voltage (neglecting shunt conductance and susceptance) are given by Eqs. (1)–(3), respectively. Here P_n (Q_n) are the sending end active (reactive) power flows and R_n (X_n) is the series resistance (reactance) of the nth distribution line. $p_{(n+1)}^{\mathrm{DG}}$ is the active power injections by DG, $q_{(n+1)}^{\mathrm{SC}}$ is the reactive power injection by SC, and $p_{(n+1)}^{L}(q_{(n+1)}^{L})$ are the total active (reactive) load demand at the receiving node.

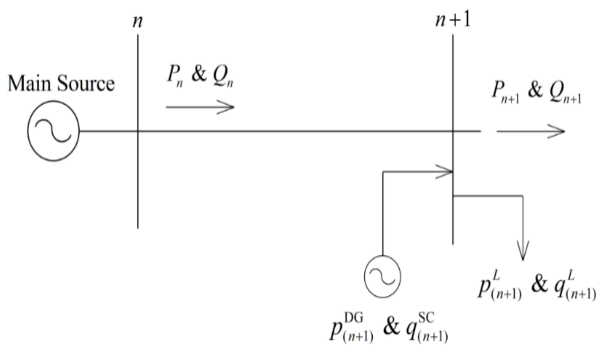


Fig. 3.1 Single-line diagram of a two-bus system

$$P_{(n+1),j} = P_{n,j} - R_n \frac{P_{n,j}^2 + Q_{n,j}^2}{V_{n,j}^2} - p_{(n+1),j};\ \forall n \in N,\ \forall j \in L \tag{1}$$

$$Q_{(n+1),j} = Q_{n,j} - X_n \frac{P_{n,j}^2 + Q_{n,j}^2}{V_{n,j}^2} - q_{(n+1),j};\ \forall n \in N,\ \forall j \in L \tag{2}$$

$$V_{(n+1),j}^2 = V_{n,j}^2 - 2\left(R_n P_{n,j} + X_n Q_{n,j}\right) + \left(R_n^2 + X_n^2\right)\frac{P_{n,j}^2 + Q_{n,j}^2}{V_{n,j}^2};\ \forall n \in N,\ \forall j \in L \tag{3}$$

Where

$$p_{(n+1),j} = p_{(n+1),j}^{L} - p_{(n+1),j}^{\mathrm{DG}};\ \forall n \in N,\ \forall j \in L \tag{4}$$

$$q_{(n+1),j} = q_{(n+1),j}^{L} - q_{(n+1),j}^{\mathrm{SC}};\ \forall n \in N,\ \forall j \in L \tag{5}$$

The set of these power flow equations are non-linear so can be solved using any suitable iterative load flow method such as backward-forward sweep power flow method. This method is especially designed for radial topologies and is also less computationally demanding than the Newton-Raphson load flow method. Moreover, the later one may fail to converge on account of high R/X ratio of distribution feeders.

In the following section, the problem of simultaneous allocation of DRs is formulated to achieve desired objectives.

3.2 PROBLEM FORMULATION

The integration of DGs and SCs alters power flow in distribution feeders. This causes reduction in annual energy losses and node voltage deviations. Therefore, the simultaneous DR allocation problem is formulated to maximize the annual energy loss reduction while maintaining better node voltage profiles. In order to limit the voltage deviation at different nodes, a hard voltage constraint is used as desired by the regulation authorities. Similarly to check the current carrying capacities of distribution feeders, a feeder ampacity constraint is essential. A multi-level piece-wise linearized annual load duration profile of the system is considered to evaluate annual energy losses of distribution feeders. The DR allocation problem is structured as single-objective constrained optimization problem where optimal number, size and location of DGs and SCs are determined simultaneously. The problem is formulated as:

$$\text{Max. } f(x) = \left(\sum_{j=1}^{N_L} \left(PLoss_{bj} H_j \right) - \sum_{j=1}^{N_L} \left(PLoss_{aj} H_j \right) \right); \forall j \in L \tag{6}$$

Subject to the system operational constraints defined as below.

3.2.1 Power flow constraint

$$g_j\left(h\right) = 0;\ \forall j \in L \tag{7}$$

Where $g_j(h)$ represents the set of power flow equations during jth load level as given by (1)-(5).

3.2.2 Node voltage constraint

All node voltages $V_{n,j}$ of the system must be maintained within the minimum and maximum permissible limits *i.e.* $V_{\min}$ and $V_{\max}$, respectively, during the optimization process as defined by the regulation authority.

$$V_{\min} \le V_{n,j} \le V_{\max}; \forall n \in N, \forall j \in L \tag{8}$$

3.2.3 Feeder ampacity constraint

The current flow in each branch must satisfy the rated ampacity of each branch.

$$I_{n,j} \le I_n^{\max};\ \forall j \in L \tag{9}$$

3.2.4 Bus compensation limit of DGs

The active power injected by DG at each bus must be within their permissible range.

$$p_{\min}^{\mathrm{DG}} \le p_n^{\mathrm{DG}} \le p_{\max}^{\mathrm{DG}};\ \forall n \in N \tag{10}$$

Where, $p_{\min}^{\mathrm{DG}}$ and $p_{\max}^{\mathrm{DG}}$ are the minimum and maximum active power generation limit at a bus, respectively.

3.2.5 Bus compensation limit of SCs

The reactive power injected by SC at each bus must be within their permissible range.

$$q_{\min}^{\mathrm{SC}} \le q_n^{\mathrm{SC}} \le q_{\max}^{\mathrm{SC}};\ \forall n \in N \tag{11}$$

Where, $q_{\min}^{\mathrm{SC}}$ and $q_{\max}^{\mathrm{SC}}$ are the minimum and maximum reactive power generation limit at a bus, respectively.

3.2.6 Penetration limit of DGs

The sum of active power injected by DGs at all candidate nodes should be less than nominal active power demand p_D of the distribution system.

$$\sum_{n=1}^{loc} p_n^{\mathrm{DG}} \le p_D;\ \forall n \in N \tag{12}$$

3.2.7 Penetration limit of SCs

The sum of reactive power injected by SCs at all candidate nodes should be less than nominal reactive power demand q_D of the distribution system.

$$\sum_{n=1}^{loc} q_n^{SC} \le q_D; \ \forall n \in N \tag{13}$$

Equations (14) and (15) prohibit the repetition of candidate sites for DRs.

$$loc_{\mathrm{a}}^{DG} \ne loc_{\mathrm{b}}^{DG}; \ a, b \in N \tag{14}$$

$$loc_{\mathrm{a}}^{\mathrm{SC}} \ne loc_{\mathrm{b}}^{\mathrm{SC}}; \ a, b \in N \tag{15}$$

Where loc^{DG} and loc^{SC} refer candidate sites for DGs and SCs, respectively. Since DRs are commercially available in discrete sizes and thus are modeled by (16) and (17).

$$p_n^{\mathrm{DG}} \le K_d P_d; \ K_d = 0, 1, 2, \ldots, ndg \tag{16}$$

$$q_n^{\mathrm{SC}} \le K_b Q_b; K_b = 0, 1, 2, \ldots, nsc \tag{17}$$

Where P_d and Q_b represent the respective unit size of DGs and SCs. K_d and K_b represent discrete dispatches of DG and number of capacitor banks, respectively.

First optimizing (6), the solution obtained provides the optimal sizes and sites of DGs and SCs, while considering the annual load profile. Next, (6) is optimized, but for each load level separately, to determine the optimal tuning of installed DRs. The additional constraints required to determine the optimal tuning of DGs and SCs are modelled as given by (18)-(19).

$$p^{DG} = K_{md} \Delta p; \ K_{md} = 0,1,2,\ldots, p^{DG} / \Delta p \tag{18}$$

$$q^{SC} = K_t \Delta q; \ K_t = 0, 1, 2, \ldots, q^{SC} / \Delta q \tag{19}$$

Where Δp and Δq represents the available commercial discrete sizes of DGs and SCs, respectively.

In the following subsequent sections attempts have been made to develop improved variants of GA, PSO, BA, CSO and TLBO by suggesting several algorithm specific modifications in their respective standard formats. Moreover, the problem search space of these metaheuristics is reduced by suggesting an intelligent search algorithm (ISA). The development of the proposed improved GA, i.e. IGA is presented in the following section.

3.3 PROPOSED IGA

Genetic algorithms (GAs) are the search and optimization procedures that are motivated by the principles of genetics and natural selection which is based upon Darwinian evolution, i.e., survival of the fittest [235]. The development of GAs is largely credited to the work of Holland [235] and Goldberg [236]. Since then GAs have evolved and become a promising tool to solve complex engineering optimization problems. The inner working of GAs involves the string duplication and substring exchange, coupled with the occasional alteration of bits. GA balances the exploration and the exploitation through genetic operators, i.e. crossover and mutation. In GA, a pool of individuals, i.e., potential solutions known as the population which is randomly created and then used to build a new, hopefully improved, pool by mimicking those of natural selection. Individuals with high fitness values are more likely to be chosen to generate the next generation. In this way, the selection pressure is applied for the continuous improvement of individuals' quality. The crossover operator in GA facilitates the creation of new individuals by combining genetic information from multiple "parents" in the population. This provides a mechanism for exploring the search space and inheriting successful genetic information. This process mimics the natural process of crossover in DNAs. The Roulette-wheel selection (RWS) may be used for selecting better fit individuals and conducting the "breeding" process of crossover. An individual's chance of being chosen for breeding is random in essence but directly proportional to its fitness status. Mutation is employed on few individuals to find new solution points in the problem search space and thus avoids stagnation of GA. Through elitism, the best individual encountered so far is ensured to survive to the next generation to avoid loss of any gain that has been achieved during the evolution process.

GA usually suffers from premature convergence to a local optimum and high processing time [9]. Premature convergence happened whenever the best solution is not improved after certain generations and that usually results in local trapping. In such situations, there are chances that this local solution tends to get multiplied. Further, if better individuals are available during genetic evolutions then there will be better chances of obtaining the global optima. Therefore, in proposed IGA, the pace of genetic evolution is enhanced by proposing brute force crossover (BFC) and acquiescent mutation (AM). BFC avails better individuals to improve convergence rate and AM avoids stagnation of GA. Further, high processing time of GA is reduced by proposing conditional fitness evaluation (CFE) that reduces the number of fitness evaluations. These proposed modifications in GA can be briefly described as below.

3.3.1 BRUTE FORCE CROSSOVER

In the conventional GA, a child becomes a parent only in the subsequent generation. In case, a child with better fitness is allowed to participate in the mating pool during the same generation in which it has been born. Then better be the child, more will be its chances to participate in the mating pool during the same generation. This approach breaks the paradigm of genetics, but is very useful for computational purposes. With this approach, there is an immediate exchange of more useful genetic information. Moreover, better is the quality of genetic information, more will be the rate of information exchange and vice-versa. Thus, the pace of genetic evolutions enhanced. In the proposed BFC, one parent is selected from the population through RWS and the other is selected randomly to preserve diversity. The current population is updated by the addition of two offspring so produced which replaces the two least fit individuals. Therefore, only better individuals survive and will participate in forthcoming genetic operations. However, if two parents are found to be identical, one of them is mutated using AM as described in the next section.

3.3.2 Acquiescent Mutation

GA has an inherent tendency of premature convergence when subjected to large-scale optimization problems. It happens as the mutation operator remains ineffective against enormous problem search space so eventually GA stagnates, i.e., the best solution not improved after certain generations. In such situations, there are chances that this local solution may get multiplied. Therefore, AM is suggested. In AM, whenever two identical parents appear in the mating pool then either of them is mutated before recombination. However, the mutation site is restricted up to the candidate DR size alone, and the candidate nodes are kept aside from this mutation. This strategy is adopted to avoid probable over divergence of the solution, as the suggested ISA, which will be described in section 3.8, serves better quality nodes in the population. Unlike BFC, all mutated individuals replace their respective counterparts irrespective of their fitness values. This provides sufficient diversity in the population and thus strengthens GA against local trappings. The proposed AM is in addition to the regular mutation of GA.

3.3.3 Conditional Fitness Evaluation

In genetic evolutions, initially the individuals explore new regions to search the global optima and as the genetic evolutions advance they tend to follow the best fit individual. Due to recombination, the percentage of best fit individuals gradually starts increasing and as the evolution advances the population may flood with numerous best fit individuals. This results in an unnecessary increased computational burden. Therefore, CFE is proposed. In CFE, each individual obtained after genetic evolutions is compared with the current best fit individual and its fitness is evaluated whenever it is found not identical to the current best fit individual. The flow chart of the proposed IGA method is presented in Fig. 3.2

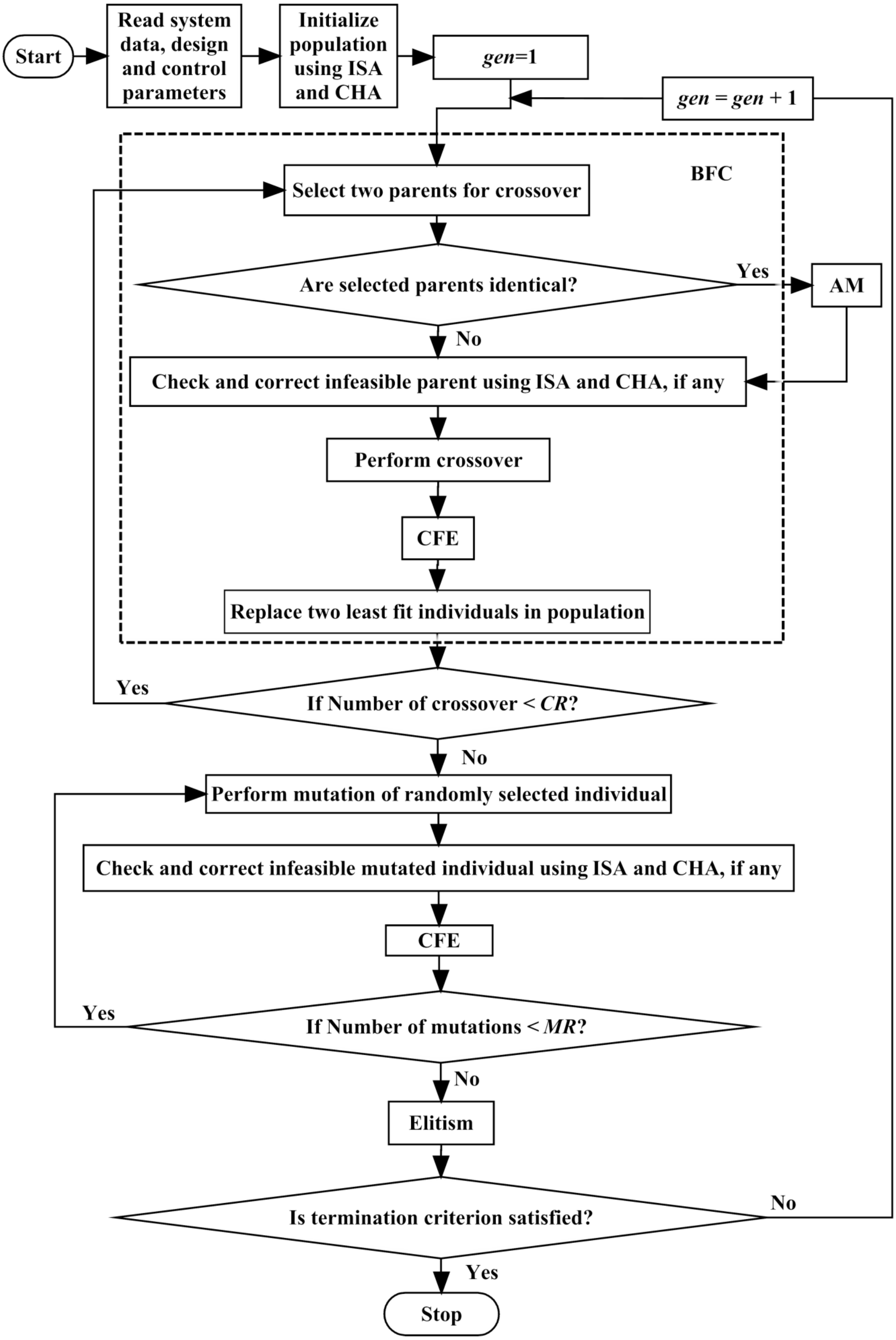


Fig. 3.2 Flowchart of the proposed IGA

PSO is another well-established meta-heuristic technique, but is inherently designed to optimize problems having continuous decision variables. Attempts have been made to make it suitable to efficiently solve DR allocation problem by suggesting improved PSO, i.e. IPSO which is described in the following section.

3.4 PROPOSED IPSO

PSO is a robust stochastic swarm computation technique which is based on the movement and intelligence of swarms [237]. The conventional PSO is initialized with a population of random solutions and searches for optima by updating particles' positions. The velocity of particles is influenced by three components namely, initial, cognitive and social components. Each particle updates its previous velocity and position vectors according to the following model of [238].

$$v_p^{k+1} = wv_p^k + c_1 \times r_1() \times \frac{pbest_p - s_p^k}{\Delta t} + c_2 \times r_2() \times \frac{gbest - s_p^k}{\Delta t} \tag{20}$$

$$s_p^{k+1} = s_p^k + v_p^{k+1} \times \Delta t \tag{21}$$

Where v_p^k is the velocity of pth particle at kth iteration, $r_1()$ and $r_2()$ are random numbers in the range [0, 1], s_p^k is the position of pth particle at kth iteration, c_1, c_2 are the acceleration coefficients, $pbest_p$ is the best position of pth particle achieved based on its own experience, *gbest* is the best particle position based on overall swarm experience, Δt is the time step, usually set to 1 s and w is the inertia weight which is allowed to decrease linearly with iterations as follows:

$$w = w_{\max} + (w_{\min} - w_{\max}) \times itr / itr_{\max} \tag{22}$$

The velocity and position updates of particles tend to surf the search space on the behalf of cognitive and social paradigm of the swarm.

PSO has shown proven potential to solve complex engineering optimization problems, but it typically shows premature convergence due to local trapping phenomenon [88]. Moreover, the intrinsic nature of PSO could only generate continuous decision variables. Thus the accuracy and efficiency of PSO suffers when it is applied to solve problems having discrete decision variables. PSO has the philosophy of "to follow the leader" [239]. So whenever the best particle stagnates, it eventually converges to local optima. If the best particle is improved by employing some mechanism, probable local trappings can be avoided. Interestingly, the incapability of PSO to produce discrete decision variables has been employed in the proposed IPSO as its affirmative strength to avoid local trappings. For this purpose, a local escape algorithm (LEA) is proposed which can be explained as:

3.4.1 LOCAL ESCAPE ALGORITHM

The LEA is proposed to provide a local random walk (LRW) to the current best particle. Suppose the current best particle contains D continuous decision variables and it is kept in the memory. Whenever this particle stagnates, say after a predefined number of iterations t_s, it is recalled and then two particles are generated from it; one by ceiling and the other by flooring of all decision variables. Now with all possible combinations of these decision variables, 2^D particles are produced, each of them with only discrete decision variables. If any particle is found infeasible, it is corrected under the guidance of constraint handling algorithm (CHA), as will be explained later on. The fitness of these particles is evaluated and is compared with that of the current best particle. If it is found better, it replaces the same. Occasionally, the current best particle suggested by PSO may be with all discrete variables. In such situations, all 2^D particles so produced will be the replica of the current best particle itself, and that makes the proposed LEA useless. To overcome this difficulty, one replica of the current best particle is created. The current best particle and its replica are mutated at randomly selected DR site and DR size before generating all possible distinct particles. However, the decision variables for the candidate locations should be selected using ISA, as it is necessary to provide a fair chance of selection for better nodes to mutated particles. An illustration of LEA is shown in Fig. 3.3. The flow chart of the proposed IPSO method is presented in Fig. 3.4.

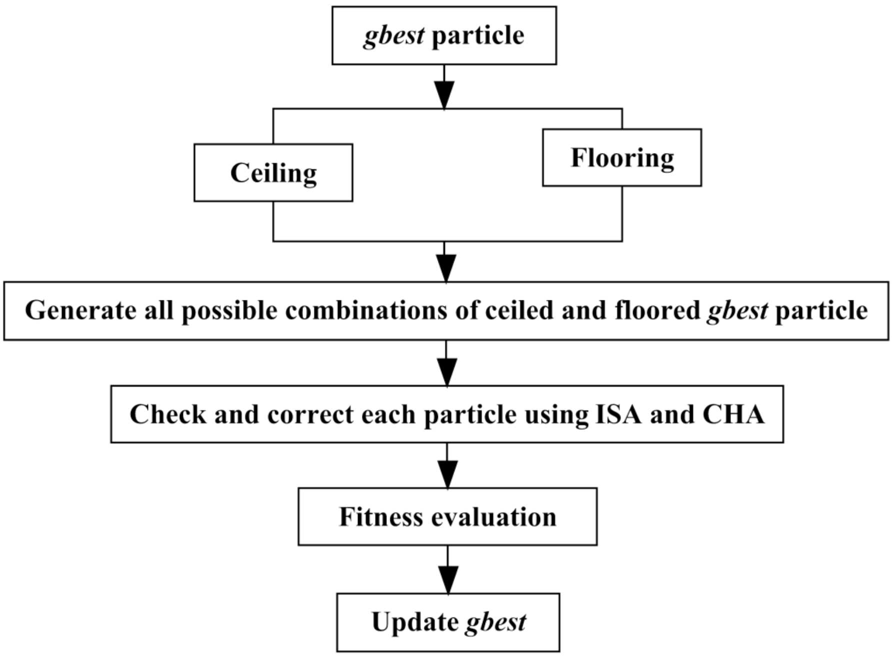


Fig. 3.3 Flowchart of proposed LEA

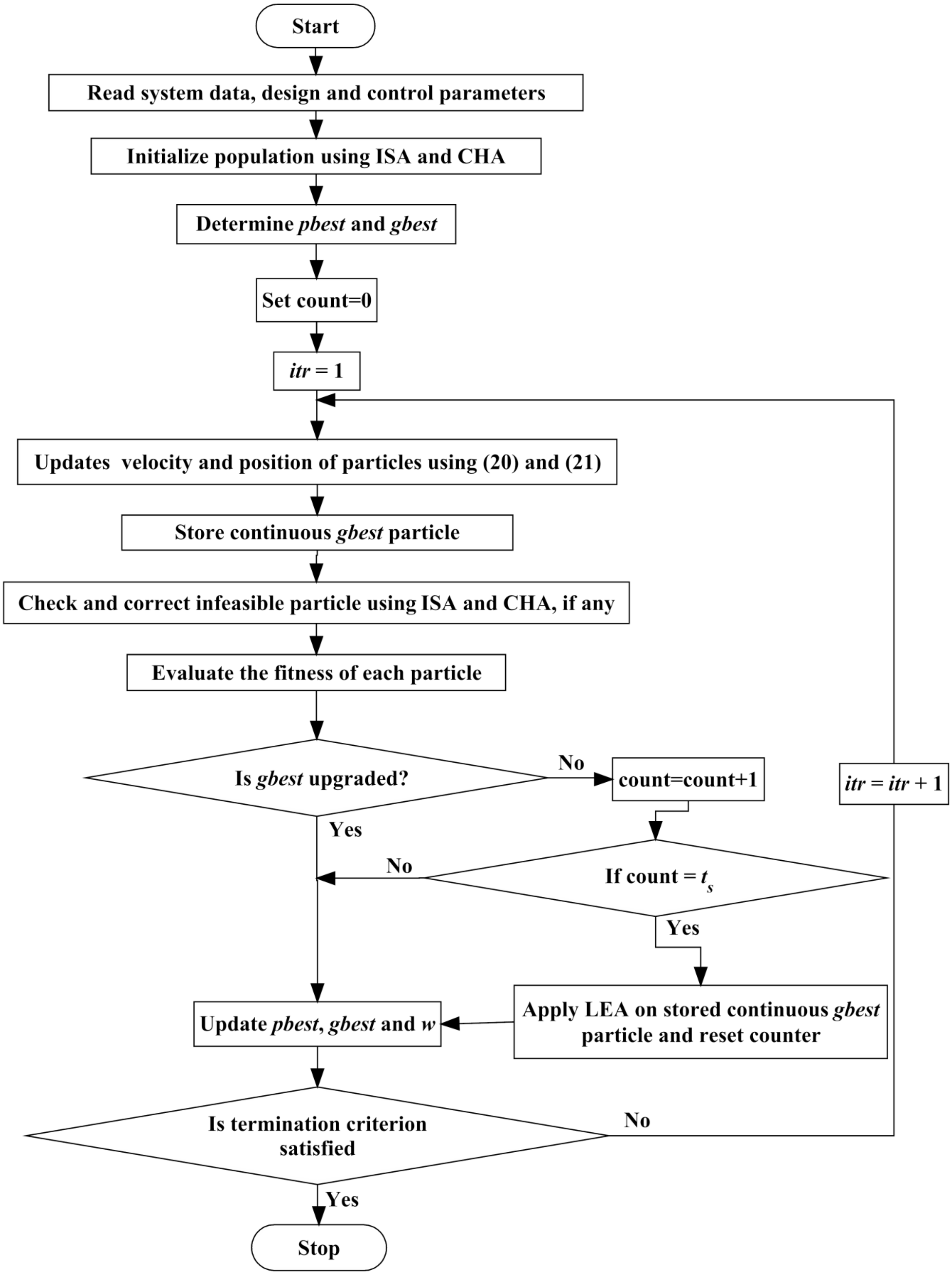


Fig. 3.4 Flowchart of the proposed IPSO

BA is one of the recently developed swarm optimization technique. BA has shown potential to solve diverse engineering optimization problems but its performance degrades while dealing with large-scale optimization problems. Therefore, improved BA, i.e. IBA is suggested to solve complex DR allocation problem which is presented in the following section.

3.5 PROPOSED IBA

BA is a recently developed bio-inspired optimization technique proposed by Xin-She Yang [229] in 2010. It is inspired by the social behaviour of bats and the phenomenon of echolocation to sense distance. BA is simple, easy to implement, significantly faster than other algorithms, and robust [240]. In BA, all bats fly randomly with definite velocity and frequency at certain position where their velocity and position are updated by assigning time varying loudness and pulse emission rate (PER). Bats can spontaneously accommodate the frequency and loudness of their emitted pulses and adjust the PER, depending on the proximity of the prey. Based on these approximations and idealization, the basic steps involves in BA are the random fly and LRW which can be briefly described as below [229].

Random Fly: Each bat is defined by its position x_b, velocity v_b, frequency f_b, loudness A_b and PER r_b in a D-dimensional problem search space. The velocity and position updates for the bth bat at the tth iteration are governed by the following set of equations.

$$f_b = f_{\min} + \left(f_{\max} - f_{\min} \right) \times \beta \tag{23}$$

$$v_b\left(t\right) = v_b\left(t-1\right) + \left(x_b\left(t\right) - x^*\right) \times f_b \tag{24}$$

$$x_b\left(t\right) = x_b\left(t-1\right) + v_b\left(t\right) \tag{25}$$

Local Random Walk: For local search, once a solution is selected among the current best solutions, a new solution for each bat is generated locally using random walk (RW) as defined below.

$$x_{new,b} = x_{old,b} + \varepsilon < A_b\left(t\right) > \quad ; rand > r_b\left(t\right) \tag{26}$$

Where *rand* is a random number in the range [0, 1] and $r_b(t)$ is the PER of the bth bat at the tth iteration. The loudness and the PER of each bat are updated with iteration using following recursive relations where α and γ are constant, each of them is usually taken as 0.9 [229].

$$A_b\left(t+1\right) = \alpha A_b\left(t\right) \tag{27}$$

$$r_b\left(t+1\right) = r_b\left(0\right)\left[1 - exp\left(-\gamma t\right)\right] \tag{28}$$

Despite of aforementioned positive features, the standard BA often experiences inappropriate convergence due to the local optima, lack of diversity in population or slow proceeding of the algorithm [240]. Moreover, BA is usually quick at the exploitation of the solution though its exploration ability is relatively poor [241]. Thus BA obtains good results only while dealing with lower-dimensional problems. Therefore, in the proposed IBA attempts have been made to adjust the loudness and PER in a better way and to enhance LRW of bats to refine its exploration and exploitation potentials, respectively. Furthermore, additional diversity in population is suggested in IBA to cope against its intense exploitation capability. The modifications suggested in proposed IBA are described below.

3.5.1 SELF-ADAPTED PULSE EMISSION RATE

The loudness and PER essentially provide a mechanism for automatic control and auto zooming into the region with promising solutions [242]. In BA, these two parameters are modeled to vary quite irrespective of each other. Moreover, both these parameters are allowed to vary too quickly in BA which leads to stagnation after some initial stage [242]. It happens because of the dominance of exploitation over exploration of the search space during initial iterations which is governed by the relative values assigned to these parameters. Therefore, self-adapted PER (SPER) is suggested where PER of each bat is allowed to vary in accordance to the loudness assigned to it and so not allowed to vary too quickly. However, the loudness assigned to each bat is governed in the same manner as in the standard BA. In this way, these two parameters become self-adapted for each bat. The suggested SPER in IBA is therefore modeled as:

$$r_b(t) = 1 - A_b(t) \tag{29}$$

3.5.2 IMPROVED LOCAL RANDOM WALK

The typical feature of BA is that it quickly finds the promising region but stagnates after few iterations. This seriously hampers the performance of BA. It possibly happen on account of inadequate LRW provided to the best bat. In BA, with $\varepsilon \in [-1,1]$ and initial loudness $A_b \in [0,1]$, the term $A_b(t)$ becomes insignificant during later iterations. Therefore, the term $\varepsilon\langle A_b(t)\rangle$ remains ineffective for most of the bats during the anaphase of the algorithm which leads to occasional LRW. Therefore, an improved LRW (ILRW) is suggested in IBA which can be described as below.

In the proposed ILRW, first M_c number of replicas of the current best bat are generated and then each of them is mutated over the randomly selected mutation site in the range [–1, 1]. However, ILRW activates only when the random number selected is less than its PER, otherwise the current best bat performs LRW, as in the standard BA. Thus ILRW confirms LRW of the current best bat during the evolutionary process. This helps to maintain a proper balance between exploration and exploitation of the search space. The best bat is replaced, if a better bat is available by ILRW.

3.5.3 DIVERSITY

BA has shown intense capability to exploit the problem search space. But, this potential when added with its inherently poor exploration potential, then its performance degrades, especially when applied to solve large-scale optimization problems. It happens because bats may even unable to identify the promising region so remains busy in exploiting the unwanted region of the search space. This eventually drains the algorithm into local optima. It is a well-known fact that the mutation operator of GA has the potential to explore new solution points in the problem search space. The extreme exploitation of BA causes lack of diversity. Therefore, very high mutation rate is desired to cope against this serious limitation of the algorithm. In proposed IBA, therefore the population is reinitialized using mutation. Fitness of all mutated bats is evaluated and the current best bat is updated, if better mutated bat is obtained. The Pseudo code of the proposed IBA is as given below:

```
Objective function f(x)
Initialize the bat population using ISA x_b, v_b and f_{b,d}; b=1, 2, … , N_b, d=1, 2, … , D
Initialize pulse rate r_b and loudness A_b
While (t < itr_max)
Generate new solutions by adjusting frequency, and updating velocities and locations/solutions
Correct infeasible solution using ISA and CHA
if (rand >r_b)
Select the current best solution
Generate a local solution (F_1) around the current best solution
else if
Make M_c copies of the current best solution
Apply ILRW
Correct infeasible solution using ISA and CHA
Select best solution (F_2) among M_c solutions
Select best solution F out of F_1 and F_2
end if
Generate a new solution by flying randomly
if (rand <A_b and f (x_b) <F)) then
Accept the new solutions
Increase r_b and reduce A_b
end if
Rank the bats and find the current best x*
t = t +1;
Apply diversity and preserve elite solution
end while
Post-processing the results and visualization.
```

CSO is relatively less known meta-heuristic technique but having unique feature of simultaneous exploration and exploitation of the search space. Though this feature is very important for large-scale optimization, but existing CSO suffers from certain inherent limitations. Attempts have been made to overcome these limitations by proposing improved CSO, i.e. ICSO which is explained in the following section.

3.6 PROPOSED ICSO

Chu and Tsai [243] proposed CSO which mimics the natural behaviour of cats. Cats have some distinct features. Cats initiate their move very slowly and finally they chase the prey very quickly. These two distinct behaviours of cats are represented by seeking and tracing modes of the algorithm. These modes are mathematically modelled and are combined together by defining a mixture ratio (*MxR*). Every cat has its own position composed of *D* dimensions, velocity for each dimension, a fitness value and a flag to identify whether the cat is in seeking or tracing mode [243]. These two modes of operation can be briefly described as given below.

Seeking Mode

In this mode, a definite number of cats are selected according to predefined value of *MxR* and each of them is subjected to multi-point mutation to explore the search space meticulously. Some terms related to this mode can be defined as:

Seeking Memory Pool (*SMP*): Number of copies of a cat formed in seeking mode

Seeking Range of selected Dimension (*SRD*): Maximum difference between the new and existing values in the dimension selected for mutation

Counts of Dimension to Change (*CDC*): Number of dimensions to be mutated

The following steps are involved in the seeking mode of CSO.

1. Make *SMP* copies of the existent position of cat.
2. Randomly plus or minus *SRD* percent of the present values in each copy according to *CDC* value and replace the existing ones.
3. Calculate the fitness values of all copies.
4. Select the best cat from *SMP* copies and replace the *q*th cat by it.
5. The remaining cats proceed to the tracing mode of the algorithm.

Tracing Mode

In this mode, the cat moves according to its own velocity among all its dimensions so that it can trace the prey, the current best fit cat. The velocity and position updates of the cat_q are governed by the following relations.

$$v_{q+1,d} = v_{q,d} + c \times r() \times \left(x_{best,d} - x_{q,d} \right) \tag{30}$$

$$x_{q+1,d} = x_{q,d} + v_{q+1,d} \tag{31}$$

Where $d(1 \leq d \leq D)$ represents the dimension, $x_{best,d}$ is the position of the best fit cat, $x_{q,d}$ is the position of cat$_q$, c is a constant and $r()$ is a random value in the range [0,1].

The unique feature of CSO is that it provides global and local search simultaneously via tracing and seeking modes, respectively. This causes better communication with the upgraded cat from the seeking mode as it is readily available to interact with the cats undergoing tracing mode of the algorithm. However, for large-scale optimization the performance of the algorithm deteriorates possibly on account weak exploitation and uncontrolled velocities of cats. The performance of the algorithm may be enhanced if the current best cat is mandatorily participated in the seeking mode to enhance the exploitation of the search space. Further, in practice the cats always review their previous experience during the tracing mode in order to maintain appropriate velocities. But, such reviewing mechanism is not present in the standard CSO. Therefore, the tracing mode needs another necessary corrective measure. In CSO, inertia weight is taken as unity. However, in order to regulate the velocity of cats, time varying inertia weight may also be included in the control equation of the tracing mode. Therefore, both seeking and tracing modes of the standard CSO are revised in the proposed ICSO as described below.

3.6.1 Revised Seeking Mode

Like some other swarm intelligence techniques, CSO is also based upon the philosophy of "To follow the leader" [239]. If the fitness of the current best cat or the leader is improved by some means, the convergence of CSO can be improved. Therefore, it is suggested that the current best cat must participate in the seeking mode of the algorithm. However, this cat performs LRW in a different way than the other cats. For this purpose, 2^D cats are generated as in LEA of IPSO, as explained in section 3.4.1. The fitness of all these cats is evaluated. The current best cat is then replaced, if better cat is available. The remaining cats perform LRW same as in the standard CSO. The proposed suggestion imposes fine local search around the current best cat as *SRD* is kept as low as ±1. Later on this positively influences the movement of the cats going through the tracing mode. So the revised seeking mode provides additional mechanism to accelerate the convergence of the algorithm.

3.6.2 Revised Tracing Mode

There is an intuitive belief that cats use their memory while chasing the prey. Cats are continuously analysing and correcting their strategy for the next move, while chasing the prey, on the basis of own best and just preceding experiences. This is essential in order to make forthcoming moves successful. This important behaviour of cats is missing in the

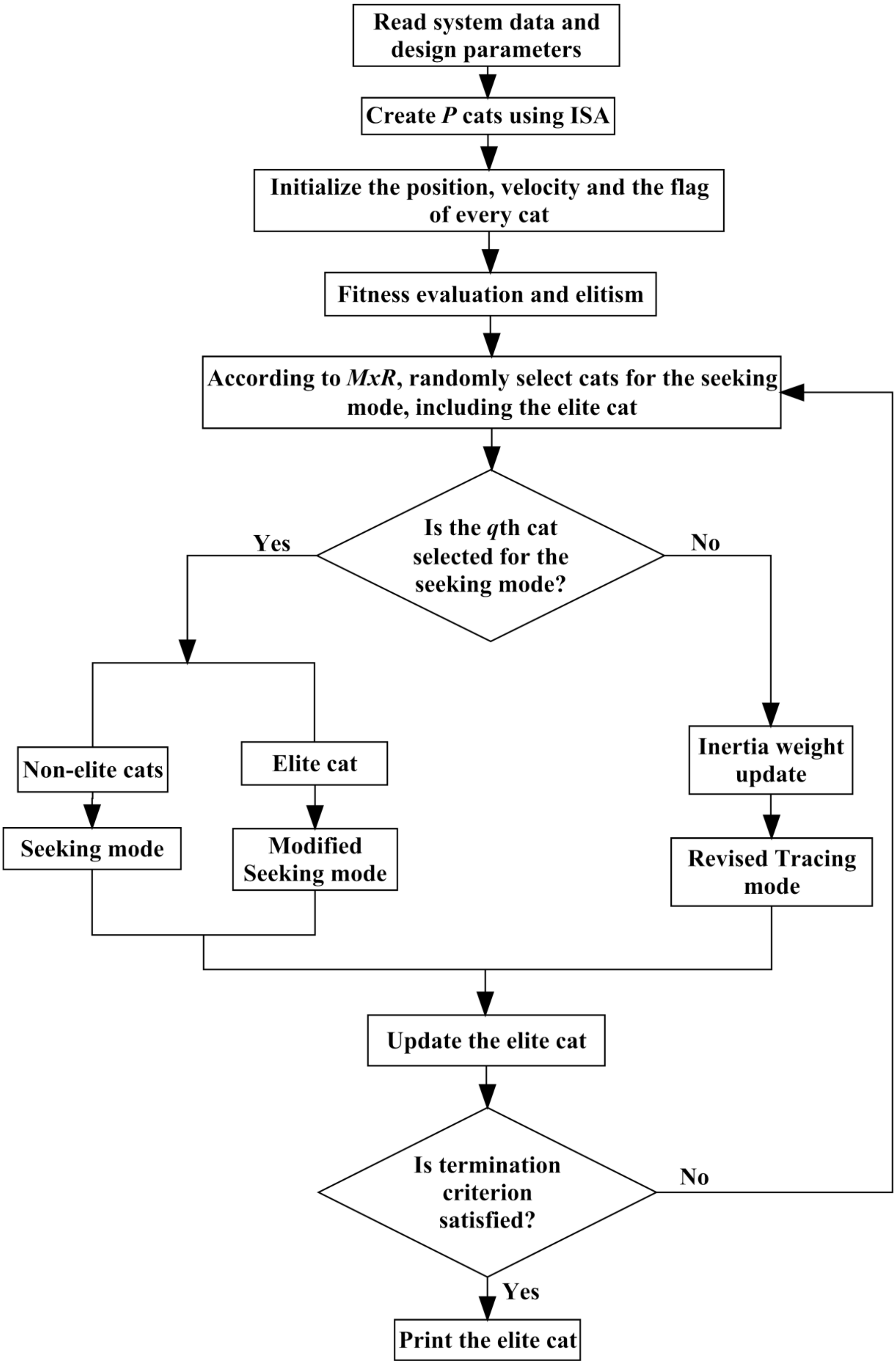


Fig. 3.5 Flowchart of the proposed ICSO

tracing mode of the standard CSO. Therefore, revised tracing mode is suggested which is composed of two phases. In the first phase, the cat is updated by tracking its own best and preceding moves. Whereas in the second phase, the cat is updated by tracking group's best move, as in the standard CSO. However, the velocities of cats should be properly regulated in the tracing mode otherwise the prey may be missed. Therefore, a time varying inertia weight is suggested in the revised tracing mode, as in PSO. The modelling of these two phases can be expressed as:

$$v_{q+\bar{1},d} = w \times v_{q,d} + c_1 \times r_1() \times \left(p_{best,d} - x_{q,d} \right) + c_2 \times r_2() \times \left(x_{q,d} - p_{pred,d} \right) \quad (32)$$

$$v_{q+1,d} = v_{q+\bar{1},d} + c \times r() \times (x_{best,d} - x_{q,d}) \quad (33)$$

Thus, cats gather appropriate velocities before entering into the second phase. The fitness of each cat is evaluated in each phase and the cat updates if better cat is available. The revised tracing mode provides adequate diversity in population as the proposed best and preceeding experiences of cats fine tune the global search. The flow chart of the proposed ICSO is shown in Fig. 3.5.

TLBO is another recently established meta-heuristic technique which has gained popularity owing to its simplicity, yet performing well to solve complex engineering optimization problems. However, its greediness towards best solution makes it unsuitable for large-scale optimization. In the next section, improved TLBO, i.e. ITLBO is proposed to overcome some limitations of existing TLBO.

3.7 PROPOSED ITLBO

TLBO is recently established swarm intelligence based optimization technique developed by Rao *et. al* [231] in 2011. It is inspired by passing on knowledge within a classroom environment, where learners first acquire knowledge from the teacher and then from the classmates [244]. The algorithm initiates with a group of tentative solutions, called learners, being dispersed randomly in the problem search space. It uses mean value of the population to update the solution and implements greediness to accept a good solution, as in artificial bee colony (ABC) algorithm [231]. In due course of time these learners update their knowledge, i.e., fitness, through two stage learning process: 'Teacher phase' and the 'Learner phase'. The ever best learner obtained through the iterative process is considered as the final solution. TLBO is simple to understand and easy to implement. The prominent feature of this powerful technique is that it is free from algorithm specific parameters and requires only common control parameters like population size and maximum iterations [231]. This makes it a class apart from other population-based search techniques [245]. The learning phases of TLBO can be summarized as below [246].

Teacher phase

In this phase, learners learn through the teacher who tries to improve the existing mean result $Mean_{d,k}$ of the class at iteration k for each dimension d towards him or her so let the new mean is $Teacher_{d,k}$. The difference of the mean results is evaluated as per following modelling.

$$\Delta Mean_{d,k} = \text{rand}\ (Teacher_{d,k} - TF_{d,k} \times Mean_{d,k}) \tag{34}$$

$$TF_{d,k} = Mean_{d,k} \,/\, Teacher_{d,k} \tag{35}$$

$$Xnew_{d,k} = Xold_{d,k} + \Delta Mean_{d,k} \tag{36}$$

Where $TF_{d,k}$ is the teaching factor (TF). The dimensions are updated using (36).

Accept $Xnew_{d,k}$, if it gives better function value.

Learner Phase

In this phase, each learner improves his or her knowledge by interacting randomly with other learners to enhance his or her knowledge. For this purpose, two learners are randomly chosen and if they have better knowledge than the learner, the difference of the knowledge is added in the learner's knowledge according to the following modelling.

$$Xnew_{d,k} = Xold_{d,k} + \text{rand}\left(X_y - X_z\right);\ f\left(X_z\right) < f\left(X_y\right) \tag{37}$$

$$Xnew_{d,k} = Xold_{d,k} + \text{rand}\left(X_z - X_y\right);\ f\left(X_y\right) < f(X_z) \tag{38}$$

Where, $y \neq z$.

Accept $Xnew_{d,k}$, if it gives better function value.

The standard TLBO suffers from poor convergence rate, local trapping, etc. on account of lack of diversity which is attributed to weak information exchange among individuals and its greediness to accept only good solutions [245]. This seriously hampers its performance while subjected to large-scale applications. The full potential of this technique however can be extracted by altering its internal mechanism in such a way that provides self-sustainable healing against these intrinsic flaws. Therefore, ITLBO is proposed to solve complex DR allocation problem by modifying both learning phases of TLBO as described in the following sections.

3.7.1 SELF-ADAPTIVE LEARNING

Several references [175, 232, 247, 248, 249, 250, 251] have attempted different mutation strategies in teaching-learning phases of the algorithm to overcome inadequate diversity and thereby enhancing the exploration potential of TLBO. However, these mutation strategies are not only slow down the convergence speed of the algorithm but also prohibit the use of information of already improved dimensions [247]. Therefore, learning phases of TLBO are modified by proposing self-adaptive learning (SAL). In SAL, each learner compares its dimensions with that of the respective dimensions of the teacher, as shown in Fig. 3.6. In case any dimension of the learner is found to be matched with the teacher, then that dimension is abandoned to participate in the computational process, as it had already achieved the maximum knowledge. Thus SAL provides dedicated search during teacher and learner phases of the algorithm as only selective dimensions are participating in the computational process.

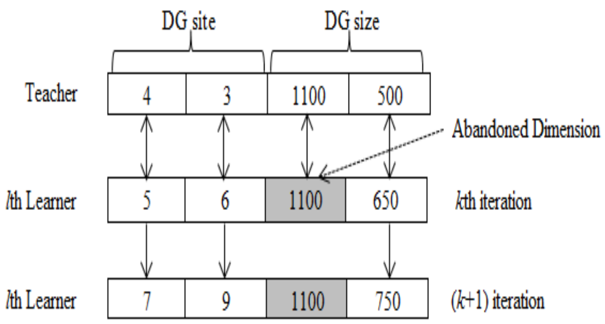


Fig. 3.6 Self-adaptive learning

3.7.2 SELF-LEARNING PHASE

Apart from the class room teaching and the interaction with other students, a student also enhances his/her knowledge by self-study. A good student always tracks its previous history and accordingly works hard to improve it or at least to maintain it. With this learning philosophy, a self-learning phase (SLP) is proposed in [248] which consider previous experience of the learner while undergoing mutation. This mutation strategy guides the learners according to their own gradient information. However, the authors have accepted that the exploitation potential reduces, especially in the anaphase of the algorithm, where it is most desired. In order to overcome this, they suggested another mutation strategy which is self-adjusted by the mean and variance of the population. But, there might be a risk of widespread mutation that degrades convergence of the algorithm. Therefore, a different SLP is proposed in ITLBO so that the learner has better opportunity to enhance its performance by interacting with himself/ herself alone, as explained below.

In proposed SLP, each learner compares his/her knowledge with that of the previous iteration, as shown in Fig. 3.7. For simplicity, the learner's structure shown in figure is only for DG placement. This comparison identifies that dimension of the learner which changes the least, and is mutated. This increases the effectiveness of the mutation operator. The mutant learner replaces the learner, if its fitness is better. If there is least change in more than one dimension, any one of them is mutated by random selection. Thus proposed SLP acts only on stagnated dimensions, especially during the anaphase of the algorithm. However, the mutation of DG sites is carried using ISA, whereas DG sizes are mutated randomly.

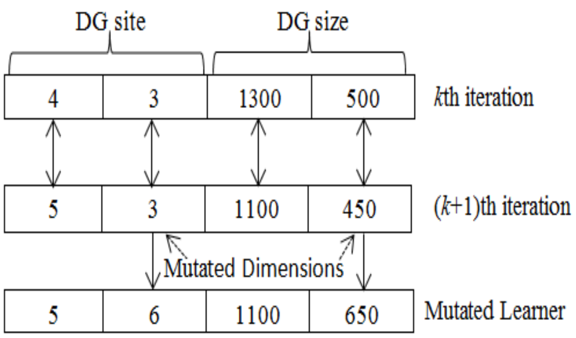


Fig. 3.7 Self-learning phase

3.7.3 Diversified Learning

The performance of algorithms, like TLBO, can be enhanced by maintaining a proper balance in exploration and exploitation of the search space. For this purpose several crossover strategies are suggested for all learners in [252] to enhance both global and local search using multi-point crossover. However, these crossover strategies may diverge the convergence on account of over diversity. In fact, the greediness of TLBO to accept only good solutions leads to possible local trapping due to inadequate diversity in population. Therefore, DL is introduced in few learners. For this purpose, two learners (parents P1 and P2) are randomly selected for crossover and the offspring (children Ch1 and Ch2) so produced are shown in Fig. 3.8.

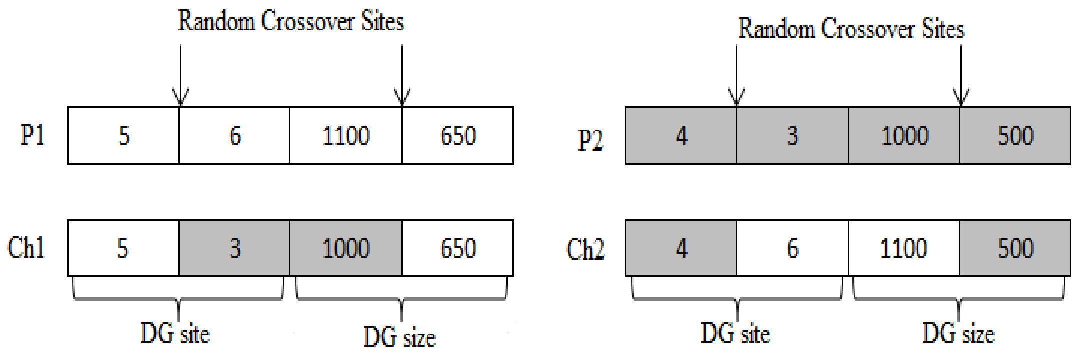


Fig. 3.8 Diversified learning

These offspring replace their parent learners in the population irrespective of their fitness values. This selection of learners enhances diversity in population by shifting the paradigm of TLBO to accept only good solutions.

3.7.4 TEACHER'S LEARNING

The teacher is always a role model for the students. The students usually follow their teacher. A good teacher must try to upgrade his or her knowledge as this could improve the mean result of the class. This can be accomplished by providing local random walk to the teacher using mutation, as in [249, 250]. In [249], the chaotic sequence is used to enrich the mutation behavior, but probabilistic LRW is provided to the teacher. A chaos perturbation mechanism is used in [250] to avoid local optima and also to improve the precision of the basic TLBO algorithm. However, chaos perturbations are allowed only in the later half portion of the computational process. These mutation strategies can generate good quality solution, but not for large dimensional problems. A more exhaustive mutation strategy is therefore desired to deal with such problems. Therefore, after teaching-learning phases, the teacher is subjected to LRW by repeated random mutations till its fitness is improved or the predefined mutation count *mc* is exhausted. This may upgrade the knowledge of teacher that can help to avoid local trappings. As in SLP, the mutation of DG sites is carried using ISA, whereas DG sizes are mutated randomly. Flowchart for teacher's learning (TL) is shown in Fig. 3.9.

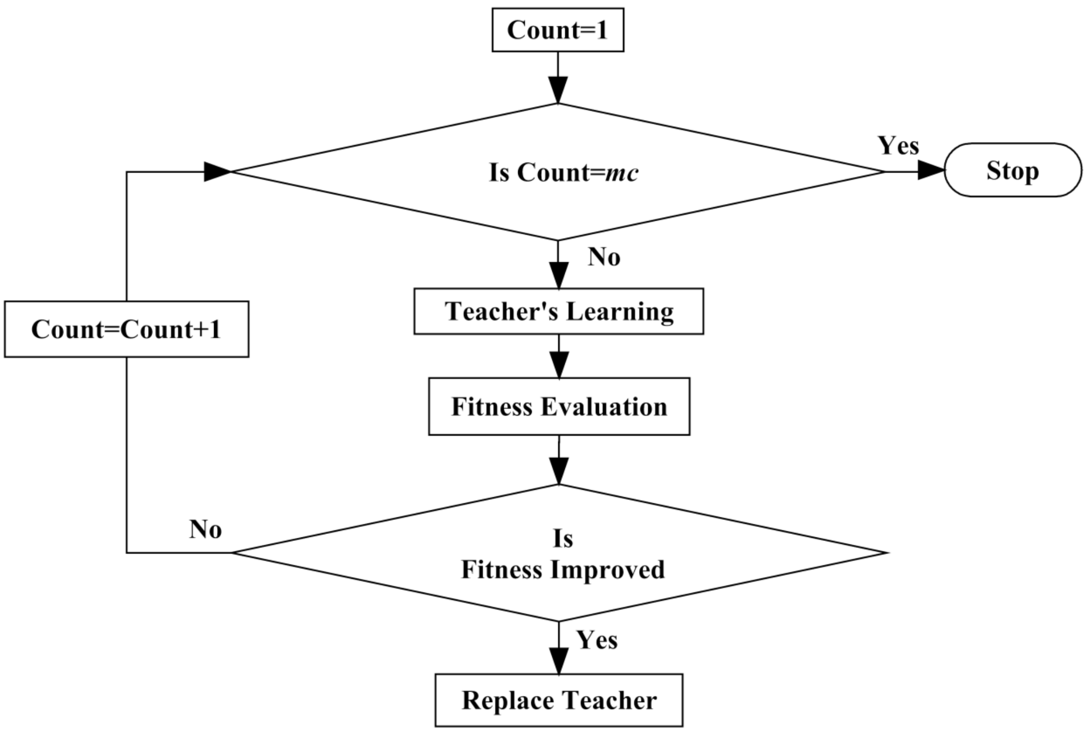


Fig. 3.9 Flowchart for teacher's learning

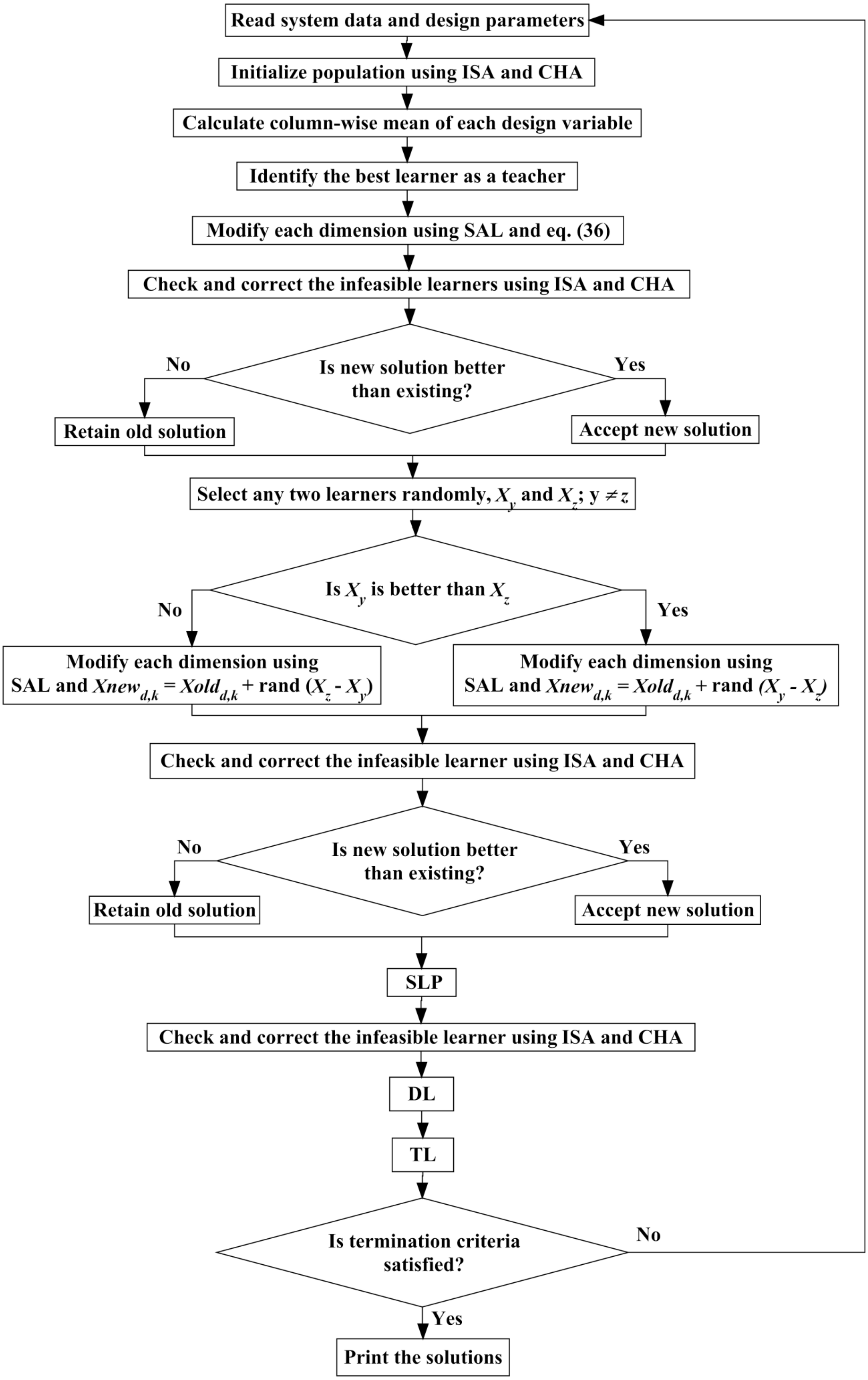


Fig. 3.10 Flowchart of the proposed ITLBO

3.7.5 ELITISM AND TERMINATION CRITERION

In standard TLBO elitism is not required as it has greediness to accept good solution at each step, but in proposed ITLBO the best learner may lose during DL. Therefore the elite learner should be preserved. The termination criterion may be selected by defining maximum iteration count or accuracy of solutions, etc. However, in the proposed method, when either the maximum iteration count is exhausted or all candidate solutions acquire the same fitness i.e. all learners have identical knowledge, the iterative learning process stops.

The flow chart of the proposed ITLBO method is presented in Fig. 3.10.

3.8 SEARCH SPACE REDUCTION USING ISA

While initializing, or otherwise, it is always preferred if all the tentative solutions spread in the problem search space in such a way that most of them lie near the promising region. But, this is a difficult task. Nevertheless, an adequate diversity is essential to explore new solution points in the search space. The engineering knowledge base, pertaining to the given optimization problem, can be utilized to restrict the problem search space. Several researchers, as mentioned in chapter 2, have restricted the search space by employing different node sensitivity based approaches. In these approaches, a node priority list (NPL) is prepared by perturbations of small capacities of SC and DG while considering power losses as the objective function. From this list, only top few nodes are selected to redefine the problem search space. Though such approaches reduce the problem search space drastically, but the solution quality deteriorates. In fact, the sensitivities are normally calculated for the base case conditions, where no such devices have been installed [53]. Furthermore, when selecting only top few nodes as the sensitive components, it did not give the true picture of the entire distribution network [253]. Therefore, none of the sensitivity based approach is fool proof and provides only a coarse guidance. So these approaches are unreliable and may cause erroneous results, as missing locations in the set of candidate locations may be optimal for DR allocation.

In the proposed approach, the node priority list (NPL) is prepared using perturbations of very small SC/DG capacities, but in a different manner. The flowchart for obtaining NPL for DG placement is shown in Fig. 3.11(a). The fitness of the objective function is evaluated by setting a test DG subsequently at all nodes of the distribution network. The node which causes the maximum change in the function value and the corresponding DG capacity are stored in an array. This test DG capacity is then placed at this node. The next optimal node is explored in the same manner and the test DG capacity is also placed at this node. The node and DG capacity are stored in the array. This process is repeated till there is an improvement in the objective function. All nodes of the array so obtained are arranged in the descending order of accumulated DG capacities. This provides NPL for DG allocation, the node corresponding to maximum DG capacity occupy top position in NPL. In this way a NPL for DGs is obtained. Similarly, NPL for SCs can be obtained by the perturbation of very small SC capacity. However, this list can only provide an approximate navigation for the selection of candidate nodes. Therefore, a probability based method is proposed for the selection of candidature of nodes from the NPL. For this purpose, the candidature of a node is decided from these lists using RWS, where the candidate nodes are selected according to their probability of priority during the computation process. Thus, all nodes remain in the search space leading to diversity in search but due to higher probability of priority to only a few nodes, the algorithm quickly picks up the best combination of nodes without much wandering. Thus, the problem search space is virtually squeezed without loss of diversity. The flow chart for the selection of candidate nodes for DRs using proposed ISA is shown in Fig. 3.11 (b).

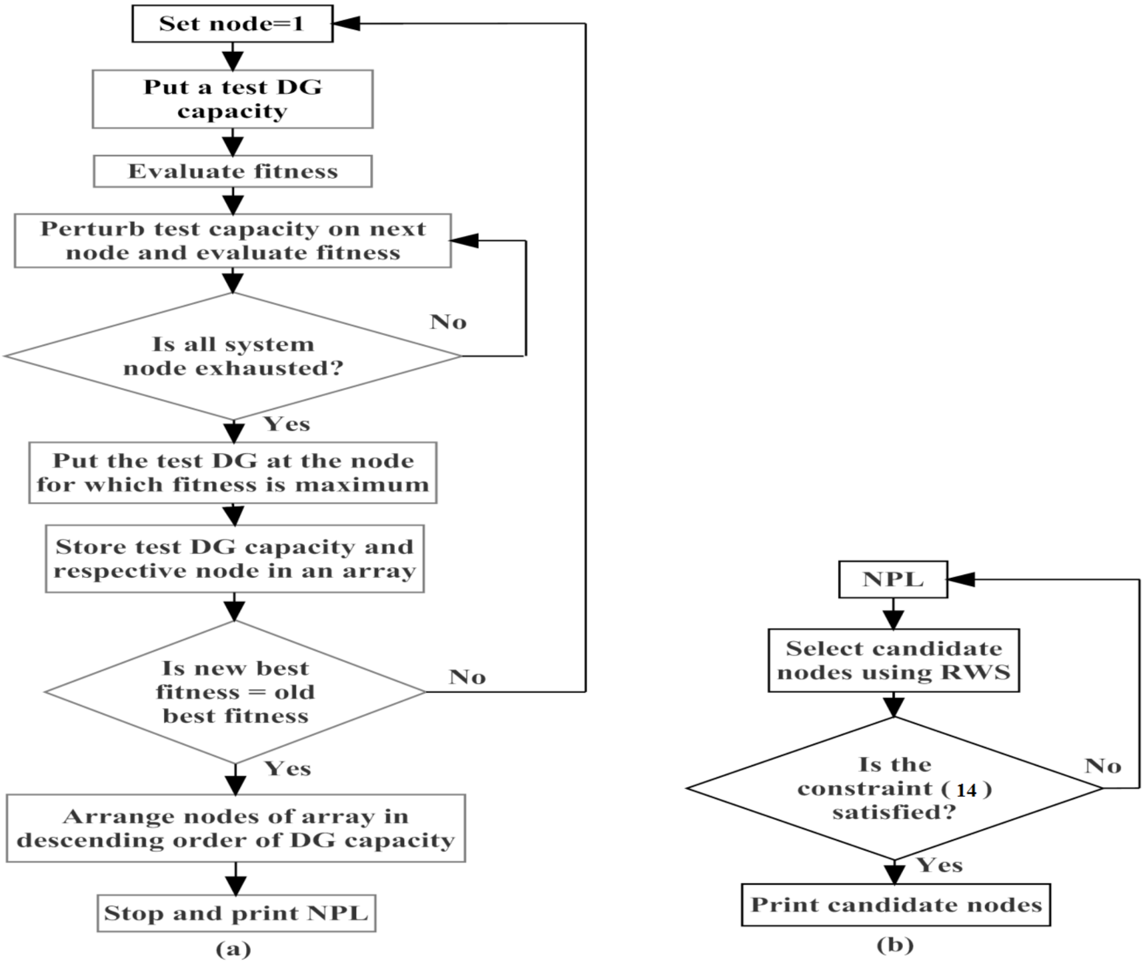


Fig. 3.11 An illustration of ISA for DG placement

3.9 CONSTRAINT HANDLING ALGORITHM

During the iterative process of any population based algorithm, the generation of infeasible individuals is a common problem in complex optimization problems due to the number of constraints involved. Therefore, CHA is always desired to repair infeasible individuals. The proposed constraint handling algorithm is described as below.

1. If a candidate node repeats for SC-DG allocation, it is replaced by selecting another node from the respective NPL using RWS.
2. If a candidate node is out of bounds with negative (positive) sign, it is kept within bounds by successive addition (subtraction) of N from its numerical value.
3. If the capacity of SC-DG at a candidate node is out of bounds, it is corrected similar as in step 2 using q^{SC}/ p^{DG} instead of N.
4. If the total number of SCs become out of bounds, then one bank is subtracted from a randomly selected candidate node in successive manner till the constraint satisfied.
5. If the total capacity of DGs is out of bounds, then its difference with the system nominal active load demand is evaluated. This difference is then divided by *loc* and the quotient so obtained is subtracted from the candidate capacity of DG at each node. This process is repeated till the difference reduces to a predefined limit, say 0.001 kW.
6. Whenever decision variables become continuous, they are rounded off to their nearest integer values.

3.10 INDIVIDUAL'S STRUCTURE

For proposed improved meta-heuristics, the structure of the individuals for simultaneous DG and SC placement is shown in Fig. 3.12 which is composed of candidate nodes and sizing for the respective candidate DGs and SCs. The candidate nodes are allocated using ISA whereas the sizing of the candidate DGs and SCs are selected randomly within their respective predefined bounds as described by (10)-(13). However, the number of locations for DGs and SCs is set more than what ought to be required and the lower bound of the sizing for DGs and SCs is set equal to zero. This strategy is thus simultaneously optimizes the number, sizing and siting of these DRs. While determining the optimal tuning of these components, the algorithm again runs with the same structure of individuals. But, the optimal locations are frozen to those values as obtained by the optimal solution. Also the limit of DG and SC sizing is restricted to the installed capacity which is provided by the optimal solution.

$$\underbrace{loc_1^{DG}, loc_2^{DG}, ...loc_{N_{DG}}^{DG}}_{\text{DG sites}} \ \underbrace{p_1^{DG}, p_2^{DG}, ...p_{N_{DG}}^{DG}}_{\text{DG sizing}} \ \underbrace{loc_1^{SC}, loc_2^{SC}, ...loc_{N_{SC}}^{SC}}_{\text{SC sites}} \ \underbrace{q_1^{SC}, q_2^{SC}, ...q_{N_{SC}}^{SC}}_{\text{SC sizing}}$$

Fig. 3.12 Individual's structure

3.11 SIMULATION RESULTS

In order to establish proposed IGA, IPSO, IBA, ICSO and ITLBO techniques, these are first applied on the benchmark IEEE 33-bus test distribution system [254] to solve the optimal allocation problem of DGs and SCs under identical system design parameters and considering same objective function as taken in [104, 177, 195, 196]. This is a 12.66 kV balanced distribution system with nominal active and reactive power demand of 3715 kW and 2300 kVAr, respectively. The initial radial topology of the distribution network is obtained by opening tie-lines as given in Table B.1. The ampacity of distribution feeders are also given in the table and the detailed system data may be referred from Table E.1. The population size and maximum iterations are uniformly set at 10 and 200, respectively for all techniques. The best result obtained after 100 independent trials of these techniques is presented and compared with other existing methods in Table 3.1. The standard GA, PSO, BA, CSO and TLBO are also applied to solve this problem and the best results obtained after 100 independent trials are also presented in table for comparison. The table shows percentage power loss reduction and installed capacity of DGs/SCs in MVAr/MW. It can be observed from the table that all proposed metaheuristics are capable to generate better results than their respective standard models and other established heuristic, analytical and PSO techniques. It is noteworthy that proposed meta-heuristic techniques are capable to generate better results even for this small-scale optimization problem.

Table 3.1 Comparison results to establish proposed improved techniques

Method	Power loss reduction (%)	DG capacity (Node)/ SC capacity (Node)
Heuristic [195]	54.66	1.00(18)/1.00(33)
PSO [196]	71.71	2.51(6)/1.46(30)
PSO [177]	72.30	2.53(6)/1.23(30)
Analytical [104]	72.28	2.60(6)/1.25(30)
GA	71.27	2.10(8)/1.30(29)
Proposed IGA	**74.38**	**2.52(6)/1.30(30)**
PSO	71.66	2.37(7)/1.30(28)
Proposed IPSO	**74.38**	**2.52(6)/1.30(30)**
BA	70.83	2.41(26)/1.10(31)
Proposed IBA	**74.05**	**2.29(6)/1.20(30)**
CSO	71.67	2.40(7)/1.30(28)
Proposed ICSO	**74.38**	**2.52(6)/1.30(30)**
TLBO	72.45	2.60(7)/1.10(29)
Proposed ITLBO	**74.38**	**2.52(6)/1.30(30)**

The effectiveness of proposed IGA, IPSO, IBA, ICSO and ITLBO techniques is now investigated on this system for the simultaneous allocation of DGs and SCs with suggested modelling to minimize annual energy losses of distribution systems. The annual load profile is assumed to be piece-wise segmented into three different load levels [74], *i.e.*, light, nominal and peak which is 50%, 100% and 160% of the nominal system load, respectively and the corresponding load durations are taken 2000 h, 5260 h and 1500 h, respectively. For base configuration the feeder power losses are 47.07, 202.50 and 575.39 kW and the minimum node voltages are 0.9583, 0.9131 and 0.8528 p. u. for the light, nominal and peak load conditions, respectively. The design parameters considered for allocating DGs and SCs is given in Table 3.2 which shows the bounds for node voltage limits as 0.94 p.u. and 1.06 p.u. The table also shows the minimum and maximum penetration limit of DGs $(p_{\min}^{DG} / p_{\max}^{DG})$ and SCs $(q_{\min}^{SC} / q_{\max}^{SC})$ considered for each candidate node. The penetration limit of DGs and SCs is considered equal to nominal active and reactive loading of the system. The table also shows that entire search space is kept open for meta-heuristic techniques as all system nodes are considered in vectors N^{SC} and N^{DG}. The NPLs obtained for respective DRs using proposed ISA approach is presented in the table. The control parameters of optimization techniques obtained after usual trade-off are presented in Table 3.3. The table shows that GA and PSO need more population size than other techniques but require lesser maximum iteration count for proper convergence whereas BA, CSO and TLBO are doing well for less number of population size and large iteration count. The proposed algorithms are developed using MATLAB® and simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM.

Table 3.2 Design parameters

Particular	Value
$V_{\min}/V_{\max}$(p.u.)	0.94/1.06
Q_b/ P_d (kVAr/kW)	300/1
$\Delta q/\Delta p$(kVAr/kW)	100/1
$q_{\min}^{SC} / q_{\max}^{SC}$ (MVAr)	0/1.2
$p_{\min}^{DG} / p_{\max}^{DG}$ (MW)	0/2
N^{SC}/ N^{DG}	1-33
NPL(SCs)	30, 24, 25, 7, 29, 32, 15, 8, 4, 23…
NPL(DGs)	25, 24, 7, 32, 30, 29, 31, 14, 8, 23…

The best solution obtained after 100 independent trials of standard and proposed improved variants of GA, PSO, BA, CSO and TLBO are presented in Table 3.4. The table shows that all standard algorithms provided different solutions for DR allocations, but the optimal solutions explored using all proposed algorithms are identical. This shows effectiveness of developed algorithms. For these solutions, the optimal DR tuning determined for corresponding load levels may be referred from Table B.2.

Table 3.3 Control parameters selected for proposed algorithms

Parameter	IGA	IPSO	IBA	ICSO	ITLBO
P	50	50	10	10	10
$itr_{\max}$	100	100	200	200	200
t_s	-	10	-	-	-
CR	0.9	-	-	-	0.2
Crossover type	Two-point Crossover	-	-	-	One-point Crossover
MxR	0.05	-	-	-	-
c				1.5	
c_1, c_2	-	2,2	-	1.6, 0.4	-
w_{min},w_{max}	-	0.1,0.9	-	0.05, 0.45	-
f_{min}/f_{max}	-	-	0/2	-	-
α/γ	-	-	0.9/0.9	-	-
M_c	-	-	5	-	-
SMP,CDC,SRD,MXR	-	-	-	5, 0.6, 2, 0.04	-
mc	-	-	-	-	5

Table 3.4 Optimal solution of DRs using standard and proposed meta-heuristics

Method	Optimal solution	
	Nodes (DG in kW)	Nodes (SC in kVAr)
GA	14(898), 25 (944), 32(934) TC:2776	14(600), 24(300), 30(900) TC:1800
PSO	15(780), 25(839), 30 (1255) TC:2874	17(300), 24(600), 30(900) TC:1800
BA	3(1381), 14(857), 29(1188) TC:3426	10(300), 16(300), 32(900) TC:1500
CSO	15(747), 24(1150), 31(1016) TC:2913	11(300), 16(300), 30(1200) TC:1800
TLBO	15(815), 24(860), 30(1157) TC:2832	12(600), 24(600), 30(900) TC:2100
IGA/IPSO/IBA/ICSO/ITLBO	14(831), 24(1005), 30(1128) TC:2964	14(300), 24(600), 30(1200) TC:2100

TC: Total capacity

Table 3.5 Comparison of power and energy loss for optimal solutions

Method	Power loss (kW)			Annual energy loss (kWh)	% Annual energy loss reduction
	Light	Nominal	Peak		
Base Case	47.07	202.50	575.39	2022398.44	-
GA	3.53	15.12	93.40	226700.42	88.79
PSO	3.51	14.31	93.77	222971.06	88.97
BA	5.99	24.51	106.32	300371.65	85.15
CSO	3.94	15.71	85.70	219070.49	89.17
TLBO	2.95	12.65	88.14	204656.04	89.88
IGA/IPSO/IBA/ICSO/ITLBO	**2.95**	**11.88**	**79.76**	**188012.10**	**90.70**

The improvement in network performance is evaluated from base case conditions after optimally placing DRs in the distribution network and the comparison results are presented in Table 3.5. The table shows the power loss obtained at each load level. The table also shows that an annual energy loss reduction of about 91% is achieved using proposed meta-heuristics. However, the results obtained using proposed techniques is better as that obtained using their respective counterparts for this complex combinatorial optimization problem. This shows that proposed variants are significantly improved.

Proposed IGA, IPSO, IBA, ICSO and ITLBO techniques have shown better results than their respective standard models. This shows that the suggested modifications in these techniques are contributing effectively. Nevertheless, it is important to investigate how and upto what extent these modifications have played their roles for enhancing the performance of techniques. A detailed investigation for the proposed techniques is presented in the following section.

3.12 INVESTIGATION OF PROPOSED META-HEURISTIC TECHNIQUES

In order to investigate the effectiveness of suggested modifications in IGA, IPSO, IBA, ICSO and ITLBO, the various proposed variants of these algorithms are abbreviated for the ease of comparison and are listed in Table 3.6. The table shows possible variants of these techniques obtained after subsequent suggested modification in each of them.

Table 3.6 Abbreviations for proposed algorithms

Algorithm variant	Description
G1	GA with BFC and ISA
IGA	G1 with AM and ISA
P1	PSO with LEA
IPSO	P1 with ISA
B1	BA with improved loudness and PER
B2	B1with ILRW
B3	B2 with diversity
IBA	B3 with ISA
C1	CSO with revised seeking mode
C2	C1 with revised tracing mode and IWU
ICSO	C2 with ISA
T1	TLBO with SAL
T2	T1 with SLP
T3	T2 with DL
T4	T3 with TL
ITLBO	T4 with ISA

The detailed investigations of the proposed variants are first carried on the basis of best and mean convergence characteristics. However, the computational performance of population based metaheuristics should be judged by performing statistical error analysis on the sampled solutions obtained after definite independent trials of algorithm. For this purpose, the proposed DR allocation method is rigorously applied to 33-bus test distribution system using each variant while keeping identical algorithm specific and common control parameters. The results obtained from this investigation are presented and discussed in the following sections.

3.12.1 COMPARISON OF CONVERGENCE CHARACTERISTICS

The progression of population based techniques is represented by their best and mean convergence characteristics. The convergence for best fitness shows how the best individual is upgrading its fitness during the evolutionary process whereas the convergence for mean fitness shows the same information for the whole population.

The convergence characteristics for the best and mean fitness obtained using GA and its developed variants are compared in Fig. 3.13. It can be observed from the figure that each suggested modification in IGA plays its distinct role. BFC improves convergence rate due to the timely utilization of better fit individuals, whereas AM avoids the stagnation of the algorithm. Though ISA tends to provide directed search but also maintains adequate diversity. Therefore, individuals explore the search space in the close proximity of the promising region where the global optima may exist. This enables IGA to find global or near global optima. These facts can be observed by comparing both best and mean convergences.

In IPSO, the distinct role of LEA and ISA can be observed from Fig. 3.14. The figure shows that LEA not only avoids several possible local trappings but also improves the mean convergence of the algorithm. It happens on account of LRW proposed for the current best particle, which if improved, guided the swarm toward the promising region. The distinguished role of ISA can be observed in terms of its fast convergence. This is on account of better initial mean fitness and by well guided swarm throughout the evolutionary process.

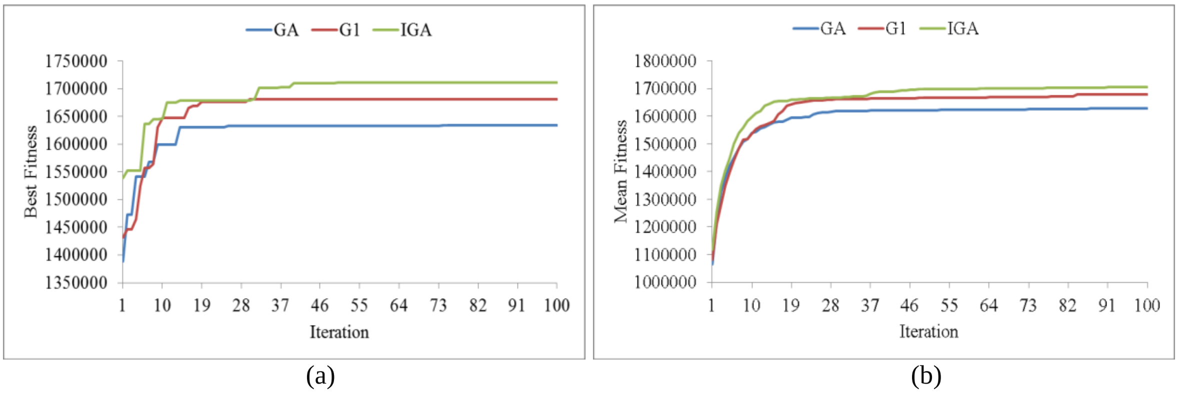
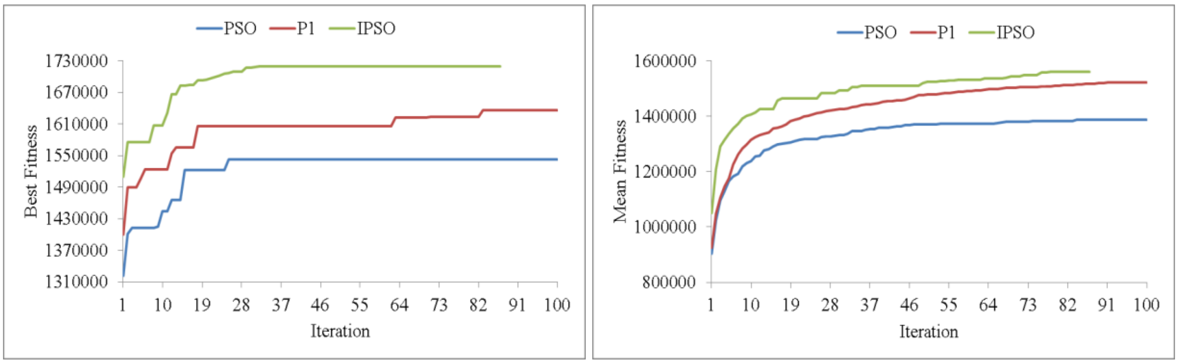


Fig. 3.13 Convergence characteristics of each variant of GA for (a) Best and (b) Mean fitness

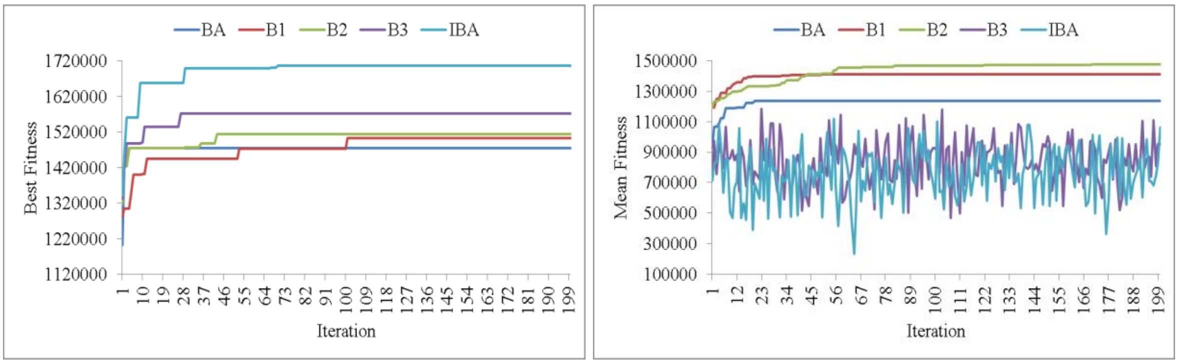


(a) (b)

Fig. 3.14 Convergence characteristics of each variant of PSO for (a) Best and (b) Mean fitness

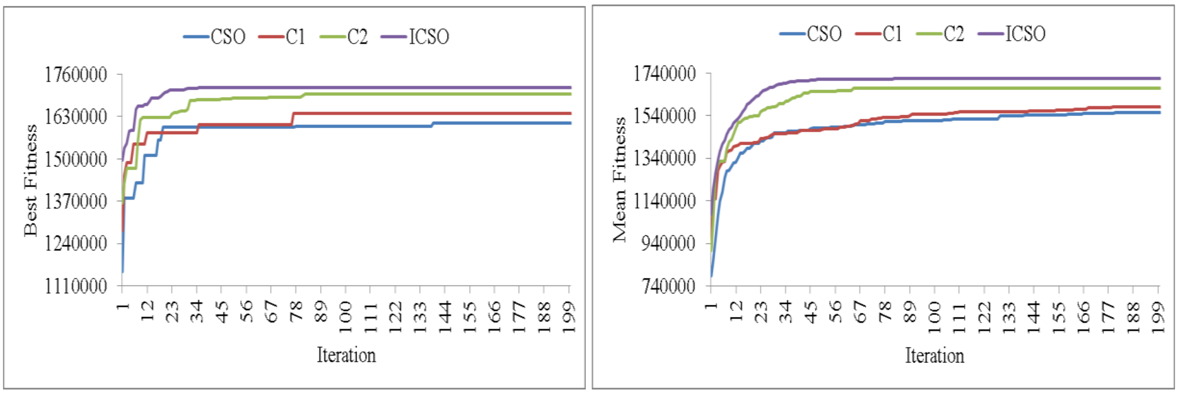
A set of convergence characteristics for BA variants is shown in Fig. 3.15. The figure shows that there is an improvement in the best convergence by each subsequent modification in BA. In the variant B1, the proposed self-adaptive loudness and PER enhance the exploration potential of BA to certain extent. Consequently, IBA finds the promising region by having more patience than the standard BA. The application of improved LRW in the variant B2 enables the algorithm to avoid many local trappings which in turn improve the mean fitness of the population. The proposed diversity searches new solution points in the search space by re-initializing the algorithm in the variant B3. So it plays crucial role to cope against the extreme exploitation potential of the BA. IBA initiates with overall better fitness than BA due to suggested ISA which provides well-directed search. In this way, the promising region is found by IBA, whereas BA fails to do so. It happens because bats fly comprehensively in the search space for better exploration of the search space. It can be observed from the Fig. 3.15 (b) that the introduction of proposed diversity causes poor fluctuating mean fitness during the evolutionary process though it enhances the convergence for the best fitness.

The set convergence characteristics for CSO variants are shown in Fig. 3.16. It can be observed from the figure that CSO has sluggish convergence owing to weak communication as cats are communicating only with the current best cat during the tracing mode. This causes poor exploration of the search space. Since CSO provides simultaneous local and global search, the exploitation potential suffers. In the light of this fact, LRW of the current best cat is employed in the variant C1. This intensifies the local search which in turn results in better global search during the tracing mode so enhances pace of the algorithm. This is in addition to the proposed revised tracing mode where communication with own best and preceding experiences of cats are also taken into consideration. This can be validated by significant improvement in the convergence of the variant C2. ISA further enhances convergences of ICSO as in other proposed techniques.



(a) (b)

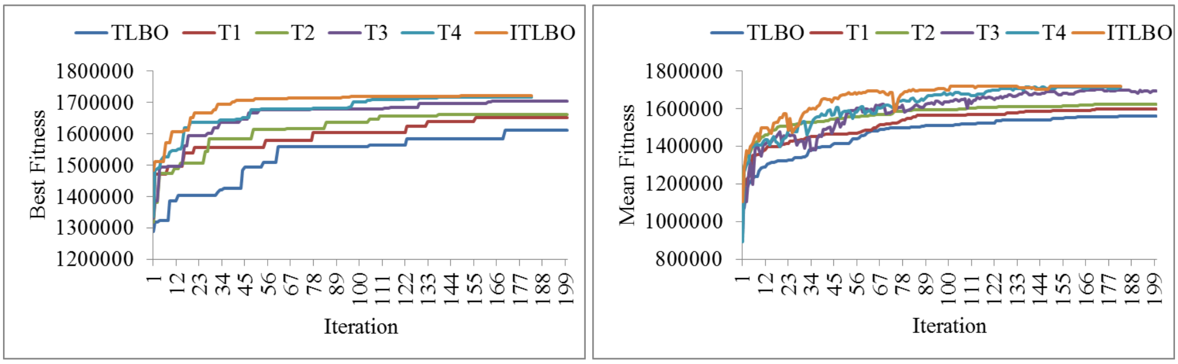
Fig. 3.15 Convergence characteristics of each variant of BA for (a) Best and (b) Mean fitness



(a) (b)

Fig. 3.16 Convergence characteristics of each variant of CSO for (a) Best and (b) Mean fitness

Finally, the effectiveness of each of modification of ITLBO is investigated. A set of convergence characteristics of TLBO variants proposed is shown in Fig. 3.17. It can be observed from the figure that there is an improvement in the convergence by each suggested modification. Like CSO, the individuals are seemed to be approaching toward the promising region in a sluggish manner in TLBO thus it eventually trapped in local optima. A better exploration of the search space is observed when SAL is employed in T1. In fact, SAL guides learners towards the teacher. However, the exploitation potential is still remains poor, and is improved when all learners are subjected to SLP that provides directed mutation so identifying better new solution points in the search space. This avoids several local trappings, as depicted from the variant T2. In variant T3, the proposed DL acts well against the inadequate diversity in population due to inherent greediness of TLBO so the algorithm picks up quickly and thus results in better convergence. The convergence of the algorithm is further improved in variant T4 which is on account of LRW executed by the teacher in TL. Again ISA plays its role for better convergence of the algorithm. It can also be observed from the figure that the mean fitness fluctuates with iterations whenever DL is employed. However, it is noteworthy that DL shifts the paradigm of TLBO and has fruitful impacts on the performance of the algorithm.



(a) (b)

Fig. 3.17 Convergence characteristics of each variant of TLBO for (a) Best and (b) Mean fitness

3.12.2 Statistical Error Analysis

The statistical error analysis carried is based upon the quality indices such as best, worst, mean, standard deviation (SD), coefficient of variation (COV) of the sample and mean CPU time. SD is a measure of mean distance of the sample from the sample mean whereas COV is SD measures as the percentage of sample mean. However, while determining the computational performance of stochastic based optimization techniques, the variance from the best sample is more important than the variance from the mean sample. Therefore, another statistical quality index, i.e. error from the best (EFB) is suggested to observe the solution quality of these techniques. Proposed EFB is given by the following expression:

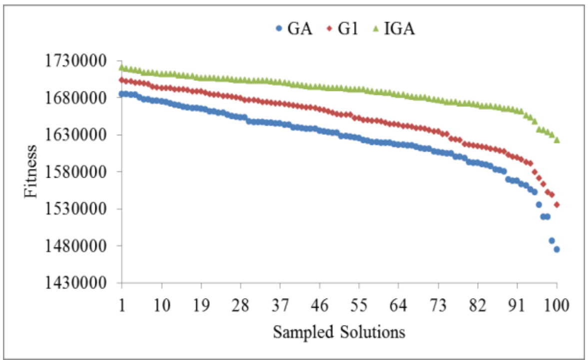
$$\mathrm{EFB} = \frac{\sqrt{\dfrac{\sum_{i=1}^{N_d}(y_i - y_b)^2}{N_d}}}{y_b} \times 100 \qquad (39)$$

Thus EFB is analogous to COV, where the mean value of the sample is being replaced by the best value. The quality of solution (QS) of the sampled solutions obtained after 100 independent trials of proposed variants is presented in Table 3.7. Since the problem of optimal allocation of DRs is modelled to maximize the objective function, higher values of best, worst and mean fitness and smaller values of SD, COV, EFB and CPU time are desired for better performing algorithm. The table reveals that IGA, IPSO, IBA, ICSO and ITLBO all have positive footprints by their each respective suggested modification. Further, each proposed algorithm is remarkably improved than its respective standard model. Among all proposed algorithms, it is BA which has shown greatest improvement, but still IBA is at the bottom among all proposed techniques. ITLBO seems to be performs as the best one among all proposed techniques.

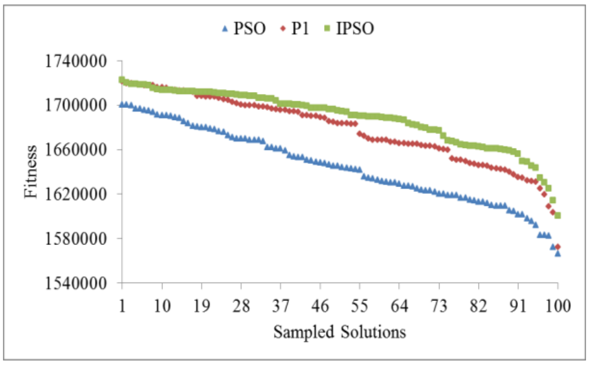
While considering computational requirements of these algorithms, the table reveals that it increases in variants P1, B2, C1 and T4 on account of LRW, which is quite obvious. The CPU time increases remarkably in variants B3 and T2 owing to re-initialization and the introduction of additional learning phase, respectively, so it is justified. Interestingly, the CPU time requirement significantly decreases in the variant G1 which shows fast convergence of GA. This is expected as proposed BFC immediately provides better solutions at the matting pool. However, the application of ISA reduces CPU time of all algorithms to some extent. In overall, the CPU time requirement of IGA, IPSO and ICSO are least whereas IBA is the most computationally demanding.

Table 3.7 Comparison of solution quality for variants of proposed techniques

Method	Variants	Best	Worst	Mean	SD	COV	EFB	CPU time (s)
GA	GA	1685014.26	1474857.53	1624513.45	42713.70	2.63	4.39	16.95
	G1	1704111.45	1534940.45	1651126.58	38012.13	2.30	3.83	5.79
	IGA	**1721075.68**	**1622454.41**	**1688656.37**	**21223.44**	**1.25**	**2.25**	**15.44**
PSO	PSO	1700703.12	1566645.89	1644846.37	33336.02	2.03	3.82	16.84
	P1	1721534.23	1572469.24	1677974.61	31069.72	1.85	3.11	18.30
	IPSO	**1722453.81**	**1600419.36**	**1688371.42**	**25641.03**	**1.51**	**2.47**	**14.26**
BA	BA	1605801.32	1263505.93	1430295.85	56224.01	3.93	11.48	7.91
	B1	1613418.25	1387625.59	1497893.89	36577.53	2.44	7.51	7.95
	B2	1648985.14	1474875.04	1543403.80	40320.23	2.61	6.85	26.06
	B3	1654194.01	1504767.69	1566538.96	30210.57	1.93	5.60	34.42
	IBA	**1721534.23**	**1585988.93**	**1654008.53**	**26593.57**	**1.61**	**4.21**	**32.14**
CSO	CSO	1679695.49	1543137.47	1624791.14	28659.78	1.76	3.69	10.36
	C1	1688675.98	1591236.42	1639497.14	27602.42	1.68	3.34	16.10
	C2	1712890.48	1631900.47	1676029.57	24922.71	1.48	2.59	16.24
	ICSO	**1723787.19**	**1651019.35**	**1706996.11**	**14840.28**	**0.87**	**1.30**	**15.05**
TLBO	TLBO	1715585.25	1570844.44	1657504.59	30019.44	1.81	3.81	14.42
	T1	1715683.29	1596660.00	1673837.82	24416.36	1.46	2.82	14.07
	T2	1720339.19	1623025.27	1678803.23	23306.75	1.39	2.77	21.77
	T3	1723743.11	1641439.39	1699503.29	18908.18	1.11	1.78	23.13
	T4	1723787.68	1652352.44	1705587.29	18316.49	1.07	1.49	26.85
	ITLBO	**1723787.68**	**1668327.89**	**1712819.64**	**9759.32**	**0.57**	**0.85**	**25.53**



(a)



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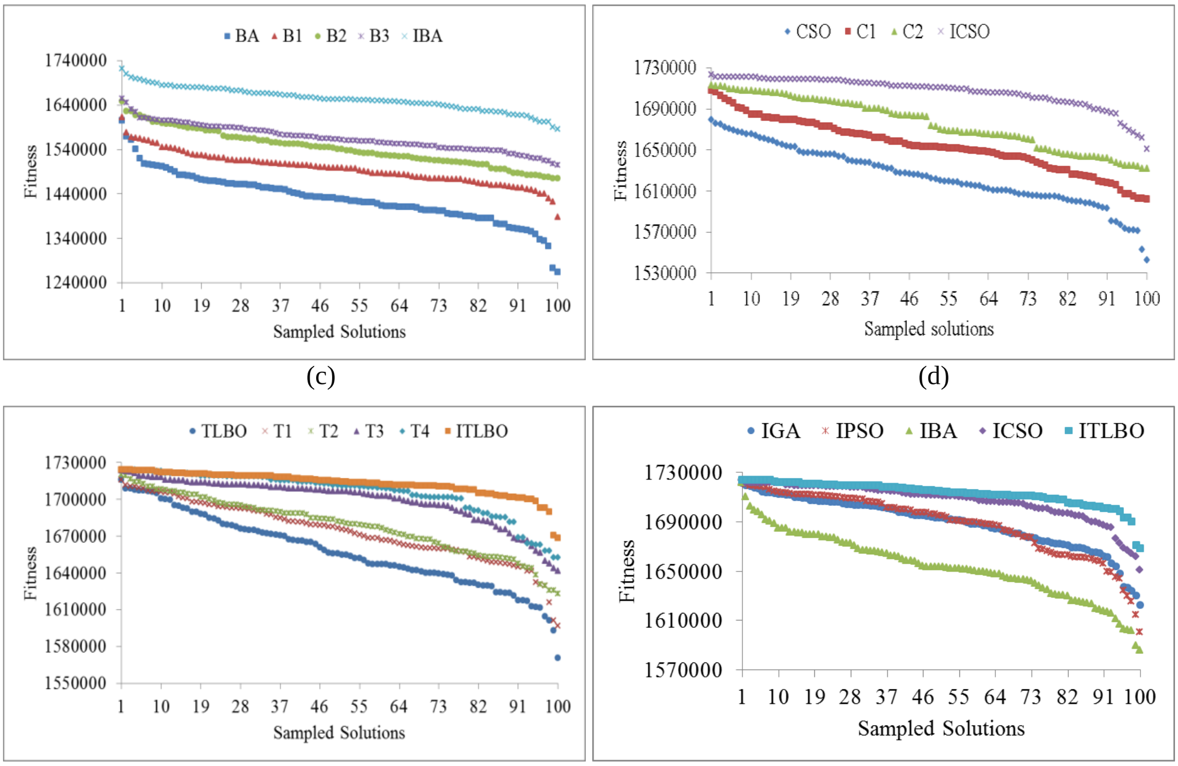


(c) (d)

(e) (f)

Fig. 3.18 Comparison of the spread of sampled solutions for the variants of (a) GA (b) PSO (c) BA (d) CSO (e) TLBO and (f) improved metaheuristics

In the last, to visualize the effect of suggested modifications in the proposed algorithms, the spread of 100 sampled solutions (in the decreasing fitness order) are presented in Fig. 3.18. Each figure is itself convey the success story about how each of the proposed algorithm being developed, as can be depicted by the fact that all sampled solutions obtained by the addition of each suggested modification are found to be improved subsequently to a good level. Moreover, the solutions generated by all proposed algorithms are found to be much better than those generated by their respective standard models. Fig. 3.18(f) compares the spread of sampled solutions of the all proposed techniques. It can be observed from the figure that both ICSO and ITLBO outperform than other proposed algorithms, though ITLBO is slightly better while both IGA and IPSO are performing equally well and IBA is the one which is rated at the least. It happens because standard BA performs inferior than the standard models of GA, PSO, CSO and TLBO.

Table 3.8 Comparison of solution quality of proposed techniques

Method	Best	Worst	Mean	SD	COV	EFB
IGA	1721075.68	1622454.41	1688656.37	21223.44	1.25	2.25
IPSO	1722453.81	1600419.36	1688371.42	25641.03	1.51	2.47
IBA	1721534.23	1585988.93	1654008.53	26593.57	1.61	4.21
ICSO	1723787.19	1651019.35	1706996.11	14840.28	0.87	1.30
ITLBO	1723787.68	1668327.89	1712819.64	9759.32	0.57	0.85

The comparison of the solution quality obtained using proposed techniques is presented at a glance in Table 3.8. The quality indices COV and EFB reveal the supremacy of ITLBO over other proposed algorithms. It is interesting to observe the COV and EFB of IBA relative to other algorithms while keeping one eye on the Fig. 3.18(f). With this observation it is not difficult to infer that EFB is a better indicator than COV to judge the performance of algorithms.

3.13 SUMMARY

This chapter proposes simultaneous allocation of DRs such as DGs and SCs in distribution systems to enhance their performance in terms of annual energy loss reduction and node voltage profile enhancement. A piecewise multilevel annual load profile of the system is considered and DRs are assumed to be controllable. The DR allocation is one of the highly complex combinatorial nonlinear optimization problems of power systems. This complex optimization problem can be solved using any stochastic meta-heuristic technique. However, the accuracy, efficiency and convergence of these techniques adversely affected when applied to solve large dimensional problems which offer enormous problem search space. Therefore, improved variants of GA, PSO, BA, CSO and TLBO algorithms are developed by suggesting several algorithm specific modifications to cope against their intrinsic limitations. Moreover, a probability-based heuristic intelligent search algorithm (ISA) is suggested to enhance the accuracy and convergence of the optimization techniques. It virtually squeezes the problem search space without loss of diversity. The proposed method is applied on the benchmark IEEE 33-bus distribution system and the application results show significant improvement in desired objectives. The developed algorithms, i.e. IGA, IPSO, IBA, ICSO and ITLBO have been exhaustively investigated on this system to solve the problem. The statistical error analysis reveals that these algorithms are significantly improved than their respective standard models and other existing metaheuristics. The study of results also shows that every suggested modification distinctly contributes toward improving the accuracy and convergence of these algorithms. The suggested ISA has shown its potential to enhance the overall performance of these algorithms.

CHAPTER 4

DISTRIBUTED RESOURCE ALLOCATION AND NETWORK RECONFIGURATION

The existing distribution systems are moving towards smart distribution systems to achieve larger socio-economic and other non-tangible benefits. The rise of smart grid is a boon not only to society as a whole but to all who are involved in the electric power industry, its customers, and its stakeholders [1]. Building of such distribution systems requires local generation of reactive and active power using DRs such as SCs and DGs. In the previous chapter different meta-heuristic techniques have been developed and investigated for DR allocation problems under certain assumptions. The aim of the study was to explore different solution techniques and to carry out a comparative analysis. For the sake of simplicity, the DRs were assumed to be dispatchable and the effects of NR were not taken into account. Moreover, the diversity among different class of customers has not been taken into consideration. It is important to note that NR is one of the established operational strategies to achieve multiple performance objectives such as power loss minimization, voltage profile enhancement, congestion management etc. NR reallocating loads from heavily loaded feeders to lightly loaded feeders by changing the network topology so balances loads among the feeders and thus decreases the real power losses and enhance node voltage profiles [211]. Therefore, practical optimal allocation of DRs, such as SCs and DGs should take into account NR also. Some researchers [104, 173, 182, 206-218] employed simultaneous DG allocation and NR to optimize the performance of distribution systems. They concluded that engaging DGs and NR simultaneously in distribution network provide a significant reduction in feeder power loss and improvement in node voltage profile. But, this simultaneous placement strategy is not realistic as the solution obtained can demand an alteration in the sites of DRs under certain loading condition, as can be seen from [182, 214]. Hung *et al*. [104] employed different combinatorial strategies for DR allocation and NR and have shown that NR should be carried before DR placement. This strategy demands lesser capacity of DRs for the given distribution system. However, under different loading conditions, optimal network topologies may be different resulting in different solutions for DR allocation problem. Infact, DR allocation is a problem of planning horizon whereas NR is an operational strategy. The practical solution demands that operational strategy should follow planning strategy. Therefore, after optimally placing DRs in the distribution network the network may be optimally reconfigured for different loading conditions to further optimize the desired objectives. However, while formulating the problem of optimal DR allocation, the possible benefits of NR should be kept in the formulation in terms of values of constraints so that the optimal solution does not demand overestimated DR capacities. Such coordinated initiatives can provide optimum benefits for the network owner and/or the network users, and can evaluate the feasibility of investment on DRs versus other traditional planning options [8]. With the advancement in control technology, it is possible to control the output of DRs if it is required under certain load conditions. The tuning (control) of DRs could be another operational strategy which maximizes the benefits of investment on DRs though controllable DRs involve extra expenditure. It will be interesting to see the effect of controllable DRs on the performance of distribution systems. In the existing literature the effect of tuning of DRs on the performance of distribution network under different operating conditions has not been thoroughly investigated. Another important issue of DR allocation problem is proper modelling of the system loads. The amount of actual benefit of DR allocation depends upon the modelling of load profile of the distribution system. Several researchers [109, 119, 201, 219] modelled the load profile using different mathematical approaches. However, the specific load profile associated with different type of feeders/buses of the system has not been duly addressed. In practice, distribution system loads are mixtures of different categories such as residential, industrial, commercial etc. The distribution system planners provide dedicated feeders to different class of customers, so each distribution bus has its own characteristic load pattern which varies hourly and seasonally. There exists definite load diversity among different class of customers which is reflected not only in the shape of the annual load profile and node voltage profiles of the system but also in the peak demand and its duration. This may affect the sizing, siting of optimal DRs and thereby the benefits of DR allocation.

In the light of above discussion, this chapter presents a new methodology to address simultaneous allocation problem of DRs in radial distribution systems by considering more realistic load profile of the system. The proposed strategy is applied on the benchmark IEEE 33-bus test distribution system and 83-bus real distribution system. The problem is solved using IGA, IPSO, IBA, ICSO and ITLBO developed in chapter 3. The effect of DR tuning and NR have been thoroughly investigated and results of the study are presented. The consequences of ignoring load diversity among distribution buses on DR sizing and expected benefits are also investigated.

4.1 ANNUAL LOAD PROFILE CONSIDERING LOAD DIVERSITY AMONG CUSTOMERS

The proper modelling of annual load profile of the distribution system is one of the most important aspects in DR allocation problem. Earlier efforts [74, 87, 90, 95, 198] addressed DR allocation problem by modelling the annual load profile of the system using piecewise multiple load levels. This provides probably the simplest modelling, but is not realistic. This modelling is crucial while dealing with any distribution system optimization problem and therefore it should be realistic to a good degree of satisfaction. In practice, a load class mix of various types of customers, i.e. residential, industrial, and commercial, should be investigated, in which every bus of the system has a different type of load connected to it [150]. Therefore, the specific load pattern associated with different distribution buses should be considered while modelling annual load profile of the system. However, this leads to a definite load diversity that exists among distribution buses. This provides a more practical scenario for the optimization problems and thus results in more practical solution for distribution system planning and operation. This load diversity plays vital role in deciding the shape of the annual load profile including peak load demand on the system and its duration, and also node voltage profiles of the system. The load demand of a customer varies with time during the day and is also affected by the ambient conditions such as temperature, humidity, air pressure, etc. Thus, feeder load profiles also face seasonal variations. The daily load profile of distribution feeders can be aggregated for a given season by considering hourly variation in load demand in order to reduce the simulation time. As shown in Fig. 4.1, a sample load profile of the distribution system can be approximated by piecewise linearization modelling for the spring/fall season. It can be observed from the figure that the aggregated daily load profile of the system consists of several load levels owing to diversities attributed to different class of customers. Similarly, the aggregated load profile of the system for other seasons may be determined by considering a suitable multiplying factor. The annual load profile of the system thus can be obtained by integrating these aggregated load profiles of various seasons of the year. In the present work, constant power load model is considered for all classes of customers.

The problem formulation for the optimal DR allocation and NR problems is presented in the following section.

4.2 PROBLEM FORMULATION

The problem of simultaneous optimal allocation of DRs is formulated to maximize annual energy loss reduction and to enhance node voltage profiles. The distribution network is then optimally reconfigured to further optimize these objectives. The proposed approach first determines the optimal number, sites and sizing of DGs and SCs. These DRs are assumed to be controllable (tuneable) so that their optimal dispatches are determined for each operating state of the system to achieve optimum objectives. As discussed earlier, while formulating DR allocation problem, the possible benefits of NR should be kept in the formulation in the form of values of constraints so that solutions of DR allocation do not demand overestimated capacities of DRs.

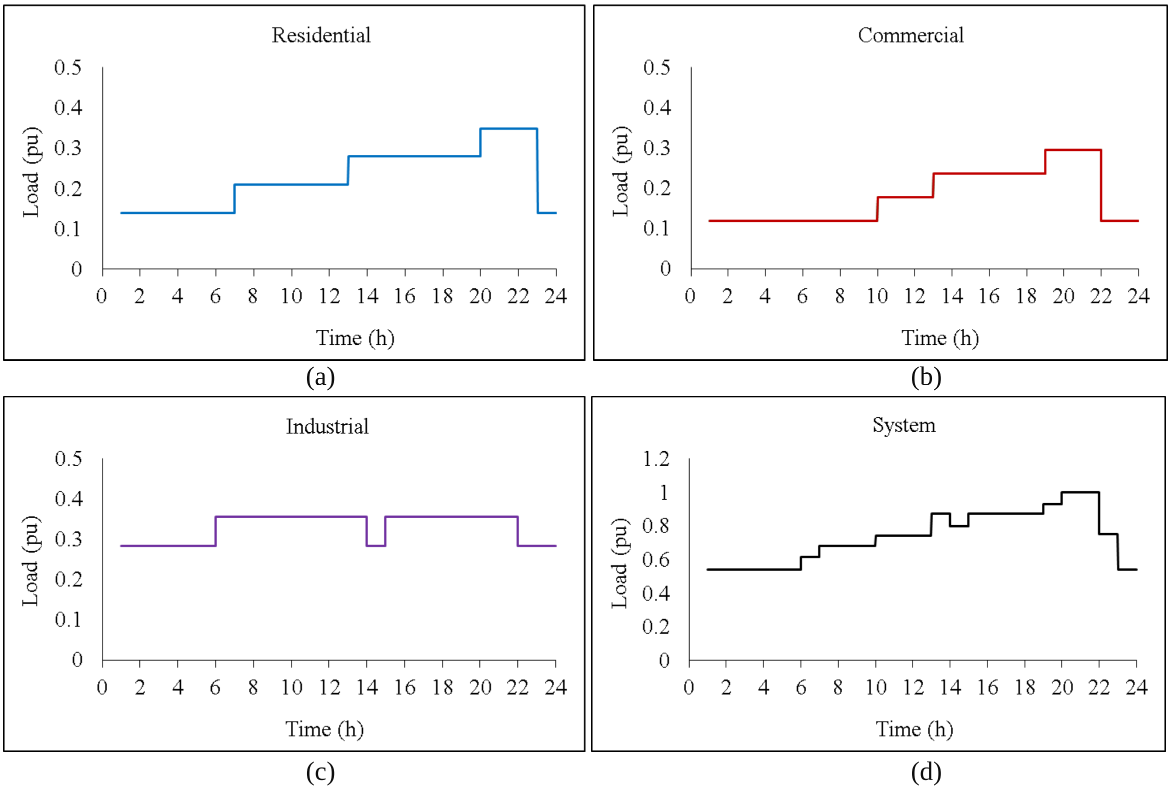


Fig. 4.1 Aggregate daily load profiles of (a) residential customers (b) commercial customers (c) industrial customers and (d) distribution system for spring/ fall season

The NR is very effective to improve node voltage profiles of distribution systems. Therefore, a soft node voltage constraint is proposed to solve DR allocation problem, instead of the conventional hard node voltage constraint. For this purpose, a user defined minimum node voltage, V_{minS} is suggested for DR allocation formulation and a node voltage penalty function λ is proposed to take care of node voltage profile of the system. The value of V_{minS} is kept lower than $V_{\min}$ under the assumption that the NR can improve V_{minS} to $V_{\min}$. The proposed penalty function imposes certain penalty on the annual energy loss reduction whenever the minimum node voltage lie within the range [V_{minS}, $V_{\min}$]. The philosophy behind suggesting the soft node voltage constraint is that DRs and NR can share the responsibility for improving node voltage profiles up to the desired level and as a consequence may result in lesser optimal DR sizing. In addition, the proposed soft node voltage constraint plays vital role while optimizing the problem using any stochastic meta-heuristic technique. First, it allows many tentative solutions for participation in the evolutionary process, otherwise these solutions declared infeasible owing to the implication of the conventional hard node voltage constraint. This may seriously hamper the computation process of optimizing algorithms. Second, in certain situations where the distribution feeder voltage profiles sag heavily during initial condition, the stochastic meta-heuristic techniques may fail even to build up initial population, if the conventional hard node voltage constraint is employed. However, these algorithms can be swiftly initialized using proposed soft node voltage constraint. In due course of time, the control mechanism of these techniques may generate better individuals having better node voltage profiles. Thus, proposed soft node voltage constraint facilitates the application of meta-heuristic techniques for DR allocation.

While performing NR, the conventional hard node voltage constraint is used to ensure minimum node voltage above certain specified voltage ($V_{\min}$). The problem formulation for optimal DR allocation and optimal NR are presented in the following section.

4.2.1 OPTIMAL ALLOCATION OF DRS

The objective function for the optimal allocation of DRs is formulated as:

$$Max.\ O.F. = \lambda\left(E_{Loss}^{base} - E_{Loss}^{DR}\right) \tag{1}$$

Where E_{Loss}^{base} and E_{Loss}^{DR} are the annual energy losses without and with DR placement and can be determined using following equation assuming piecewise linearized multi-level annual load profile of the system.

$$E_{Loss} = \sum_{s=1}^{N_s} D_s \left(\sum_{j=1}^{L} H_{j,s} \left(\sum_{r=1}^{N_r} R_r \frac{P_{r,j,s}^2 + Q_{r,j,s}^2}{\left|V_{r,j,s}\right|^2} + \sum_{i=1}^{N_i} R_i \frac{P_{i,j,s}^2 + Q_{i,j,s}^2}{\left|V_{i,j,s}\right|^2} + \sum_{c=1}^{N_c} R_c \frac{P_{c,j,s}^2 + Q_{c,j,s}^2}{\left|V_{c,j,s}\right|^2} \right)\right) \tag{2}$$

Where, λ is the proposed node voltage penalty function which is given by

$$\lambda = \frac{1}{1+\left(Max\left(\Delta V_{r,j,s},\ \Delta V_{i,j,s},\ \Delta V_{c,j,s}\right)\right)} \quad \forall r,i,c \in N, \forall j \in L \tag{3}$$

The equation (3) shows that λ is determined by evaluating maximum node voltage deviation among all system nodes while considering all load levels, where $\Delta V_{r,j,s}$, $\Delta V_{i,j,s}$, $\Delta V_{c,j,s}$ denotes the voltage deviation of the rth residential node, ith industrial node and cth commercial node at jth load level of the sth season. N and L denote the set of system nodes and load levels. Node voltage deviation $\Delta V_{r,j,s}$ at rth residential feeder for jth load level of the sth season are calculated by proposing (4). Similarly, $\Delta V_{i,j,s}$ and $\Delta V_{c,j,s}$ can also be defined.

$$\Delta V_{r,j,s} = \begin{cases} 1-\left|V_{r,j,s}\right| & ;V_{\text{minS}} < V_{r,j,s} < V_{\min} \\ 0 & ;V_{\min} \le V_{r,j,s} \le V_{\max} \\ \text{a very large number} & ;\text{else} \end{cases} \tag{4}$$

The different constraints used to solve *O.F.* are defined as below.

1. Power flow equations

The sum of the power purchased from utility grid and the total power generated by the different sources in the distribution system must be balanced by the local load demand and the power loss in the lines. For a radial network, a set of recursive equations are used to model the power flow in the network as given by (5)-(9).

$$P_{n+1} = P_n - R_n \frac{P_n^2 + Q_n^2}{V_n^2} - p_{n+1};\ \forall n \in N \tag{5}$$

$$Q_{n+1} = Q_n - X_n \frac{P_n^2 + Q_n^2}{V_n^2} - q_{n+1};\ \forall n \in N \tag{6}$$

$$V_{n+1}^2 = V_n^2 - 2\left(R_n P_n + X_n Q_n\right) + \left(R_n^2 + X_n^2\right) \frac{P_n^2 + Q_n^2}{V_n^2};\ \forall n \in N \tag{7}$$

$$p_{n+1} = p_{n+1}^{L} - p_{n+1}^{\text{DG}};\ \forall n \in N \tag{8}$$

$$q_{n+1} = q_{n+1}^{L} - q_{n+1}^{\text{SC}};\ \forall n \in N \tag{9}$$

2. Feeder current constraint

The current flow in each distribution line must be below or equal to the rated ampacity. This imposes feeder current constraints which can be expressed as

$$I_n \le I_n^{\max};\ \forall n \in N \tag{10}$$

3. Bus compensation limit

The total active and reactive power injected by DRs at each bus must be within their permissible range as defined by

$$p_{n,\min}^{DG} \le p_n^{DG} \le p_{n,\max}^{DG};\ \forall n \in N \tag{11}$$

$$q_{n,\min}^{\text{SC}} \le q_n^{\text{SC}} \le q_{n,\max}^{\text{SC}};\ \forall n \in N \tag{12}$$

4. System compensation limit

The sum of total active and reactive power injected by DGs and SCs in the distribution system should be less than nominal active and reactive power demand of the system, respectively. For *loc* number of candidate locations of DGs/SCs, the system compensation limit is defined by

$$\sum_{n=1}^{loc} p_n^{DG} \le p_D \quad ;\forall n \in N \tag{13}$$

$$\sum_{n=1}^{loc} q_n^{\mathrm{SC}} \le q_D \quad ;\forall n \in N \tag{14}$$

Equation (15) and (16) prohibits the repetition of candidate sites for DGs and SCs, respectively. Since DGs and SCs are commercially available in discrete sizes so are modeled by (17) and (18).

$$loc_a^{\mathrm{DG}} \ne loc_b^{\mathrm{DG}};\ a,b \in N \tag{15}$$

$$loc_a^{\mathrm{SC}} \ne loc_b^{\mathrm{SC}};\ a,b \in N \tag{16}$$

$$p_n^{DG} \le K_d P_d;\ K_d = 0,1,2,...,ndg \text{ and } \forall n \in N \tag{17}$$

$$q_n^{\mathrm{SC}} \le K_b Q_b;\ K_b = 0,1,2,...,nsc \text{ and } \forall n \in N \tag{18}$$

First optimizing the objective function given by (1), the optimal solution obtained provides the optimal number, sizing and siting of DRs, while considering the annual load profile. Next, (1) is optimized to determine the optimal tuning of these installed DRs, but now for each system state separately. For this optimization the sites for DRs are kept freeze and their sizing is restricted to that provided by the optimal solution. The additional constraints defined to determine optimal tuning of DRs are modelled as below.

$$p_n^{DG} = K_{md}\Delta p;\ K_{md} = 0,1,2,..., p_n^{DG} / \Delta p;\ \forall n \in N \tag{19}$$

$$q_n^{\mathrm{SC}} = K_t \Delta q;\ K_t = 0,1,2,...,\ q_n^{\mathrm{SC}} / \Delta q\ ;\ \forall n \in N \tag{20}$$

4.2.2 NETWORK RECONFIGURATION

The NR problem of distribution systems is solved to minimize feeder power loss and is formulated as
Minimize,

$$P_{Loss} = \sum_{s=1}^{N_s}\sum_{j=1}^{L}\left(\sum_{r=1}^{N_r} R_r \frac{P_{r,j,s}^2 + Q_{r,j,s}^2}{\left|V_{r,j,s}\right|^2} + \sum_{i=1}^{N_i} R_i \frac{P_{i,j,s}^2 + Q_{i,j,s}^2}{\left|V_{i,j,s}\right|^2} + \sum_{c=1}^{N_c} R_c \frac{P_{c,j,s}^2 + Q_{c,j,s}^2}{\left|V_{c,j,s}\right|^2} \right) \tag{21}$$

Subject to the following constraints.

1. Radial topology constraint

The reconfigured network topology must be radial, i.e. with no closed path. Therefore, the radiality constraint for the zth radial topology is defined as

$$\Phi_j(z) = 0 \tag{22}$$

2. Node voltage constraint

All node voltages $V_{r,j,s}$ of the residential nodes must be maintained within the minimum and maximum permissible limits *i.e*. $V_{\min}$ and $V_{\max}$, respectively using conventional hard node voltage constraint as shown by (23). Similarly, node voltage constraint for industrial and commercial nodes can also be defined.

$$V_{\min} \le V_{r,j,s} \le V_{\max};\ \forall r \in N_r, \forall j \in L \tag{23}$$

The other problem constraints used are same as defined by (5)-(10). While solving the NR problem, the radial topology constraint is handled using the method of [255]. However, while attempting NR problem, loop-wise Branch Priority Lists (BPLs), instead of NPL, is required. For this purpose, the given distribution network is configured in mesh topology by closing all tie-lines so have as many loops as the number of tie-lines. The branch currents are then measured by performing load flow. Each BPL is specific to its loop and consists of the set of loop branches and corresponding currents. However, these branches are arranged in the descending order of their currents. In this way one independent BPL can be obtained for each loop of the distribution network. Now the candidate branches can be selected by applying RWS to each BPL by providing maximum priority to the branch being placed at the top position in BPLs. While optimizing the problem using proposed meta-heuristics, ISA provides more priority to better candidate branches which should be open to get radial topologies having less power losses. This causes population of the algorithm to flourish with better radial topologies, though maintains adequate diversity. This eventually enhances the performance of the algorithm. The proposed method is applied on small and large distribution systems and the results of simulations are presented and investigated in the following section.

4.3 SIMULATION RESULTS

The proposed method for the simultaneous allocation of DRs is applied on the benchmark IEEE 33-bus test distribution system [254] and 83-bus Taiwan Power Company (TPC) real distribution system [256]. The initial data of these systems are given in Table C.1. The detailed data with single line diagrams of the systems may be referred from the Appendix E. The load factors and corresponding load durations considered for different customers are presented in Table C.2. The load levels 1-9, 10-18 and 19-27 are considered for spring/fall, winter and summer seasons, respectively. The system design parameters selected for simulations are presented in Table C.3, and the NPLs and BPLs used in ISA are given in Table C.4. The algorithm specific control parameters considered for case study 1 are taken same as in chapter 3, and for the case study 2 are given in Table C.5. The problem is optimized using the algorithms developed in chapter 3, namely IGA, IPSO, IBA, ICSO and ITLBO. As the proposed method is new, its validation with the existing literature is not possible. The simulation results obtained are investigated and presented.

4.3.1 CASE STUDY 1: IEEE 33-BUS TEST DISTRIBUTION SYSTEM

The system is identical as used in chapter 3. The common control parameters selected for IGA, IPSO, IBA, ICSO and ITLBO algorithms are shown in Table C.6. The best solution obtained after 100 independent trials of these algorithms are presented in Table 4.1. It may be observed from the table that all proposed algorithms provide same solutions of DG and SC placement in terms of number of units, their capacities and locations. This shows that all proposed techniques have identical potential to explore optimal solution for this system. The total optimal DG capacity obtained is 2173 kW and the total optimal SC capacity obtained is 1200 kVAr. Whereas, the active and reactive nominal load demands of the system are 3715 kW and 2300 kVAr, respectively. Thus the proposed simultaneous placement strategy allows nearly 58% DG penetration and 52% capacitor penetration. The network performance is evaluated by implementing this solution and the results obtained may be referred from Table C.7. The table shows power losses, minimum node voltage at each system state after applying this solution. From the table it has been observed that the placement of fixed DRs causes nearly 81 % annual energy loss reduction and improves the minimum voltage by nearly 7% as shown in Table 4.1. Thus proposed method provides substantial enhancement in objectives with fixed DR operation because the optimal solution is with higher DR penetration.

Table 4.1 Optimal solution for case study 1

Methods	Optimal location (Optimal installed capacity)		A	B
	Node (DG in kW)	Node (SC in kVAr)		
IGA, IPSO, IBA, ICSO, ITLBO	14(494), 24(960), 30(719) TC: 2173	12(300), 25(300), 30(600) TC: 1200	80.79	6.81

A: Annual energy loss reduction (%), B: Improvement in minimum node voltage (%)

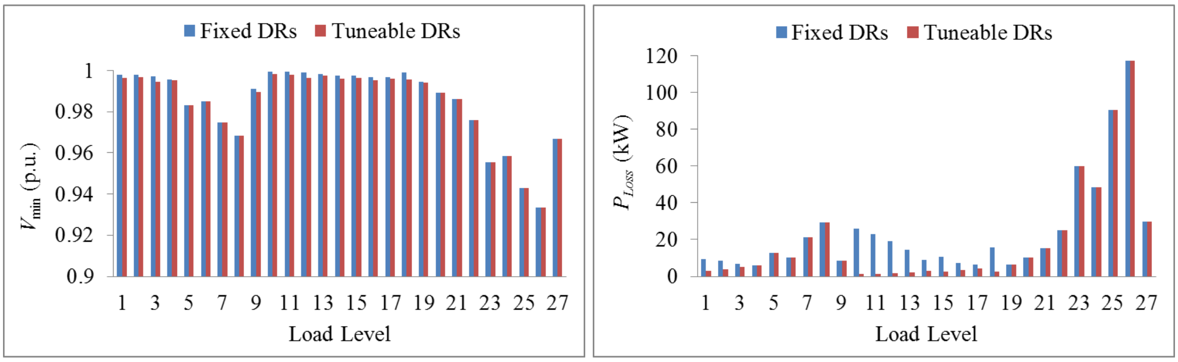
Table 4.2 System operation with different scenarios

System operation	A	B
Fixed DRs	80.79	6.81
Tuned DRs	85.71	6.81
Fixed DRs and NR	85.58	9.60
Tuned DRs and NR	88.72	9.60

A: Annual energy loss reduction (%), B: Improvement in minimum Node voltage (%)

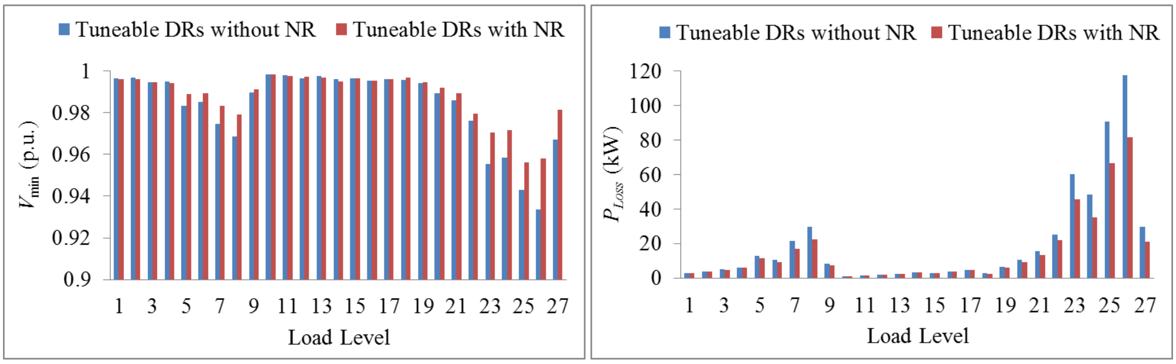
It is important to investigate the effectiveness of tuneable DRs and NR on the performance of distribution systems. For this purpose, the ITLBO is applied at each load level separately to optimize the objective function (1). However, the sites for DRs are kept the same and their sizing is restricted to their installed capacities. This provides the optimal power dispatches of DRs. For each load level, the power losses and node voltage profile are determined. The results so obtained for all 27 states of the system are presented in Table C.7. Similar exercise is carried for NR with fixed and tuneable DRs separately and the results of the study are presented in Table C.8. The consolidated results for different system operation pertaining to DR placement and NR are presented in Table 4.2. It can be observed from the table that tuning of DRs provides annual energy loss reduction of 85.71 % which is almost 5 % more than that obtained with fixed DR operation. However, there is no improvement in the minimum node voltage. The table also shows that with fixed DRs, the NR causes further annual energy loss reduction of almost 5% and also an improvement in minimum node voltage from 6.81% to 9.60%. But, when the distribution network is optimally reconfigured after optimal DR tuning, an annual energy loss reduction of about 8% is achieved with the same improvement in minimum node voltage while comparing with fixed DR operation.

From the analysis it appears that with given DR allocation, the NR strategy is more effective as compared to the tuning of DRs for improving the annual performance of distribution network. Each of the strategy causes equal amount of loss reduction, but NR causes improvement in node voltage profiles whereas DR tuning apparently has no effect on the same. Thus, the NR seems to be better strategy than DR tuning. It may be noted that both tuning of DR and NR are operational strategies. However, relative cost involves in tuneable DRs is higher than the cost involves in NR. Looking to the cost and complexity involved in DR tuning and NR, they may be avoided by marginally sacrificing the performance of distribution systems.



(a) (b)

Fig. 4.2 Effect of DR tuning on (a) node voltage profile enhancement (b) feeder power loss reduction

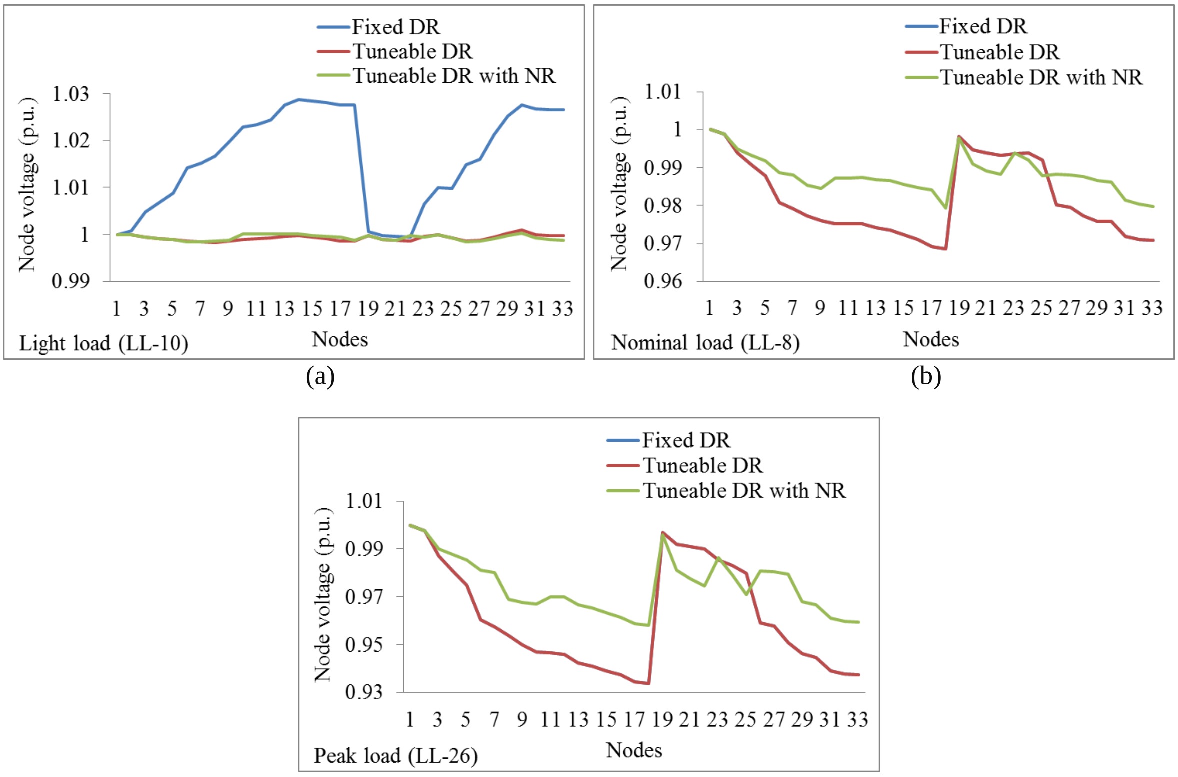


(a) (b)

Fig. 4.3 Effect of NR on (a) node voltage profile enhancement (b) feeder power loss reduction

In order to carry out in-depth studies of the effects of tuneable DRs and NR, the network performance is analysed for different load conditions (states) of the distribution system while considering various scenarios of DR placement and NR. The effect of DR tuning on minimum node voltages and feeder power losses that occurred at 27 states considered are presented in Fig. 4.2. From Fig. 4.2(a) it can be seen that minimum node voltages are hardly affected by DR tuning. This reveals that system node voltage profiles may not be much affected by DR tuning. However, power losses are found to be reduced substantially during the lightly loaded season of the year (LL-10 to LL-18), as shown in Fig. 4.2(b). The impact of NR on the performance of distribution system can be observed from Fig. 4.3. The figure shows that NR is very effective for both node voltage enhancement and power loss reduction during the season 3 (LL-19 to LL-27), the heavily loaded season of the year. But, it is almost ineffective during lightly loaded season of the year. Thus DR tuning effectively reduces power losses, but only during light load conditions, whereas NR is important to enhance system performance during stringent load conditions.

Further, the impact of DR tuning and NR on node voltage profiles is investigated. For simplicity, only 3 critical states (out of total 27 states) of the distribution system are considered for this study, i.e. light load (LL-10), nominal load (LL-8) and the peak load (LL-26) of the year. The comparison of node voltage profiles are presented in Fig. 4.4. It can be observed from the figure that DR tuning is crucial to suppress node voltages during light load conditions. But, it is found to be ineffective at nominal and peak load conditions, as can be seen from Figs 4(b) & 4(c) having identical voltage profiles for the system operation with fixed and tuneable DRs. However, NR is found to be very effective under nominal and peak load conditions, but it is not so for light load conditions. It may be concluded from these snap shots that DR tuning and NR behave in different manner against system node voltages; DR tuning is very effective to drop down node voltages during light load conditions whereas NR plays crucial role to enhance node voltage profiles of the system during nominal and peak load conditions.



(c)

Fig. 4.4 Node voltage profiles for (a) light, (b) nominal and (c) peak load level

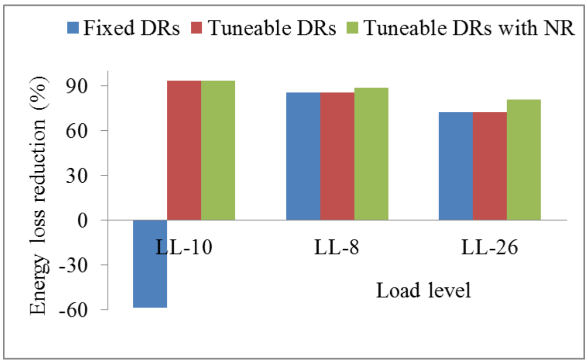


Fig. 4.5 Effect of DR tuning and NR on energy loss reduction for case study 1

Next, the effectiveness of DR tuning and NR on energy loss reduction is presented in Fig. 4.5. Again the three states of the distribution system are considered. The figure shows that DR tuning effectively reduces power loss during light load conditions which would otherwise increase significantly. It can be concluded from the figure that both DR tuning and NR are not very effective for loss reduction during nominal and peak load conditions.

Table 4.3 Comparison of solution quality of proposed techniques

Methods	Best	Worst	Mean	SD	COV	EFB
GA	794802.18	726130.42	774240.76	15357.97	1.98	3.23
IGA	**795547.82**	**764317.96**	**792630.02**	**4258.69**	**0.54**	**0.65**
PSO	794999.76	684172.29	769457.97	15683.66	2.04	3.77
IPSO	**795547.82**	**750760.91**	**788048.65**	**9559.26**	**1.21**	**1.53**
BA	724940.41	550640.49	638515.12	34002.09	5.33	12.81
IBA	**795547.82**	**701397.45**	**758665.50**	**20593.82**	**2.71**	**5.31**
CSO	787241.53	721601.29	767344.63	13584.11	1.77	3.06
ICSO	**795547.82**	**770395.83**	**792159.07**	**4698.66**	**0.59**	**0.72**
TLBO	789755.39	734202.13	777743.89	10695.59	1.38	2.04
ITLBO	**795547.82**	**786621.66**	**794637.81**	**1666.07**	**0.21**	**0.24**

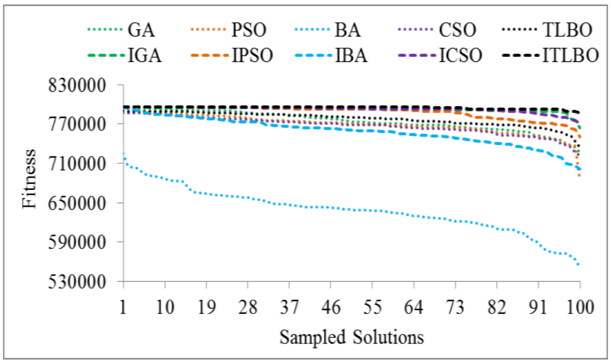


Fig. 4.6 The spread of sampled solutions obtained by GA, PSO, BA, CSO, TLBO, IGA, IPSO, IBA, ICSO and ITLBO

Finally, the comparison of the solution quality obtained when standard and proposed algorithms are applied to solve DR allocation problem is presented in Table 4.3. The table reveals that all proposed algorithms have been improved significantly than their respective standard counterparts. However, the performance of all proposed algorithms is found to be satisfactory. The comparison of COVs and EFBs shows that ITLBO is doing well than other algorithms for this complex optimization problem. These facts can also be verified from Fig. 4.6 showing the comparison of the spread of 100 sampled solutions obtained using these algorithms. It can be observed from the figure that despite of several improvements suggested in IBA, its performance remains inferior to other improved algorithms.

4.3.2 Case Study 2: 83-Bus Real Distribution System

It is 11.4 kV three-phase balanced Taiwan Power Company (TPC) distribution system. The nominal active and reactive load demands of the system are 28.35 MW and 20.70 MVAr, respectively. The proposed method is applied to this system using IGA, IPSO, IBA, ICSO and ITLBO algorithms. For this case study, the population size and maximum iterations taken for proposed algorithms are presented in Table C.9 and the optimal solutions obtained after 100 trials of these algorithms is presented in Table 4.4. It can be observed from the table that the optimal solutions obtained using these algorithms are different for this system. However, the fitness values of these solutions lie within a narrow range of 1.25%. This shows that all optimal solutions explored by these algorithms are in close proximity. The table also shows percentage annual energy loss reduction and improvement in minimum node voltage using these solutions. It can be seen that about 52% loss reduction and 5.5% improvement in minimum node voltage can be achieved with fixed DR operation. Thus different solutions obtained using proposed algorithms enhance the performance of the distribution network by almost same margin. This shows that all proposed algorithms are doing equally good for this large-scale optimization problem. However, the solution obtained using ITLBO is slightly better and is used for further investigations. For this solution, the optimal tuning of DRs is determined for each system state. The network performance obtained after installing fixed and tuneable DRs in the system is presented in Table C.10. Similarly, the network performance is also evaluated by optimally reconfiguring the distribution network with fixed and tuneable DRs separately and the results obtained are presented in Table C.11.

Table 4.4 Optimal solutions for case study 2

Method	Optimal location (Optimal installed capacity)		F	A	C
	Node (DG in kW)	Node (SC in kVAr)			
IGA	6(1900), 12(2400), 28(1900), 71(1500), 79(2200) TC:9900	6(1500), 12(1800), 31(1800), 71(1200), 79(1500) TC:7800	1310097	51.84	5.45
IPSO	6(1900), 12(2700), 28(1700), 33(1900), 79(2200), TC:10400	6(1500), 12(1800), 31(1800), 71(1200), 79(1500) TC:7800	1307854	51.75	5.45
IBA	6(1900), 12(2400), 28(2000), 53(1600), 79(2200) TC:10100	7(1200), 12(1800), 31(1800), 71(1200), 79(1500) TC:7500	1294212	51.21	4.95
ICSO	6(1800), 12(2500), 28(2000), 33(1900), 79(2200) TC:10400	6(1500), 12(1800), 31(1800), 71(1200), 79(1500) TC:7800	1310580	51.86	5.34
ITLBO	6(1900), 12(2500), 28(2000), 71(1500), 79(2200) TC:10100	6(1500), 12(1800), 31(1800), 71(1200), 79(1500) TC:7800	1310704	51.86	5.45

F: Fitness of optimal solution (kWh), A: Annual energy loss reduction (%), B: Improvement in minimum node voltage (%)

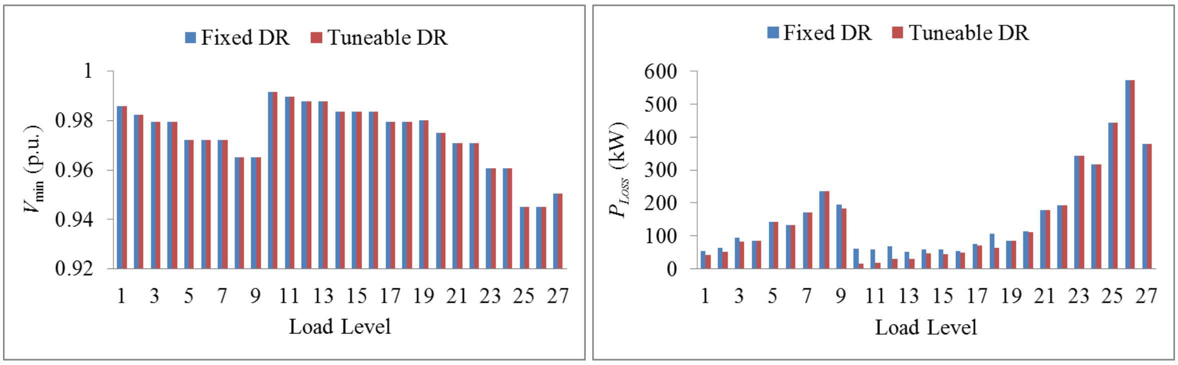
The consolidated performance results for various scenarios of DR placement and NR are presented in Table 4.5. The table shows that DR tuning provides an annual energy loss reduction of about 4% whereas it is about 9% by NR (with fixed DR operation). Both DR tuning and NR are seemed to almost ineffective to enhance minimum node voltage. Thus these strategies are not much effective to enhance network performance for this system. In fact this system is already well configured in base case conditions so NR has small margin available to further enhance the performance of distribution system. Thus DR tuning and NR may be avoided for this system by marginally sacrificing the performance.

Table 4.5 System operation with different scenarios

System operation	A	B
Fixed DRs	51.86	5.46
Tuned DRs	55.86	5.46
Fixed DRs and NR	60.82	5.67
Tuned DRs and NR	61.55	5.67

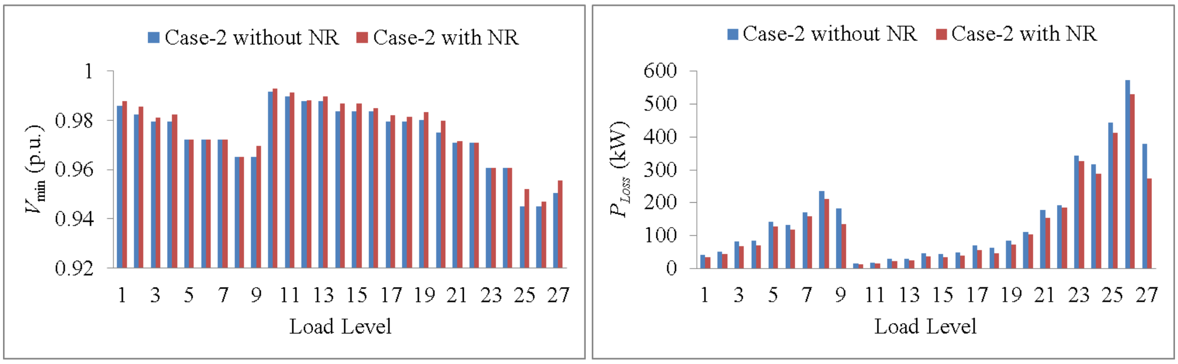
A: Annual energy loss reduction (%), B: Improvement in minimum node voltage (%)

It is important to investigate the impact of DR tuning and NR on the performance of distribution system at different load conditions as presented in Fig. 4.7 and 4.8. Fig. 4.7 shows that DR tuning is not effective to enhance minimum node voltages but it reduces power loss during light load conditions. However, NR marginally contributes to enhance the minimum node voltages and to reduce feeder power losses, as can be seen from Fig. 4.8. The impact of DR tuning and NR on node voltage profiles is compared in Fig. 4.9 showing voltage profiles for light, nominal and peak load conditions. Once again it has been observed that DR tuning plays crucial role to suppress node voltages during light load conditions whereas NR is enhancing node voltage profiles during remaining load conditions. The effectiveness of DR tuning and NR on energy loss reduction is presented in Fig. 4.10. The figure shows that DR tuning effectively reduces power loss during light load condition alone where NR is not much effective. However, DR tuning is ineffective to reduce power loss for nominal and peak load conditions, but NR marginally reduces the same, as in case study 1.



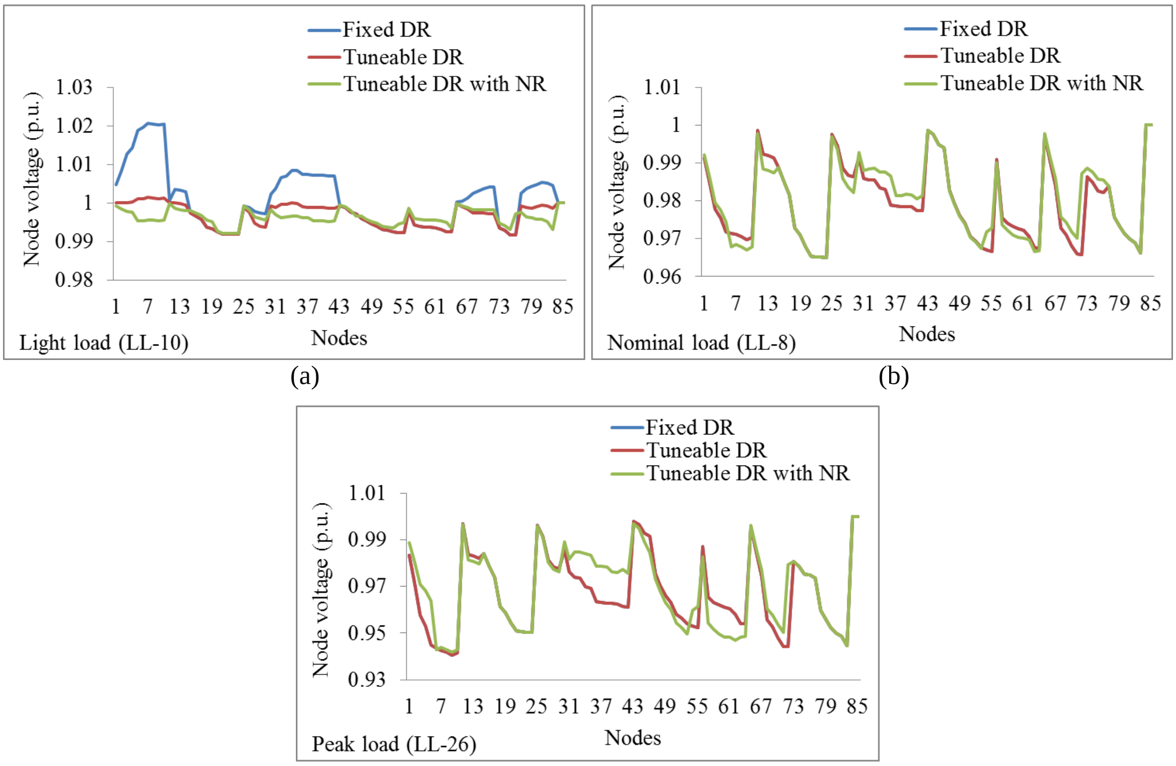
(a) (b)

Fig. 4.7 Effect of DR tuning on (a) node voltage profile enhancement (b) feeder power loss reduction



(a) (b)

Fig. 4.8 Effect of NR on (a) node voltage profile enhancement (b) feeder power loss reduction



(c)

Fig. 4.9 Node voltage profiles for (a) light, (b) nominal and (c) peak load level

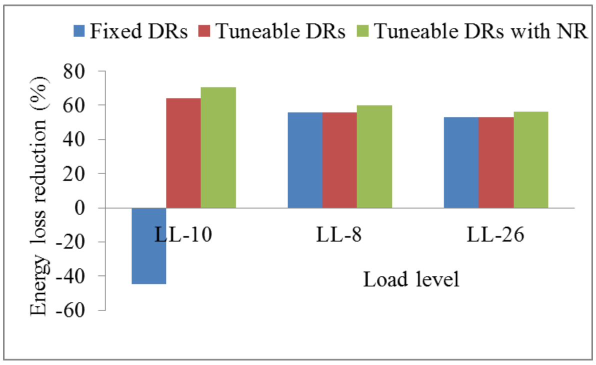


Fig. 4.10 Effect of DR tuning and NR on energy loss reduction for case study 2

From the above discussion it may be inferred that even with adequate placement of DGs and SCs in the distribution systems, the node voltages may shoot to unacceptable level during light load conditions. In such conditions, DR tuning may play an effective role to supress these voltages within acceptable limits. During heavy load conditions the voltage of some of the nodes may drop to unacceptable values. These voltages can be improved by NR. However, both DR tuning and NR have marginal effect on the power loss reduction.

Table 4.6 Comparison of solution quality of proposed techniques

Methods	Best	Worst	Mean	SD	COV	EFB
GA	1087682.31	927991.53	999388.81	32795.13	3.28	8.66
IGA	**1243712.21**	**1167878.14**	**1219097.88**	**15243.07**	**1.25**	**2.33**
PSO	1121970.85	933717.56	1011867.75	44512.76	4.39	10.58
IPSO	**1249611.12**	**1191359.23**	**1226234.22**	**12540.24**	**1.02**	**2.12**
BA	853214.36	485588.26	685988.86	81165.01	11.83	21.79
IBA	**1221678.72**	**1128330.54**	**1166667.77**	**23331.04**	**1.99**	**4.89**
CSO	1018584.57	743502.23	897903.37	52258.32	5.82	12.91
ICSO	**1249948.88**	**1206143.67**	**1237617.83**	**8049.92**	**0.65**	**1.18**
TLBO	1213078.70	1132665.62	1171893.54	22881.40	1.95	3.88
ITLBO	**1250354.72**	**1235351.28**	**1244658.23**	**3817.92**	**0.31**	**0.55**

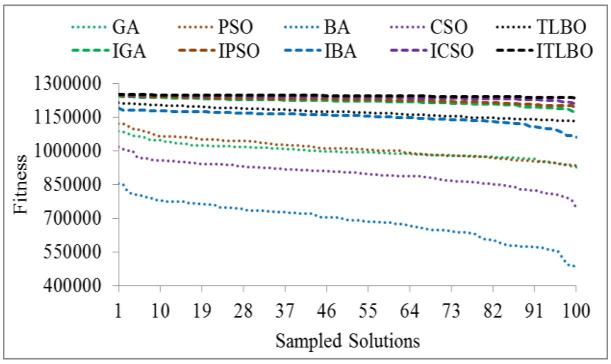


Fig. 4.11 The spread of sampled solutions obtained by GA, PSO, BA, CSO, TLBO, IGA, IPSO, IBA, ICSO and ITLBO

In order to investigate the performance of proposed algorithms for large-scale optimization problem, their solution quality obtained after 100 independent trials is compared with that obtained by applying their respective standard algorithms and the results obtained are presented in Table 4.6. The table reveals that the performance of standard algorithms suffers badly while subjected to large-scale problems, but all proposed algorithms still perform well. However, it is ITLBO which performs well for this large-scale system also. Fig. 4.11 shows the comparison of the spread of 100 sampled solutions generated by these algorithms. It can be clearly seen from the figure that except IBA, all other improved algorithms are capable to generate practically comparable solutions. It can also be observed that IBA has gained maximum improvement by proposed suggestions yet its performance remains inferior to other improved algorithms. The figure shows the reason behind the fact that the performance of BA is inferior than GA, PSO, CSO and TLBO algorithms.

4.4 Discussion

In this chapter, the problem of optimal allocation of DRs is attempted by giving due consideration to load diversity that exists among distribution buses. The strategic location of diverse customers in distribution network does not affect annual load demand of the system, however, it affects the shape of annual load profile, the peak load demand its duration, and also node voltage profiles of distribution feeders. Without these realistic concerns of practical distribution systems, serious errors may involve while dealing with distribution system optimization problems. Several works [74, 173, 182, 198, 211, 214, 219], and many others have reported in literature where the aggregate annual load profile of the system is modelled by three level piecewise linearization without considering this load diversity. In order to understand and appreciate the proposed method, simulations are also carried while considering three stepped piecewise linearized annual load profile with load durations taken same as in the above cited references. The load factors of 0.6, 1.0 and 1.4 are considered to represent light, nominal and the peak load demand of the system. The DR allocation problem is solved for the case study 1 using ITLBO and the best solution obtained may be referred from Table C.12. The comparison of the network performance for optimal solutions obtained with and without considering load diversity is presented in Table 4.7.

Table 4.7 Comparison of results and consequences of not considering load diversity

Network performance index	Not considering load diversity	Considering load diversity
Annual energy loss reduction (%),	92.67	88.71
Optimal DG capacity (kW)	2837	2170
Optimal SC capacity (kVAr)	1800	1200
False indication for annual energy loss saving (%)	114.77	115.68

It can be observed from the table that the percentage annual energy loss reduction is more (92.67%) while load diversity is not considered, but it involves about 150% more DR capacity. However, interesting results are obtained if the solution, without considering load diversity, is being implemented in the distribution network where actually the load diversity exists. The results so obtained show that the annual energy loss reduction is reduced from 92.67% to 71.60%. Thus it provides wrong signal for the actual savings in annual energy losses. The table also shows that with this implementation, the false indication for the annual energy loss saving to be as high as 115% of the actual savings. The detailed calculation for this false indication may be referred from Table C.13. It is noteworthy that this false indication is with about 150% overcapacity of DRs. Thus the ignorance of load diversity among distribution buses may originates serious errors in the planning and operation of distribution systems.

The importance of proposed node voltage penalty function can be discussed while solving DR allocation problem for case study 2 where the lower limit for hard node voltage constraint is kept at 0.9400 p. u. It is noteworthy that the minimum node voltage is being raised from 0.8962 p. u. to 0.9470 p. u. by employing both DR tuning and NR. Therefore, it can be easily understand that without proposed liquidity (soft node voltage constraint) in the voltage penalty function, the meta-heuristic techniques just fail to initialize thus cannot be applied. In fact, this liquidity opens the throttle for many individuals of the meta-heuristics which would otherwise being prohibited from the computational process in lieu of conventional hard node voltage constraint. Once the algorithms are initialized, the potential of these techniques finds new solution points in the problem search space having better fitness values. Thus, the algorithms proceed with so called *infeasible individuals* by imposing little penalty on their fitness values in the view that they would become feasible during the evolutionary process. This hypothesis has been successfully implemented to obtain fruitful results. Another advantage of voltage penalty function is that it divides the whole burden of voltage profile enhancement on DRs and NR. For instance the optimal solution for DR allocation for the case study 2 enhances minimum node voltage from 0.8962 p. u. to 0.9335 p. u. So this solution is selected with a small penalty using proposed method. However, this voltage is further raised to 0.9470 p. u. by NR. Instead, higher DR capacity is required to raise the voltage up to this mark. But, it will be highly capital intensive as DR capacity requirement varies tangentially for every unit rise in system minimum node voltage. This shows the importance of proposed method which considers NR while formulating DR allocation problem.

4.5 SUMMARY

The chapter presents a new method to address the simultaneous allocation problem of DRs in radial distribution systems to maximize annual energy loss reduction and to enhance node voltage profiles. In real distribution systems, definite load diversity exists among distribution buses owing to various types of customers and their seasonal variations in load demand. With these concerns, a more realistic annual load profile of the system is modelled to solve the DR allocation problem so provide more practical solution. The proposed method is applied on the benchmark IEEE 33-bus test distribution system and 83-bus real distribution system and the problem is solved using IGA, IPSO, IBA, ICSO and ITLBO developed in chapter 3. The application results shows that the actual amount of benefits in desired objectives is somewhat reduced while considering more realistic annual load profile. Furthermore, the impact of system operation strategies, viz. DR tuning and NR have been thoroughly investigated. The simulation results reveal that with adequate penetration of DRs, both DR tuning and NR strategies does not seem to be much effective. Alternatively, the system operation with fixed DRs and fixed network topology may be a better choice to avoid complexities in system operation. Finally the impact of load diversity on DR sizing and expected benefits in objectives are also investigated. The results of study through some light on the vitality of considering load diversity among distribution buses while dealing with DR planning and operation of distribution systems.

CHAPTER 5

LONG TERM ALLOCATION OF DISTRIBUTED RESOURCES IN DISTRIBUTION SYSTEMS

The roadmap of future distribution envisions widespread deployment of RESs. The integration of RESs such as SPVs and WTs in distribution systems is gaining momentum. These energy resources seem to be the only option to a sustainable energy supply infrastructure since they are neither exhaustible nor polluting [5]. The renewable energy-based DGs are mostly with intermittent power output and are non-dispatchable. Most of the research work in existing literature assume that DGs are dispatchable and controllable, which is not accurate since renewable energy-based DGs are mostly non-dispatchable power sources with intermittent power output. However, for short term evaluation of performance of DG allocation, DGs may be considered as dispatchable and controllable under the assumption that all RESs are supported by energy storage devices. These storage devices effectively make RES dispatchable. In the previous two chapters also, DGs were assumed to be disptchable as the focus was to evaluate annual performance of distribution systems. However, while formulating a long term DG allocation problem, it is not practical to assume all DG units as dispatchable power sources. For long term DG allocation problem, the intermittent nature of RES needs to be considered. It is not technically feasible to integrate non-dispatchable DGs without the support of dispatchable alternative energy sources (AESs) such as fuel cells, micro turbines (MTs), biomass unit, etc. Thus, feasible DG allocation problem needs to consider a generation mix of different type of DGs (dispatchable and non dispatchable). The placement of DG units also needs the support of reactive power sources. The lack of attention to reactive power injection at the planning stage may lead to potential increase in investment cost and improper allocation of DG units [160]. The DGs, with dispatchable and nondispatchable generations may exhibit several techno-economic benefits to various stakeholders. However, the actual amount of benefits achieved depends whether or not the stochastic nature of load demand is considered. In fact, the load demand of the power system is a major source of uncertainty in power system planning [109]. Therefore, while dealing with intermittency in power generation from RESs, it is imperative to consider the stochastic nature of load demand along distribution buses. With these considerations, the complexity of DR allocation problem increases. This chapter attempts to address the long term DR allocation problem under intermittent nature of RESs and stochastic nature of load demands.

DisCo planners venture to implement new DR planning strategies for their network in order to meet the load growth economically, serve their customers with a reliable electricity supply, and survive in the competitive electricity market [257]. Generally, the main goals of DisCos are the cost minimization and improvement in the performance of distribution system while the DG operator's main aim is to maximize the revenue by selling electricity to customers and the grid [258]. The optimal DG sizing obtained by considering only technical objectives may lead to higher DG investments and may become financial burden to utilities. On the other hand, if the optimal DG sizing has been obtained by considering only economic aspects, it may not fulfill the technical performance requirements for the current and future load demand [219]. Therefore, a suitable methodology is highly desired to handle efficiently techno-economic benefits while dealing with planning and/or operation problems of distribution systems. In the planning model of DG allocation, several parameters such as capital costs, load growth, market prices, fuel price, revenue collection, etc. have to be taken into account. With these concerns, the optimal allocation of DRs in distribution systems becomes a mixed-integer, hard combinatorial optimization problem and requires appropriate deterministic or probabilistic modeling for sizing and power dispatch from these DRs.

In this chapter a new methodology is proposed for the optimal allocation of DRs such as SPV, WT, MT units and shunt capacitors (SCs) while considering uncertainties and variability in load and renewable generations. The uncertainties in load and generation are effectively handled by proposing a deterministic uncertainty set rather than a probability distribution of uncertain data which is very difficult to obtain. The optimum sizing and siting problem of DRs is first solved to maximize net present value (NPV) of the project while considering various cost terms pertaining to capital investment on DRs, their operation and maintenance cost, emission charges and the revenues generated from customers and grid transaction. The optimal tuning of DRs is then evaluated for their day-ahead optimal scheduling by considering several techno-economic objectives. The overall methodology is investigated on the bench mark IEEE 33-bus test distribution system [254] and results of investigations are presented. The impact of network reconfiguration as proposed in chapter 4 has also been investigated.

5.1 MODELLING OF INTERMITTENT POWER GENERATION AND STOCHASTIC LOAD DEMAND

The accuracy of DR planning solution in uncertain environment depends mainly upon the handling of uncertain data of load and generation, the number of system states considered and the modelling of load profile of the system. In order to deal with the uncertainty of load and generation, different methods have been proposed in literature such as Monte Carlo Simulation (MCS) [152, 225], analytical methods [119, 179], probabilistic methods [5, 109, 171, 220], approximate methods [10, 221, 222, 259] and fuzzy set theory [260], etc. However, these methods may exhibit some limitations depending upon the nature of the problem. MCS may be computationally demanding, analytical methods are inaccurate on account of unrealistic mathematical assumptions, probabilistic methods are arduous with dynamically changing system states. Though approximate methods are free from these limitations, but when several load levels are considered, it requires significant computational time which generally makes their use impractical [86], especially with the involvement of large number of input random variables, the number of simulations could be even greater than in the MCS [261]. Moreover, in above mentioned methods the process of modelling uncertainty is based either on the known statistical data or on the known probability distribution function of input variables which is usually very difficult to obtain.

Furthermore, the stochastic nature of wind speed and solar irradiance data requires careful modelling to minimize the prospective errors that would otherwise affect the solution of DR planning. The degree of accuracy also depends upon how many system states being considered for simulation. The planning horizon considered for DR allocation is usually spanning around 20-25 years. Therefore, the selection of total system states should be suitably trade-off between accuracy and computation time incurred by the solution technique. In Ref. [179, 223, 262] total 24 system states have been considered to represent an average day of the year. This simplified modelling however ignores seasonal variations in load and power generation and also load diversity among different distribution buses. So a practical planning solution may not be expected. Therefore, a more accurate modelling is desired by considering adequate number of system states that also taken in to account the diversity in load and generation among system buses.

In this chapter a different approach is adapted to address load and generation uncertainties by generating a more realistic deterministic uncertainty set. This deterministic uncertainty set does not require a probabilistic distribution of uncertain data. Moreover, the load data set also taken into account the load diversity among different type of customers as considered in chapter 4.

5.2 PROPOSED UNCERTAINTY MODEL

Recently, Wang *et al.* [223] introduced polyhedral uncertainty sets to deal with the uncertainty of intermittent generations from RESs and the stochastic load demand. They claimed that these polyhedral uncertainty sets require limited information such as the mean, lower and upper bounds of the uncertain data which are easier to obtain from the historical data or estimated with certain confidence intervals in practice. The authors admitted that the degree of uncertainty has to be adjusted taking into account the trade-off between the robustness and conservativeness of the solution. However, the selection of data spread (DS) and the budget of uncertainty (BOU) is a difficult task. These parameters have been considered constant in [223] while generating synthetic data for load demand or power generation at system buses so it may lead to conservative solution. Moreover, the results may be affected seriously if both DS and BOU considered are either overestimated or underestimated. In fact, this spread must be made self-adaptive with the prevailing conditions of generation/load demand on system buses. Therefore, new polyhedral uncertainty sets are proposed which requires historical data of a year only. The annual information so available on hourly basis is segmented into twelve segments, one for each month. The hourly mean and SD of the monthly data is used to generate proposed polyhedral uncertainty sets. In the proposed modelling, DS and BOU depend upon the mean and SD of the data set. The proposed method is based upon the facts such as the annual data for load, solar insolation and wind speed are available, wind speed and solar insolation remains constant for the particular hour at distribution buses. And, the annual load growth rate, annual inflation rate, wind speed and solar insolation do not increase during the planning horizon.

The polyhedral uncertainty set $W_{y,m,t}^{ldr}$ for the load demand of residential node n at time t month m of the planning horizon Y is proposed as.

$$W_{y,m,t}^{ldr} = \left\{ \chi_{n,y,m,t}^{ldr} \in R^{ldr} : \underline{\omega}_{n,y,m,t}^{ldr} \le \chi_{n,y,m,t}^{ldr} \le \overline{\omega}_{n,y,m,t}^{ldr} \right\};\ \forall n \in N_r,\ \underline{\omega}_{n,y,m,t}^{ldr} = \omega_{n,y,m,t}^{ldr} - k\sigma_{n,y,m,t}^{ldr},\ \overline{\omega}_{n,y,m,t}^{ldr} = \omega_{n,y,m,t}^{ldr} + k\sigma_{n,y,m,t}^{ldr}$$
$$s.t.\ \hat{\omega}_{n,y,m}^{ldr} - k\hat{\sigma}_{n,y,m}^{ldr} \le \hat{\chi}_{n,y,m}^{ldr} \le \hat{\omega}_{n,y,m}^{ldr} + k\hat{\sigma}_{n,y,m}^{ldr} \qquad (1)$$

Where, ω-terms denote available data and χ-terms denote the synthetic data to be generated.

The DS for the load demand of node n at time t for month m of the year y is described by the interval $\left[\underline{\omega}_{n,y,m,t}^{ldr},\ \overline{\omega}_{n,y,m,t}^{ldr} \right]$, say for the residential node.

The uncertain load demand at the node *n* at time *t* for month *m* in year *y* is constrained by the DS $(\omega^{ldr}_{n,y,m,t} \pm k\sigma^{ldr}_{n,y,m,t})$. Where, $\sigma^{ldr}_{n,y,m,t}$ is the SD of the hourly load demand over the month *m* for the residential node *n* at time *t* in the planning year *y*. Higher the load diversity, larger will be the value of $\sigma^{ldr}_{n,y,m,t}$ and vice-versa. Thus DSs at various system buses become self-adaptive. The synthetic load data so generated is further constrained by proposing BOUs. This has been also made self-adaptive by employing mean values of $\omega^{ldr}_{n,y,m,t}$ and $\sigma^{ldr}_{n,y,m,t}$, *i.e.* $\hat{\omega}^{ldr}_{n,y,m}$ and $\hat{\sigma}^{ldr}_{n,y,m}$, respectively. So BOU is suggested as $[\hat{\omega}^{ldr}_{n,y,m} \pm k\hat{\sigma}^{ldr}_{n,y,m}]$. In proposed modelling, DS and BOU are generalized by employing the user defined coefficient *k*. In this work it has been taken as 1.0. Similarly, DSs and BOUs are defined for the industrial and commercial buses and therefore the polyhedral uncertainty sets for the industrial and commercial customers may be defined as

$$\begin{aligned} &W^{ldi}_{y,m,t} = \left\{ \chi^{ldi}_{n,y,m,t} \in R^{ldi} : \underline{\omega}^{ldi}_{n,y,m,t} \le \chi^{ldi}_{n,y,m,t} \le \overline{\omega}^{ldi}_{n,y,m,t} \right\};\ \forall n \in N_i,\ \underline{\omega}^{ldi}_{n,y,m,t} = \omega^{ldi}_{n,y,m,t} - k\sigma^{ldi}_{n,y,m,t},\ \overline{\omega}^{ldi}_{n,y,m,t} = \omega^{ldi}_{n,y,m,t} + k\sigma^{ldi}_{n,y,m,t} \\ &s.t.\ \hat{\omega}^{ldi}_{n,y,m} - k\hat{\sigma}^{ldi}_{n,y,m} \le \hat{\chi}^{ldi}_{n,y,m} \le \hat{\omega}^{ldi}_{n,y,m} + k\hat{\sigma}^{ldi}_{n,y,m} \end{aligned} \tag{2}$$

$$\begin{aligned} &W^{ldc}_{y,m,t} = \left\{ \chi^{ldc}_{n,y,m,t} \in R^{ldc} : \underline{\omega}^{ldc}_{n,y,m,t} \le \chi^{ldc}_{n,y,m,t} \le \overline{\omega}^{ldc}_{n,y,m,t} \right\};\ \forall n \in N_c,\ \underline{\omega}^{ldc}_{n,y,m,t} = \omega^{ldc}_{n,y,m,t} - k\sigma^{ldc}_{n,y,m,t},\ \overline{\omega}^{ldc}_{n,y,m,t} = \omega^{ldc}_{n,y,m,t} + k\sigma^{ldc}_{n,y,m,t} \\ &s.t.\ \hat{\omega}^{ldc}_{n,y,m} - k\hat{\sigma}^{ldc}_{n,y,m} \le \hat{\chi}^{ldc}_{n,y,m} \le \hat{\omega}^{ldc}_{n,y,m} + k\hat{\sigma}^{ldc}_{n,y,m} \end{aligned} \tag{3}$$

In the similar way, the uncertainty sets for power generation from SPV and WT units may also be defined as presented below.

$$\begin{aligned} &W^{SPV}_{y,m,t} = \left\{ \chi^{SPV}_{n,y,m,t} \in R^{SPV} : \underline{\omega}^{SPV}_{n,y,m,t} \le \chi^{SPV}_{n,y,m,t} \le \overline{\omega}^{SPV}_{n,y,m,t} \right\};\ \forall n \in N,\ \underline{\omega}^{SPV}_{n,y,m,t} = \omega^{SPV}_{n,y,m,t} - k\sigma^{SPV}_{n,y,m,t},\ \overline{\omega}^{SPV}_{n,y,m,t} = \omega^{SPV}_{n,y,m,t} + k\sigma^{SPV}_{n,y,m,t} \\ &s.t.\ \hat{\omega}^{SPV}_{n,y,m} - k\hat{\sigma}^{SPV}_{n,y,m} \le \hat{\chi}^{SPV}_{n,y,m} \le \hat{\omega}^{SPV}_{n,y,m} + k\hat{\sigma}^{SPV}_{n,y,m} \end{aligned} \tag{4}$$

$$\begin{aligned} &W^{WT}_{y,m,t} = \left\{ \chi^{WT}_{n,y,m,t} \in R^{WT} : \underline{\omega}^{WT}_{n,y,m,t} \le \chi^{WT}_{n,y,m,t} \le \overline{\omega}^{WT}_{n,y,m,t} \right\};\ \forall n \in N,\ \underline{\omega}^{WT}_{n,y,m,t} = \omega^{WT}_{n,y,m,t} - k\sigma^{WT}_{n,y,m,t},\ \overline{\omega}^{WT}_{n,y,m,t} = \omega^{WT}_{n,y,m,t} + k\sigma^{WT}_{n,y,m,t} \\ &s.t.\ \hat{\omega}^{WT}_{n,y,m} - k\hat{\sigma}^{WT}_{n,y,m} \le \hat{\chi}^{WT}_{n,y,m} \le \hat{\omega}^{WT}_{n,y,m} + k\hat{\sigma}^{WT}_{n,y,m} \end{aligned} \tag{5}$$

The unique feature of the proposed polyhedral uncertainty set is that it automatically considers the diversity in load or generation at different system buses. For the instance, the load diversity factor is smaller for commercial customers whereas it is pretty high for the residential customers. Therefore, DSs and BOUs obtained will be smaller for commercial and relatively larger for the residential customers. Similarly DSs and BOUs will be more for WTs than SPVs. Thus, the proposed method provides less conservative solutions for DR planning and operation. The flow chart for generating synthetic data is shown in Fig. 5.1.

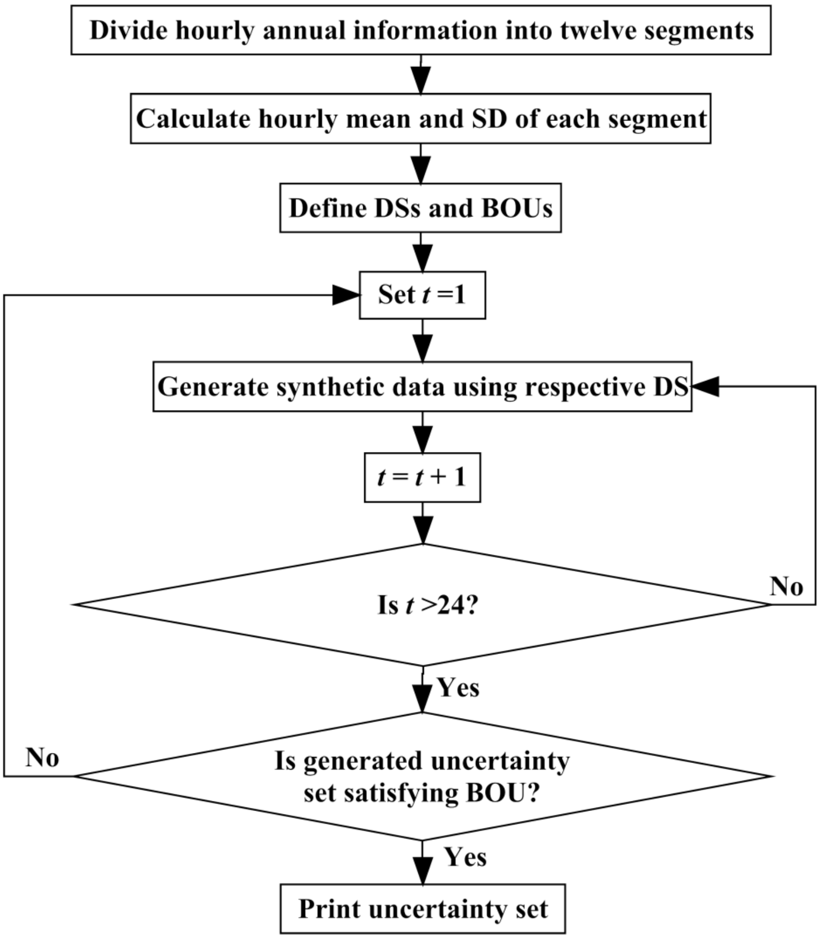


Fig. 5.1 Flow chart for the generation of synthetic data

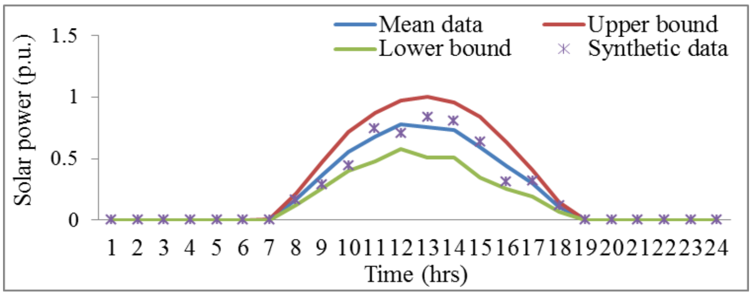


Fig. 5.2 Representation of synthetic data generated for SPV power generation

A sample for the synthetic data generated for the power generation from SPV unit is shown in Fig. 5.2. It can be observed from the figure that DSs are varying hourly on account of their self-adaptive feature; it remains zero whenever there is no generation, remains smaller during morning and evening hours, but becomes wider during the afternoon hours due to more solar insolation. This self-adaptive feature is of great significance while dealing uncertainty in load demand at various system buses as each bus has its own characteristic load pattern due to diversity of load demand among distribution buses. This is usually not the case while dealing with uncertainty of the power generation from RESs, or otherwise, the proposed uncertainty model easily takes care as in case of uncertainty of load demand at system buses.

5.3 PROBLEM FORMULATION

The aim of the long-term DR allocation planning problem is to determine the optimal number, locations, sizes and mix of DGs and SCs to optimize several techno-economic objectives while considering several network operational constraints. The problem is solved over the planning horizon which is decided by the useful life of RESs such as SPVs and WTs, AES like MTs and SCs. Since the distribution system consists of dedicated feeders to cater residential, industrial and commercial loads, the power generation from RESs and stochastic load demand of each system bus is modelled using proposed uncertainty sets. The problem is formulated to maximize the net profit by subtracting the capital investment on DRs and other variable costs relevant to DR operations from the amount of revenue generated by the sale of electricity to customers and the grid over the given planning period. Net present Value (NPV) based approach is used to determine the net profit. Thereafter, DR operation problem is solved to determine the day-ahead optimal scheduling of MTs and SCs with the available power generations from RESs and given load demand. The objective considered is to maximize the hourly net profit, i.e. the difference between the net revenue generated from the sale of electricity to the customers and the grid and the variable charges incurred to operate DRs, while maintaining better node voltage profiles. The DR planning problem is formulated in the following section.

5.3.1 DR PLANNING PROBLEM

For a planning horizon of Y years, the NPV of capital investment cost, variable cost of DRs and the net revenue generated by the sale of energy to the customers and/or grid is evaluated. The objective function is therefore formulated to maximize net profit of DR allocation project in terms of NPVs as defined below:

$$Max.\ O.\ F. = \lambda\left(C_{rev} - C_{inv} - C_{o\&m} - C_{fl} - C_{emi}\right) \tag{6}$$

Where

$$C_{rev} = \sum_{y=1}^{Y}\gamma_y\left(\sum_{m=1}^{M} D_{y,m}\sum_{t=1}^{T}\left(C_y^{sg}\sum_{n=1}^{N} p_{y,m,t,n}^{suplus}H_{y,m,t} - C_y^{bg}\sum_{n=1}^{N} p_{y,m,t,n}^{deficient}H_{y,m,t} + C_y^{sc}\sum_{n=1}^{N} p_{y,m,t,n}^{ldr,ldi,ldc}H_{y,m,t}\right)\right);\ \ \gamma_y = \left[\frac{1}{1+dr}\right]^y \tag{7}$$

The surplus power generated from DGs $p_{y,m,t,n}^{suplus}$ is sold to the grid, whereas the deficiency in generated power $p_{y,m,t,n}^{deficient}$ is purchased from the grid. The net revenue cost is obtained by the summation of this transaction of energy and the energy sold to the customers. γ_y is the present worth factor depends upon the discount rate dr.

$$C_{inv} = \sum_{n=1}^{N}\left(C_{inv}^{SPV}IC_n^{SPV} + C_{inv}^{WT}IC_n^{WT} + C_{inv}^{MT}IC_n^{MT} + C_{inv}^{SC}IC_n^{SC}\right) \tag{8}$$

This is the capital investment cost of DRs which includes different initial costs against purchase, construction, installation, testing, etc.

$$C_{o\&m} = \sum_{y=1}^{Y} \gamma_y \left(\sum_{m=1}^{M} D_{y,m} \sum_{t=1}^{T} \left(MC_y^{SPV} \sum_{n=1}^{N} p_{y,m,t,n}^{SPV} H_{y,m,t}^{SPV} + MC_y^{WT} \sum_{n=1}^{N} p_{y,m,t,n}^{WT} H_{y,m,t}^{WT} + MC_y^{MT} \sum_{n=1}^{N} p_{y,m,t,n}^{MT} H_{y,m,t}^{MT} + MC_y^{SC} \sum_{n=1}^{N} q_{y,m,t,n}^{SC} H_{y,m,t}^{SC} \right) \right) \quad (9)$$

This is the cost incurred in the operation and maintenance of DRs, and the fuel and emission cost incurred in total energy generated by MTs is given by:

$$C_{fl} = \sum_{y=1}^{Y} \gamma_y \left(\sum_{m=1}^{M} D_{y,m} \left(C_y^{fl} \sum_{n=1}^{N} \left(p_{y,m,n}^{MT} H_{y,m}^{MT} \right) \right) \right) \quad (10)$$

$$C_{emi} = \sum_{y=1}^{Y} \gamma_y \left(\sum_{m=1}^{M} D_{y,m} \left(C_y^{emi} \sum_{n=1}^{N} \varepsilon p_{y,m,n}^{MT} H_{y,m}^{MT} \right) \right) \quad (11)$$

And λ is the node voltage penalty function as defined in chapter 4.

Different technical and operational constraints are:

1. Power flow constraints

Non-linear power flow equations (12)-(17) are used for load flow.

$$P_{y,m,n+1} = P_{y,m,n} - P_{y,m,n}^{loss} - p_{y,m,n+1}^{ldr,ldi,ldc} + p_{y,m,n+1}^{SPV} + p_{y,m,n+1}^{WT} + p_{y,m,n+1}^{MT};\ \forall y \in Y, \forall m \in M, \forall n \in N_r, N_i, N_c \quad (12)$$

$$Q_{y,m,n+1} = Q_{y,m,n} - Q_{y,m,n}^{loss} - q_{y,m,n+1}^{ldr,ldi,ldc} + q_{y,m,n+1}^{SC};\ \forall y \in Y, \forall m \in M,, \forall n \in N_r, N_i, N_c \quad (13)$$

$$V_{y,m,n+1}^2 = V_{y,m,n}^2 - 2(R_n P_{y,m,n} + X_n Q_{y,m,n}) + S_{y,m,n}^{loss};\ \forall y \in Y, \forall m \in M, \forall n \in N \quad (14)$$

Where,

$$P_{y,m,n}^{loss} = \left(\sum_{r=1}^{N_r} R_r \frac{P_r^2 + Q_r^2}{|V_r|^2} + \sum_{i=1}^{N_i} R_i \frac{P_i^2 + Q_i^2}{|V_i|^2} + \sum_{c=1}^{N_c} R_c \frac{P_c^2 + Q_c^2}{|V_c|^2} \right) \quad (15)$$

$$Q_{y,m,n}^{loss} = \left(\sum_{r=1}^{N_r} X_r \frac{P_r^2 + Q_r^2}{|V_r|^2} + \sum_{i=1}^{N_i} X_i \frac{P_i^2 + Q_i^2}{|V_i|^2} + \sum_{c=1}^{N_c} X_c \frac{P_c^2 + Q_c^2}{|V_c|^2} \right) \quad (16)$$

$$S_{y,m,n}^{loss} = \left(\sum_{r=1}^{N_r} \left(R_r + jX_r \right) \frac{P_r^2 + Q_r^2}{|V_r|^2} + \sum_{i=1}^{N_i} \left(R_i + jX_i \right) \frac{P_i^2 + Q_i^2}{|V_i|^2} + \sum_{c=1}^{N_c} \left(R_c + jX_c \right) \frac{P_c^2 + Q_c^2}{|V_c|^2} \right) \quad (17)$$

2. Nodal DR capacity constraint

Nodal active/ reactive compensation limits of DRs are kept within pre-specified limits.

$$p_{n,\min}^{SPV,WT,MT} \le p_{y,m,n}^{SPV,WT,MT} \le p_{n,\max}^{SPV,WT,MT};\quad \forall y \in Y, \forall m \in M, \forall n \in N \quad (18)$$

$$q_{n,\min}^{\mathrm{SC}} \le q_{y,m,n}^{\mathrm{SC}} \le q_{n,\max}^{\mathrm{SC}};\quad \forall y \in Y, \forall m \in M, \forall n \in N \quad (19)$$

3. DR penetration limit constraint

The sum of total active and reactive power injected by DGs and SCs at all candidate nodes should be less than nominal active and reactive power demand of the distribution system, respectively.

$$\sum p_{y,m,n}^{SPV,WT,MT} \leq p_D; \quad \forall y \in Y, \forall m \in M, \forall n \in N \tag{20}$$

$$\sum q_{y,m,n}^{SC} \leq q_D; \quad \forall y \in Y, \forall m \in M, \forall n \in N \tag{21}$$

4. Feeder current constraint

Feeder currents should be maintained within specified thermal limits.

$$I_{y,m,n} \leq I_n^{\max}; \quad \forall y \in Y, \forall m \in M, \forall n \in N \tag{22}$$

The individual structure used in DR planning problem is defined as shown in Fig. 5.3.

$$\underbrace{loc_1^{SPV} \ldots loc_{N_{DG}}^{SPV}}_{\text{SPV sites}} \underbrace{p_1^{SPV} \ldots p_{N_{DG}}^{SPV}}_{\text{SPV sizing}} \underbrace{loc_1^{WT} \ldots loc_{N_{DG}}^{WT}}_{\text{WT sites}} \underbrace{p_1^{WT} \ldots p_{N_{DG}}^{WT}}_{\text{WT sizing}} \underbrace{loc_1^{MT} \ldots loc_{N_{DG}}^{MT}}_{\text{MT sites}} \underbrace{p_1^{MT} \ldots p_{N_{DG}}^{MT}}_{\text{MT sizing}} \underbrace{loc_1^{SC} \ldots loc_{N_{SC}}^{SC}}_{\text{SC sites}} \underbrace{q_1^{SC} \ldots q_{N_{SC}}^{SC}}_{\text{SC sizing}}$$

Fig. 5.3 Individual structure for DR planning problem

5.3.2 DR Operation

The solution obtained from DR planning stage provides optimal number, sizing and sites for DR allocation. With this optimal DR installation, the optimal dispatches from MTs and SCs have to be determined while considering each system state, say one hour. Each system state is characterized by certain intermittent power generation from installed RESs and load demand among distribution buses which have been handled using proposed uncertainty sets. Therefore, the objective function is formulated to maximize the net profit of the system state by considering net revenue generated and the variable charges incurred for DR operations. The objective function for DR operation problem is formulated as follows:

$$Max.\ O.\ F. = C_{rev} - C_{o\&m} - C_{fl} - C_{emi} \tag{23}$$

Where, C_{rev}, $C_{o\&m}$, C_{fl} and C_{emi} are the revenue collection from grid and/or customer, operation and maintenance cost, fuel cost and emission cost and are defined as given below.

$$C_{rev} = \sum_{st=1}^{24} \left(C_y^{sg}\, p_{st}^{suplus} - C_y^{bg}\, p_{st}^{deficient} + C_y^{sc}\, p_{st}^{ldr,ldi,ldc} \right) \tag{24}$$

$$C_{o\&m} = \sum_{st=1}^{24} \left(MC_y^{SPV}\, p_{st}^{SPV} + MC_y^{WT}\, p_{st}^{WT} + MC_y^{MT}\, p_{st}^{MT} + MC_y^{SC} q_{st}^{SC} \right) \tag{25}$$

$$C_{fl} = C_y^{fl} \sum_{st=1}^{24} p_{st}^{MT} \tag{26}$$

$$C_{emi} = C_y^{emi} \varepsilon \sum_{st=1}^{24} p_{st}^{MT} \tag{27}$$

Subject to the power flow constraints as defined in DR planning problem. The system node voltages and line currents must be maintained within prescribed limits for each system state *st* which are constrained, as in chapter 4. The maximum nodal compensation limit of MTs and SCs at each state is defined by their installed capacities as obtained from DR planning.

$$0 \le p_{st}^{MT} \le p_{ins}^{MT} \tag{28}$$

$$0 \le p_{st}^{SC} \le p_{ins}^{SC} \tag{29}$$

Here p_{ins}^{MT} and p_{ins}^{SC} are the obtained installed capacities of MTs and SCs. The individual structure used for optimization is defined as shown in Fig. 5.4.

$$\underbrace{p_1^{MT} \ldots p_{N_{DG}}^{MT}}_{\text{MT control setting}} \quad \underbrace{q_1^{SC} \ldots q_{N_{SC}}^{SC}}_{\text{SC control setting}}$$

Fig. 5.4 Individual structure for DR operation problem

5.4 Simulation Results and Discussion

The proposed method is investigated on the benchmark IEEE 33-bus test distribution system [254]. The initial system data for this system may be referred from Table C.1. The division of residential, industrial and commercial nodes can be referred from Table C.3. Various parameters used to calculate the investment and maintenance cost of different DRs, fuel and emission charges of MTs, and the purchase and selling charges of electric energy are shown in Table 5.1. These cost parameters and energy prices shown in the table are for the first year of the planning period. The intermittency in power generation from MT and SCs is ignored for simplicity. The design parameters considered for the distribution system is presented in Table 5.2. In the view of long planning horizon for DR allocation project, the minimum and maximum bounds of node voltages are considered as 0.80 and 1.06 p.u., respectively. The annual rate of increase for these monetary parameters is taken as 6% and remains constant during the planning horizon of 20 years. The annual discount rate is taken as 5%, and the annual growth of the load demand for all categories of customers is assumed to be constant at 3%. The other design parameters related to maximum and minimum DR penetration at single node are also given in the table. The discrete increment size for SPV, WT and MT units is set as 30 kW. It is assumed that SC banks are available in the size of 300 kVAr having tap setting available after discrete interval of 100 kVAr.

The hourly generation data considered for SPVs and WTs may be referred from [263] and [264], respectively. This data is unitized to obtain hourly generation factors which are then used to generate the synthetic data using proposed polyhedral uncertainty sets. Similarly, the polyhedral uncertainty sets are determined for load demand among distribution buses. The synthetic data for load and renewable generations are obtained using Eqns. (1)-(5). While considering load data for the consecutive years, the annual load growth factor is taken into account before generating the synthetic data. The ITLBO developed in chapter 3 is employed to solve both planning and operation problems of DR allocation. The population size and maximum iterations for ITLBO are set to 10 and 200, respectively. The other algorithmic specific parameters of the technique may be referred from Table 3.3 of chapter-3. The proposed algorithm is developed using MATLAB® 7.10 and simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM.

Table 5.1 Parameters for calculating corresponding costs

Parameter	Value	Parameter	Value
C_{inv}^{WT} (\$/kW)	1882	MC_y^{SC} (\$/kVArh)	0.0002
C_{inv}^{SPV} (\$/kW)	2125	C_y^{fl} (\$/kWh)	0.0335
C_{inv}^{MT} (\$/kW)	2293	C_y^{emi} (\$/kg)	0.02
C_{inv}^{SC} (\$/kVAr)	40	C_y^{sg} / C_y^{sc} (\$/kWh)	0.059
MC_y^{WT} (\$/kWh)	0.01	C_y^{bg} (\$/kWh)	0.055
MC_y^{SPV} (\$/kWh)	0.01	ε(kg/ kWh)	0.003
MC_y^{MT} (\$/kWh)	0.012	-	-

Table 5.2 Design Parameters for test distribution system

Parameter	Value	Parameter	Value
dr (%)	5	N_{DG} /N_{SC}	5/5
Y	20	$q_{n,\min}^{SC}$ / $q_{n,\max}^{SC}$ (MVAr)	0/1.2
IR_C (%)	6	$p_{n,\min}^{SPV}$ / $p_{n,\max}^{SPV}$ (MW)	0/7.5
IR_L (%)	3	$p_{n,\min}^{WT}$ / $p_{n,\max}^{WT}$ (MW)	0/6
$V_{\min}$ (p.u.)	0.80	$p_{n,\min}^{MT}$ / $p_{n,\max}^{MT}$ (MW)	0/0.6
$V_{\max}$ (p.u.)	1.06	Q_b/ P_d (kVAr/kW)	300/30

The DR planning problem is solved to determine the optimal installed capacities and siting of DRs. The results so obtained are employed to solve DR operation problem which provides day-ahead scheduling of installed MTs and SCs. Finally, the distribution network is optimally reconfigured for each system state to further enhance the performance of distribution system. The results obtained are presented and analysed in the following sections.

5.4.1 DR PLANNING

The DR planning problem is solved for 20 years to determine the optimal installed capacities and siting of DRs. The best solution obtained after 50 independent trials of ITLBO is presented in Table 5.3. The table shows the optimal sites and sizing of mix-DR model. It can be observed from the table that the optimal installed capacity obtained for SPV, WT, MT and SC units are 7470 kWp, 6000 kWp, 570 kW and 1500 kVAr, respectively. The table also shows that the optimal sites for DGs and SCs are not the same. For this solution, various costs associated with the planning horizon are presented on the basis of NPVs for comparison in Table 5.4. From the table it may be observed that NPV of the project is 8.47 million US$. It is noteworthy that the NPV of the profit without DRs for the same planning horizon is only 0.55 million US$. This shows that proposed DR planning is highly profitable. The NPV of total revenue collection is 49.43 million US$ out of which about 77% revenue is collected from the customers and the remaining 23% is collected from the grid. The table also shows that the capital investment and total variable charges of DRs are about 57% and 25%, respectively of the NPV of total revenue collected.

Table 5.3 Optimal solution of the DR planning problem

SPV		WT		MT		SC	
Node	Capacity (kWp)	Node	Capacity (kWp)	Node	Capacity (kW)	Node	Capacity (kVAr)
2	5670	2	4050	16	330	4	300
29	1800	7	1950	32	240	14	300
-	-	-	-	-	-	30	900

Table 5.4 Various cost items during the planning period (in million US$)

Total revenue from customers	Total revenue from grid	Total revenue	Total variable cost	Capital cost	Net profit
37.86	11.57	49.43	12.43	28.53	8.47

The annual power generation from RESs and MTs are shown in Fig. 5.5. The figure shows that the annual generation from SPVs remains almost constant during the planning horizon, but this is not true for WTs. The mean generation from SPVs, WT and MTs are found to be 15.42, 18.25 and 5.00 million units, respectively. The mean capacity factor for SPVs and WTs are thus obtained as 0.2357 and 0.3472, respectively.

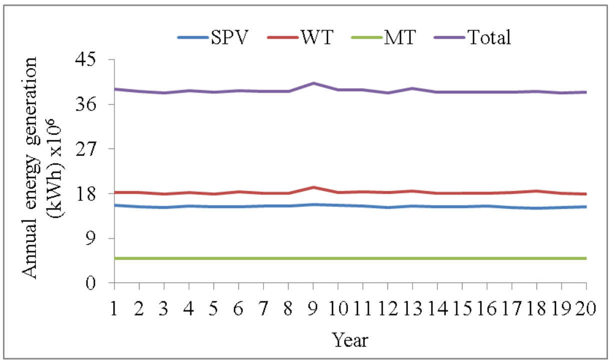


Fig. 5.5 Annual power generations from non-diapatchable and dispachable DGs

The annual energy delivered to customers during the planning period is shown in Fig. 5.6 which increases from 21.54 to 37.96 million units during the planning horizon. This growth in energy demand is about 176% on account of constant load growth model adapted. The annual revenue collected from the customers and the grid is shown in Fig. 5.7. The figure shows that the annual revenue increased from 2.28 to 6.72 million US$, which shows a growth of about 295%. This happens due to the consideration of annual increase in energy charges. The annual variable charges incurred for various DRs are compared in Fig. 5.8. It can be observed from the figure that variable charges are significant for MTs as it involves fuel charges which are much more as compared to the O&M charges of SPVs and WTs. Therefore, total variable charges increases from 0.57 to 1.71 million US$ till the end of planning period.

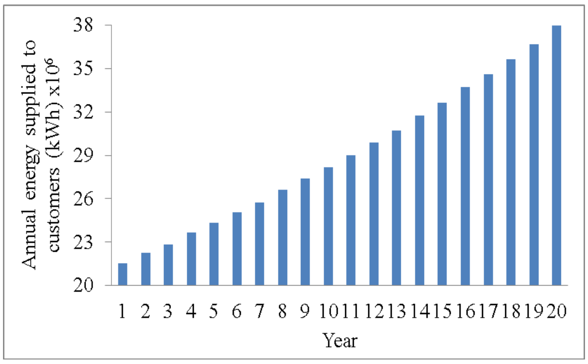


Fig. 5.6 Annual energy supplied to customers

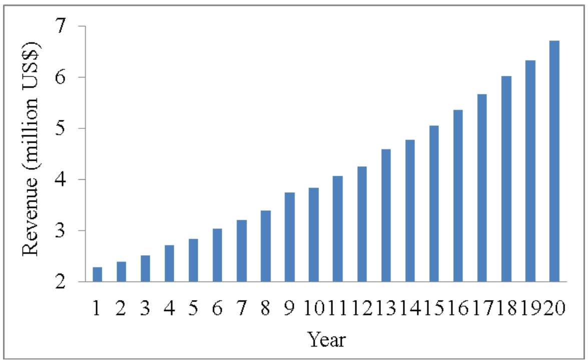


Fig. 5.7 Annual revenue collection from grid and customers

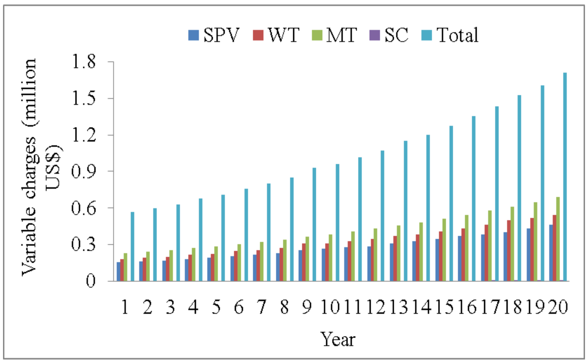


Fig. 5.8 Annual variable charges for DRs

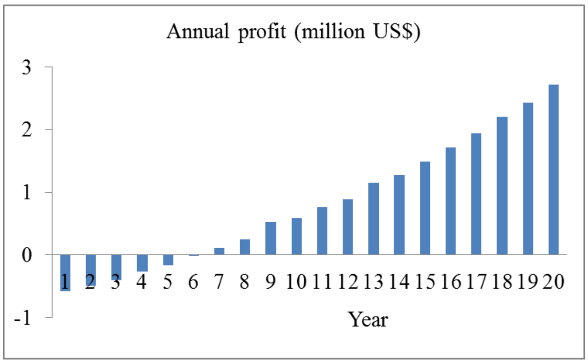


Fig. 5.9 Annual profits of the project

Annual profits in million US$ which could be earned from this DR planning project are presented in Fig. 5.9. The figure shows that the annual profit remains negative for the first 6 years and the project starts earning profit from the seventh year of the planning period. This shows financial viability of the project. The annual energy loss reduction due to DR placement is shown in Fig. 5.10. It can be observed from the figure that significant loss reduction occurs every year. The figure shows that both active and reactive energy loss reduction increases during initial years and touches about 76% at 12th year. Thereafter become more or less constant and finally marginally decrease to about 72%. This shows that the effectiveness of DRs is at its maximum during middle period of planning. The reason behind the fact is that load grows every year, but DR capacity is fixed, so the effectiveness of DRs will be at maximum during middle period of the planning horizon.

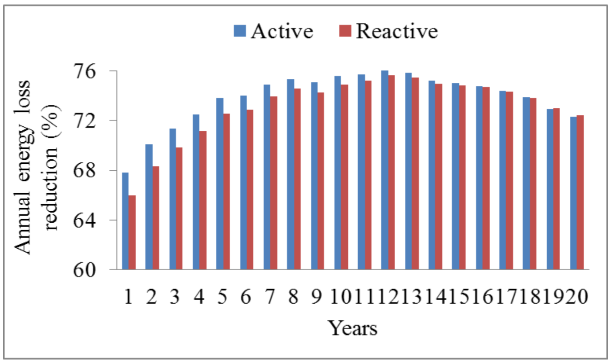
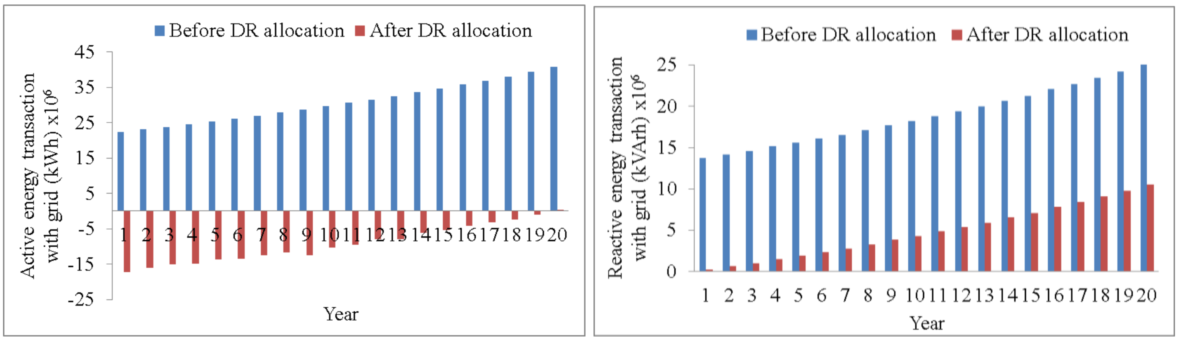


Fig. 5.10 Percentage annual active and reactive energy loss reduction after DR allocation

The comparison of grid transactions for active and reactive energy, before and after DR allocation is presented in Fig. 5.11. The net annual active energy transaction with grid is negative throughout the planning period as shown in Fig. 5.11(a). It implies that net active energy transaction to the grid is positive every year. However, this transaction has a decreasing trend with annual increase in load demand. In the last year, this transaction becomes negative with a small value. However, the same is not true for annual reactive energy transactions as shown in Fig. 5.11(b). The figure shows that every year, the transaction of reactive energy increases in proportional to increase in load demand. In fact, the optimal capacity of SCs is limited by the lightest load conditions prevail during the planning horizon to avoid over voltages. However, a wide difference exists between the minimum and maximum loading of the distribution network while considering long-term DRs planning. Therefore, the optimal capacity obtained for SCs is much less than that of DGs so the solution is demanding more reactive energy from the grid for every progressive year.



(a) (b)

Fig. 5.11 Comparison of annual (a) active and (b) reactive energy transaction with grid before and after DR allocation

It is known that one of the objectives of the optimal DR allocation is peak load shaving. The percentage peak power loss reduction after DR allocation is shown in Fig. 5.12. The figure shows that there is more than 50 % reduction in peak power loss highlighting the importance of peak shaving by DR allocation.

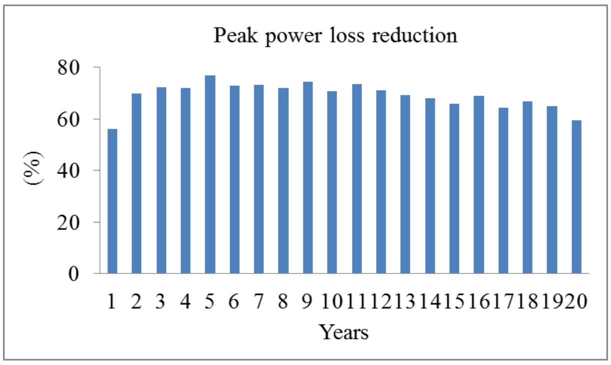


Fig. 5.12 percentage peak power loss reduction

Finally, the impact of DRs on node voltage profiles is shown in Fig. 5.13. The figure reveals that DRs substantially improve minimum node voltage profiles during peak hours and their effectiveness increases as the load demand increases. The minimum node voltage during the whole planning period is found as 0.8834 p.u. However, this voltage is improved by optimal tuning of DRs and NR.

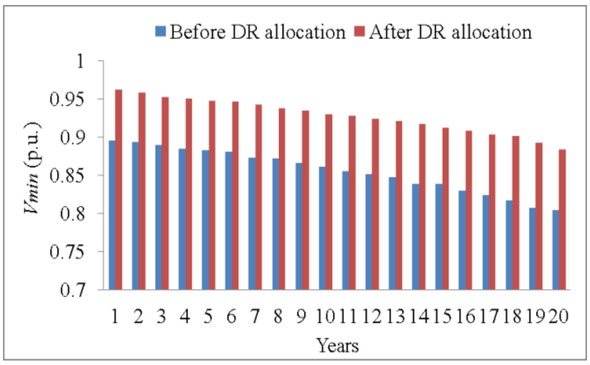


Fig. 5.13 Comparison of annual minimum node voltage before and after DR allocation

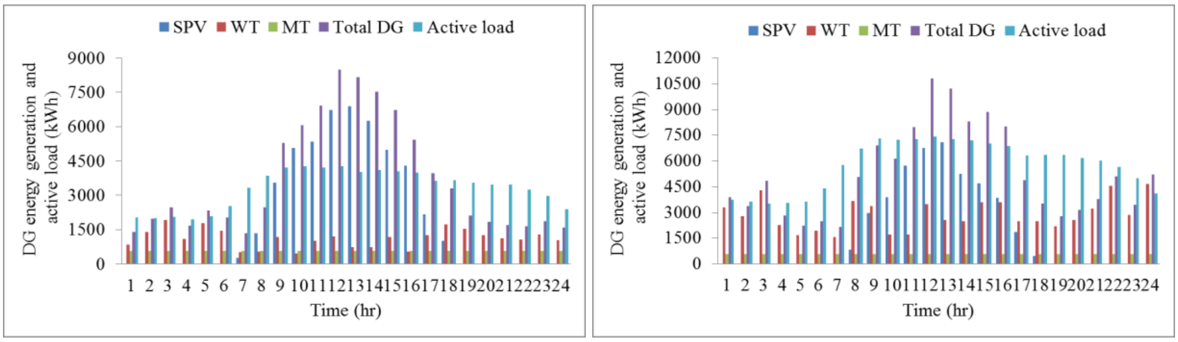
5.4.2 DR OPERATION

After obtaining the optimal solution for long-term planning of DR allocation, the optimal tuning of MTs and SCs are determined for each concerned state of the distribution network. For this purpose the algorithm runs again to determine the day-ahead optimal scheduling of MTs and SCs while considering intermittency and variability in the generation from RESs and load demand. The best solution obtained after 50 independent trials of the algorithm is considered. A sample result obtained for July 1st of the first year and Jan 1st of final year of the planning period are presented in Table D.1 and Table D.2. The tables show the load factors to simulate stochastic load demand of all categories of customers and the energy generation from RESs on hourly basis. These months have been considered as the mean solar insolation is at maximum in the month of July and mean wind speed is at maximum in the month of January. With these load and generations, the economic performance of the system is evaluated for each system state as shown in Table D.3 and Table D.4. These tables show the revenue collected from the grid and customers, net revenue and variable charges incurred to operate DRs for each hour. These variable charges include O&M charges of DRs and fuel charges of MTs. The hourly profit so obtained is also presented in tables. The consolidated economic performance obtained for day-ahead scheduling of DRs for the first and final year is presented in Table 5.5. The table shows that in the first year, the revenue paid to the grid is smaller but negative (energy being exported to the grid) which is due to over generation from DGs. However, fixed charges are very high owing to the very first year of the planning, so net daily profit is negative. But, in the final year of planning the profit is very high despite importing energy from the grid.

Table 5.5 Economic performance of the system for day-ahead scheduling of DRs

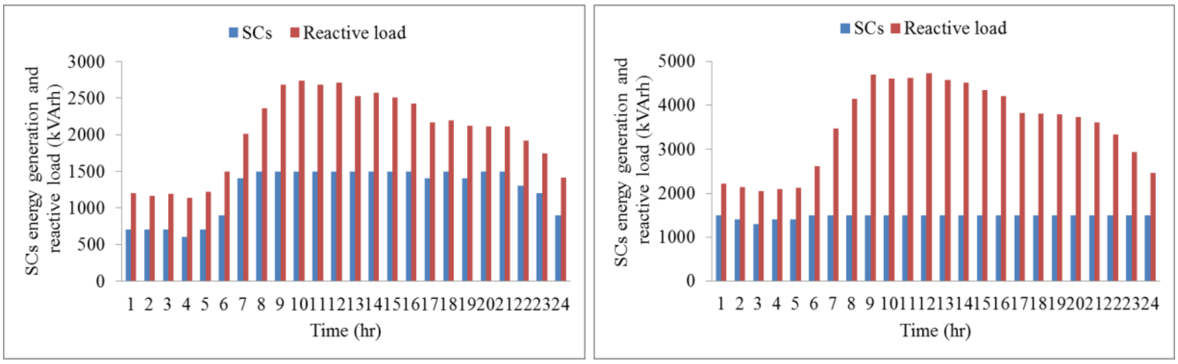
Month,Year	Revenue from customers (US$)	Revenue paid to grid (US$)	Net revenue (US$)	Variable charges (US$)	Fixed charges (US$)	Net profit (US$)
July, First	4677.98	-540.62	5218.59	1374.66	6283.56	–2439.62
Jan, Final	26207.25	2756.81	23450.57	5618.54	6283.56	11548.47

The graphics about the hourly active energy generation from various DGs, total generation from DGs and active energy demand on the system is shown in Fig. 5.14. It can be seen from the figure that power generation from SPVs and WTs is somewhat complementary to each other. This is beneficial as it tends to reduce grid transactions. It is noteworthy that due to intermittent nature of RESs, the power demand may or may not be supplied by DGs alone even when they are capable to meet the peak load demand. This leads to the necessity of energy storage components in distribution systems while integrating with RESs. Fig. 5.15 shows hourly reactive energy generation from SCs and hourly reactive energy demand on the system for the first and last year. It can be seen from the figure that capacitor tuning is required during initial years, but not much required during final years for the reasons discussed in the section 5.5.1.



(a) (b)

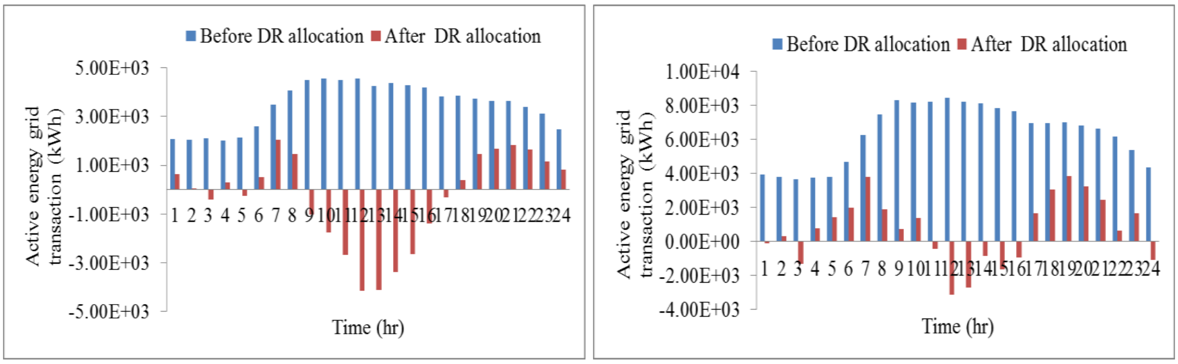
Fig 5.14 Hourly SPV, WT, MT, total generation and active load on the system in (a) first year (b) 20th year



(a) (b)

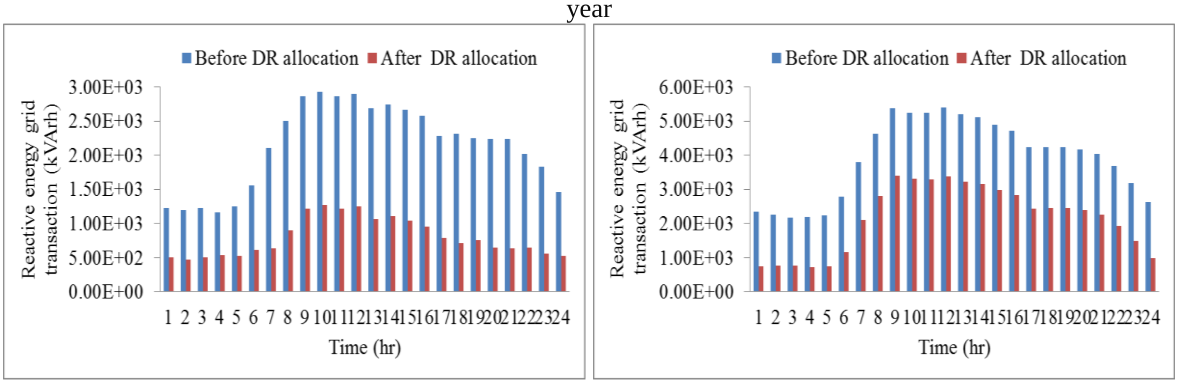
Fig 5.15 Hourly reactive energy generation from SCs and reactive load on the system in (a) first year (b) 20th year

The hourly transactions of active and reactive energy from the grid are shown in Fig. 5.16 and 5.17, respectively. It can be observed that grid transactions are reduced significantly by DR allocation. Moreover, the active power is exported to the grid during afternoon hours. It happens due to surplus power generated from SPVs. However, this transaction decreases for the last year on account of increased load demand. It is found that the grid transaction of active energy is -9.87% of the demand during the day of the first year, i.e. net energy flow is toward the grid. However, during the day of the final year, the grid import is reduced by 89.16% of the active energy demand. On the other hand, the reactive energy import from the grid of these days is reduced by 62.7% and 44.88%, respectively. It is observed that the grid transaction for reactive energy never becomes negative so over voltages cannot develop during the day for this optimal placement of SCs.



(a) (b)

Fig. 5.16 Comparison of active energy grid transaction before and after DR allocation in (a) first year (b) 20th year



(a) (b)

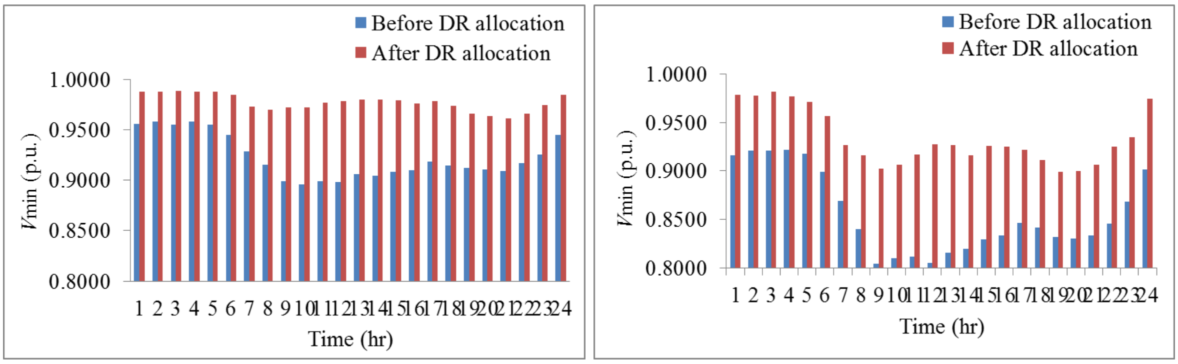
Fig. 5.17 Comparison of reactive energy grid transaction before and after DR allocation in (a) first year (b) 20th year

The Table 5.6 shows energy equations for the day-ahead scheduling of DRs. It can be seen that there is a surplus active energy generation of about 11% from DGs in the first year but the deficiency is only about 9% in the final year. This indicates that an average daily grid transaction remains around 10% of the load demand during the planning horizon. So the solution for DR allocation seems to be good for micro-grid applications. The table also shows higher figures for the deficiency in reactive energy, which is quite obvious. When this deficiency is supplied through the grid, the voltage profiles of the system deteriorate, so need remedial measures.

Table 5.6 Energy equations for day-ahead scheduling of DRs

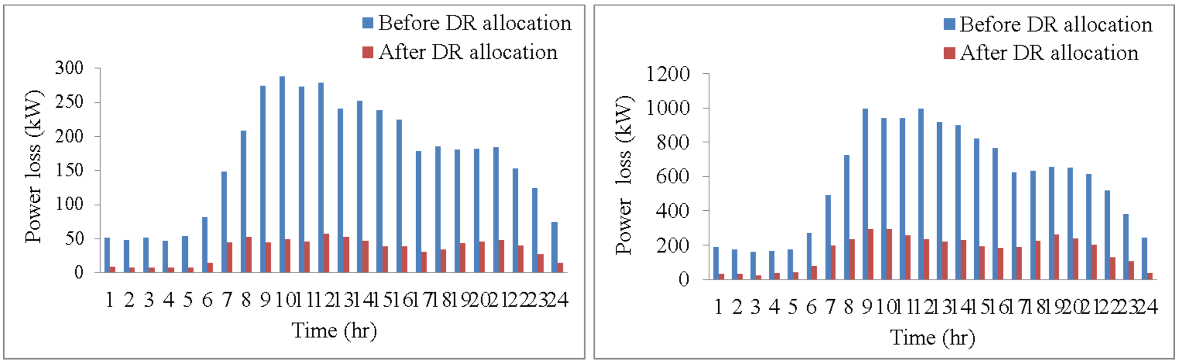
Month, Year	Active energy generation from DGs (kWh)	Active energy demand (kWh)	Active energy deficit (%)	Reactive energy generation from SGs (kVArh)	Reactive energy demand (kVArh)	Reactive energy deficit (%)
July, First	88321	79288	-11.39	29904	48421	38.24
Jan, Final	125985	138516	9.05	35500	84694	58.08

The improvement in node voltage profiles by DR allocation is presented in Fig. 5.18. The figure shows the improvement in minimum node voltage for each state of the day. It can be observed from the figure that significant improvement is achieved by DR allocation which is equally true for the first and final year. All node voltage profiles are satisfactory for the first year as the minimum voltage for peak load is 0.9617 p.u., but it touches 0.90 p.u. in the final year. It happens due to long-term planning for DR allocation as the load has been raised by the factor of 2.67 during the planning horizon. Therefore, remedial measures for shunt compensation or other voltage enhancement strategies may be implemented at regular intervals during the planning period. Furthermore, a significant energy loss reduction can be seen at each state after DR allocation as shown in Fig. 5.19. This can be observed for both first and the final year. This loss reduction is about 80% in the first year which is found to be about 71% in the final year. This shows that the effectiveness of DRs for energy loss reduction is reduced with increased load demand. It probably happen as the optimal DG capacities obtained in the DR planning solution is limited by cost functions. However, the network performance can be further enhanced by optimal NR. Therefore, the impact of NR is investigated after optimally placing DRs as discussed in the following section.



(a) (b)

Fig. 5.18 Comparison of minimum node voltage in (a) first year (b) 20th year



(a) (b)

Fig. 5.19 Comparison of power loss for the (a) first year (b) 20th year

5.4.3 Network Reconfiguration

The distribution network is optimally reconfigured for each state of the distribution system to further enhance its performance. The hourly scheduling of optimal configurations of the distribution network obtained may be referred from Table D.5 which shows optimal network topologies for each system state. The impact of NR on feeder loss occurred during various states of the distribution network for the day of first and final year is presented in Fig. 5.20. Figures show power loss reduction for each system state by DR allocation so the daily energy losses are found to be reduced from 79.81% to 84.48% in day of the first year, while it is reduced from 71.39% to 77.77% in the day of the final year. Thus NR causes further energy loss reduction of 4.67% and 6.38% for first year and final year respectively. It is noteworthy that the loss reduction contributed by NR is more when network loading is more and vice-versa. It happened because NR reallocates load among distribution feeders so reduces feeder power losses. As a result more loss reduction is observed in the corresponding hours of the last year. This implies that stringent load conditions can be effectively handled using NR. Another important aspect of the NR can be seen from Fig. 5.21 showing comparison of minimum node voltage measured for each system state. It can be seen from the figure that the NR is capable to enhance node voltage profiles which have been already significantly improved by optimal DR placement. The NR is able to perform so on account of its inherent tendency of load balancing. This can be verified from the Fig. 5.21 (b) where the node voltage profiles are enhanced to a maximum during peak load hours where the minimum node voltage being enhanced from 0.8988 p. u. to 0.9225 p. u. Thus NR enhances the performance of distribution system during stringent load conditions.

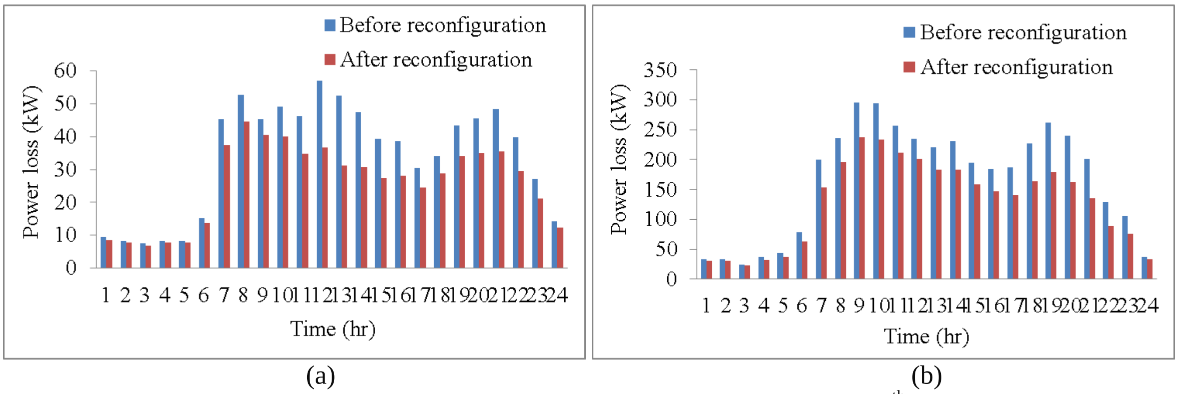


Fig. 5.20 Comparison of power loss for the (a) first year (b) 20th year

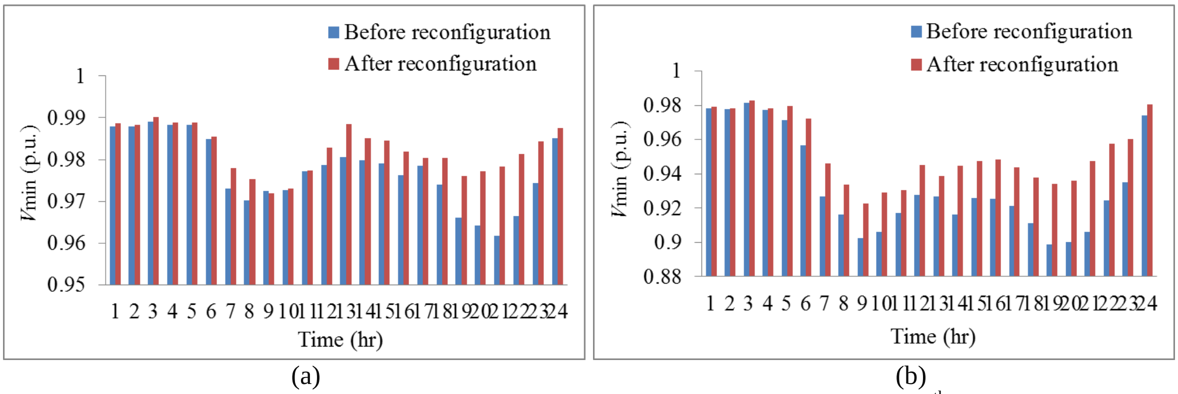


Fig. 5.21 Comparison of minimum node voltage in (a) first year (b) 20th year

Finally, the solution quality obtained after 50 independent trials of ITLBO while solving DR planning problem is presented in Table 5.7. The table shows that proposed ITLBO is also performing well for this hard combinatorial problem as indicated by the small values of COV and EFB. The table shows mean simulation time of about 5 h. This large CPU time is on account of total 24x12x20 system states being considered to optimize the problem. For DR operation problem, the CPU time is reduced by the factor of 240. The spread of all sampled solutions (in the descending order of fitness), is shown in Fig. 5.22. The figure shows that all sampled solutions are close to each other. This pictorially shows the effectiveness and robustness of ITLBO to solve complex optimization problems.

Table 5.7 Solution quality of ITLBO

Best (million US$)	Worst (million US$)	Mean (million US$)	SD (million US$)	COV	EFB	CPU time (h)
8.39	8.27	8.33	0.037	0.44	0.89	5.09

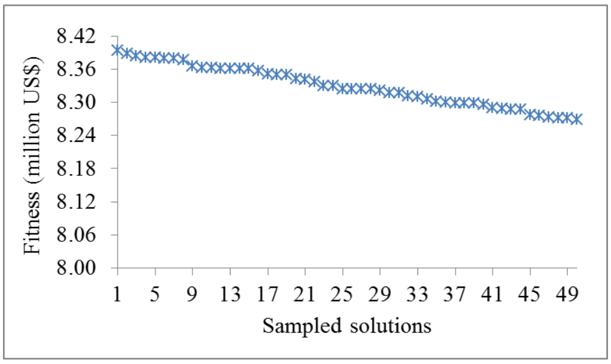


Fig. 5.22 Spread of sampled solutions for ITLBO

5.5 SUMMARY

This chapter proposes a new methodology for the long-term simultaneous allocation of DRs in distribution systems by employing mix-DG model that consists of RESs such as SPVs and WTs along with AES like MTs along with SCs. Since RESs exhibits intermittency in power generation, the stochastic nature of load demand has also been taken into account while formulating DR allocation problem to provide a more realistic planning solution. The uncertainty and variability in load and generation data at various distribution buses is efficiently handled by proposing new polyhedral uncertainty sets which requires only historical data for one year rather than a probability distribution of uncertain data. The self-adaptability of the suggested uncertainty sets is the unique feature of proposed modeling to generate more reliable synthetic data. The modeling is free from assumptions so provides less conservative solution for DR allocation. The ITLBO suggested in chapter 3 is used as an optimizing tool to solve the problem. The long-term DR planning problem is solved to optimize NPV of the project and then the DR operation problem is solved for the day-ahead scheduling of MTs and SCs to optimize daily profit incurred by the utility. The distribution network is then optimally reconfigured for each system state to further enhance the desired technical objectives. The performance of the proposed method is investigated on the benchmark IEEE 33-bus test distribution system. A detailed investigation is carried to inference techno-economic performance of the system. The application results reveal that proposed method effectively reduces the burden on the substation, improves the performance of distribution systems and provides almost self-sustainability in energy generation with optimum investment on DRs.

CHAPTER 6

CONCLUSIONS AND FUTURE RESEARCH SCOPE

The present trends towards deregulation and competitive business environment are forcing electric utilities to improve the efficiency and reliability of electrical power supply and its usage. The distribution system is the most important link between electric utility and end users to achieve efficiency and reliability in electrical power delivery and its usage. Therefore, lots of changes are taking place around the globe in electrical power distribution system. The legacy distribution systems are being converted into smart distribution systems with an emphasis to improve the performance of electrical power distribution systems. The placement of distributed resources (DRs) such as distributed generations (DGs) and shunt capacitors (SCs) is one of the key technology areas to realize the goals of smart distribution systems and to improve the performance of distribution systems. DGs can provide more reliable, secured and self-sustainable operation of distribution systems with lesser carbon footprints, and can deliver quality power to the customers. However, most of the DGs are operated at unity power factor therefore their increased penetration levels demand adequate support of reactive power which can be easily provided by installing SCs in distribution networks. The active and reactive power flow can be independently and effectively regulated by optimally placing and controlling these DRs in distribution systems. However, their placement strategies in distribution network are not independent. In this view, their simultaneous placement strategy may be more beneficial. Similarly, the network reconfiguration (NR) is one of the established operational strategies of modern distribution systems to achieve multiple performance objectives such as power/energy loss minimization, voltage profile enhancement, line congestion management etc. Therefore, the optimal allocation of DRs should also take into account NR. Similarly there are certain other issues with the penetration of renewable energy based DGs such as SPVs and WTs. These DGs are not dispatchable. It is not technically feasible to integrate non-dispatchable DGs without the support of dispatchable alternative energy sources (AESs) such micro turbines (MTs). There are some other important consideration with regards to proper modelling of load and uncertainties related to intermittency in power generation from these DGs. Therefore, there is a need to formulate more realistic DR placement strategies which reflect the ground realities of modern distribution systems otherwise the solutions obtained may be counterproductive.

In the present work, the problems of simultaneous allocation of DRs have been addressed. More practical formulation for DR allocation is developed keeping in view more realistic operational issues of modern distribution systems. The simultaneous allocation problem of DRs is a complex optimization problem. The complexity of the problem is further increased when more realistic operational issues of modern distribution systems are considered. The present thesis work primarily addresses the simultaneous placement of DRs to achieve optimum benefits in terms of annual energy loss reduction and node voltage profile enhancement. The framework of the DR allocation problem is made more realistic in a gradual manner by considering multi-level piecewise linearization of annual load profile, load diversity among distribution buses due to diverse customers and seasonal variations in their load demand, and variability and uncertainty in load demand and local generation from renewable DGs, etc. The problem is developed in a stepwise manner to provide realistic solutions for DR allocation planning and operation. In addition, the impact of load diversity, DR power control and NR, interaction of diverse intermittent DGs and stochastic load demand on the performance of distribution systems have also been thoroughly investigated and presented. The simultaneous DR allocation problem is characterized as a non-linear, mixed-integer, complex combinatorial optimization problem of power systems. Therefore, improved variants of well-established techniques like GA and PSO, and some of recently-established techniques like BA, CSO and TLBO are proposed, which are yet not explored to solve DR allocation problems. The effectiveness of the proposed improved variants of these metaheuristics is investigated on standard test bench as well as real distribution system. The results of study are investigated and presented.

In chapter 3, the simultaneous DR allocation problem is formulated to maximize annual energy loss reduction and to enhance node voltage profiles while considering multi-level piece-wise load profile and assuming DGs to be dispatchable and controllable. The problem is solved by proposing improved variants of existing GA, PSO, BA, CSO and TLBO techniques by suggesting several algorithm specific modifications to cope against their respective intrinsic limitations. In addition to this, an intelligent search algorithm (ISA) is suggested to restrict the problem search space of metaheuristics, so improve their overall performance. The proposed method is applied on the benchmark IEEE 33-bus test distribution system and the application results obtained are presented. The effectiveness of developed algorithms is thoroughly investigated and presented.

Following conclusions are drawn from this chapter.

1. There is a scope of improvement in existing metaheuristic techniques for complex optimization problem of DR allocation. The developed IGA, IPSO, IBA, ICSO and ITLBO perform better than their respective standard models and existing metaheuristics for the optimal DR allocation problem of distribution systems.
2. The modifications suggested for improved algorithms are effectively contributing towards enhancing the convergence, accuracy and efficiency of these algorithms.
3. Proposed ISA disperses tentative solutions near the promising region so virtually reduces the problem search space of metaheuristics. This feature makes the algorithms more efficient.
4. The statistical error analysis reveals that all proposed algorithms are improved to a good degree of accuracy. Although ITLBO performs better than other proposed algorithms, but is more computationally demanding on account of inherent two-phase learning process of TLBO.
5. Despite several improvements, IBA is found to be least among all proposed algorithms in terms of performance. It happens as the standard BA performs quite inferior than other standard algorithms considered.
6. The simultaneous placement strategy of DRs is very effective to improve energy efficiency and voltage profiles of distribution systems.

In Chapter 4, the simultaneous DR allocation problem of distribution systems is extended to more practical operating conditions by considering load diversity that exists among distribution buses owing to various types of customers and their seasonal variation in load demand. The problem is formulated by proposing soft node voltage constraint using penalty function approach to overcome the restrictive use of metaheuristics for real distribution systems facing heavy sag in voltage profiles. In order to obtain a more practical solution, the effectiveness of DR tuning and NR has also been investigated. In addition, the consequences of ignoring load diversity among distribution buses while allocating optimal DRs in distribution network is also examined. The IGA, IPSO, IBA, ICSO and ITLBO developed in chapter 3 are employed as optimization tools to check their effectiveness on large-scale optimization problems. The proposed method is applied on the benchmark IEEE 33-bus test distribution system and 83-bus real distribution system and the application results obtained are investigated and presented.

The following conclusions are drawn from this chapter.

1. The simultaneous placement of DRs and optimal NR provides significant annual energy loss reduction and enhancement in node voltage profiles in distribution systems.
2. For distribution systems having adequate deployment of DGs and SCs, the DR tuning and NR has shown somewhat complementary impact on distribution system performance improvement. The DR tuning provides substantial feeder power loss reduction and suppression of node voltage profile during light load conditions, where the NR is not so effective. On the other hand, NR enhances node voltage profiles with marginal power loss reduction during remaining load conditions, where the DR tuning remains almost ineffective.
3. The load diversity exists among distribution buses on account of the type and location of customers and seasonal variations in their load demand plays crucial role in deciding the optimal solution for DR allocation, the ignorance of the same may involve serious errors to distribution system planning and operation.
4. While optimizing DR allocation problem, the proposed node voltage penalty function plays vital role by employing soft node voltage constraint; on the one hand it provides smooth functioning of stochastic-based meta-heuristic techniques to solve the problem and on the other hand it considers NR while determining optimal allocation of DRs, thus causes reduced optimal sizing of DRs.
5. Developed IGA, IPSO, IBA, ICSO and ITLBO perform better than their respective standard models to solve large-scale DR allocation problems.

In Chapter 5, the simultaneous DR allocation problem of distribution systems is further extended in a more realistic way by considering a mix DG model that consists of SPVs, WTs and MTs. The long-term DR planning and operation problem is formulated by giving due consideration to the variability and intermittency in load demand and power generation among distribution buses. The uncertainty in load demand from diverse customers and power generation from RESs is efficiently handled by proposing new deterministic polyhedral uncertainty sets. The unique feature of these sets is their self-adaptability to cater uncertain data so is free from assumptions. The DR planning problem is first solved to maximize NPV based profit of the project. Thereafter, the DR operation problem is solved to determine the day-ahead optimal scheduling of MTs and SCs for each state of the system separately. With this solution, the distribution network is optimally reconfigured to further enhance the technical objectives. DR planning and operation problems are optimized using ITLBO. The proposed method is applied on the benchmark 33-bus test distribution system and results of study are investigated and presented.

Following conclusions are drawn from this chapter.

1. The proposed long-term DR planning demonstrates the advantages in terms of techno-economic benefits gained by the distribution system. The optimal solution obtained using proposed method reveals that the DR project is highly profitable, yet effectively reduces the burden on the substation, improves energy efficiency and delivers power to customers by maintaining better node voltage profiles.
2. The self-adaptive feature of proposed polyhedral uncertainty sets efficiently deals with the uncertainty and variability in load demand and power generation at distribution buses so provides less conservative solutions for DR planning and operations under uncertain environment of distribution system states.
3. The optimal solution obtained for DR planning provides almost self-sustainability in energy generation so it can be useful for micro-grid applications having adequate energy storage.
4. The power generations from SPVs and WTs supplements each other to some extent which is beneficial to curtail grid transactions.
5. The optimal reconfiguration of distribution network plays distinct role to further enhance the performance of distribution systems, more specifically, during stringent load conditions.
6. Remedial measures for shunt compensation or other voltage enhancement strategies may be implemented at regular intervals during the planning period otherwise voltage profiles may sag heavily at the end of planning period.
7. The solution quality reveals that the ITLBO is also doing well for this highly complex combinatorial optimization problem.

SALIENT CONTRIBUTIONS

Major contributions of the thesis may be summarized as below.

1. Developed the improved version of the following five algorithms to solve large-scale complex optimization problems of DR allocation in distribution systems under diverse operating conditions.
   (a) IGA
   (b) IPSO
   (c) IBA
   (d) ICSO, and

(e) ITLBO

2. Development of ISA which can be embedded with any population based meta-heuristic technique to enhance its performance while solving optimal DR allocation or NR problems of distribution systems.
3. Suggested node voltage penalty function that effectively maintains better node voltage profiles and also facilitates meta-heuristic techniques to solve DR allocation problems in the view of NR.
4. Proposed a new formulation for the long-term DR planning which takes into account mix DG model along with SCs, load diversity and uncertainty of load and generation.
5. Proposed self-adaptive polyhedral uncertainty sets which are capable of handling the uncertainties in load and generations.
6. Investigated the relative effectiveness of the DR tuning and NR on the performance of distribution systems having adequate DRs penetration.

FUTURE RESEARCH SCOPE

The present research work is focused around the net profit maximization for DR planning. However, the problem may be extended with the inclusion of grid transaction minimization as another objective. This may lead to a new solution for DR allocation which will be more suitable for micro-grid applications. In the present work, only type-1 DGs have been assumed which are the sources of active power only. This work can be extended by considering other types of DGs and energy storage devices. In the present methodology, the variability and uncertainty in load demand and power generation at distribution buses are considered whereas it is ignored in fuel and energy pricing, future load growth, discount rate, etc. A better modelling may be worked out by considering uncertainty in these design parameters of the DR allocation project. In future research work the DR operation problem may be formulated to reflect market conditions such as distribution network pricing, demand response, congestion management, peak shaving etc. The tap setting of distribution transformer is an effective way to counter the voltage variation in the presence of DGs. In future research work the effect of optimal tapping of distribution transformer may also be considered for DR allocation problems.

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APPENDIX A

TABLE A.1
LITERATURE SURVEY ON OPTIMAL CAPACITOR PLACEMENT

Ref.	Objectives	Constraints	Methodologies
[32]	1,2,3	1,2	Decomposition techniques and the feasible direction method
[35]	1,2	2,6,7	Local Variations Method
[39]	2,3	1,2	Simulated Annealing
[40]	1,2,3	1,2	Genetic Algorithm
[41]	1,2	2,6	Fuzzy Reasoning Method
[42]	2,3	1,2,6	Tabu Search based Algorithm
[43]	2,3	2,12	Quadratic Integer Programming
[44]	1	1	Numerical Method
[45]	2,3,5	2	Genetic Algorithm
[46]	1,2	2,7	Genetic Algorithm
[47]	2,3	2	Greedy search technique
[48]	2,3,4	1	Fuzzy Expert System
[49]	2,3	1,2,6,12	Immune Algorithm
[50]	2	2,3,6	Branch and Bound, and Genetic Algorithm
[51]	1,2,3	1	Graph Search Algorithm
[52]	1	1,2	Artificial Neural Network
[53]	2,3	1,2,6	Hybrid TS, GA and SA Approach
[54]	2,3	1,2	GA
[55]	2,3	1,2,6	Elite-based Simplex-GA hybrid approach combined with multipop-GA
[56]	1,2,3	2,6,7	GA
[57]	1,2,3	2,6,7	Local Variations and Maximum Sensitivities Selection
[58]	1,2,3	2,6,7	Fuzzy Set Theory
[59]	2,3	1,2,7	Heuristic Search Technique and Simulated Annealing
[60]	2,3,4	1,2,6,7	Particle Swarm Optimization
[61]	2,3,4,5	1	Hybrid Fuzzy-GA method
[9]	2,3	1,2	Microgenetic Algorithms and Fuzzy Logic
[62]	1,2,5	1,2,5	Nondominated Sorting Genetic Algorithm
[63]	1,2,8	1,2,6,7,13	Exhaustive Method
[64]	1,2,5	1,2,3	Improved Evolutionary Programming
[65]	1,2	1,2,4,6	Ant Colony Search Algorithm (ACSA)
[66]	2,3	1,6	Memetic-Algorithm
[67]	2,3,5	-	Fuzzy Evolutionary Programming Algorithm
[68]	2,3,4	1,2,3	Genetic Algorithm
[69]	1,2,5	1,2,4,6	Robust Searching Hybrid Differential Evolution Method
[70]	1,2,3	1,2,6,7	Hybrid Genetic Algorithm and Fuzzy Logic
[71]	1,2	1,8,9	Heuristic Constructive Algorithm
[72]	1,4	1,3,10,11	Mixed-Integer Linear Programming
[73]	1,2,3	1,2,3,6	Conic Programming and Mixed Integer Linear Programming
[74]	2,3,5	1	Fuzzy-GA Method
[75]	1,2,3,6	1,6	Particle Swarm Optimization
[76]	2,3,4	1,2,4,6,9	Combination of Fuzzy, Forward Update, and Genetic Algorithm approaches
[77]	1,2,3	2,9,12	Candidate Node Identification Algorithm and Variational Technique Algorithm
[78]	1,2	1,2,6,7	Hybrid Particle Swarm Optimization
[79]	1,2,5	1,2,6,7,12,13	Micro-Genetic Algorithms and Reduction of the Feasible Region Techniques
[80]	1,2	1,2,3,11	Simulated Annealing
[81]	1,2	1,2,4,6	Plant Growth Simulation Algorithm
[82]	2,3	1,2,6,7	Hybrid Fuzzy Logic and Immune-Based Algorithm
[83]	1,2,3	2,4,9	Bacterial Foraging Optimization
[84]	2,3,5,8	1,2,7	Bacterial Foraging Oriented by Particle Swarm Optimization Algorithm

TABLE A.1 (Continued…)
LITERATURE SURVEY ON OPTIMAL CAPACITOR PLACEMENT

Ref.	Objectives	Constraints	Methodologies
[85]	1,2	1,2,11	Elitist Non-Dominated Sorting Genetic Algorithm (NSGA II) Enhanced with Local Search
[86]	1,2,5	1,2,12,13	Micro-Genetic Algorithm
[38]	2,3	1	Direct Search Algorithm
[87]	2,3	1,2	Particle Swarm Optimization
[88]	1,2,5	1,2,6	Self-Adaptive Modified Honey Bee Mating Optimization
[89]	1,2	1,3,12	Heuristic Search Method
[90]	1,2,3	2	PSO-ACS Algorithm
[91]	1,2	2,12	Hybrid Discrete Particle Swarm Optimization and Genetic Algorithm Approach
[92]	1,5	1,2,3,4,5,12	Cuckoo Search-based Algorithm
[93]	2,3	1,2,3,4,5,12	Differential Evolution and Pattern Search Approach
[94]	1,2,5	1,2,3,4,5,12	Artificial Bee Colony Algorithm
[95]	2,3	2,6,12	Teaching Learning Based Optimization
[96]	1,2	1,2,3,6	CODEQ (Hybrid Chaotic Search, Opposition-based Learning, Differential Evolution (DE) and Quantum Mechanics)
[97]	1,2	1,2	Gravitational Search Algorithm
[98]	2,3	1,2,3,6,9	Bat Algorithm (BA) and Cuckoo Search (CS)
[99]	1	1,2,3	Bacterial Foraging Optimization Algorithm (BFOA)
[100]	2,3	1,2,6	Modified Monkey Search Optimization Technique
[101]	1,2	1,2,4,6	Particle Swarm Optimization

TABLE A.2
LITERATURE SURVEY ON OPTIMAL DG PENETRATION

Ref.	Objectives	Constraints	Methodologies
[114]	1	-	Hereford Ranch Algorithm
[118]	1,12	-	2/3 Rule
[125]	1	7,12,15	Tabu Search (TS)
[126]	1,2,4,11	2,7,16,17	Genetic Algorithm
[119]	1	-	Analytical Method
[127]	1	2,12,15,16	Genetic Algorithm and Tabu Search
[128]	11	1,2,10,14,16,17	Genetic Algorithm
[129]	2,12,13	2,4,16,17	Double Trade-Off Method
[130]	2,3,10,14	1,2,16	Genetic Algorithm and an ε-constrained method
[131]	1	-	Analytical Method
[132]	1,4	2,5,10	Genetic Algorithm
[120]	1	-	Analytical Method
[112]	1	1,2,3	Genetic Algorithm
[133]	1,8	2,16	Hybrid GA and Optimal Power Flow
[134]	1,3	2,7,17	Particle Swarm Optimization
[4]	1,10,12	-	Continuation Power Flow
[135]	3	15	Ant Colony System Algorithm
[136]	1,2,15	2,16	Non-dominated Sorting Genetic Algorithm
[137]	2,4	2,16	Non-dominated Sorting Genetic Algorithm and Max-Min Method
[138]	1	-	Analytical Method
[111]	1,11	1,2,7,16	Ordinal Optimisation Method
[139]	1,10,12	1,2,16	Genetic Algorithm
[140]	1	-	Kalman Filter Algorithm
[106]	8	1,2,16	AC Optimal Power Flow
[123]	1	-	Analytical Expressions
[141]	1,3,4	2,15,16	Discrete Particle Swarm Optimization and Genetic Algorithm
[5]	2	1,2,10,13,16	Mixed Integer Nonlinear Programming
[142]	1,12	2,16	Artificial Bee Colony Algorithm
[143]	1	2,7,14,16	Voltage Index Analysis and Variational Algorithm
[144]	17	1,2,3,16	Genetic Algorithm
[145]	1,12	1,2	Particle Swarm Optimization
[146]	1	2,12,15,16	Imperialist Competitive algorithm
[147]	1,10	1,7,14	Bee Colony Optimization Algorithm
[148]	1,8	2,16	Non-dominated Sorting Genetic Algorithm and Max-Min Method
[149]	1,4,12,15	2,7,16	Dynamic Programming
[150]	1,10,12,15	2,3,16	Particle Swarm Optimization
[151]	1	1,2,9,15,16	Artificial Bee Colony
[152]	1,4,8	1,2,7,10,16	Monte Carlo Simulation-Embedded Genetic-Algorithm-based approach
[153]	1,12	2,3	Fuzzy and Clonal Selection Algorithm
[154]	1,3,12,14,15	1,2,3	Genetic Algorithm
[155]	2,4,7,9	1,2	Genetic Algorithm
[156]	1,4,12	1,2,7	Group Search Optimizer
[157]	1,4,17	2,7,16	Genetic Algorithm
[158]	1,4	2,7,10,16	Discrete Particle Swarm Optimization and Optimal Power Flow
[159]	1,4,10	1,2,6,10,11,15,16	Optimal Power Flow and Genetic Algorithm
[160]	4,14	2,7,9,10,15,16	TRIBE Particle Swarm Optimization and Ordinal Optimization

TABLE A.2 (Continued…)
LITERATURE SURVEY ON OPTIMAL DG PENETRATION

Ref.	Objectives	Constraints	Methodologies
[161]	1,6	1,2,7,9,15,16	Imperialist Competition Algorithm
[162]	1,5,12	1,2,7,16	Combined Fuzzy-genetic Algorithm/ Particle Swarm Optimization
[163]	1	1,2,16	Loss Sensitivity Factors and Simulated Annealing
[164]	1,5,12	2,7,15	Particle Swarm Optimization
[165]	1	2,15,16	Differential Evolution
[166]	1	2,15,16	Artificial Bee Colony Algorithm
[167]	1	1,3,7	Multi-Membered Non-Recombinative Evolution Strategy, Bare Bones Particle Swarm Optimization and Differential Evolution
[168]	1,15	1,2,15,16	Evolutionary Particle Swarm Optimization method
[169]	1,5	15	Particle Swarm Optimization
[170]	12,13	2,4,5,16	Evolutionary Programming
[171]	2	1,2,7,15,16	Evolutionary Programming
[103]	1,12	1,2,7	Cuckoo Search
[172]	1,4,14,15	2,16	Hybrid Improved Particle Swarm Optimization Algorithm and Monte Carlo Simulation
[173]	2	1,2,3,7,14	Heuristic Algorithm
[174]	1,12	2,7	Improved Multi-Objective Harmony Search Algorithm
[175]	1	-	Modified Teaching–Learning Based Optimization Algorithm
[176]	11	1,2,4,8	Particle Swarm Optimization
[177] 2	1	1,2,16,18	Particle Swarm Optimization
[178]	1,5	-	Modal Analysis and Continuous Power Flow
[179]	1	2,10,15	Analytical method
[180]	1,5	1,2	Particle Swarm Optimization
[181]	5	2,3,4,10,16	Mixed-Integer Nonlinear Programming
[182]	1	2,3	Harmony Search Algorithm
[183]	2,3,10	1,2,10,13,15	Monte Carlo methods
[184]	3	1, 2, 14, 15, 20	Tabu Search Algorithm
[185]	1, 4, 12	1, 2, 15,20	Bacterial Foraging Optimization Algorithm
[186]	2, 4, 5, 9, ,12	1, 2, 7, 14	Cloud Theory Adapted GA
[187]	1, 4, 18	1, 2, 20	Particle Swarm Optimization
[188]	1	1	Analytical Approach
[189]	1, 5, 12	1,2,7,15	Chaotic Artificial Bee Colony
[190]	1, 4, 5, 18	1, 2, 20	Hybrid Ant Colony Optimization and Artificial Bee Colony Algorithm
[191]	1, 12	1, 2, 14, 15, 16, 20	Backtracking Search Optimization Algorithm

APPENDIX B

TABLE B.1
BRIEF DATA OF IEEE 33-BUS TEST DISTRIBUTION SYSTEM

Particular	Value
Line voltage (kV)	12.66
p_D (kW)	3715
q_D (kVAr)	2300
I_n^{max} (N_b)	400(1,2), 250(3-5, 18-20, 22-29), 150(6-17, 21, 30-37)
Sectionalizing switches	1-32
Tie-switches	33-37
Base configuration with open switches	33 to 37
Power Loss (kW)	47.07/202.50/575.39
Minimum node voltage (p.u.)	0.9583/0.9131/0.8528

TABLE B.2
OPTIMAL SOLUTION AND OPTIMAL TUNING OF DRS

Method	Optimal tuning					
	Light		Nominal		Peak	
	Nodes (DG in kW)	Nodes (SC in kVAr)	Nodes (DG in kW)	Nodes (SC in kVAr)	Nodes (DG in kW)	Nodes (SC in kVAr)
GA	14(404), 25(445), 32(459) TD: 1308	14(200), 24(300), 30(500) TD: 1000	14(801), 25 (880), 32(912) TD: 2593	14(400), 24(300), 30(900) TD: 1600	14(898), 25(944), 32(934) TD: 2776	14(600), 24(300), 30(900) TD: 1800
PSO	15(355), 25(428), 30(546) TD: 1329	17(100), 24(300), 30(500) TD: 900	15(721), 25(839), 30 (1091) TD: 2651	17(300), 24(600), 30(900) TD: 1800	15(780), 25(839), 30 (1255) TD: 2874	17(300), 24(600), 30(900) TD: 1800
BA	3(803), 14(353), 29(523) TD: 1679	10(200), 16(100), 32(400) TD: 700	3(1381), 14(717), 29(1076) TD: 3174	10(300), 16(200), 32(900) TD: 1400	3(1381), 14(857), 29(1188) TD: 3426	10(300), 16(300), 32(900) TD: 1500
CSO	15(366), 24(560), 31(466) TD: 1392	11(100), 16(100), 30(500) TD: 700	15(728), 24(1112), 31(963) TD: 2803	11(300), 16(200), 30(1000) TD: 1500	15(747), 24(1150), 31(1016) TD: 2913	11(300), 16(300), 30(1200) TD: 1800
TLBO	15(360), 24(544), 30(521) TD: 1425	12(200), 24(300), 30(500) TD: 1000	15(724), 24(860), 30(1085) TD: 2669	12(500), 24(500), 30(900) TD: 1900	15(815), 24(860), 30(1157) TD: 2832	12(600), 24(600), 30(900) TD: 2100
IGA/IPSO/IBA /ICSO/ITLBO	14(368), 24(520), 30(524) TD: 1412	14(200), 24(300), 30(500) TD: 1000	14(748), 24(1003), 30(1057) TD: 2808	14(300), 24(500), 30(1000) TD: 1800	14(831), 24(1005), 30(1128) TD: 2964	14(300), 24(600), 30(1200) TD: 2100

TD: Total Dispatch

APPENDIX C

TABLE C.1
INITIAL DATA OF TEST SYSTEMS

Particular	Case study 1	Case study 2
Line Voltage (kV)	12.66	11.40
p_D (kW)	3715	28350
q_D (kVAr)	2300	20700
Sectionalizing switches	1-32	1-83
Tie-switches	33-37	84-96
Base Configuration	33 to 37	84 to 96
Power loss at peak load (kW)	423.59	1083.19
Minimum node voltage at peak load (p.u.)	0.8740	0.8962

TABLE C.2
LOAD FACTORS AND LOAD DURATION FOR DIFFERENT SEASONS

S	*L*	R	I	C	H_j	S	*L*	R	I	C	H_j
Spring/fall	1	0.40	0.80	0.40	7	Winter	15	0.48	0.48	0.48	1
	2	0.40	1.00	0.40	1		16	0.48	0.60	0.60	1
	3	0.60	1.00	0.40	3		17	0.60	0.60	0.60	2
	4	0.60	1.00	0.60	3		18	0.60	0.48	0.24	1
	5	0.80	1.00	0.80	5	Summer	19	0.56	1.12	0.56	7
	6	0.80	0.80	0.80	1		20	0.56	1.40	0.56	1
	7	0.80	1.00	1.00	1		21	0.84	1.40	0.56	3
	8	1.00	1.00	1.00	2		22	0.84	1.40	0.84	3
	9	1.00	0.80	0.40	1		23	1.12	1.40	1.12	5
Winter	10	0.24	0.48	0.24	7		24	1.12	1.12	1.12	1
	11	0.24	0.60	0.24	1		25	1.12	1.40	1.40	1
	12	0.36	0.60	0.24	3		26	1.40	1.40	1.40	2
	13	0.36	0.60	0.36	3		27	1.40	1.12	0.56	1
	14	0.48	0.60	0.48	5		-	-	-	-	-

L: Load level, H_j: Load duration (hrs), R, I, C : Load factor for Residential, Industrial and Commercial customer in p.u.

TABLE C.3
SYSTEM DESIGN PARAMETERS

Parameters	Case study 1	Case study 2
Q_b/ P_d (kVAr/kW)	300/1	300/100
$\Delta q/\Delta p$ (kVAr/kW)	100/1	100/1
$q_{n,\min}^{\mathrm{SC}} / q_{n,\max}^{\mathrm{SC}}$ (MVAr)	0/1.2	0/6.6
$p_{n,\min}^{DG} / p_{n,\max}^{DG}$ (MW)	0/2	0/9
$V_{\mathrm{minS}}/ V_{\min}/ V_{\max}$ (p.u.)	0.90/0.94/1.06	0.90/0.94/1.06
$loc^{\mathrm{SC}} / loc^{\mathrm{DG}}$	1-33	1-83
N_s	3	3
N_L	27	27
N_{DG} /N_{SC}	5/5	8/8
D_s (spring/winter/summer)	121/122/122	121/122/122
$I_n^{\max}(n)$	400(1,2), 250(3-5, 18-20, 22-29), 150(6-17, 21, 30-37)	500(1-6, 11, 12, 15-19, 25-28, 30, 31, 43-45, 47-52, 56-58, 65-71, 73-75, 77-79), 250(7-10, 13-14, 20-24, 29,32-42, 46, 53-55, 59-64, 72, 76, 80-96)
Residential Feeders	2-15	15-24, 30-42, 47-55, 56-64
Industrial Feeders	23-29	11-14, 25-29, 43-46, 73-76
Commercial Feeders	16-22, 30-33	1-10, 65-72, 77-83

TABLE C.4
NPL AND BPLS OBTAINED USING PROPOSED ISA

Priority Lists		Case study 1	Case study 2
NPL	SCs	30, 24, 25, 7, 29, 32, 15, 8, 4, 23…	31, 71, 79, 28, 19, 75, 12, 6, 45, 51…
	DGs	25, 24, 7, 32, 30, 29, 31, 14, 8, 23…	71, 79, 28, 31, 19, 12, 75, 6, 34, 51…
BPLs		7, 33, 6, 20, 19, …/10, 11, 9, 8, 35, …/10, 11, 9, 14, 13, …/28, 37, 27, 26, 25, …/32, 36, 17, 7, 16, …	84, 55, 54, 5,…,/86/7, 72, 87, 85,…/84, 63, 55, 64,…/63, 64, 62, 61,…/88, 13, 76, 72,…/89, 14, 16, 12,…/92, 32, 28, 27,…/90, 26, 16/ 42, 95, 39, 40,…/33, 34, 32, 94,…/33, 39, 38, 37,…/89, 82, 83, 88,…

TABLE C.5
ALGORITHM SPECIFIC CONTROL PARAMETERS SELECTED FOR PROPOSED TECHNIQUES

Parameters	IGA	IPSO	IBA	ICSO	ITLBO
t_s	-	10	-	-	-
Crossover rate	0.9	-		-	0.2
Crossover type	Two-point Crossover	-	-	-	One-point Crossover
Mutation rate	0.05	-		-	-
C	-	-		1.5	-
c_1, c_2	-	2, 2		1.6, 0.4	-
$w_{\min}$, $w_{\max}$	-	0.1,0.9		0.05, 0.45	-
$f_{\min}/\ f_{\max}$	-	-	0/ 2	-	-
A	-	-	0.98	-	-
M_c	-	-	5	-	-
F	-	-	0.6	-	-
M	-	-	–2/2	-	-
SMP,*CDC*,*SRD*,*MR*	-	-	-	5, 0.6, 2, 0.04	-
mc	-	-	-	-	5

TABLE C.6
COMMON CONTROL PARAMETERS SELECTED FOR PROPOSED TECHNIQUES FOR CASE STUDY 1

Parameters	IGA	IPSO	IBA	ICSO	ITLBO
Population size	50	50	10	10	10
$itr_{\max}$	100	100	200	200	200

TABLE C.7
NETWORK PERFORMANCE WITH FIXED AND TUNEABLE DRS FOR CASE STUDY 1

Load level	Base case		Fixed DRs		Tuneable DRs			
	Ploss	$V_{\min}$	Ploss	$V_{\min}$	Node (DG in kW)	Node (SC in kVAr)	Ploss	$V_{\min}$
1	46.45	0.9626	9.57	0.998	14(307), 24(794), 30(500)	12(200), 25(300), 30(400)	2.97	0.9966
2	57.19	0.9598	8.31	0.9978	14(314), 24(960), 30(546)	12(200), 25(300), 30(500)	3.79	0.9968
3	71.44	0.9527	6.72	0.9973	14(424), 24(960), 30(585)	12(200), 25(300), 30(500)	5.14	0.9946
4	93.11	0.9454	5.97	0.9958	14(462), 24(960), 30(711)	12(300), 25(300), 30(600)	5.92	0.9951
5	141.20	0.9295	12.78	0.9833	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	12.78	0.9833
6	125.76	0.9316	10.41	0.9852	14(494), 24(931), 30(719)	12(300), 25(300), 30(600)	10.40	0.9851
7	175.25	0.9209	21.20	0.9747	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	21.20	0.9747
8	202.53	0.9131	29.41	0.9685	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	29.41	0.9685
9	94.12	0.9383	8.61	0.9911	14(494), 24(905), 30(680)	12(300), 25(300), 30(500)	8.37	0.9895

TABLE C.7 (Continued…)
NETWORK PERFORMANCE WITH FIXED AND TUNEABLE DRS FOR CASE STUDY 1

Load level	Base case		Fixed DRs		Tuneable DRs			
	Ploss	Vmin	Ploss	Vmin	Node (DG in kW)	Node (SC in kVAr)	Ploss	Vmin
10	16.33	0.9779	25.92	0.9994	14(187), 24(481), 30(298)	12(100), 25(200), 30(300)	1.09	0.9983
11	20.08	0.9762	22.91	0.9993	14(195), 24(585), 30(318)	12(100), 25(200), 30(300)	1.33	0.9979
12	24.99	0.9721	19.09	0.9992	14(250), 24(601), 30(352)	12(100), 25(200), 30(300)	1.85	0.9965
13	32.36	0.9679	14.38	0.9984	14(275), 24(607), 30(418)	12(200), 25(200), 30(400)	2.14	0.9977
14	48.52	0.9588	8.83	0.9975	14(360), 24(606), 30(526)	12(200), 25(200), 30(500)	3.05	0.9962
15	43.26	0.96	10.65	0.9976	14(359), 24(512), 30(496)	12(200), 25(200), 30(500)	2.73	0.9966
16	59.74	0.954	7.04	0.9968	14(387), 24(625), 30(596)	12(200), 25(200), 30(600)	3.55	0.9954
17	68.73	0.9495	6.36	0.9967	14(452), 24(643), 30(623)	12(300), 25(200), 30(600)	4.35	0.9962
18	32.67	0.9637	15.71	0.9991	14(364), 24(527), 30(390)	12(200), 25(200), 30(300)	2.74	0.9956
19	93.30	0.947	6.50	0.9945	14(438), 24(960), 30(719)	12(300), 25(300), 30(600)	6.36	0.9943
20	115.05	0.9429	10.31	0.9892	14(486), 24(960), 30(716)	12(300), 25(300), 30(600)	10.32	0.9891
21	144.29	0.9326	15.30	0.986	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	15.30	0.986
22	189.44	0.9219	25.23	0.9761	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	25.23	0.9761
23	291.03	0.8985	60.17	0.9554	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	60.17	0.9554
24	258.88	0.9017	48.50	0.9583	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	48.50	0.9583
25	364.61	0.8856	90.59	0.943	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	90.60	0.943
26	423.59	0.8740	117.40	0.9335	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	117.41	0.9335
27	191.73	0.9116	29.66	0.9669	14(494), 24(960), 30(719)	12(300), 25(300), 30(600)	29.66	0.9669

TABLE C.8
NETWORK PERFORMANCE FOR FIXED AND TUNEABLE DRS WITH NR FOR CASE STUDY 1

Season	Load Level	Fixed DRs with NR				Tuneable DRs with NR			
		Optimal configuration	A	B	C	Optimal configuration	A	B	C
Season-1	1	3, 6, 9, 17, 33	6.09	0.9981	86.88	7, 8, 9, 25, 36	2.91	0.9960	93.73
	2	6, 9, 17, 25, 33	4.93	0.998	91.38	7, 8, 9, 26, 36	3.61	0.9961	93.68
	3	7, 9, 17, 25, 33	5.10	0.9961	92.86	7, 9, 21, 25, 36	4.69	0.9945	93.43
	4	7, 21, 25, 34, 36	5.81	0.9943	93.76	7, 8, 9, 25, 36	5.84	0.9942	93.72
	5	7, 8, 9, 26, 35	11.31	0.9888	91.99	7, 8, 9, 26, 35	11.31	0.9888	91.99
	6	7, 8, 9, 25, 35	9.26	0.9894	92.63	7, 8, 9, 25, 35	9.26	0.9894	92.64
	7	7, 9, 27, 34, 35	17.06	0.9834	90.27	7, 9, 27, 34, 35	17.06	0.9834	90.27
	8	7, 8, 9, 17, 28	22.45	0.9793	88.91	7, 8, 9, 17, 28	22.45	0.9793	88.91
	9	7, 8, 9, 15, 37	7.61	0.9912	91.91	7, 8, 9, 15, 37	7.28	0.9911	92.27
Season-2	10	3, 7, 11, 16, 33	18.43	1	-12.83	7, 9, 17, 21, 37	1.05	0.9983	93.54
	11	3, 6, 11, 15, 33	15.08	1	24.88	7, 9, 21, 26, 36	1.29	0.9977	93.57
	12	3, 7, 10, 16, 33	12.54	1	49.81	7, 9, 21, 25, 37	1.65	0.9973	93.38

TABLE C.8 (Continued…)
NETWORK PERFORMANCE FOR FIXED AND TUNEABLE DRS WITH NR FOR CASE STUDY 1

	Load Level	Optimal configuration	A	B	C	Optimal configuration	A	B	C
Season-2	13	3, 7, 10, 17, 33	9.60	1	70.32	7, 8, 9, 25, 36	2.09	0.9968	93.53
	14	4, 7, 9, 17, 33	6.68	1	86.24	7, 8, 9, 25, 36	3.02	0.9948	93.77
	15	3, 9, 16, 33, 37	8.22	1	81.00	7, 9, 17, 21, 37	2.73	0.9963	93.69
	16	5, 7, 9, 17, 33	5.81	0.9988	90.28	33, 34, 35, 36, 37	3.55	0.9954	94.06
	17	7, 9, 16, 33, 37	5.95	0.9964	91.35	33, 34, 35, 36, 37	4.35	0.9962	93.67
	18	3, 7, 9, 15, 33	11.76	1	64.00	7, 9, 16, 21, 37	2.48	0.9968	92.41
Season-3	19	7, 21, 26, 32, 34	5.93	0.9945	93.64	7, 8, 9, 26, 36	6.01	0.9944	93.56
	20	6, 27, 32, 34, 35	9.06	0.9921	92.13	6, 27, 32, 34, 35	9.11	0.9919	92.08
	21	7, 8, 9, 27, 36	13.32	0.9892	90.77	7, 8, 9, 27, 36	13.32	0.9892	90.77
	22	7, 8, 28, 32, 34	21.73	0.9796	88.53	7, 8, 28, 32, 34	21.73	0.9796	88.53
	23	7, 9, 28, 34, 36	45.38	0.9704	84.41	7, 9, 28, 34, 36	45.38	0.9704	84.41
	24	7, 9, 28, 34, 36	35.22	0.9717	86.40	7, 9, 28, 34, 36	35.22	0.9717	86.40
	25	7, 10, 28, 32, 34	66.68	0.9561	81.71	7, 10, 28, 32, 34	66.68	0.9561	81.71
	26	7, 10, 28, 34, 36	81.45	0.9579	80.77	7, 10, 28, 34, 36	81.45	0.9579	80.77
	27	7, 8, 9, 15, 26	20.88	0.9815	89.11	7, 8, 9, 15, 26	20.88	0.9815	89.11

A: Power loss (kW), B: Minimum node voltage (p. u.), C: Energy loss reduction (%)

TABLE C.9
COMMON CONTROL PARAMETERS SELECTED FOR PROPOSED TECHNIQUES FOR CASE STUDY 2

Parameters	IGA	IPSO	IBA	ICSO	ITLBO
Population size	100	100	20	20	20
itr_{max}	200	200	300	300	300

TABLE C.10
NETWORK PERFORMANCE WITH FIXED AND TUNEABLE DRS FOR CASE STUDY 2

Load level	Base case		Fixed DRs		Tuneable DRs			
	Ploss	*V*min	Ploss	*V*min	Node (DG in kW)	Node (SC in kVAr)	Ploss	*V*min
1	117.76	0.9728	54.77	0.9859	6(1258), 12(2148), 28(1698), 71(1001), 79(1420)	6(900), 12(1600), 31(1100), 71(800), 79(1000)	41.89	0.9859
2	146.03	0.9728	62.72	0.9823	6(1234), 12(2500), 28(1955), 71(1005), 79(1457)	6(800), 12(1700), 31(1200), 71(800), 79(1000)	50.97	0.9823
3	182.85	0.9728	94.11	0.9793	6(1230), 12(2498), 28(2000), 71(1004), 79(1449)	6(900), 12(1700), 31(1700), 71(800), 79(1100)	83.35	0.9793
4	234.72	0.9586	84.99	0.9793	6(1871), 12(2452), 28(2000), 71(1479), 79(2136)	6(1400), 12(1800), 31(1700), 71(1200), 79(1500)	84.88	0.9793
5	362.51	0.9438	141.76	0.9722	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800), 71(1200), 79(1500)	141.76	0.9722
6	334.24	0.9438	133.81	0.9722	6(1866), 12(2146), 28(1727), 71(1500), 79(2200)	6(1500), 12(1400), 31(1800), 71(1200), 79(1500)	133.26	0.9722
7	463.01	0.9286	171.99	0.9722	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800),71 (1200), 79(1500)	171.99	0.9722
8	531.81	0.9286	234.88	0.9651	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800), 71(1200), 79(1500)	234.88	0.9651
9	275.89	0.9601	195.9	0.9651	6(1252), 12(2154), 28(1769), 71(1003), 79(1407)	6(900), 12(1500), 31(1800), 71(800), 79(1100)	184.14	0.9651

TABLE C.10 (Continued…)
NETWORK PERFORMANCE WITH FIXED AND TUNEABLE DRs FOR CASE STUDY 2

Load level	Base case		Fixed DRs		Tuneable DRs			
	Ploss (kW)	Vmin (p.u.)	Ploss (kW)	Vmin (p.u.)	Node (DG in kW)	Node (SC in kVAr)	Ploss	Vmin
10	41.81	0.9839	60.48	0.9916	6(741), 12(1307), 28(1025), 71(572), 79(869)	6(500), 12(900), 31(700), 71(500), 79(600)	14.97	0.9916
11	51.76	0.9839	58.77	0.9895	6(751), 12(1588), 28(1293), 71(602), 79(843)	6(600), 12(1100), 31 (700), 71(500), 79(600)	18.05	0.9895
12	64.78	0.9839	68.65	0.9877	6(763), 12(1609), 28(1281), 71(594), 79(876)	6(600), 12(1200), 31(1000), 71(500), 79(600)	29.57	0.9877
13	82.81	0.9756	52.41	0.9877	6(1093), 12(1604), 28(1215), 71(889), 79(1322)	6(800), 12(1100) , 31(1000), 71(700), 79(900)	30.11	0.9877
14	126.98	0.9672	57.76	0.9835	6(1487), 12(1630), 28(1299), 71(1211), 79(1699)	6(1100), 12(1100), 31(1400), 71(900), 79(1200)	47.15	0.9835
15	117.04	0.9672	59.47	0.9835	6(1545), 12(1270), 28(999), 71(1203), 79(1747)	6(1200), 12(900), 31(1400), 71(900), 79(1200)	44.21	0.9835
16	160.81	0.9586	54.5	0.9835	6(1875), 12(1656), 28(1312), 71(1459), 79(2135)	6(1300), 12(1100), 31 (1400), 71(1200), 79(1500)	48.2	0.9835
17	184.75	0.9586	75.15	0.9793	6(1871), 12(1599), 28(1260), 71(1500), 79(2110)	6(1400), 12(900), 31(1700), 71(1200), 79(1500)	69.47	0.9793
18	97.19	0.9764	106.23	0.9793	6(747), 12(1315), 28(1063), 71(622), 79(813)	6(500), 12(1000), 31(1700), 71(500), 79(600)	63.89	0.9793
19	234.11	0.9614	85.56	0.9801	6(1730), 12(2500), 28(2000), 71(1417), 79(1970)	6(1200), 12(1800), 31(1600), 71(1100), 79(1400)	84.59	0.9801
20	290.83	0.9614	112.47	0.9749	6(1738), 12(2500), 28(1989), 71(1443), 79(1983)	6(1300), 12(1800), 31(1700), 71(1000),79(1400)	111.63	0.9749
21	364.37	0.9614	178.09	0.9708	6(1751), 12(2500), 28(2000), 71(1423), 79(2022)	6(1300), 12(1800), 31(1800), 71(1000), 79(1400)	177.24	0.9708
22	469.86	0.9408	192.05	0.9708	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800), 71(1200), 79(1500)	192.05	0.9708
23	731.35	0.9191	343.68	0.9607	6(1898), 12(2500), 28(2000), 71(1500), 79(2200)	6(1400), 12(1700), 31(1800), 71(1200), 79(1500)	343.68	0.9607
24	674.63	0.9191	316.77	0.9607	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800), 71(1200), 79(1500)	316.77	0.9607
25	943.46	0.8962	442.45	0.945	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800), 71(1200), 79(1500)	442.45	0.945
26	1083.19	0.8962	573.24	0.945	6(1900), 12(2500), 28(2000), 71(1500), 79(2200)	6(1500), 12(1800), 31(1800), 71(1200), 79(1500)	573.24	0.945
27	553.11	0.9433	379.28	0.9504	6(1737), 12(2483), 28(2000), 71(1404), 79(2003)	6(1400), 12(1800), 31(1800), 71(1100), 79(1400)	378.58	0.9504

TABLE C.11
NETWORK PERFORMANCE FOR FIXED AND TUNEABLE DRS WITH NR FOR CASE STUDY 2

Season	Load Level	Fixed DRs with NR				Tuneable DRs with NR			
		Optimal configuration	A	B	C	Optimal configuration	A	B	C
Season-1	1	12, 20, 28, 34, 35, 42, 53, 59, 66, 76, 86, 90, 96	28.45	0.9886	75.84	28, 34, 38, 42, 54, 64, 76, 79, 85, 86, 87, 89, 90	34.49	0.9879	70.71
	2	12, 20, 28, 34, 37, 42, 53, 59, 67, 76, 86, 90, 96	37.10	0.9856	74.59	28, 34, 39, 42, 54, 64, 70, 76, 79, 85, 86, 89, 90	43.35	0.9856	70.32
	3	12 20 28 34 38 42 53 60 69 76 86 90 96	58.85	0.9844	67.82	6, 20, 28, 34, 38, 42, 54, 70, 76, 86, 89, 90, 96	67.69	0.9811	62.98
	4	28, 34, 38, 42, 54, 64, 70, 76, 79, 85, 86, 89, 90	69.02	0.9825	70.60	28, 34, 38, 42, 54, 64, 71, 76, 79, 85, 86, 89, 90	70.26	0.9822	70.07
	5	6, 34, 36, 42, 54, 64, 72, 76, 86, 89, 90, 91, 92	128.26	0.9722	64.62	6, 34, 36, 42, 54, 64, 72, 76, 86, 89, 90, 91, 92	128.26	0.9722	64.62
	6	6, 12, 28, 34, 38, 42, 54, 64, 86, 87, 88, 90, 91	110.91	0.9753	66.82	6, 34, 36, 42, 54, 64, 72, 76, 86, 89, 90, 91, 92	118.34	0.9722	64.59
	7	6, 34, 36, 42, 54 63, 72, 76, 86, 89 90, 91, 92	159.08	0.9722	65.64	6, 34, 36, 42, 54, 63, 72, 76, 86, 89, 90, 91, 92	159.08	0.9722	65.64
	8	34, 36, 42, 55, 72 76, 85, 86, 89, 90, 91, 92, 96	212.62	0.9651	60.02	6, 34, 36, 42, 54, 63, 72, 76, 86, 89, 90, 91, 92	211.90	0.9651	60.16
	9	12, 34, 35, 42, 54, 59, 68, 76, 78, 86, 90, 92, 96	110.86	0.9761	59.82	6, 20, 34, 35, 42, 54, 76, 86, 87, 89, 90, 92, 96	134.50	0.9697	51.25
Season-2	10	18, 19, 26, 35, 42, 46, 50, 57, 74, 86, 87, 90, 96	25.37	0.9947	39.33	28, 34, 38, 42, 54, 64, 76, 79, 85, 86, 87, 89, 90	12.29	0.993	70.61
	11	12, 16, 19, 28, 35, 42, 46, 50, 57, 75, 86, 90, 96	24.06	0.9965	53.52	28, 34, 38, 42, 54, 64, 70, 76, 79, 85, 86, 89, 90	14.89	0.9914	71.24
	12	2, 12, 18, 20, 28, 36, 42, 58, 75, 86, 90, 94, 96	27.48	0.9893	57.58	6, 20, 28, 34, 38, 42, 54, 76, 86, 87, 89, 90, 96	23.40	0.9881	63.88
	13	4, 12, 20, 28, 36, 42, 60, 66, 74, 86, 90, 94, 96	22.75	0.9941	72.52	28, 34, 38, 42, 54, 64, 76, 79, 85, 86, 87, 89, 90	24.90	0.9896	69.93
	14	5 86 87 64 60 76 12 28 90 42 34 35 78	30.12	0.9895	76.28	54 86 69 85 64 88 12 28 90 42 34 38 79	37.53	0.9867	70.45

TABLE C.11 (Continued…)
NETWORK PERFORMANCE FOR FIXED AND TUNEABLE DRS WITH NR FOR CASE STUDY 2

		Fixed DRs with NR				Tuneable DRs with NR			
	Load Level	Optimal configuration	A	B	C	Optimal configuration	A	B	C
Season-2	15	5, 12, 28, 34, 35, 42, 60, 64, 76, 78, 86, 87, 90	27.61	0.9875	76.41	12, 28, 34, 39, 41, 54, 59, 64 69, 79, 86, 88 90	34.38	0.9867	70.63
	16	5, 12, 28, 34, 35, 42, 64, 66, 76, 78, 85, 86, 90	32.08	0.9885	80.05	12, 28, 34, 38, 42, 54, 59, 64, 69, 79, 86, 88, 90	39.48	0.9849	75.45
	17	12, 28, 34, 35, 42, 54, 64, 68, 76, 79, 85, 86, 90	45.43	0.9833	75.41	28, 34, 38, 42, 54, 64, 76, 79, 85, 86, 87, 89, 90	55.38	0.9821	70.02
	18	5, 12, 20, 28, 34, 35, 42, 59, 74, 86, 87, 90, 96	40.46	0.9905	58.37	6, 12, 20, 28, 34, 38, 42, 54, 70, 86, 88, 90, 96	46.97	0.9813	51.67
Season-3	19	5, 28, 34, 39, 42, 64, 70, 76, 79, 85, 86, 89, 90	68.76	0.9837	70.63	28, 34, 39, 42, 54, 64, 70, 76, 79, 85, 86, 89, 90	73.25	0.9833	68.71
	20	5, 39, 42, 64, 70, 76, 79, 85, 86, 89, 90, 92, 94	97.45	0.977	66.49	5, 28, 33, 42, 54, 64, 71, 76, 79, 86, 89, 90, 93	103.13	0.9797	64.54
	21	6, 20, 34, 38, 42, 54, 70, 76, 86, 89, 90, 92, 96	148.12	0.9732	59.35	6, 20, 34, 38, 42, 54, 70, 76, 86, 89, 90, 92, 96	153.28	0.9716	57.93
	22	6, 34, 38, 42, 54, 64, 76, 86, 87, 89, 90, 91, 92	184.31	0.9708	60.77	6, 34, 38, 42, 54, 64, 76, 89, 86, 87, 90, 91, 92	184.31	0.9708	60.77
	23	6, 34, 37, 42, 54, 63, 72, 86, 88, 89, 90, 91, 92	323.60	0.9607	55.75	6, 34, 37, 42, 54, 63, 72, 86, 88, 89, 90, 91, 92	326.37	0.9607	55.38
	24	6, 34, 36, 42, 54, 63, 72, 76, 86, 89, 90, 91, 92	288.45	0.9607	57.24	6, 34, 36, 42, 54, 63, 72, 76, 86, 89, 90, 91, 92	288.45	0.9607	57.24
	25	6, 34, 37, 42, 54, 61, 72, 86, 88, 89, 90, 91, 92	413.29	0.952	56.19	6, 34, 37, 42, 54, 61, 72, 86, 88, 89, 90, 91, 92	413.29	0.952	56.19
	26	6, 34, 37, 42, 54, 62, 72, 86, 88, 89, 90, 91, 92	529.27	0.947	51.14	6, 34, 37, 42, 54, 62, 72, 86, 88, 89, 90, 91, 92	529.27	0.947	51.14
	27	6, 20, 34, 36, 42, 54, 69, 76, 86, 89, 90, 92, 96	266.03	0.9573	51.90	6, 20, 34, 36, 42, 54, 69, 76, 86, 89, 90, 92, 96	273.44	0.9554	50.56

A: Power loss (kW), B: Minimum node voltage (p. u.), C: Energy loss reduction (%)

TABLE C.12
OPTIMAL SOLUTION FOR DR ALLOCATION AND OPTIMAL NR WITHOUT CONSIDERING LOAD DIVERSITY FOR CASE STUDY 1

Load level	Optimal location (Optimal sizing)		Optimal configuration
	Node (SCs in kVAr)	Node (DGs in kW)	
Light	14(200), 24(300), 30(600) TC: 1100	14(449), 24(638), 30(624) TC: 1711	7, 9, 17, 35, 37
Nominal	14(300), 24(600), 30(900) TC: 1800	14(740), 24(1059), 30(1038) TC: 2837	7, 9, 17, 25, 35
Peak	14(300), 24(600), 30(900) TC: 1800	14(740), 24(1059), 30(1038) TC: 2837	7, 9, 28, 34, 36

TC: Total capacity

TABLE C.13
CALCULATION FOR FALSE ANNUAL ENERGY LOSS SAVING

Particular (MWh)	Value
Base case annual energy loss*(a)	1837.77
Annual energy loss*(b)	134.58
Annual energy loss savings*(c) = (a)-(b)	1703.2
Base case annual energy loss (d)	984.63
Annual energy loss#(e)	283.91
Annual energy loss savings#(f) = (d)-(e)	700.72
False annual energy loss savings# (g) = (c)-(f)	1002.48
Annual energy loss (h)	111.12
Actual annual energy loss savings (i) = (d)-(h)	873.51
Percentage false annual energy loss saving (j) = 100*(g)/(i)	114.77

*without considering load diversity, # implementing solution (without considering load diversity) in distribution system having load diversity

APPENDIX D

TABLE D.1
OPTIMAL SCHEDULING OF MTS AND SCS FOR JULY 1ST OF THE FIRST YEAR

Hour	Load Factors			SPV generation (kWh)		WT generation (kWh)		Optimal scheduling MTs (kWh)		Optimal scheduling SCs (kVArh)		
	R	I	C	Node 2	Node 29	Node 2	Node 7	Node 16	Node 32	Node 4	Node 14	Node 30
1	0.61	0.59	0.43	0.00	0.00	564.15	271.63	330	240	100	200	400
2	0.57	0.66	0.38	0.00	0.00	942.27	453.68	329	240	100	200	400
3	0.63	0.62	0.39	0.00	0.00	1289.97	621.10	330	240	100	200	400
4	0.60	0.61	0.36	0.00	0.00	741.43	356.99	329	240	100	200	400
5	0.62	0.66	0.40	0.00	0.00	1195.25	575.49	330	240	100	200	400
6	0.72	0.76	0.55	0.00	0.00	977.57	470.68	329	240	100	200	600
7	0.81	1.08	0.79	191.63	60.84	353.57	170.24	330	238	300	300	800
8	0.86	1.26	1.00	1022.43	324.58	367.80	177.09	330	238	300	300	900
9	0.82	1.29	1.32	2692.71	854.83	794.81	382.69	325	240	300	300	900
10	0.81	1.29	1.38	3839.32	1218.83	298.94	143.93	330	239	300	300	900
11	0.76	1.34	1.32	4063.54	1290.01	678.96	326.91	330	240	300	300	900
12	0.81	1.35	1.31	5098.01	1618.42	816.25	393.01	330	238	300	300	900
13	0.79	1.26	1.20	5220.63	1657.34	488.26	235.09	330	239	300	300	900
14	0.93	1.22	1.19	4739.41	1504.57	486.62	234.30	329	236	300	300	900
15	0.92	1.23	1.12	3788.14	1202.58	789.86	380.30	330	239	300	300	900
16	1.01	1.20	1.00	3266.66	1037.03	365.42	175.94	329	240	300	300	900
17	1.02	1.10	0.81	1636.32	519.47	843.15	405.96	329	240	300	300	800
18	1.11	1.00	0.83	757.24	240.39	1161.83	559.40	330	239	300	300	900
19	1.25	0.79	0.79	14.06	4.46	1036.24	498.93	329	240	300	300	800
20	1.29	0.66	0.83	0.00	0.00	856.98	412.62	330	240	300	300	900
21	1.35	0.59	0.83	0.00	0.00	760.45	366.14	329	240	300	300	900
22	1.33	0.61	0.64	0.00	0.00	726.25	349.67	330	239	300	300	700
23	1.20	0.62	0.56	0.00	0.00	864.80	416.38	330	240	300	300	600
24	0.79	0.63	0.49	0.00	0.00	693.01	333.67	330	240	200	200	500

TABLE D.2
OPTIMAL SCHEDULING OF MTS AND SCS FOR JANUARY 1ST OF THE 20TH YEAR

Hour	Load Factors			SPV generation (kWh)		WT generation (kWh)		Optimal generation MTs (kWh)		Optimal generation SCs (kVArh)		
	R	I	C	Node 2	Node 29	Node 2	Node 7	Node 16	Node 32	Node 4	Node 14	Node 30
1	1.07	1.14	0.80	0.00	0.00	2232.63	1074.97	326	239	300	300	900
2	1.01	1.15	0.76	0.00	0.00	1888.87	909.46	325	239	300	300	800
3	1.08	1.06	0.68	0.00	0.00	2896.38	1394.55	328	240	300	300	700
4	1.02	1.14	0.71	0.00	0.00	1517.55	730.67	330	236	300	300	800
5	1.14	1.04	0.73	0.00	0.00	1133.74	545.87	330	235	300	300	800
6	1.31	1.31	0.93	0.00	0.00	1305.89	628.76	329	238	300	300	900
7	1.40	1.87	1.38	0.00	0.00	1067.64	514.05	329	240	300	300	900
8	1.43	2.21	1.80	621.30	197.24	2475.92	1192.11	330	239	300	300	900
9	1.41	2.16	2.38	2253.98	715.55	2272.31	1094.08	330	234	300	300	900
10	1.32	2.27	2.29	2948.35	935.98	1144.18	550.90	330	239	300	300	900
11	1.35	2.33	2.25	4340.06	1377.80	1148.91	553.18	329	240	300	300	900
12	1.37	2.36	2.32	5137.94	1631.09	2348.34	1130.68	329	238	300	300	900
13	1.47	2.30	2.14	5371.23	1705.15	1730.67	833.28	329	240	300	300	900
14	1.63	2.15	2.06	3975.78	1262.15	1689.37	813.40	329	236	300	300	900
15	1.65	2.12	1.91	3571.49	1133.81	2425.03	1167.61	328	239	300	300	900
16	1.74	2.05	1.76	2923.43	928.07	2427.36	1168.73	329	240	300	300	900
17	1.77	1.84	1.49	1400.93	444.74	1666.25	802.27	329	238	300	300	900
18	1.94	1.70	1.45	338.90	107.59	1687.90	812.69	330	238	300	300	900

TABLE D.2 (Continued…)

OPTIMAL SCHEDULING OF MTS AND SCS FOR JANUARY 1ST OF THE 20TH YEAR

Hour	Load Factors			SPV generation (kWh)		WT generation (kWh)		Optimal generation MTs (kWh)		Optimal generation SCs (kVArh)		
	R	I	C	Node 2	Node 29	Node 2	Node 7	Node 16	Node 32	Node 4	Node 14	Node 30
19	2.28	1.43	1.38	0.00	0.00	1488.65	716.76	330	238	300	300	900
20	2.29	1.19	1.45	0.00	0.00	1738.81	837.21	330	237	300	300	900
21	2.37	1.11	1.34	0.00	0.00	2172.98	1046.25	327	239	300	300	900
22	2.31	1.06	1.13	0.00	0.00	3069.23	1477.78	329	238	300	300	900
23	2.01	1.01	0.96	0.00	0.00	1937.81	933.02	328	239	300	300	900
24	1.31	1.07	0.92	0.00	0.00	3142.39	1513.00	330	240	300	300	900

TABLE D.3

ECONOMIC PERFORMANCE OF THE SYSTEM ON JULY 1ST OF THE FIRST YEAR

Time (hr)	Revenue from customers ($)	Revenue from Grid ($)	Net revenue($)	Variable charges($)	Profit ($)
1	119.08	34.21	84.87	34.47	50.40
2	118.25	2.62	115.63	40.02	75.61
3	121.06	-24.88	145.94	45.22	100.72
4	115.35	16.28	99.07	37.03	62.04
5	123.33	-14.29	137.61	43.82	93.80
6	148.73	28.53	120.20	40.59	79.62
7	196.39	111.63	84.76	33.92	50.84
8	227.34	79.54	147.80	45.10	102.70
9	248.22	-61.22	309.44	73.29	236.15
10	252.05	-103.19	355.24	81.23	274.01
11	248.34	-157.77	406.11	89.86	316.24
12	252.07	-245.69	497.77	105.43	392.33
13	236.56	-242.39	478.95	102.24	376.71
14	242.25	-199.21	441.46	95.69	345.77
15	238.47	-156.27	394.74	87.83	306.91
16	234.76	-82.39	317.16	74.67	242.48
17	214.15	-18.52	232.67	60.25	172.41
18	215.74	22.15	193.59	53.41	140.18
19	208.65	80.14	128.50	41.74	86.76
20	204.70	92.15	112.55	38.97	73.59
21	204.19	99.75	104.44	37.49	66.95
22	191.46	90.21	101.26	36.94	64.32
23	175.88	63.63	112.24	39.02	73.22
24	140.96	44.37	96.59	36.42	60.17
Sum	4677.98	-540.62	5218.59	1374.66	3843.94

TABLE D.4

ECONOMIC PERFORMANCE OF THE SYSTEM ON JANUARY 1ST OF THE 20TH YEAR

Time (hr)	Revenue from customers ($)	Revenue from Grid ($)	Net revenue($)	Variable charges($)	Profit ($)
1	706.64	-19.72	726.37	189.68	536.69
2	684.47	51.04	633.43	173.12	460.31
3	664.94	-249.67	914.60	221.55	693.05
4	675.24	139.61	535.63	155.75	379.87
5	683.37	248.97	434.41	137.36	297.05
6	834.28	350.47	483.80	145.90	337.90
7	1088.09	670.27	417.84	134.86	282.97
8	1272.14	335.97	936.16	228.11	708.05
9	1383.32	124.75	1258.60	286.74	971.86
10	1366.61	241.49	1125.10	263.19	861.91
11	1378.19	-84.79	1463.00	322.27	1140.73
12	1405.70	-596.00	2001.70	412.76	1588.94

TABLE D.4 (Continued…)

ECONOMIC PERFORMANCE OF THE SYSTEM ON JANUARY 1ST OF THE 20TH YEAR

Time (hr)	Revenue from customers ($)	Revenue from Grid ($)	Net revenue($)	Variable charges($)	Profit ($)
13	1377.49	-512.51	1890.00	393.54	1496.46
14	1364.47	-163.29	1527.80	331.98	1195.82
15	1328.90	-311.59	1640.50	350.16	1290.34
16	1299.63	-182.13	1481.80	323.16	1158.64
17	1198.05	288.96	909.08	222.28	686.80
18	1200.19	539.06	661.14	178.54	482.60
19	1201.72	677.34	524.38	154.74	369.64
20	1166.42	575.29	591.14	166.49	424.65
21	1138.70	429.52	709.18	186.99	522.19
22	1067.54	115.84	951.70	229.76	721.94
23	943.52	291.98	651.54	175.95	475.59
24	777.61	-204.07	981.68	233.67	748.01
Sum	26207.25	2756.81	23450.57	5618.54	17832.03

TABLE D.5

OPTIMAL CONFIGURATION IN 1ST YEAR AND 20TH YEAR OF PLANNING HORIZON

First year of planning horizon				20th year of planning horizon			
Hour	Optimal configuration	Hour	Optimal configuration	Hour	Optimal configuration	Hour	Optimal configuration
1	7, 10, 12, 32, 37	13	10, 13, 26, 33, 34	1	10, 32, 33, 34, 37	13	6, 9, 13, 28, 32
2	9, 12, 24, 33, 34	14	10, 13, 26, 33, 34	2	10, 32, 33, 34, 37	14	6, 9, 13, 36, 37
3	9, 12, 24, 33, 34	15	9, 13, 28, 33, 34	3	3, 9, 12, 32, 33	15	6, 9, 13, 32, 37
4	5, 8, 10, 32, 37	16	7, 9,12, 28, 34	4	9, 32, 33, 34, 37	16	6, 9, 13, 32, 37
5	8, 12, 24, 33, 34	17	6, 10, 13, 28, 32	5	7, 9, 34, 36, 37	17	6, 9, 13, 32, 37
6	8, 9, 32, 33, 37	18	9, 33, 34, 36, 37	6	6, 9, 13, 15, 37	18	6, 9, 13, 32, 37
7	7, 9, 32, 34, 37	19	9, 32, 33, 34, 37	7	6, 9, 13, 32, 37	19	6, 9, 13, 36, 37
8	7, 10, 32, 34, 37	20	10, 28, 32, 33, 34	8	6, 9, 13, 31, 37	20	6, 9, 13, 36, 37
9	9, 13, 28, 32, 33	21	9, 28, 33, 34, 36	9	6, 9, 13, 32, 37	21	6, 9, 13, 15, 37
10	9, 13, 28, 33, 34	22	9, 28, 33, 34, 36	10	6, 9, 13, 32, 37	22	9, 13, 33, 36, 37
11	9, 13, 28, 33, 34	23	9, 32, 33, 34, 37	11	6, 9, 13, 32, 37	23	6, 9, 13, 15, 37
12	10, 13, 27, 33, 34	24	7, 8, 9, 36, 37	12	6, 9, 13, 32, 37	24	10, 13, 32, 33, 37

APPENDIX E

The single-line diagrams, line and bus data of and other relevant data of various test distribution systems considered for simulation of different techniques throughout this thesis are given in this appendix.

1. IEEE 33-BUS TEST DISTRIBUTION SYSTEM

This test distribution system and its data are referred from [254]. It is a 12.66 kV distribution system with 32 sectionalizing switches and 5 tie-switches. The nominal active and reactive loadings are 3,715 kW and 2,300 kVAr respectively.

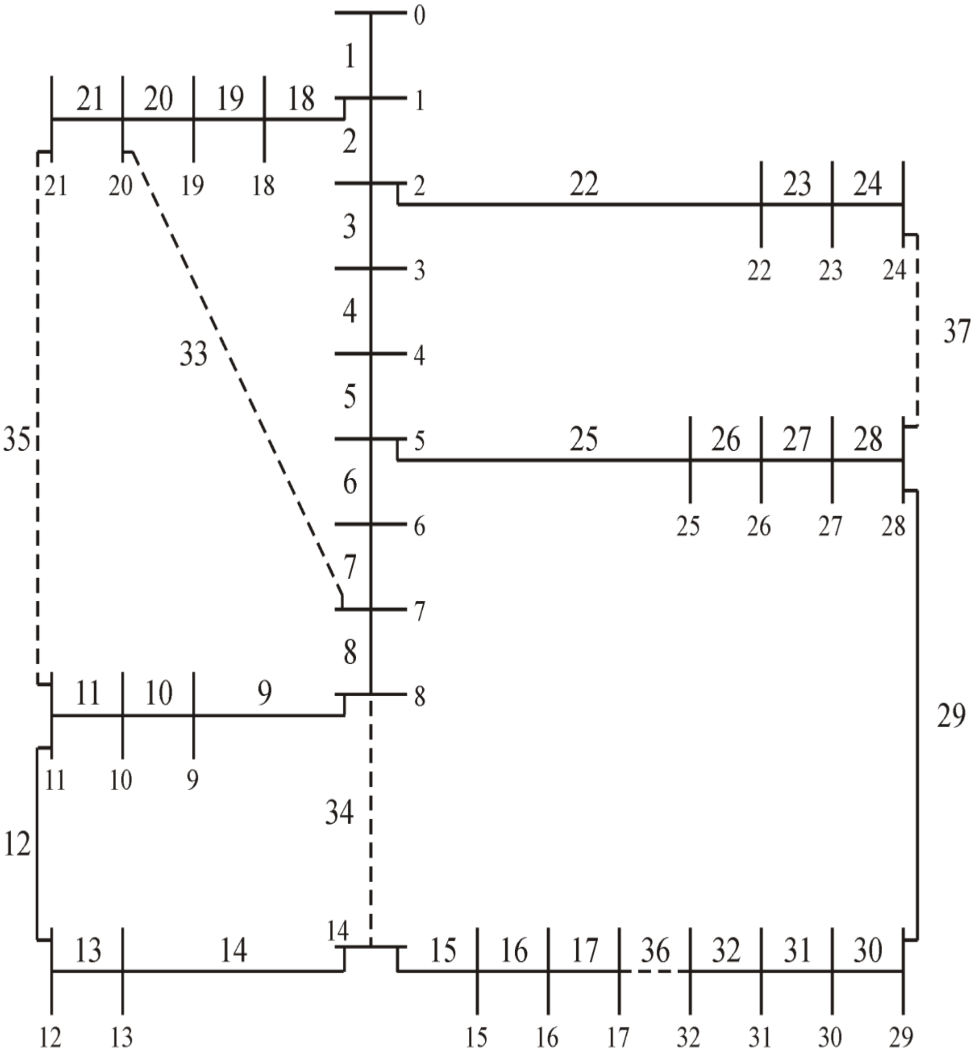

Fig. E.1 Single line diagram of 33-bus system

TABLE E.1
BUS DATA OF 33-BUS SYSTEM

Bus number	Load		Bus number	Load	
	Active load (kW)	Reactive load (kVAr)		Active load (kW)	Reactive load (kVAr)
1	0.00	0.00	18	90.00	40.00
2	100.00	60.00	19	90.00	40.00
3	90.00	40.00	20	90.00	40.00
4	120.00	80.00	21	90.00	40.00
5	60.00	30.00	22	90.00	40.00
6	60.00	20.00	23	90.00	50.00
7	200.00	100.00	24	420.00	200.00
8	200.00	100.00	25	420.00	200.00
9	60.00	20.00	26	60.00	25.00
10	60.00	20.00	27	60.00	25.00
11	45.00	30.00	28	60.00	20.00
12	60.00	35.00	29	120.00	70.00
13	60.00	35.00	30	200.00	600.00
14	120.00	80.00	31	150.00	70.00
15	60.00	10.00	32	210.00	100.00
16	60.00	20.00	33	60.00	40.00
17	60.00	20.00			

TABLE E.2
LINE DATA OF 33-BUS SYSTEM

Line number	Bus from	Bus to	Line resistance (Ω)	Line reactance (Ω)	Ampacity (A)
1	1	2	0.0922	0.0470	400
2	2	3	0.4930	0.2512	400
3	3	4	0.3661	0.1864	250
4	4	5	0.3811	0.1941	250
5	5	6	0.8190	0.7070	250
6	6	7	0.1872	0.6188	150
7	7	8	0.7115	0.2351	150
8	8	9	1.0299	0.7400	150
9	9	10	1.0440	0.7400	150
10	10	11	0.1967	0.0651	150
11	11	12	0.3744	0.1298	150
12	12	13	1.4680	1.1549	150
13	13	14	0.5416	0.7129	150
14	14	15	0.5909	0.5260	150
15	15	16	0.7462	0.5449	150
16	16	17	1.2889	1.7210	150
17	17	18	0.7320	0.5739	150
18	2	19	0.1640	0.1565	250
19	19	20	1.5042	1.3555	250

TABLE E.2 (Continued…)
LINE DATA OF 33-BUS SYSTEM

Line number	Bus from	Bus to	Line resistance (Ω)	Line reactance (Ω)	Ampacity (A)
20	20	21	0.4095	0.4784	250
21	21	22	0.7089	0.9373	150
22	3	23	0.4512	0.3084	250
23	23	24	0.8980	0.7091	250
24	24	25	0.8959	0.7071	250
25	6	26	0.2031	0.1034	250
26	26	27	0.2842	0.1447	250
27	27	28	1.0589	0.9338	250
28	28	29	0.8043	0.7006	250
29	29	30	0.5074	0.2585	250
30	30	31	0.9745	0.9629	150
31	31	32	0.3105	0.3619	150
32	32	33	0.3411	0.5302	150
33	8	21	2.0000	2.0000	150
35	9	15	2.0000	2.0000	150
35	12	22	2.0000	2.0000	150
36	18	33	0.5000	0.5000	150
37	25	29	0.5000	0.5000	150

2. 83-BUS TEST DISTRIBUTION SYSTEM

It is an 11.4 kV practical distribution network of Taiwan Power Company [256]. The system consists of 11 feeders, 83 normally closed sectionalizing switches, and 13 normally open tie switches. The nominal active and reactive loadings are 28,350 kW and 20,700 kVAr respectively.

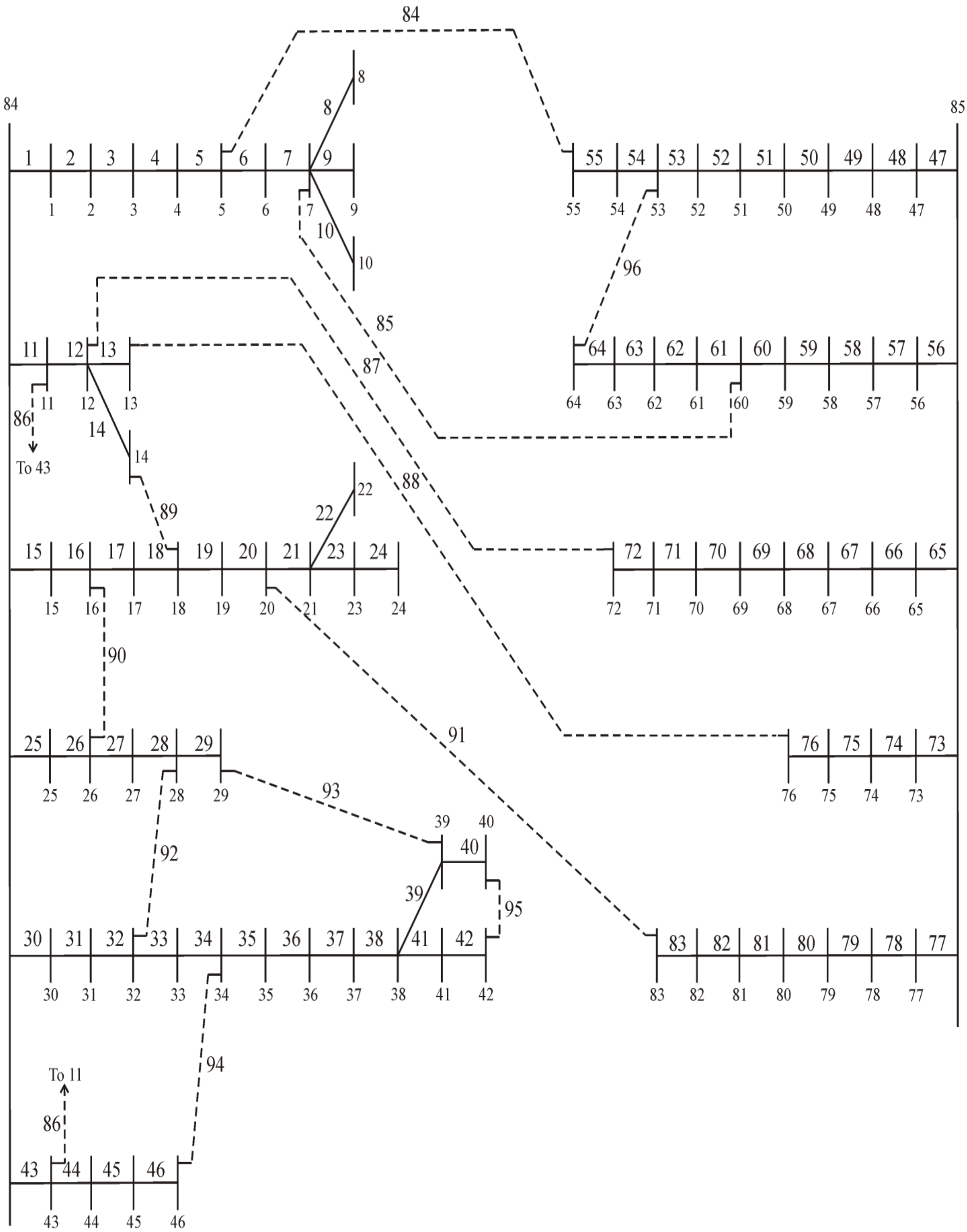

Fig. E.2 Single line diagram of 83-bus system

TABLE E.3
BUS DATA OF 83-BUS SYSTEM

Bus number	Load		Bus number	Load	
	Active load (kW)	Reactive load (kVAr)		Active load (kW)	Reactive load (kVAr)
1	0.00	0.00	44	30.00	20.00
2	100.00	50.00	45	800.00	700.00
3	300.00	200.00	46	200.00	150.00
4	350.00	250.00	47	0.00	0.00
5	220.00	100.00	48	0.00	0.00
6	1100.00	800.00	49	0.00	0.00
7	400.00	320.00	50	200.00	160.00
8	300.00	200.00	51	800.00	600.00
9	300.00	230.00	52	500.00	300.00
10	300.00	260.00	53	500.00	350.00
11	0.00	0.00	54	500.00	300.00
12	1200.00	800.00	55	200.00	80.00
13	800.00	600.00	56	0.00	0.00
14	700.00	500.00	57	30.00	20.00
15	0.00	0.00	58	600.00	420.00
16	300.00	150.00	59	0.00	0.00
17	500.00	350.00	60	20.00	10.00
18	700.00	400.00	61	20.00	10.00
19	1200.00	1000.00	62	200.00	130.00
20	300.00	300.00	63	300.00	240.00
21	400.00	350.00	64	300.00	200.00
22	50.00	20.00	65	0.00	0.00
23	50.00	20.00	66	50.00	30.00
24	50.00	10.00	67	0.00	0.00
25	50.00	30.00	68	400.00	360.00
26	100.00	60.00	69	0.00	0.00
27	100.00	70.00	70	0.00	0.00
28	1800.00	1300.00	71	2000.00	1500.00
29	200.00	120.00	72	200.00	150.00
30	0.00	0.00	73	0.00	0.00
31	1800.00	1600.00	74	0.00	0.00
32	200.00	150.00	75	1200.00	950.00
33	200.00	100.00	76	300.00	180.00
34	800.00	600.00	77	0.00	0.00
35	100.00	60.00	78	400.00	360.00
36	100.00	60.00	79	2000.00	1300.00
37	20.00	10.00	80	200.00	140.00
38	20.00	10.00	81	500.00	360.00
39	20.00	10.00	82	100.00	30.00
40	20.00	10.00	83	400.00	360.00
41	200.00	160.00	84	0.00	0.00
42	50.00	30.00	85	0.00	0.00
43	0.00	0.00			

TABLE E.4
LINE DATA OF 83-BUS SYSTEM

Line number	Bus from	Bus to	Line resistance (Ω)	Line reactance (Ω)	Ampacity (A)
1	84	1	0.1944	0.6624	500
2	1	2	0.2096	0.4304	500
3	2	3	0.2358	0.4842	500
4	3	4	0.0917	0.1883	500
5	4	5	0.2096	0.4304	500
6	5	6	0.0393	0.0807	500
7	6	7	0.0405	0.1380	250
8	7	8	0.1048	0.2152	250
9	7	9	0.2358	0.4842	250
10	7	10	0.1048	0.2152	250
11	84	11	0.0786	0.1614	500
12	11	12	0.3406	0.6944	500
13	12	13	0.0262	0.0538	250
14	12	14	0.0786	0.1614	250
15	84	15	0.1134	0.3864	500
16	15	16	0.0524	0.1076	500
17	16	17	0.0524	0.1076	500
18	17	18	0.1572	0.3228	500
19	18	19	0.0393	0.0807	500
20	19	20	0.1703	0.3497	250
21	20	21	0.2358	0.4842	250
22	21	22	0.1572	0.3228	250
23	21	23	0.1965	0.4035	250
24	23	24	0.1310	0.2690	250
25	84	25	0.0567	0.1932	500
26	25	26	0.1048	0.2152	500
27	26	27	0.2489	0.5111	500
28	27	28	0.0486	0.1656	500
29	28	29	0.1310	0.2690	250
30	84	30	0.1965	0.3960	500
31	30	31	0.1310	0.2690	500
32	31	32	0.1310	0.2690	250
33	32	33	0.0262	0.0538	250
34	33	34	0.1703	0.3497	250
35	34	35	0.0524	0.1076	250
36	35	36	0.4978	1.0222	250
37	36	37	0.0393	0.0807	250
38	37	38	0.0393	0.0807	250
39	38	39	0.0786	0.1614	250
40	39	40	0.2096	0.4304	250
41	38	41	0.1965	0.4035	250
42	41	42	0.2096	0.4304	250

TABLE E.4 (Continued…)
LINE DATA OF 83-BUS SYSTEM

Line number	Bus from	Bus to	Line resistance (Ω)	Line reactance (Ω)	Ampacity (A)
43	84	43	0.0486	0.1656	500
44	43	44	0.0393	0.0807	500
45	44	45	0.1310	0.2690	500
46	45	46	0.2358	0.4842	250
47	85	47	0.2430	0.8280	500
48	47	48	0.0655	0.1345	500
49	48	49	0.0655	0.1345	500
50	49	50	0.0393	0.0807	500
51	50	51	0.0786	0.1614	500
52	51	52	0.0393	0.0807	500
53	52	53	0.0786	0.1614	250
54	53	54	0.0524	0.1076	250
55	54	55	0.1310	0.2690	250
56	85	56	0.2268	0.7728	500
57	56	57	0.5371	1.1029	500
58	57	58	0.0524	0.1076	500
59	58	59	0.0405	0.1380	250
60	59	60	0.0393	0.0807	250
61	60	61	0.0262	0.0538	250
62	61	62	0.1048	0.2152	250
63	62	63	0.2358	0.4842	250
64	63	64	0.0243	0.0828	250
65	85	65	0.0486	0.1656	500
66	65	66	0.1703	0.3497	500
67	66	67	0.1215	0.4140	500
68	67	68	0.2187	0.7452	500
69	68	69	0.0486	0.1656	500
70	69	70	0.0729	0.2484	500
71	70	71	0.0567	0.1932	500
72	71	72	0.0262	0.0528	250
73	85	73	0.3240	1.1040	500
74	73	74	0.0324	0.1104	500
75	74	75	0.0567	0.1932	500
76	75	76	0.0486	0.1656	250
77	85	77	0.2511	0.8556	500
78	77	78	0.1296	0.4416	500
79	78	79	0.0486	0.1656	500
80	79	80	0.1310	0.2640	250
81	80	81	0.1310	0.2640	250
82	81	82	0.0917	0.1883	250
83	82	83	0.3144	0.6456	250
84	5	55	0.1310	0.2690	250

TABLE E.4 (Continued…)
LINE DATA OF 83-BUS SYSTEM

Line number	Bus from	Bus to	Line resistance (Ω)	Line reactance (Ω)	Ampacity (A)
85	7	60	0.1310	0.2690	250
86	11	43	0.1310	0.2690	250
87	12	72	0.3406	0.6994	250
88	13	76	0.4585	0.9415	250
89	14	18	0.5371	1.0824	250
90	16	26	0.0917	0.1883	250
91	20	83	0.0786	0.1614	250
92	28	32	0.0524	0.1076	250
93	29	39	0.0786	0.1614	250
94	34	46	0.0262	0.0538	250
95	40	42	0.1965	0.4035	250
96	53	64	0.0393	0.0807	250

PUBLICATIONS

Following papers have been published/accepted out of this thesis work.

INTERNATIONAL JOURNALS

1. Neeraj Kanwar, Nikhil Gupta, K.R. Niazi, Anil Swarnkar, and R.C. Bansal, "Simultaneous allocation of distributed energy resource using improved particle swarm optimization," *Applied Energy, Elsevier*, vol. 185, pp. 1684–1693, 2017. DOI:10.1016/j.apenergy.2016.01.093
2. Neeraj Kanwar, Nikhil Gupta, K.R. Niazi, and Anil Swarnkar, "Simultaneous allocation of distributed resources using improved teaching learning based optimization," *Energy Conversion and Management, Elsevier*, vol. 103, pp. 387–400, 2015. DOI:10.1016/j.enconman.2015.06.057
3. Neeraj Kanwar, Nikhil Gupta, K.R. Niazi, and Anil Swarnkar, "Improved meta-heuristic techniques for simultaneous capacitor and DG allocation in radial distribution networks," *International Journal of Electrical Power & Energy Systems, Elsevier*, vol. 73, pp. 653–664, 2015. DOI:10.1016/j.ijepes.2015.05.049
4. Neeraj Kanwar, Nikhil Gupta, K.R. Niazi, and Anil Swarnkar, "Optimal allocation of distributed energy resources using improved meta-heuristic techniques," *Electric Power Components and Systems, Taylor & Francis*, vol. 44, Issue. 13, pp. 1466–1477, 2016. DOI: 10.1080/15325008.2016.1172682
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6. Neeraj Kanwar, Nikhil Gupta, K.R. Niazi, and Anil Swarnkar, "Optimal distributed generation allocation in radial distribution systems considering customer-wise dedicated feeders and load patterns," *Journal of Modern Power and Clean Energy, Springer*, vol. 3, Issue 4, pp. 475–484, 2015. DOI:10.1007/s40565-015-0169-0
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9. Neeraj Kanwar, Nikhil Gupta, K.R. Niazi, and Anil Swarnkar, "Optimal DG Allocation in Distribution Networks using Cat Swarm Optimization," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 13, Issue 8, pp. 626–631, 2016. DOI:10.19026/rjaset.13.3048

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1. Neeraj Kanwar, Nikhil Gupta, Anil Swarnkar, K. R. Niazi, and R. C. Bansal, "New sensitivity based approach for optimal allocation of shunt capacitors in distribution networks using PSO," Energy Procedia: *The 7th International Conference on Applied Energy (ICAE2015), Elsevier*, vol. 75, pp. 1153–1158, 28–31 March 2015.
2. Neeraj Kanwar, Nikhil Gupta, K. R. Niazi, Anil Swarnkar, and R. C. Bansal, "Multi-objective optimal DG allocation in distribution networks using bat algorithm," *3rd Southern African Solar Energy Conference (SASEC2015)*, Kruger National Park, South Africa, 11–13 May 2015.
3. Neeraj Kanwar, Nikhil Gupta, K. R. Niazi, Anil Swarnkar, and R.C. Bansal, "Application of TLBO for distribution network planning via coordination of distributed generation and network reconfiguration," *9th IFAC Symposium on Control of Power and Energy Systems (CPES)*, IIT Delhi, vol. 48, Issue 30, pp. 25–30, 9–11 December 2015.
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NATIONAL CONFERENCE

1. Neeraj Kanwar, Pawan Saini, Nikhil Gupta, Anil Swarnkar, and K. R. Niazi, "Genetic algorithm based method for capacitor placement using new sensitivity based approach," *18th National Power Systems Conference (NPSC)*, Guwahati, 18–20 December 2014. DOI: 10.1109/NPSC.2014.7103784