MULTI-OBJECTIVE NETWORK RECONFIGURATION IN CONTEMPORARY DISTRIBUTION SYSTEMS

Ph.D. Thesis

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April, 2018

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Submitted in

Fulfilment of the requirements for the degree of

Doctor of Philosophy

by

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April, 2018

CERTIFICATE

This is to certify that the thesis entitled "**Multi-Objective Network Reconfiguration in Contemporary Distribution Systems**" being submitted by **Mr. Praveen Kumar (ID: 2012REE9529)** is a bonafide research work carried out under my supervision and guidance in fulfillment of the requirement for the award of the degree of **Doctor of Philosophy** in the Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur, India. The matter embodied in this thesis is original and has not been submitted to any other University or Institute for the award of any other degree.

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DECLARATION

I, **Praveen Kumar**, declare that this thesis entitled, "**Multi-Objective Network Reconfiguration in Contemporary Distribution Systems**" and the work presented in it, are my own. I confirm that:

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- I have acknowledged all main sources of help.
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ACKNOWLEDGEMENT

I would like to express my heartfelt indebtedness to the wonderful people for their indispensable assistance during my doctoral study. I feel immense pleasure to express my sincerest gratitude to my supervisor Dr. Nikhil Gupta, Department of Electrical Engineering, MNIT, Jaipur for his invaluable guidance, keen interest, constant encouragement, incessant inspiration and continuous help throughout the period. His vast experience and realistic approach have been of great help to me in successfully completing of this research work.

I am grateful to my co-supervisor Prof. K.R. Niazi, Department of Electrical Engineering, MNIT, Jaipur for his generosity, expertise and guidance. He is a perennial source of inspiration and information for me. I am indebted to him for prompting me time and again to reach closer to my goals.

I would like to acknowledge the esteemed members of Departmental Research Committee Prof. Manoj Fozdar, Dr. Anil Swarnkar and Dr. Rajeev Tiwari for their cooperation, suggestions and discussion throughout the study. My special thanks goes to Dr. Anil Swarnkar for being a perpetual pillar of support.

I would like to express my regards to Prof. Udaykumar R Yaragatti, Director MNIT, Jaipur for extending all kinds of infrastructure and other facilities which made my research work hassle free. I am also thankful to Dr. Vikas Gupta Head, Electrical Engineering Department and Dr. H. P. Tiwari, Chairman DPGC, for creating a good research environment in the department and encouraging me to complete my research work. My thanks are also due to all the faculty and research fellows of the Department for their support.

I would like to give a special appreciation to my parents, wife Dr. Kalpana Agrawal, daughter Aarushi and son Adit for their patience, moral support in every way possible. They are there to provide me a helping hand at every step.

(Praveen Kumar)

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 the 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 operation of distribution systems.

This thesis addresses new issues related to distribution NR while considering the presence of renewable DGs and SCs to improve power quality and reliability of the system. 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, dynamic pricing, etc. The existing reliability indices have been modified so have more meaningful in the present scenario of existing distribution systems. Attempts have been made to give new dimensions to the framework of service restoration problems. Since the presence of optimally placed distributed resources can sufficiently manage power flow among distribution feeders, a new day-ahead NR strategy is suggested to minimize switching operations. The diversity, uncertainty and variability pertaining to load demand and power generation among distribution buses are duly incorporated in the problem formulations to create more practical scenario of contemporary distribution systems. With these concerns, the complexity of NR problem is raised by many folds. Therefore, improved variants of standard GA and PSO algorithms are developed by utilizing the concept of super sense whenever creating offspring during the computational process. These developed algorithms have successfully solved such complex optimization problems accurately and efficiently. Proposed methods are applied to standard as well as real distribution systems. The results of study are thoroughly investigated and presented. The application results reveal the importance of NR while dealing with performance improvement and service restoration problems of contemporary distribution systems.

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NOMENCLATURE

c_1, c_2	Acceleration coefficients
COV_b	Coefficient of variation for best fitness
COV_m	Coefficient of variation for mean fitness
D	System's average duration interruption index
$DV(i,n)$	Node voltage deviations for *i*th network topology during *n*th system state
DV_{min}/DV_{max}	Minimum and maximum value of node voltage deviation index
$EL(\mathrm{i,n})$	Energy losses for the *i*th network topology during *n*th system state
EL_{min}/EL_{max}	Minimum and maximum value of feeder power loss index
E_{Loss}	Energy loss during the day
ENS	Energy not supplied
ENS_{min}/ENS_{max}	Minimum and maximum value of energy not supplied index
F	System's average interruption frequency index
F_{in}	Objective function for loss minimization for the *i*th network topology at *n*th system state
$F(i)/\ T(i)/\ ENS(i)/\ D(i)$	$F/T/ENS/D$ for the *i*th candidate topology
$F(i,n)/T(i,n)/ENS(i,n)/\ D(i,n)$	$F(i)/\ T(i)/\ ENS(i)/\ D(i)$ for *i*th topology at *n*th system state
F_{min}/F_{max}	Minimum and maximum value of System average interruption frequency index
$gbest$	Best particle position based on overall swarm experience
$g_j(i)$	Set of power flow equations for *i*th network topology
$I(b, j, nom)^2$	Current in the *j*th distribution feeder in base configuration during nominal load conditions
$I(i\ , j, n)$	Current in the *j*th feeder for *i*th network topology during *n*th system state
I_j^{max}	Maximum current of *j*th branch (p.u.)
I_{jn}	Current of *j*th line at *n*th system state (p.u.)
itr	Iteration count
itr_{max}	Maximum iteration count
$k_e(n)$	Energy price prevailed at *n*th system state
$KVA(j)$	Apparent load demand of *j*th node
$KVA(\mathrm{j, n})$	Apparent load demand of *j*th node at *n*th system state
$KW(j)$	Active load demand on the *j*th distribution feeder
$KW(\mathrm{j, n})$	Active load demand at *j*th system node for *n*th system state
$LD(\mathrm{n})$	Load duration for the *n*th system state
LP	Set of load priority in the system
N	Set of system states
N_b	Set of system branches
N_c	Set of system nodes
P	Population size
$pbest_p$	Best position of *p*th particle achieved based on its own experience

$P_{c,n}/Q_{c,n}$	Active/reactive power flow in *c*th commercial feeders at *n*th state (kW/kVAr)
$p^{DG}{}_{j+1}$	Active power generation from DG at the (*j*+1)th node (kW)
P_{Dq}	Load demand of the *q*th priority
P_{DR}	Energized load during grid failure condition
$P^{for}{}_{SPV}$	Forecasted generation of solar phovoltaic
$P^{for}{}_{WT}$	Forecasted generation of wind turbine
$P^{gen}{}_{MT}$	Power generation from micro turbine
$P_{i,n}$ $/Q_{i,n}$	Active/reactive power flow in *i*th industrial feeders at *n*th state (kW/kVAr)
$P_{j,}/P_{j+1}$	Real power flow in line *j*/(*j*+1)th node(kW)
p_{j+1}/q_{j+1}	Net active/reactive power at the (*j*+1)th node(kW/kVAr)
$p^L{}_{j+1,}$ $q^L{}_{j+1}$	Active/reactive load demand at (*j*+1)th node(kW/kVAr)
$PLoss_{bn}/PLoss_{an}$	Network power loss in *i*th radial topology before/after network reconfiguration
P_{MT}	Load demand of micro turbine
$P^n loss$	Feeder power loss for the *n*th state
$P^{pre}{}_D$	Pre-estimated load demand
$P_{r,n}/Q_{r,n}$	Active/reactive power flow in *r*th residential feeders at *n*th state (kW/kVAr)
$P^{res}{}_{MT}$	Reserve of micro turbine
P_{SPV}	Power generation from solar phovoltaic
P_{WT}	Power generation from wind turbine
$Q_{j,}$ Q_{j+1}	Reactive power flow in line *j*/(*j*+1)(kVAr)
$q^{SC}{}_{j+1}$	Reactive power injection by SCs at the *(j+1)*th node (kVAr)
$r(j)$	Repair time of *j*th feeder
$r_1(.),r_2(.)$	Random numbers in the range [0, 1]
R_j	Line resistance of the *j*th line(Ω)
R^{ld}	Polyhedral uncertainty set generated for uncertain load demand
s^k , s^{k+1}	Displacement of particle at *k*th/(*k*+1)th iteration
s_p^k / s_p^{k+1}	Position of *p*th particle at *k*-th/(*k*+1)-th iteration
T	System's average interruption unavailability index
T_{min}/T_{max}	Minimum and maximum value of System average interruption unavailability index
$U(i,, j, n)$	*U*(*j*) for *i*th topology at *n*th system state
$U(j)$	Unavailability index of *j*th feeder
$\mathrm{V_{j,}}$ $\mathrm{V_{j+1}}$	Voltage magnitude of j/(j+1)th node (p.u.)
V_{jn}	Voltage of *j*th node at *n*th system state (p.u.)
V_{jn}	Absolute value of voltage of *j*th node during *n*th system state
v^k , v^{k+1}	Velocity of particle at *k*th/(*k*+1)th iteration
v_p^k / v_p^{k+1}	Position of *p*th particle at *k*th/(*k*+1)th iteration
$V_{max,}V_{min}$	Maximum/minimum limits of node voltage (p.u.)

v_{pbest}, v_{gbest}	Velocity of the *pbest*/*gbest* particle
$V_{r,n}/V_{i,n}/V_{c,n}$	Voltage at *r*th/*i*th/*c*th node of residential/ industrial/commercial feeder (p.u.) at *n*th *state*
V_s	Absolute value of the source voltage
w	Inertia weight
$W_{m,n}^{ld}$	SPDUS for load demand of *j*th node at state *n* for the *m*th month
w_{min}, w_{max}	Maximum/minimum bounds of inertia weight
ξ	Selection rate
X_j	Line reactance of the *j*th line (Ω)
$\chi_{j,m,n}^{ld}$	Synthetic data generated for *j*th node at state *n* for the *m*th month
z	Coefficient of uncertainty
$\gamma(k)$	Selection ratio during *k*th generation/iteration
Δt	Time step (s)
$\zeta(i, j,n)$	Failure rate in the *j*th distribution feeder at *n*th system state
$\lambda(j)$	Failure rate of *j*th feeder
$\hat{\omega}_{j,m}^{ld}$	Mean of the hourly mean of the forecasted load demand at *j*th node for the *m*th month
$\omega_{j,m,n}^{ld}$	Uncertain available data of load for *j*th node at state *n* for the *m*th month
$\underline{\omega}_{j,m,n}^{ld} / \overline{\omega}_{j,m,n}^{ld}$	Lower/upper bound of uncertain available data of load consumption for *j*th node at state *n* for the *m*th month
$\hat{\sigma}_{j,m}^{ld}$	SD of $\hat{\omega}_{j,m}^{ld}$
$\sigma_{j,m,n}^{ld}$	SD of hourly load demand for *j*th node at state *n* for the *m*th month
$\Phi_n(i)$	Closed path for *i*th network topology for *n*th state
$\mu(i, n)$	Overall fuzzy membership function for the *i*th network topology during *n*th system state
$\mu_{DV}^{MIN}(b)$	Minimum fuzzy membership function of $\mu_{DV}(b, n)$for the base topology
$\mu_{DV}^{MIN}(o)$	Minimum fuzzy membership function of $\mu_{DV}(o, n)$ for the optimal topology
$\mu_F(b, n)/\mu_T(b, n)/ \mu_{ENS}(b, n)/\mu_{EL}(b, n)/ \mu_{DV}(b, n)$	Fuzzy membership function of *reliability and power quality indices* for the base topology during *n*th system state
$\mu_F(i,n)/\mu_T(i,n)/\mu_{ENS}(i,n)/ \mu_{EL}(i,n)/\mu_{DV}(i,n)$	Fuzzy membership function for $F(i,n)$/ $T(i,n)$/ $ENS(i,n)$/ $EL(i,n)$/ $DV(i,n)$
$\mu_F(o, n)/\mu_T(o, n)/ \mu_{ENS}(o, n)/ \mu_{EL}(o, n)/ \mu_{DV}(o, n)$	Fuzzy membership function of reliability and power quality indices for the optimal topology during nth system state
$\mu_F^M(\mathrm{b})/ \mu_T^M(\mathrm{b})/ \mu_{ENS}^M(\mathrm{b})/ \mu_{EL}^M(b)$	Aggregate fuzzy membership function of $\mu_F(b, n)$/ $\mu_T(\mathrm{b}, n)$/$\mu_{ENS}(b, n)$/$\mu_{EL}(\mathrm{b}, n)$ for the base topology
$\mu_F^M(o)/ \mu_T^M(o)/ \mu_{ENS}^M(o)/ \mu_{EL}^M(o)$	Aggregate fuzzy membership function of $\mu_F(o, n)$/ $\mu_T(o, n)$/$\mu_{ENS}(o, n)$/$\mu_{EL}(o, n)$ for the optimal topology

ABBREVIATIONS

ABC	Artificial bee colony algorithm
ACO	Ant colony optimization
ACSA	Ant colony search algorithm
AES	Alternative energy sources
ANN	Artificial neural network
BA	Bat algorithm
BFA	Bacterial forging algorithm
BOU	Budget of uncertainty
CG	Current generation
CNR	Conventional network reconfiguration
CPU	Central processing unit
CSO	Cat swarm optimisation
DE	Differential evolution
DG	Distributed generators
DNO	Distributed network operators
DNR	Day-ahead network reconfiguration
DR	Distributed resources
DS	Data spread
ENS	Energy not supplied
ESS	Energy storage systems
GA	Genetic algorithm
GSA	Gravitational search algorithm
HSA	Harmony search algorithm
HPSO	Hybrid particle swarm optimization
LS	Long lived swarm
MT	Micro turbine
NR	Network reconfiguration
PED	Pre estimated demand
PSO	Particle swarm optimisation
RAM	Random access memory
RES	Renewable energy source
SAIDI	System average interruption duration index

SAIFI	System average interruption frequency index
SC	Shunt capacitor
SD	Standard deviation
SPDUS	Self-adaptive polyhedral deterministic uncertainty sets
SPV	Solar photo voltaic
SS	Short lived swarm
SSGA	Super sense genetic algorithm
SSPSO	Super sense particle swarm optimisation
TLBO	Teaching learning based optimisation
TPC	Thai power company
WT	Wind turbine

CHAPTER 1

INTRODUCTION

The electric power industries have witnessed many reforms in recent years. The concept of smart grid is taking shape with broader objectives to improve reliability, efficiency, power quality and safety of power delivery and its usage. The potential promise of the smart grid include 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]. However, major changes are taking place at distribution level to achieve the objectives of smart grid. The existing distribution systems are therefore moving toward smart distribution systems to achieve larger socio-economic and other non-tangible benefits [2]. It is important to note that majority of power quality and reliability issues are related to distribution systems and majority of power or energy losses occur in distribution systems owing to their low operating voltage levels. A typical distribution system accounts for 40% of the cost to deliver power and 80% of customers' reliability problems [3]. Studies show that as much as 13% of the total power generated is wasted on account of Joule's heating in the distribution networks [4]. The present trend towards deregulation and competitive business environment are compelling electric distribution utilities to improve their efficiency and reduce cost whereas customers are becoming more sensitive to reliability and power quality. Massive deployment of distributed resources (DRs) such as distributed generations (DGs), shunt capacitors (SCs) and renewable energy resources are taking place in distribution systems to realize the objectives of smart distribution systems. The present trend behind the high DG penetration in distribution systems evolved primarily on account of decreased capital cost of renewable DGs, environmental concerns, self-sustainability, peak shaving etc. The DGs deployed in distribution system are mostly renewable energy based such as SPVs and WTs. These energy resources are characterized by intermittency and uncertainty in power generation. For satisfactory system operation, therefore, the integration of dispatchable DGs like MTs and SCs becomes essential which leads to mix-DR model. Moreover, the loads on the distribution systems are also stochastic in nature. Therefore, structural characteristics and operational strategies of contemporary distribution system are changing. The electric utilities must constantly evolve to meet the changing requirements and operational strategies of electrical distribution systems.

The distribution network reconfiguration (NR) is one of the most effective operational strategies to improve the performance of distribution systems. It can effectively control both active and reactive power in distribution networks by merely exchanging the status of sectionalizing (normally closed) and tie-switches (normally open). Though network reconfiguration was fundamentally devised for service restoration during fault, but has been successfully used for improving the diverse performances of distribution system via loss reduction, voltage profile enhancement, reliability improvement, etc.

In legacy distribution systems the structure of the network is normally a mesh configuration, but it is operated in radial configuration to reduce fault level and to reduce the cost of protective schemes [5, 6]. The network operation is thus essentially constrained by the radial topology constraint. The radiality of distribution system introduces many problems such as higher power loss, inferior voltage profile, poor feeder load balancing, etc. The mesh distribution network is operated in radial mode by changing the open/close status of the tie/sectionalizing switches. For a given distribution network, there might be several possible radial configurations. A given radial configuration may be good under certain load conditions, but may not be economical for other. Similarly, one radial configuration may be satisfactory from the point of loss reduction, but may not be suitable from the point of view of feeder load balancing or reliability. The optimal network reconfiguration strategies attempt to address multiple objectives of distribution system performance.

About 70 years ago Merlin and Back [7] emphasized the utility of NR for power loss reduction by optimally balancing the load among distribution feeders. Since then, NR becomes an effective operational strategy to improve the multiple performance objectives of distribution systems such as loss minimization, voltage profile improvement, reliability enhancement, congestion management, etc. The network reconfiguration may be effectively used to achieve optimum performance of distribution systems even during the fault periods.

In contemporary distribution system with wide spread distributed energy resources, NR can also play crucial role to achieve self-healing objective of smart distribution systems, under fault conditions with and without loss of grid connection. It is worth to mention that future distribution system may also operate in isolated mode in case of grid failure. Under such condition the local power generation by DGs and SCs may partially feed critical distribution loads during abnormal conditions. The NR can help to shed non critical loads on priority basis so as to maximize the supply to important loads of the systems. This definitely enhances system reliability. However, the task is extremely difficult on account of satisfying power balance equations within distribution network while considering the variability and uncertainty of the load demand and power generation of renewables. With these concerns, NR becomes highly complex combinatorial exercise and requires development of new NR strategies for future distribution systems. The actual amount of benefit achieved through NR is governed by proper problem formulation that must fully addresses the realities of practical distribution systems.

The Distribution planners usually provide dedicated feeders to cater different class of customers, i.e. residential, industrial, and commercial, etc. and each has typical load profile [8]. Definite load diversity therefore exists among distribution buses which plays vital role in deciding the load profile of the system. Thus, variability exists among distribution buses owing to load demand and power generation and that should be duly addressed while formulating distribution optimization problem like NR. This, however, increases complexity of the NR problem by many folds thus makes it highly challenging task. The literature shows various population-based meta-heuristic techniques like [9-24]. These optimization techniques have the potential to efficiently solve complex NR problem of distribution systems. They though do not guarantee global optima, but are capable to provide a set of narrow-range solutions in the close proximity of the global optima, each of which have very good practical acceptance. These meta-heuristics are governed by some heuristic rules and have relative advantages and disadvantages. So there is always scope to improve their performance.

The roadmap of future distribution systems envisions widespread deployment of renewable energy sources (RESs) such as SPVs and 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 [25]. 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 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 have been adopted for mix-DG model to be implemented in future distribution systems [26]. This approach has revolutionized the frame work of optimal NR problems and thus intended to devise new formulations and methodologies to achieve more practical solutions. However, the mix-DG model possess additional challenges on account of the interactions of diverse time-variant energy sources and stochastic load demand. With these concerns, the NR problem of distribution systems assume different dimension and thus requires different treatment.

Contemporary distribution systems passes through various states during a day due to the integration of diverse energy resources, most of them have variability and intermittency in power generation, and also on account of stochastic nature of load demand. More specifically, distribution loads have diverse load characteristics owing to variety of customers. This time varying load and generation patterns when incorporated in NR problem formulation suggests hourly topological changes which is neither feasible nor practical. Therefore to develop new strategy that involves minimum switching operations is highly desired for existing active distribution systems.

The conventional optimal NR allocation problem has been solved using analytical, numerical, exhaustive search, heuristic or 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 need linearized modeling whereas exhaustive search methods suffer from the curse of dimensionality, so are not suitable for large-scale systems. Heuristic methods are very fast and provide promising solution, typically when subjected to solve loss minimization problems. On the other hand meta-heuristic techniques are robust and guarantees global or near global optima, but are computationally demanding. However, this limitation is not critical in the present scenario of available high speed computational platforms. 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. This leads to probably the most discussed disadvantage of metaheuristics. Metaheuristics may be broadly divided into evolutionary algorithms, like genetic algorithms (GAs), differential evolution (DE), etc. and swarm intelligence based techniques such as particle swarm optimization (PSO), ant colony optimization (ACO), teaching learning based optimization (TLBO), etc. GA and PSO may be called as the founder algorithms of these two broad classes of metaheuristics. However, GA suffers from high processing time and premature convergence [27], whereas particle swarm optimization (PSO) usually trapped into local optima [28]. These metaheuristics therefore requires 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.

In the light of above discussion this thesis attempts to reinvestigate the problem of multi-objective network reconfiguration for contemporary distribution systems. It aims to analyze the effect of reconfiguration on the overall performance of contemporary and future distribution systems and to reinvestigate solutions methodologies for network reconfiguration of contemporary and future distribution systems. This thesis explores solution methodologies for optimal reconfiguration of distribution systems in the presence of renewable DGs for service restoration, reliability enhancement and performance improvement while satisfying several network operational constraints. More realistic modeling is suggested by considering variability in power generation from renewable DGs and diversity in load demand among distribution buses. It is important to note that placement of DRs can also achieve some of the objectives of network reconfiguration and therefore it will be interesting to analyze the need of NR in such situations. In this thesis improved variants of some of the existing metaheuristics have been developed to complex NR problems of contemporary distribution systems. The applicability of developed methods has been thoroughly investigated on standard test distribution system. The results of the study are investigated and presented in the view of relevance of NR for contemporary distribution systems.

In the following chapter, comprehensive literature survey in the area of optimal allocation of DRs in distribution systems and NR is presented. A critical review of the literature has been carried out and on the basis of critical reviews, the objectives of the thesis are formulated.

CHAPTER 2

LITERATURE SURVEY

The distribution network reconfiguration (NR) is a well-known operational strategy to enhance reliability and improve performance of distribution systems, besides service restoration. It is the processes that alter topology of distribution network by merely exchanging the on/off status of sectionalizing and tie-switches. Distribution systems are generally structured in mesh but operated in radial configuration that optimizes certain objectives while satisfying operational constraints. For a given distribution network there might be several possible radial configurations. Finding a radial configuration, which optimizes the multiple objectives, is a difficult multi constrained combinatorial optimization problem. As the size of the network increases, the complexity of this problem increases. The complexity of the problem further increases in contemporary distribution system due to the stochastic nature of customer's power demands and presence of distributed generations. A lot of research has been conducted during the past decades to address the NR problem of radial distribution systems while considering a variety of objectives such as loss minimization voltage profile improvement, reliability enhancement, service restoration, etc. by considering different scenarios such as type of DRs and their mode of power generations, type of load profile and the type of NR strategy. The single or multi-objective NR problem is solved 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 contemporary 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 NETWORK RECONFIGURATION IN PASSIVE DISTRIBUTION SYSTEMS

Legacy distribution systems are passive without the presence of distributed generations. Merlin and Back [7] were first to report a method for NR to minimize line losses. They formulated the problem as a mixed-integer non-linear optimization problem and solved it through a discrete branch-and-bound technique. The method may not provide the global optimal solution due to the loop interaction problem. Civanlar *et al.* [23] suggested a branch exchange type heuristic algorithm to minimize real power loss under the assumption that the distribution system is well compensated and the phase angles of the bus voltages were neglected. Shirmohammadi and Hong [29] also presented a branch-exchange heuristic strategy for minimization of real power loss of a distribution network. Solution algorithm was initiated with a meshed network as in [7] and the lines with minimum current were opened successively till the desired radial topology is achieved. Baran and Wu [30] developed two approximate power flow methods with varying degree of accuracy. A branch-exchange heuristic of [23] was used for power loss reduction and load balancing. But, the method does not guarantee the global optimal solution. Similarly, Taylor and Lubkeman [31], Goswami and Basu [32], Augugliaro *et al.* [33], Kashem *et al.* [34], Kashem and Ganpathi [35], Huang and Chin [36], Gohokar *et al.* [37], Schmidt *et al.* [38], Gomes *et al.* [39], Raju and Bijwe [40] and several other works reported who solve reconfiguration problem for loss minimization using modified branch-exchange heuristics.

Later on the reconfiguration problem was attempted as a multi-objective optimization problem using heuristic rules. Das [41] suggested a fuzzy multi-objective approach for feeder reconfiguration which incorporates a heuristic rule base. Multiple objectives are considered for load balancing among the feeders and also to minimize the real power loss, deviation of nodes voltage, and branch current constraint violation. Ref. [42] followed the same method as in [41] except the difference that the overall fuzzy membership was calculated by weighted addition instead of min-max approach. Savier and Das [43] presented fuzzy multi-objective approach for distribution network reconfiguration using conventional branch exchange heuristic. Martin and Gil [44] presented a branch exchange heuristic approach to solve the reconfiguration problem by a switching operation in order to reduce the power loss of distribution systems. Unlike the conventional branch exchange algorithm, the proposed algorithm was based on the direction of the branch power flows.

Though these heuristic approaches are very fast but usually converges to suboptimal solutions when applied to large scale problems or while optimizing multi-objective problems. Moreover they converge to a single solution that might not be a feasible solution for the current state of the distribution network.

With the advent of fast computational facilities, researchers attracted toward these techniques which requires excessive computation before obtaining the global or near global optima. Several works reported have used Artificial Neural Network as an optimizing tool to solve reconfiguration problem. Kim *et al*. [45] proposed ANN where neural network developed was capable to provide the optimal solution for loss minimization of both constant and sudden load variations, and it also has the capability of a high-speed control strategy decision. Kim showed that the method using ANN is more suitable for on-line implementation compared with quadratic programming, simulated annealing and heuristic methods. Similarly, Bouchard *et al*. [20], Kashem *et al.* [47], Jin and Jiaja [48], Salazar *et al.* [49] and Siti *et al.* [50] also successively solve the reconfiguration problem. However, the training time of ANN was very large and the results affected if the ANN is under trained or over trained. Another difficulty is with the availability of real data to train ANN remains unresolved.

Meanwhile, several evolutionary and swarm intelligence-based optimization techniques such as genetic algorithm (GA), differential evolution (DE), ant colony optimization (ACO), particle swarm optimization (PSO), etc. have been attempted to solve this problem. The functioning of these heuristic approaches is independent of the nature of objective function and problem constraints, and converges to global or near global optima. Nara *et al*. [51] were first to introduce genetic algorithm (GA) as an optimizing tool for this problem. Since then several works [9-17, 52-62] have been reported who attempted this potential technique. GA is simple and easy to implement, but the tuning of operators may affect its performance. It has been observed that GA has extraordinary exploration potential, but its exploitation is weak and thus it causes premature convergence.

PSO is a very powerful swarm intelligence based technique which has been successfully applied to solve diverse engineering optimization problems. The special feature of this technique is that it governs only by a single control equation. PSO is inherently designed for continuous decision variables. Even then, several researchers [18-21] applied this technique to optimize reconfiguration problem. However, the accuracy, convergence and efficiency of PSO greatly suffers from parameter tuning otherwise it usually converges to suboptimal solution. Many efforts [63-67] have been reported to improve the overall performance of this technique by varying modulations of inertia weight, modifying cognitive/social behavior of the swarm, redesigning control equation or by restricting particle velocity using constriction factor approach or otherwise, etc.

Several other swarm and evolutionary techniques such as ACO [68-72], Simulated Annealing [73-76], Linear Programming [77], Immune Algorithm [78], Evolutionary Programming [79-80], Differential Evolution [81], Tabu Search [82-83], Honey Bee Mating Optimization [84], etc. can also successfully solve this problem.

2.2 NETWORK RECONFIGURATION IN CONTEMPORARY DISTRIBUTION SYSTEMS

The electric power industries have witnessed many reforms in the recent years. Building of such distribution systems requires local generation of reactive and active power using distributed energy resources such as shunt capacitors, distribution static compensator and dispersed or distributed generations (DGs), etc. These components allow increased efficiency, more reliability and better power quality. Moreover, they also facilitate effective utilization and life extension of existing distribution system infrastructure [1]. Therefore, the existing distribution systems are moving towards smart distribution systems to achieve larger socio-economic and other non-tangible benefits.

Distributed generations (DGs) refer to small generating units typically connected to the utility grid in parallel near load centers and can satisfy these objectives. Proper placement of DG is essential otherwise it may adversely affect the system [8]. Recently, several works have been reported who attempted optimal allocation of DG units in distribution systems using a variety of techniques such as GA, PSO, Artificial Bee Colony (ABC), Evolutionary Programming (EP), Bacterial Forging Algorithm (BFA), Harmony Search Algorithm (HSA), Gravitational Search Algorithm (GSA), etc.[85-96]. However, most of these optimization techniques require tuning of their algorithm-specific parameters: GA requires the crossover probability, mutation rate, and selection method; PSO requires learning factors, the variation of weight, and the maximum value of velocity; ABC requires the limit value; and HSA requires the harmony memory consideration rate, pitch adjusting rate and number of improvisations [97], etc. In fact, this parameter tuning is highly computationally demanding but is very crucial as it affects the performance of the algorithms.

In distribution systems shunt capacitors (SCs) are installed at certain locations to improve the performance of distribution systems in term of loss minimization voltage improvement etc. The SCs are essentially deployed in the distribution system to supply reactive power. The presence of SC significantly affects power flow among distribution feeders. Therefore location and capacity of SC is greatly affected by network reconfiguration. There are many possible approaches for optimal capacitor placement. Capacitor may be placed before network reconfiguration and may be placed after network reconfiguration. Some strategies suggest mixed approaches for capacitor placement. Ahmadi and Marti [98] optimally determined the different control variables, such as switchable capacitors, voltage regulators, and system configuration to satisfy various objectives, like loss minimization and voltage profile improvement by using Linearized power-flow equations and the problem is formulated as mixed-integer quadratic programming. Shuaiba *et al*. [99] reduced the power loss by first using the sensitivity analysis to reduce the search space and to arrive at an accurate solution for recognizing the locality of capacitors and then using the Gravitational Search Algorithm.

Smart grid requires integrated solutions of optimal allocation of DGs and network reconfiguration that reflect coexistence of multiple strategies to achieve higher energy efficiency and good quality power supply. The reconfiguration of active distribution networks play a vital role to achieve the objectives of smart grid in much better way as it can regulate the flow of both active and reactive power in the distribution feeders and transformers. Recently some work have been reported who solve the network reconfiguration problem in the multi-objective framework. Guedes *et al*. [100] suggested a new and efficient multi-objective branch exchange heuristic approach to solve the network reconfiguration problems. The authors claim that their method provides a feasible switching plan for all Pareto solutions. Andervazh *et al*. [101] proposed a Pareto-based multi-objective distribution network reconfiguration using PSO algorithm. The objectives considered are minimization of power loss, the number of switching operations and deviations of bus voltages. They employed probabilistic heuristics and graph theory techniques to improve the stochastic random search of the PSO. Some researchers [60, 95-96,101-104] have employed network reconfiguration in conjunction with the optimal allocation of DGs and acknowledged that this strategy is more useful to improve the performance of distribution systems. Zhang and Fu [60] employed joint optimization to solve DG allocation and network reconfiguration. However, this strategy is not realistic since the solution obtained can demand an alteration in both network topology and sites of DGs for different load scenarios. In practice, the network topology can be altered, but not the DG sites.

Lueken *et al*. [105] study showed that for a reconfigurable network net present value analysis of automated switch technology shows that the return on investment is negative for this test network when considering only loss reduction, but that the investment is attractive under certain conditions when reconfiguration is used to minimize curtailment. Rao *et al*. [95] presented a meta-heuristic Harmony Search Algorithm (HSA) to simultaneously reconfigure and identify the optimal locations for installation of DG units in a distribution network. They considered different scenarios of DG placement and reconfiguration of network to study the performance of the proposed method. Pilo *et al*. [106] study reveals that, modern distribution planning algorithms should emulate the new environment to produce expansion and strategic plans for guiding the evolution of system in times of financial restrictions and concluded that it is important to integrate smart grid operation within planning algorithms by allowing integration of renewable resources. Capitanescu *et al*. [107] paper explores how the DG hosting capacity of active distribution systems can be increased by means of network reconfiguration, both static, i.e., grid reconfiguration at planning stage, and dynamic, i.e., grid reconfiguration using remotely controlled switches as an active network management scheme. When many periods are considered the algorithm breaks down the large problem size.

Syahputra *et al*. [108] suggests that high performance distribution network optimization has become an important issue in the presence of DGs and can be achieved by optimal network reconfiguration. The study showed that the optimal configuration of the distribution network is able to significantly reduce both power loss and node voltage deviations. Guan *et al*. [109] uses Decimal coded quantum particle swarm optimization to solve feeder reconfiguration of DGs and applies decimal encoding to quantum particle swarm optimization, which can decrease the particle length, generate few infeasible solutions and have better search efficiency. Anjum *et al*. [110] in his study discussed the classification of DGs, problem formulation related to DSR and DG and then results are compared with and without DG with ACO, Heuristic etc. Tehboub *et al.* [111] proposed a strategy for distribution system reconfiguration proposed for minimizing the annual energy losses in the presence of distributed generators and variability in active and reactive power demand. Further energy loss reduction is obtained by grid automation and including the possibility of interchanging a predefined number of configurations that minimize annual energy losses. Bizuayehu *et al*. [112] shows the analysis of a distribution system subject to reconfiguration with high wind penetration over a period of 24 hours and to meet this objective, the reconfiguration problem is solved through mixed integer linear programming considering the stochasticity of the variables, where the balance between load and generation is satisfied at the lowest cost. Reza *et al*. [113] presented a hybrid method of meta-heuristic and heuristic algorithms, to boost robustness and shorten the computational time to achieve network minimum loss configuration with renewables. Chidanandappa *et al*. [22] proposed an algorithm for the reconfiguration of active distribution system using genetic algorithm and forward backward load flow method with time varying load condition. The algorithm provides various switching patterns for the optimal reconfiguration which gives minimum voltage, minimum loss and reduces the switching operation after satisfying the constraints. Rajaram *et al*. [114] applied Modified plant growth simulation to minimize real power loss because it does not require barrier factors or crossover rates. They dealt with the objectives and constraints separately. This is continuous guiding search algorithm along with changing objective function because power from distributed generation is continuously varying so this can be applied for real time applications with required modifications. Chen *et al*. [115] proposed a methodology to deal with segmented-time reconfiguration problem of distribution networks coupled with segmented-time reactive power control of distributed generators. They used the strategy of grouping branches mathematical problem and a hybrid particle swarm optimization (HPSO) method to search the optimal solution. To avoid trapping in local optima fuzzy adaptive inference is integrated into basic HPSO method. Pons and Repetto [116] showed that in order to satisfy the power balance at the local level, the distribution system operators are interested in the minimisation of the power exchange with the transmission network and maximising the local consumption of DG energy. They presented a topological reconfiguration procedure, based on the branch exchange technique, for maximisation of the local consumption of renewable energy.

Recently some works reported [95, 104] employed different combinatorial strategies of DGs allocation. But, according to their proposed strategy, network reconfiguration should be carried before the addition of DG units. In fact, the problem of planning horizon should be dealt before optimizing any operational strategy otherwise it may lead to erroneous results [117].

The aforementioned literature does not include the stochastic variations in load demand and the uncertainty related with the intermittent power output from DGs. Wu *et al.* [118] studied network reconfiguration with DGs and concluded that DG has the effects of loss reduction improvement over feeders and the topological structures of optimum network without DG are different from those with DG. Zidan and Saadamy [119] obtained the optimal configuration for each season of the year for minimizing annual energy losses and by considering switching operation costs. The DG power and varying load uncertainty are considered by creating a probabilistic generation load model that combines all possible operating conditions of the renewable distributed generators with the probability of their occurrence. Zidan *et al*. [120] proposed a GA based algorithm taking into consideration the uncertainty related to renewable distributed generation output power and the load variability. They considered three scenarios for distributed generation and the network configuration having constraint of line current limit, voltage limit and radial topology. Haghight and Zeng [121] proposed two steps for obtaining minimum loss configuration. They first enforce the radiality constraint and then power flows are computed for the worst operating conditions over the uncertainty sets. They proposed master slave structure for the optimization problem and also presented optimization model for network configurations and losses are derived in two steps. First the radiality constraint is ensured before knowing the actual system loads and output level of renewable generation and then Power flows are computed to achieve minimum network losses considering the worst operating conditions over the uncertainty sets. Researchers [95, 122] proposed a multi-objective algorithm to solve stochastic distribution feeder reconfiguration problem in the presence of distributed wind power generation and fuel cells. They considered uncertainty in wind power and solve the problem using population-based meta-heuristic techniques.

The reliability enhancement is an important issue of concern in modern distribution systems. The distribution network reconfiguration can be effectively used to improve the reliability of power supply to end users. Mendoza *et al*. [15] proposes an evolutionary-based micro-genetic algorithm for multi-objective reconfiguration in distribution networks by minimizing the losses and reliability indices. They generated well-distributed Pareto optimal solutions to the multi-objective reconfiguration problem and established that compact trade-off region exists between the power losses and the reliability indices. Narimani *et al*. [123] presented a technique for solving the multi-objective reconfiguration of radial distribution systems with regard to distributed generators. This considers reliability, operation cost and loss simultaneously and uses Enhanced Gravitational Search Algorithm (EGSA) having special mutation strategy for reducing the processing time and improving solution quality to avoid being trapped in local optima. Fard *et al.*[124] suggest a method to employ the distribution feeder reconfiguration as a reinforcement strategy to enhance the reliability of the distribution systems and several wind power sources are considered to assess their effects on the reliability indices. They proposed a method based on harmony search algorithm to improve the ability to explore the problem search space.

Gupta *et al*. [24] presented a method to improve the reliability and power quality of distribution systems using network reconfiguration by formulating two new objective functions to address power quality and reliability issues for the reconfiguration problem. They proposed a single objective function to address feeder power loss, system's node voltage deviation, system's average interruption frequency index, system's average interruption unavailability index and energy not supplied are transformed into a single objective function and then solved using GA based method. Fard *et al*. [125] established a method for reliability improvement by defining a cost function to include the cost of active power losses of the network and the customer interruption costs simultaneously. To find the customer interruption cost data the composite customer damage function is applied. A novel self-adaptive modification method based on the clonal selection algorithm is proposed as the optimization tool. Fard *et al*. [126] investigated the optimal feeder reconfiguration and found this to be a valuable and cheaper approach to increase the load balance, reduce the amount of power losses, and improve the voltage of the buses.

Zhang *et al*. [127] suggest a multi-agent system based distributed control solution that can realize optimal generation control and the solution is designed based upon an improved distributed gradient algorithm, which can address both equality and inequality constraints. Reliability is improved by introduction of N-1 rule to design the communication network topology. Murthy *et al*.[128] presented the effect of reconfiguration in the presence of distributed generation (DG) in radial distribution system to improve the voltage stability with different load models by using Artificial Bee Colony (ABC) algorithm. The NR selects the best set of branches to be opened, one from each loop, such that the reconfigured radial distribution system possesses desired performance characteristics. Jahromi *et al*. [129] shows that daily load curves of different types of distribution consumers, during various types of days (weekdays and holidays) and seasons (summer and winter),are used to obtain the best reconfiguration hours during a day. They used genetic algorithm to obtain the optimum configuration during each time interval having objective function of loss and energy not supply. The configuration is changed by the remote controlled switches for the speedy operation.

Paterakis *et al*. [130] developed a method for Day-ahead Network Reconfiguration (DNR) by means of minimizing active power losses and a set of commonly used reliability indices. They used lexicographic optimization to solve the multi-objective optimization problem and the reliability indices are developed with a mixed-integer linear programming approach. Lopez *et al*. [131] presented a mixed-integer second-order conic programming model for the robust reconfiguration of electrical distribution systems, considering the minimisation of active power losses and reliability constraints. The uncertainty at the reliability data is considered by using a linear and adjustable robust approach. The reliability indices SAIDI, SAIFI are calculated as functions of the switch status.

In contemporary distribution systems with imbedded DGs and SCs, network reconfiguration can also be effectively used for service restoration. In fact self-healing through advance protective scheme and network reconfiguration is one of the most important objectives of smart distribution systems. Kotamarty *et al*. [132] discusses a procedure for evaluating the impact of site and size on both the original distribution power system as well as a reconfigured power system after a fault. They showed that using these alternative energy and other traditional energy sources, in the distribution power system, allows the development of a new paradigm related to distributed generation (DG). Botea *et al*. [133] discussed the reconfiguration problem for supply restoration when the switching cost is higher, the network reverts to its normal configuration quickly, the electricity loss and the load imbalance in a temporary suboptimal configuration are of less importance. They proposed optimal informed search algorithms and introduced heuristics for reconfiguration and Combining A with admissible cost. Song *et al*. [134] defined and classified the smart control functions for the Distributed Energy Resources units in the Smart Distribution Network. The integration schemes are introduced for the SDN with DER units. They proved the effectiveness of the scheme by implementing this into the Korean Smart Distribution Management System (KSDMS) as operation schemes for loss reduction and service restoration. Pavanaand Triveni [135] proposes the MST-Kruskal's technique for determining optimal target network for minimization of the power losses, maximization of the load balance and for restoration of the power after network reconfiguration.

Quevedo *et al*. [136] suggested to apply energy storage systems and renewable energy sources for the overloaded and increased power loss DS. They presented an optimal contingency assessment model using two-stage stochastic linear programming including wind power generation and a generic ESS. They propose that in case of contingencies, energy storage systems (ESS) and renewable energy sources (RES) can be applied to improve operating conditions. They presented two-stage stochastic linear programming including wind power generation and a generic ESS, and obtained the best radial topology by determining the best switching sequence to solve contingencies. Huang *et al*. [137] proposed an algorithm to realize synchronous optimization of both main network and island restorations that are used to find the global optimization solution. The proposed method breaks the loops in the distribution systems by matrix operations and significantly improve calculation speeds.

The loads and DGs generation in distribution systems keep changing with time. Therefore an optimal configuration obtained for certain loads and distributed generation conditions may no longer be optimal under new operating conditions. How often NR is to be performed, depends on various factors such as switching cost, reduction in loss, maximization of income etc. Cho *et al*. [138] find out optimal load which obtain best network reconfiguration result according to time-varying load demand and DG generation. The proposed method show how to select the most optimal load considering not only time-varying demand and DGs generation but also the number of switching for maximizing income. Study by Reza *et al*. [139] considers the uncertainty related to renewable distributed generation output power and the load variability by proposing a mathematical model to minimize daily network losses by applying hourly reconfigurations. This is a mixed integer second-order cone programming problem and is solved by MOSEK solver by considering the load demand variations and renewable power generation fluctuations during a day. Alcaraz *et al*. [140] suggest a two-phase approach for optimal short-term operational scheduling with intermittent renewable energy resources (RES) in an active distribution system. Initially the amount of purchased power from the market and the unit status of distributed generation (DG) is determined and feeds the data for a real-time scheduling coordination with hourly network. Golshannavaz *et al*.[141] proposed an algorithm that targets to optimally control active elements of the network, distributed generations and responsive loads for minimize the day-ahead total operation costs. This algorithm uses hourly network reconfiguration by placing remote control switches. Chen *et al*. [142] suggests day-ahead scheduling model considering renewable energy generation like forecasting errors of wind speed, solar radiation intensity and loads are formulated as interval numbers so as to avoid any need for accurate probability distribution. For the optimization of nodal voltage deviation and network power losses, order relation of interval numbers is used to transform the proposed interval optimal scheduling model into a deterministic optimization problem which can be solved using the harmony search algorithm. Reja *et al*. [143] proposed day-ahead NR in active distribution systems by applying hourly reconfiguring strategy. They considered the variability in load and power generation from DGs during the day and reconfigure distribution network for loss minimization.

2.3 CRITICAL REVIEW

In the present competitive deregulated environment of power distribution utilities, there is stringent pressure to maximize annual profits while on the other hand the customers are sensitive to get good quality of power supply with adequate reliability. Literature shows that the integration of optimally placed DGs and SCs in distribution systems can achieve these objectives to a great extent. Furthermore, the stringent environmental laws and declining trend in the installation cost of renewable DGs has made them very popular in contemporary distribution systems. Therefore, future distribution system can be seen with deep penetration of these DRs. This, however, greatly affects the power transactions from the utility grid and also the flow of power among distribution feeders in such a way that distribution systems may be operated with very good energy efficiency and node voltage profiles. The NR is a well-known operational strategy of distribution systems which has been extensively studied and successfully implemented for service restoration, enhance system reliability and also to enhance system performance by minimizing feeder power losses and node voltage deviations under normal and abnormal conditions. In this context, it is essential to reinvestigate the extent of benefit that would be extracted by optimal reconfiguration of contemporary distribution systems.

From the abovementioned literature review it is evident that NR problem has gained new dimensions in the context of contemporary distribution systems being well equipped with diverse energy resources such as renewable DGs, AESs and SCs. These renewable DGs are characterized by uncertainty and intermittency in power generation, therefore the stochastic nature of load profile needs due consideration while formulating NR problem. With these considerations, the distribution network states are now becoming dynamic thus needs exploration of new and more practical NR strategy while addressing service restoration and network performance of distribution systems by giving due consideration to performance improvement versus minimization of switching operations. Moreover, realities of practical distribution systems such as load diversity among distribution buses on account of different type of distribution customers should be addressed to avoid counterproductive solution. With these concerns, the complexity of NR problem increases by many folds. This intends new more realistic problem formulations, methodologies, strategies and the application of more accurate optimization techniques to solve NR problems. This definitely has shifted the paradigm of formulation and solving distribution system optimization problems in the context of contemporary distribution systems. The NR problem of distribution system therefore needs reinvestigation while employed to solve diverse vital objectives pertaining to system performance improvement, reliability enhancement, system restoration. The distribution systems should be more reliable and secured. The reliability of electric distribution systems is the strict function of Joule's heating developed along various power distribution components. The distribution feeders are pretty long so are ones among other distribution components which are usually more prone to faults. The future distribution systems may have most undergrounded feeders to reduce the frequency of occurrence of faults as it directly enhances system reliability. The reliability indices therefore need to be reviewed in the view of Joule's heating as this heating is much more important in under-ground feeders than in over-head distribution feeders. A new formulation therefore required to address reliability concerns for NR problems of distribution systems. Moreover, the power quality and power reliability issues show conflicting nature while solving NR problems. Therefore, a multi-objective problem formulation should be devised in order to provide most compromising solution to distribution system operators.

While considering optimization techniques, the evolutionary and swarm intelligence-based metaheuristics have successfully solved the NR problem of distribution systems, but are computationally demanding and needs cumbersome parameter tuning through experimentations. Several improved variants of these techniques are available in literature which has enhanced their performance by improving the internal working, introducing additional control parameters or by hybridization with other suitable technique, etc. However, the overall performance of the standard model of these techniques may be significantly enhanced by just attacking on the inherent limitations of these techniques. Whatever be the modification suggested for improved variants, they should be simple to understand and easy to implement. Therefore, there is a need of time to develop simplified but efficient models of standard metaheuristics.

On the basis of critical reviews, following research objectives have been formulated for the thesis work.

1. To carry out exhaustive literature survey in the area of distribution network reconfiguration (NR) for service restoration, reliability enhancement and distribution system performance improvement and to study existing optimization techniques to solve NR problems of distribution systems.
2. To develop improved variants of existing metaheuristic techniques and investigate their applicability to solve small and large-scale NR problems of contemporary distribution systems.
3. To propose multi-objective formulation for optimal NR problem of contemporary distribution systems to simultaneous optimize reliability and power quality objectives while considering practical feeder power flow constraints and stochastic variation in load demand and power generation from renewable DGs.
4. To develop new strategies for both on-grid and off-grid service restoration and investigate the impact of NR to enhance the performance of active distribution systems during abnormal operating conditions.
5. To propose new NR strategy and formulations for NR problems while considering various distribution system states owing to variability, diversity and uncertainty of load demand and power generation among distribution buses, and reinvestigate the effectiveness of NR and the strategy proposed in the context of contemporary distribution systems.

In this chapter, an exhaustive literature survey in the area of distribution network reconfiguration (NR) for service restoration, reliability enhancement and distribution system performance improvement have been carried. The literature survey also includes existing optimization techniques to solve NR problems of distribution systems. A critical review of the literature is also presented to identify the research gaps. In the following chapter improved variants of existing metaheuristic techniques have been developed for network reconfiguration of contemporary distribution systems. In the following chapter improved variants of GA and PSO techniques have been developed to solve small and large-scale NR problems of contemporary distribution systems.

CHAPTER 3

PROPOSED META-HEURISTIC METHODS FOR DISTRIBUTION NETWORK RECONFIGURATION

The network reconfiguration problem is a highly complex combinatorial non-linear optimization problem of distribution systems. The complexity of this problem has increased many folds in contemporary distribution systems due to the presence of distributed energy resources and tunable compensating devices. A lot of research work has been carried in the area of DNR for single and multiple objectives including service restoration. This has led to the development of different approaches. The problem has been earlier solved using several mathematical approaches [144-145] and heuristic methods [29-44,146-152] while considering certain assumptions or solving for loss minimization of small-scale distribution systems. Later on population-based meta-heuristics such as GA [9-17, 52-62], PSO [18-21], ACO [68-72], TLBO [8,153-154], BA [155-156], CSO [157-158], etc. have been exploited to solve complex multi objectives DNR problems. In the recent past several new meta-heuristic techniques have been evolved and lot of work has been contributed on the further refinement of existing metaheuristics. Among all metaheuristics, GA and PSO are of great interest as are not only the very first developments of evolutionary and swarm intelligence-based techniques respectively, but also had provided platform to develop numerous well-established metaheuristics as mentioned above. Moreover, these two fundamental techniques are still on the center of focus of researchers to enhance their performance by suggesting various improved variants and only some of them can be mentioned as refined GA [9-10], fuzzy GA [13,53,59], enhanced GA [11], hybrid GA [12,62], adaptive GA [60], micro GA [15], dedicated GA [16], discrete PSO [18], modified PSO [19], self-adaptive PSO [20] and enhanced integer coded PSO [21]. This is due to the fact that both GA and PSO are simplest to understand and easiest to implement while solving diverse engineering optimization problems. However, the complexity of engineering optimization problems is consistently increasing with time as the systems are now becoming more and more complex on the one hand and the business environment becomes more and more competitive on the other hand. Moreover, rational issues and concerns have to be considered while formulating the problem in order to provide more realistic scenarios so obtained more practical solutions that can withstand successfully in the present competitive environment. The literature witnessed many successful attempts where GA and PSO have been improved [159-168]. However, these attempts worked out on the improvement of inner working of these techniques by suggesting different methods for crossover or mutation operators of GA or by redefining the control parameters of PSO. Nevertheless, attempt has yet not been addressed where the human intelligence element is incorporated along with the artificial intelligence of these techniques. The coalition between these two intelligences may enhance the performance of these techniques as the human intelligence can play vital role without affecting the inner working of these techniques. The human intelligence element when incorporated in GA and PSO enables them to have super sense during the selection process of these techniques. In this chapter, different variants of GA and PSO named as (super sense GA) SSGA and (super sense PSO) SSPSO respectively have been developed by incorporating the human intelligence element in their basic models. These developed variants have been investigated to solve the NR problem on standard test systems with and without diverse distributed resources. The results of investigations are analyzed and presented.

3.1 Network Reconfiguration In Contemporary Distribution Systems

Network reconfiguration (NR) is one of the well-known and most effective operational strategies to improve the efficiency, reliability and power quality of distribution systems, apart from service restoration.

Distribution networks are generally structured in mesh but operated in radial topology for effective co-ordination of their protective schemes and to reduce the fault level [5]. For a given distribution network there might be millions of possible radial topologies. Therefore, the determination of one particular radial topology that optimizes desired objectives while satisfying certain specified network operational constraints is a hard complex combinatorial exercise. In fact, the optimal NR may be said as one of the complex optimization problem of power system. On the one hand, the combinatorial nature of the problem increases with the increase in the size of the distribution systems. In recent years, the legacy passive distribution systems are being transformed into active distribution systems by the widespread deployment of renewable DGs as they provide green energy economically and efficiently at the doorsteps of the end users. However, the integration of these RESs lead to additional complexities to power system operators which are primarily concerned with the intermittency associated with their power generation, bi-direction power flows among distribution feeders and alarming over voltages among distribution nodes. Further, the distribution systems have a variety of customers each have characteristic load pattern that is not only stochastic in nature but also varies with seasons. This leads to the consideration of several time varying states of the distribution system due to prevailing load and generation patterns of distribution buses. Therefore, the reconfiguration of distribution networks needs to be performed frequently to achieve optimum performance of distribution systems while the feeder currents and node voltage constraints need to be stringent while solving NR problems.

The trend towards deregulation and competitive business environment are forcing electric utilities to improve their energy efficiency and reduce cost while consumers are becoming more sensitive to reliability and power quality. In this context, optimal NR becomes vital strategy for the distribution network operators (DNOs) since the majority of the power quality and reliability issues are related to distribution systems and majority of the power losses occur in distribution systems owing to their low operating voltage levels. Therefore, distribution system design and operation are becoming critical for financial success of electric utilities and customer's satisfaction.

3.2 PROBLEM FORMULATION FOR DISTRIBUTION NETWORK

The NR problem is formulated to minimize power loss reduction for the given system state n and to maintain node voltages within prescribed limits while considering distribution system well equipped with distributed resources such as DGs and SCs. The problem is formulated as:

$$\text{Max. } F_{in} = \left(PLoss_{bn} - PLoss_{an} \right); \forall n \in N \tag{3.1}$$

where, $PLoss_{bn} / PLoss_{an}$ are network power loss in the ith radial topology before and after NR for nth system state.

Subject to the system operational constraints defined below.

The sum of the power supplied from the utility grid and the total power generated by the different DRs being installed in the distribution system must be balanced by the local load demand and feeder power losses. For a radial network, a set of recursive equations are used to model the power flow in the network as given by (3.2)-(3.6).

$$P_{j+1} = P_j - R_j \frac{P_j^2 + Q_j^2}{V_j^2} - p_{j+1};\ \forall j \in N_c \tag{3.2}$$

$$Q_{j+1} = Q_j - X_j \frac{P_j^2 + Q_j^2}{V_j^2} - q_{j+1};\ \forall j \in N_c \tag{3.3}$$

$$V_{j+1}^2 = V_j^2 - 2\left(R_j P_j + X_j Q_j \right) + \left(R_j^2 + X_j^2 \right) \frac{P_j^2 + Q_j^2}{V_j^2};\ \forall j \in N_c \tag{3.4}$$

$$p_{j+1} = p_{j+1}^{L} - p_{j+1}^{\mathrm{DG}};\ \forall j \in N_c \tag{3.5}$$

$$q_{j+1} = q_{j+1}^{L} - q_{j+1}^{\mathrm{SC}};\ \forall j \in N_c \tag{3.6}$$

1. Node voltage constraint

All node voltages V_{jn} of the nodes at state $j$must be maintained within the minimum and maximum permissible limits *i.e.* $V_{\min}$ and $V_{\max}$, respectively as defined below

$$V_{\min} \le V_{jn} \le V_{\max};\ \forall n \in N; \forall j \in N_c \tag{3.7}$$

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

$$I_{jn} \le I_j^{\max};\ \forall n \in N, \forall j \in N_c \tag{3.8}$$

3. Radial topology constraint

The reconfigured network topology must be radial, i.e. with no closed path. Therefore, the radiality constraint for the ith radial topology at nth system state is defined as

$$\Phi_n(i) = 0; \forall n \in N \tag{3.9}$$

While dealing with NR problem using any population-based optimization technique, the radiality constraint imposes the biggest hurdle as all tentative solutions must represents radial topologies without any islanding. In the present work, the codification proposed by [5] is used to handle the radiality constraint. This is a rule-based codification to check and correct the infeasible radial topologies. According to this codification, following three rules are framed which are based on graph theory to identify and correct infeasible individuals whenever appeared in the computational process.

Rule 1: Each candidate switch must belong to its corresponding loop vector.

Rule 2: Only one candidate switch can be selected from one common branch vector.

Rule 3: All the common branch vectors of a prohibited group vector cannot participate simultaneously to form an individual. For further details about the loop vector, common branch vector and prohibited group vector, Ref. [5] may be referred.

3.3 HANDLING UNCERTAINTY MODELING FOR LOAD AND GENERATION

Several probabilistic and deterministic techniques have been suggested in the recent past to handle uncertainty and variability of load demand and power generation from renewable DGs. Recently, Wang *et al.* [169] suggested deterministic polyhedral uncertainty sets to deal with the uncertainty of intermittent generations from RESs and the stochastic load demand. They claimed that these 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. But, the proposed model has limitation that the selection of data spread (DS) and budget of uncertainty (BOU) is a difficult task. Therefore, these parameters are taken constant in [169] while generating synthetic data for load demand or power generation at system buses. However, 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 the authors' view, these parameters must be made self-adaptive with the prevailing conditions of generation/load demand at system buses. Therefore, new self-adaptive polyhedral deterministic uncertainty sets (SPDUS) are proposed in [170] which require historical uncertain data only for a year. According to this model, the available annual hourly information is segmented into twelve segments each consists of a data set of matrix 24x*m*, i.e. one for each month. The hourly mean and standard deviation (SD) of the monthly data is used to generate SPDUS. In this modeling, DS and BOU depend upon the mean and SD of the data set matrix. The self-adaptive feature of SPDUS is based upon the philosophy that the variations in uncertain data is governed by the law of nature, therefore the modeling must faithfully follow the law of natural distribution. Therefore the method of [170] is employed to deal with variability and uncertainty of load demand and power generation. In this method the SPDUS $W^{ld}_{m,n}$ for the load demand of the node *j* at state *n* of the month *m* is defined as

$$\left.\begin{aligned} W^{ld}_{m,n} = \left\{\chi^{ld}_{j,m,n} \in R^{ld} : \underline{\omega}^{ld}_{j,m,n} \le \chi^{ld}_{j,m,n} \le \overline{\omega}^{ld}_{j,m,n}\right\}; \\ \forall j \in N_c \\ \underline{\omega}^{ld}_{j,m,n} = \omega^{ld}_{j,m,n} - z\sigma^{ld}_{j,m,n} \\ \overline{\omega}^{ld}_{j,m,n} = \omega^{ld}_{j,m,n} + z\sigma^{ld}_{j,m,n} \end{aligned}\right\} s.t.\ \hat{\omega}^{ld}_{j,m} - z\hat{\sigma}^{ld}_{j,m} \le \hat{\chi}^{ld}_{j,m} \le \hat{\omega}^{ld}_{j,m} + z\hat{\sigma}^{ld}_{j,m} \tag{3.10}$$

where, ω-terms denote available data and χ-terms denote the synthetic data to be generated. In the similar way, the uncertainty sets of power generation from SPV and WT units may also be defined.

The DS for the load demand of node *j* at state *n* for month *m* is described by the interval $\left[\underline{\omega}^{ld}_{j,m,n},\ \overline{\omega}^{ld}_{j,m,n}\right]$. The uncertain load demand at the node *j* at state *n* for month *m* is constrained by the DS $(\omega^{ld}_{j,m,n} \pm z\sigma^{ld}_{j,m,n})$. Where, $\sigma^{ld}_{j,m,n}$ is the SD of the hourly load demand over the month *m* for the node *j* at state *n*. The synthetic load data so generated is further constrained by BOUs. The lower and upper limits of BOU are $[\hat{\omega}^{ld}_{j,m} \pm z\hat{\sigma}^{ld}_{j,m}]$. Similarly, the uncertainty sets for SPVs and WTs can be developed. The value of *z* depends upon the strategic location where renewables have been placed. Its value is considered as unity in the present work.

The unique feature of SPDUS 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, SPDUS method provides less conservative solutions for DR planning and operation.

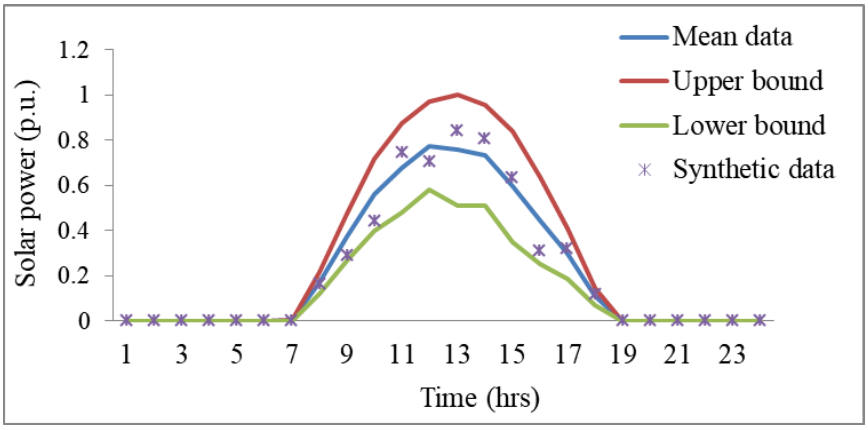


Fig. 3.1 Representation of synthetic data generated for SPV power generation

A sample for the synthetic data generated for the power generation from SPV unit is shown in Fig. 3.1. 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 uncertainty model easily takes care as in case of uncertainty of load demand at system buses.

3.4 Proposed Super Sense GA For Network Reconfiguration

GAs are derivative free adaptive heuristic search algorithm inspired by the concept of natural selection and genetics. The development of GA is largely credited to the work of Holland [171] and Goldberg [172]. Since then GAs have evolved and become a promising tool to solve diverse engineering optimization problems [5]. GA is initialized with random population (tentative solutions) dispersed in the problem search space to simulate the survival of the fittest individuals over consecutive iterations called generations. The population consists of individuals of character strings that are analogous to the chromosome that we see in our DNA. Depending upon the genotype coding, each chromosome possesses a characteristic fitness value decided by the objective function to be optimized. Higher the fitness value of an individual, better will be the chances of its survival. The individuals are allowed to participate in the evolutionary process from one generation to next generation. Selection, crossover, mutation and termination are the basic operators of GA. The law of natural selection and genetic drift lead to the evolution of better and better individuals during the evolutionary process. The genetic drift is imposed by genetic operators, namely crossover and mutation. Crossover is the main operator of GA that selects two individuals (parents) and brings them together on the matting pool. The offspring so produced have diverse genotype coding that help to explore the problem search space. However, this diversity in population is not sufficient so GA may stagnate, i.e. there is no improvement in the mean fitness of individuals. This usually leads to local trapping. In order to avoid this, a small percentage of the population is mutated. The mutation provides sudden genetic drift thus pulls individuals out of the hat. GA is assumed to be terminated after pre-specified generations, and the best individual obtained during the complete evolutionary process is treated as the solution of the problem being optimized. Elitism is used to preserve the best individual obtained in each generation.

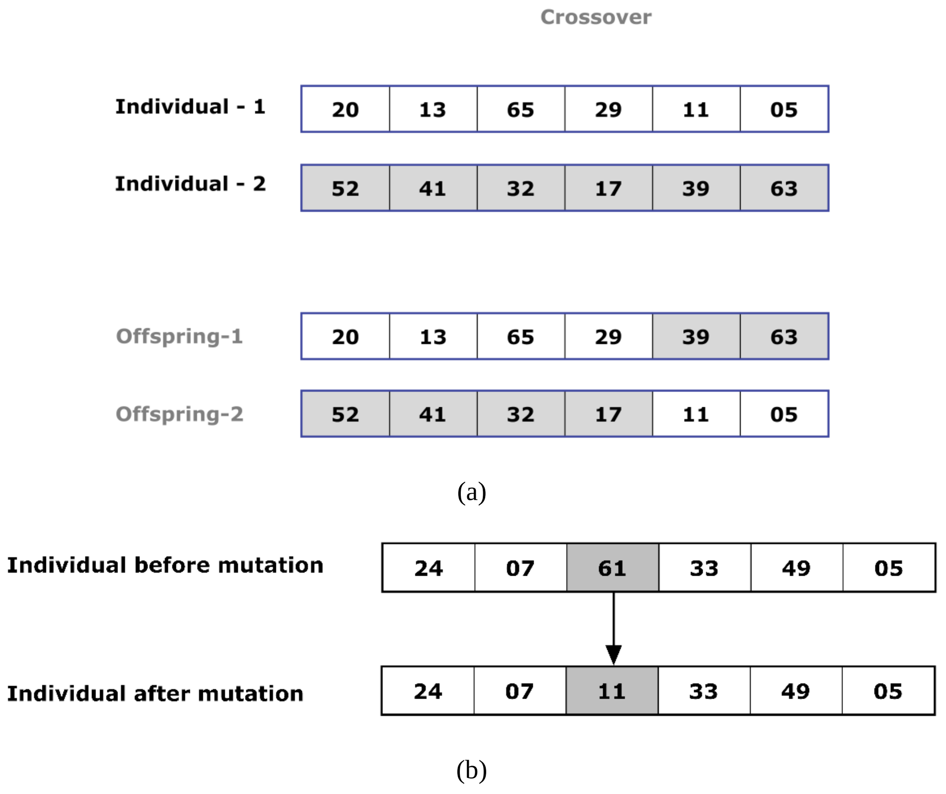


Fig. 3.2 Demonstration of GA (a) Crossover (b) Mutation

While considering network reconfiguration problem of distribution systems, a set of definite number of switches (co-tree branches) may represent an individual having decimal genetic coding represented by the set of switches such that their opening provides a radial topology of the distribution network while all loads remain energized. Therefore, the structure of individuals for GA may be considered by the string of switches as shown in Fig. 3.2. The length of string is restricted to the number of tie-lines in the distribution system. The figure also illustrates the crossover and mutation of GA.

The standard GA suffers from limitations such as poor convergence, local trapping, etc. while dealing with complex optimization problems. Though GA possesses very good communication among individuals using crossover operator, but the diversity is lost whenever two identical parents are selected at the mating pool. The chances of the selection of such identical parents increase as the algorithm progresses. Therefore, the diversity is most likely to be lost during anaphase of algorithm and it leads to premature convergence of GA. Several attempts have been reported in literature who experimented on various methods to modify crossover or mutation operators. In fact, the full potential of these techniques can be extracted if attempts are made to alter their internal mechanism in such a way that provides self-sustainable healing against their intrinsic flaws [173]. Nevertheless, it will be interesting to see the improved performance of GA without altering the internal mechanism of standard GA. This could be possible if the human intelligence is embedded with the artificial intelligence of meta-heuristic techniques. The fundamental difference between the artificial and human intelligence is that human beings can sense and react accordingly. With this theme, Super Sense GA (SSGA) is proposed in this work. The internal working of the SSGA is identical to that of standard GA, but the selection of individuals is biased by the human intelligence element. In GA, and all other evolutionary and swarm-intelligence-based metaheuristics, the decision variables are selected in a random or probabilistic fashion to form individuals without considering their ability to affect the objective function to be optimized. In SSGA, though the selection process is probability based, however, it also considers the ability of decision variables with regards to the fitness value of the objective function. In order to incorporate this sense in SSGA, both the genotype coding and the fitness of each child is compared with their parents and the decision is taken to determine whether or not the genotype coding of offspring has improved their fitness. The genetic information so obtained is stored into two different archives; the Archive-A, if the fitness improves otherwise in the Archive-X. Moreover, these archives also store the frequency of genetic information being stored. In each generation a definite percentage of population is selected from these archives on probabilistic basis that depends upon the frequency of genetic information stored.

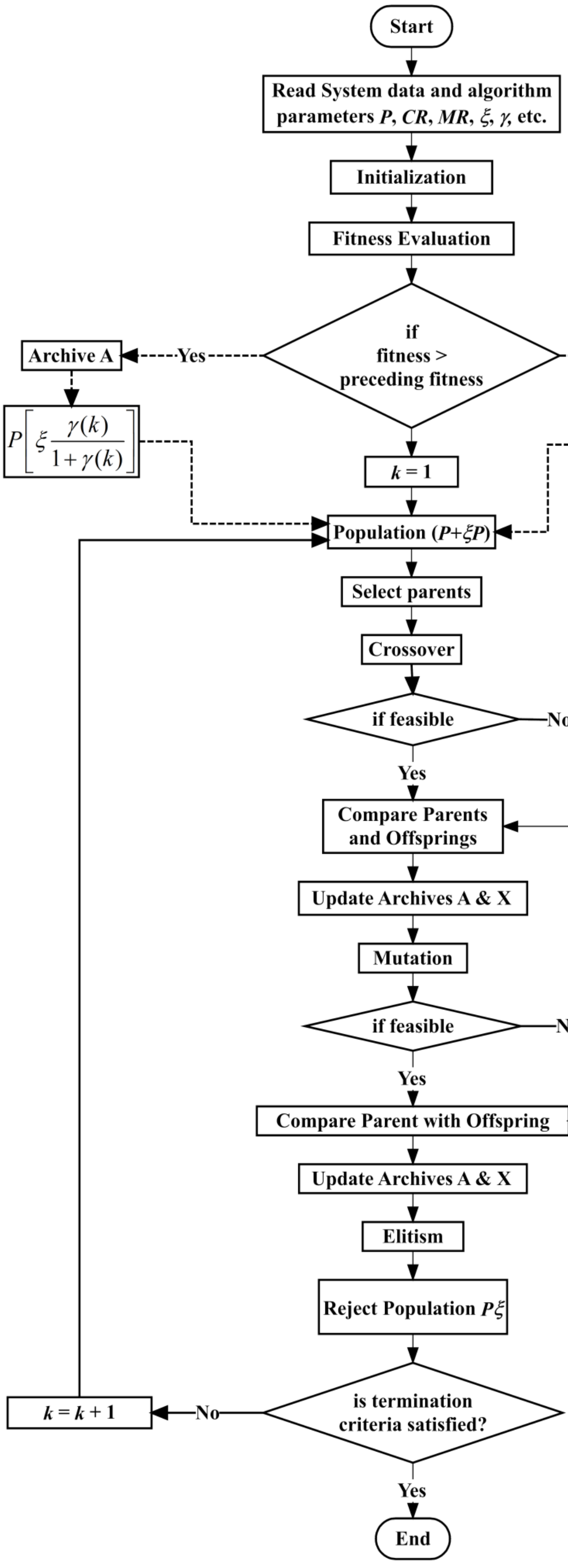


Fig. 3.3 Flow chart of proposed SSGA

These individuals are allowed to participate in the evolutionary process. The Archive-A is likely to provide better fit individuals in the population so that better offspring may produce, whereas the reverse may be true while considering the selection of population from the Archive-X. The role of proposing Archive-X is that it maintains adequate diversity in population. The selection of total population from these archives is defined as the selection rate ξ which is defined as the definite fraction of the population size being used for GA. The selection ratio $\Upsilon(k)$for the population generation has also been defined as the ratio of population being generated from Archive-A and Archive-X during *k*th generation. Adequate values of these parameters are desired. Higher values of the selection rate may unnecessarily increase the computational burden of GAs, whereas sufficient smaller values do not appreciably influence the performance of algorithm. Therefore, 0.5 may be an ideal choice for the selection rate. However, care has to be taken so that total population generated ($P + \xi P$) be even numbered. On the other hand, the selection ratio is randomly selected within the range [1, 4] such that even numbered population is generated from each achieve. The crossover and mutation operators are kept same as in the standard GA. SSGA terminates when the maximum generations are exhausted. The population is replenished in each generation by replacing ξP of least fit individuals from the population by the equal number of individuals being generated through archives. The flow chart of SSGA is shown in Fig. 3.3.

3.5 Proposed Super Sense PSO For Network Reconfiguration

PSO is inspired by the social behavior of bird flocking or fish schooling and is one of the most popular swarm intelligence-based optimization technique developed by Kennedy and Eberhart in 1995 [174]. The algorithm is initialized with a population (called a swarm) of candidate solutions (called particles). These particles are allowed to fly randomly in the problem search space. The movements of the particles are guided by their own best known position *Pbest* in the search-space (cognitive behavior) as well as the entire swarm's best known position *gbest* (social behavior) using a single control equation. In due course of time, particles update their position vectors in the problem search space in accordance to cognitive and social behaviors. However these two movements are supported by the time varying inertia weight to impart necessary momentum to particles. This is schematically demonstrated in Fig. 3.4. Each particle updates its previous velocity and position vectors according to the following model [175]:

$$v_p^{k+1} = wv_p^k + c_1 \times r_1(\cdot) \times \frac{pbest_p - s_p^k}{\Delta t} + c_2 \times r_2(\cdot) \times \frac{gbest - s_p^k}{\Delta t} \tag{3.11}$$

$$s_p^{k+1} = s_p^k + v_p^{k+1} \times \Delta t \tag{3.12}$$

where, v_p^k is the velocity of pth particle at kth iteration, $r_1(\cdot)$ and $r_2(\cdot)$ 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:

$$w = w_{\max} + (w_{\min} - w_{\max}) \times itr / itr_{\max} \tag{3.13}$$

where, $w_{\min}$ and $w_{\max}$ are the minimum and maximum bounds of the inertia weight respectively, $itr_{\max}$ is the maximum iteration count and itr is the current iteration count.

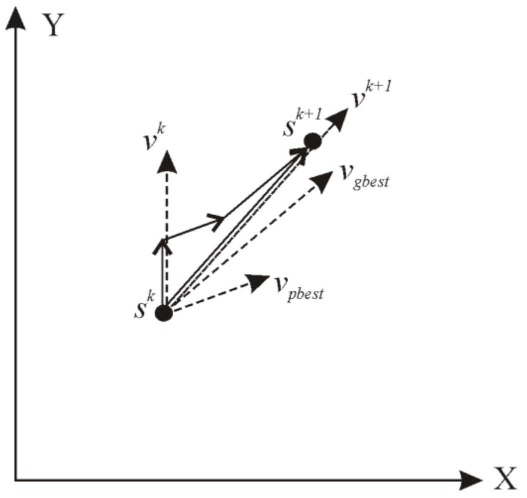


Fig. 3.4 Demonstration of PSO

Researchers have paid attention towards PSO primarily on account of its simplicity, convergence speed, and robustness, yet having potential to obtain global or near global solution. However, PSO has inherent tendency of local trapping while subjected to solve complex optimization problems. It happened due to over speeding of particles that leads to poor local search. Several modified versions of PSO have been reported in the recent past to enhance its performance by modulating inertia weight [83,176-177], improvising cognitive and social behavior [64, 67,177] using constriction factor approach [162,178], modifying the control equation of PSO [66,179-182], or squeezing the search space [181-182], etc. However, some of these suggested versions of PSO require several experimentations for parameter setting or needs some additional mechanism to avoid local trapping or to regulate particle's velocity in order to maintain a better balance between cognitive and social behavior of the swarm [183].

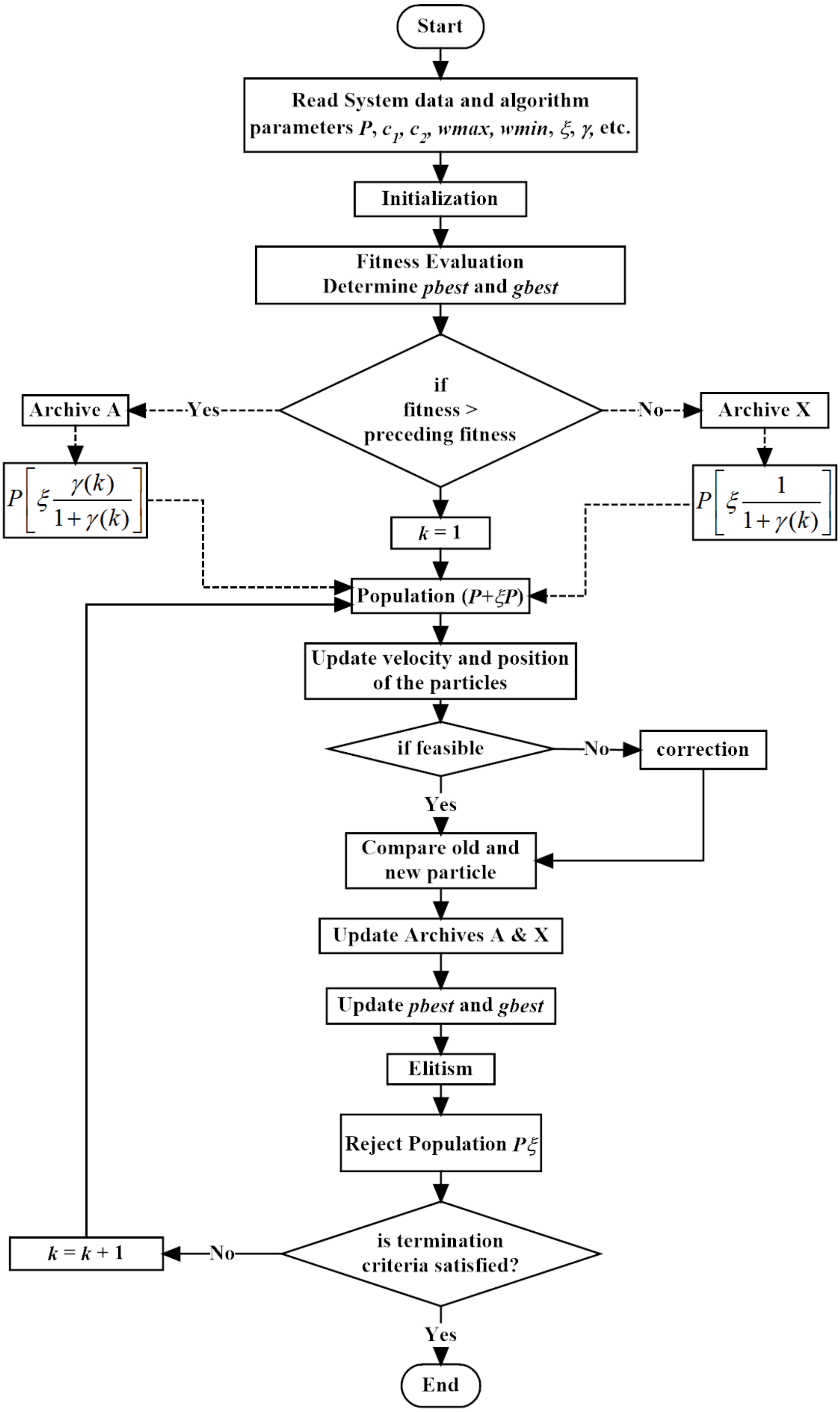


Fig. 3.5 Flow chart of proposed SSPSO

Moreover, the intrinsic nature of PSO could only generate continuous decision variables thus both accuracy and convergence may affect while it is applied to the optimization problems having discrete decision variables [173]. Therefore, a suitable variant of PSO is highly desired that can efficiently solve complex network reconfiguration problem after overcoming these limitations. In the present work the idea of human intelligence, as suggested in SSGA, is also attempted in PSO to enhance its overall performance without altering internal working of the algorithm. The variant of PSO so developed is therefore named as super sense PSO (SSPSO).

In SSPSO, the particles are updated through iterations using the same control equation as in PSO, but some particles are added to the swarm during its movement using Archive A and Archive X with certain selection rate and selection factor as in SSGA. However, care has to be taken as the procession of PSO algorithm is different than that of GA where every particle has to track its best movement. Therefore, the position of particles in the swarm should not be altered during the computational process. So it is necessary that the particles generated from archives to replenish the swarm shall not survive in the next iteration. Thus the population so generated may be called as short-lived swarm (SS), and accordingly the initial population generated by randomization may be called as long-lived swarm (LS). In this way, SSPSO differs from SSGA where the population generated from archives may survive longer according to the Darwian's principle. The particles belong to LS governed by the principles of PSO, but a doubt arises while considering particles belonging to SS. It is due the fact that how can these particles track their best movement when their life span is limited to only one iteration, at least theoretically. But, these particles can be allowed to track the best movement of all those particles which occupy the same position in the swarm. This may be looked as a breakthrough from the basic philosophy of PSO. However, this theme contributed towards better diversity in population. PSO usually suffers from lack in diversity on account of weak communication among particles as particles can communicate only with their own best and group's best particles. This eventually leads to local trapping phenomenon in PSO. On the contrary, in SSPSO the particles belonging to SS are generated through archives which are being formed on the basis of quality communication among particles of the whole swarm. This feature may provide better exploration of the search space, as good as provided by the genetic drift using the multi-point mutation in GA. The particles of both LS and SS follow the leader, and the best fit particle of the swarm is copied and kept preserved during each iteration so that it can never lost even when it is generated from SS. The flow chart of SSPSO is shown in Fig. 3.5.

3.6 SIMULATION RESULTS AND DISCUSSION

The performance of developed SSGA and SSPSO is investigated by solving NR problem of distribution systems. For this purpose, simulations are carried on two case studies by selecting IEEE 33-bus test distribution system [30] and 83-bus TPC real distribution system [68]. The single line diagram and brief data of these systems are given in Table 3.1. It can be observed from the table that 33-bus system consists of 37 lines including 5 tie-lines whereas 83-bus system has 96 lines including 13 tie-lines. This shows that the problem search space offered by 83-bus system is much larger than that offered by 33-bus system while solving NR problem using meta-heuristic techniques. The single line diagram, and detailed bus and line data of these systems may be referred from Table A1 and Table A2 in Appendix.

TABLE 3.1
BRIEF DATA OF THE TEST SYSTEMS

Particular	**33- bus system**	**83- bus system**
Line voltage (kV)	12.66	11.40
Nominal active power demand (kW)	3715	28350
Nominal reactive power demand (kVAr)	2300	20700
Sectionalizing switches	1-32	1-83
Tie-switches	33-37	84-96
Base configuration with open lines	33 to 37	84 to 96
Power loss (kW)	202.5	531.99
Minimum node voltage (pu)	0.9131	0.9285

It has been assumed that both distribution systems are equipped with SPVs, WTs, MTs and SCs. The consideration of intermittency in power generation from renewables and stochastic nature of load demand is taken into account by assuming suitable factors for power generation and load demand which are based upon historical data available for the particular place. The historical generation data considered for SPVs and WTs are taken from [184,185] respectively. The load and generation profiles of renewable DGs considered for 24 states of a day are given in Table 3.2.Though distribution network can be optimally reconfigured for any system state, but the state 15 is selected as it has fair generation from both SPVs and WTs while the load demand is adequate.

The developed SSGA and SSPSO are applied to both distribution systems and the results obtained are compared with their respective standard counterparts. The algorithmic specific parameters used for these algorithms are shown in Table 3.3. Each algorithm runs for 100 independent trials and the best result obtained is considered for comparison. A statistical error analysis is finally performed to investigate the relative performance of these techniques. Intel(R) i5, 3.2 GHz, 4GB RAM is the platform used for computation.

TABLE 3.2
LOAD AND GENERATION FACTORS FOR RENEWABLE DGS

State	Load/Generation factor			State	Load/Generation factor		
	Load	WT	SPV		Load	WT	SPV
1	0.5421	0.556	0	13	0.8711	0.896	0.967
2	0.5421	0.507	0	14	0.8000	0.894	0.921
3	0.5421	0.484	0	15	0.8711	0.799	0.820
4	0.5421	0.454	0	16	0.8711	0.688	0.625
5	0.5421	0.45	0	17	0.8711	0.704	0.398
6	0.6132	0.49	0	18	0.8711	0.728	0.158
7	0.6829	0.397	0.008	19	0.9303	0.763	0
8	0.6829	0.435	0.203	20	1.0000	0.784	0
9	0.6829	0.587	0.453	21	1.0000	0.806	0
10	0.7421	0.698	0.563	22	0.7513	0.823	0
11	0.7421	0.748	0.794	23	0.5421	0.88	0
12	0.7421	0.796	0.934	24	0.5421	0.911	0

TABLE 3.3
ALGORITHM SPECIFIC PARAMETERS SELECTED

Parameter	GA	SSGA	PSO	SSPSO
CR	0.9	0.9	-	-
MR	0.05	0.05	-	-
C_1	-	-	2	2
C_2	-	-	2	2
$Wmin$	-	-	0.1	0.1
$Wmax$	-	-	0.9	0.9
ξ	-	0.5	-	0.5
Υ	-	1-4	-	1-4

It is customary to first establish proposed SSGA and SSPSO. For this purpose these techniques are applied to both 33-bus and 83-bus systems at nominal load but without any DRs so that the results obtained for NR may be compared with that available in literature. The comparison results so obtained are presented in Table 3.4 and 3.5, respectively. It can be observed from the table that proposed GA and PSO are capable to explore the solution same as available in literature for both the case studies. This shows the effectiveness of proposed techniques to solve large scale reconfiguration problems.

TABLE 3.4
COMPARISON RESULTS FOR IEEE 33-BUS TEST DISTRIBUTION SYSTEM

Methods	**Optimal configuration (switches to be opened)**	**Power loss (kW)**	**Minimum node Voltage (pu)**
RGA [9]	7, 9, 14, 32, 37	139.55	0.9378
Heuristic [39]	7, 9, 14, 32, 37	139.55	0.9378
Heuristic [44]	7, 9, 14, 32, 37	139.55	0.9378
GA [14]	7, 9, 14, 32, 37	139.55	0.9378
HBMO [84]	7, 9, 14, 32, 37	139.55	0.9378
GA [5]	7, 9, 14, 32, 37	139.55	0.9378
SSGA	7, 9, 14, 32, 37	139.55	0.9378
SSPSO	7, 9, 14, 32, 37	139.55	0.9378

TABLE 3.5
COMPARISON RESULTS FOR IEEE 83-BUS TEST DISTRIBUTION SYSTEM

Methods	**Optimal configuration (switches to be opened)**	**Power loss (kW)**	**Minimum node voltage (pu)**
HBMO [84]	7, 14, 34, 39, 42, 55, 62, 72, 83, 86, 88, 90, 92	482.14	0.9529
SAPSO-MSFLA /SAPSO/MSFLA [20]	7, 14, 34, 39, 42, 55, 62, 72, 83, 86, 88, 90, 92	480.94	0.9529
AIS-ACO [69]	7, 13, 34, 39, 42, 55, 62, 72, 86, 89, 90, 91, 92	471.14	0.9479
SA/GA/ACSA [68]	7, 13, 34, 39, 41, 55, 62, 72, 83, 86, 89, 90, 92	469.88	0.9532
GA [61]	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	469.87	0.9532
GA [5]	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	469.87	0.9532
SSGA	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	469.87	0.9532
SSPSO	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	469.87	0.9532

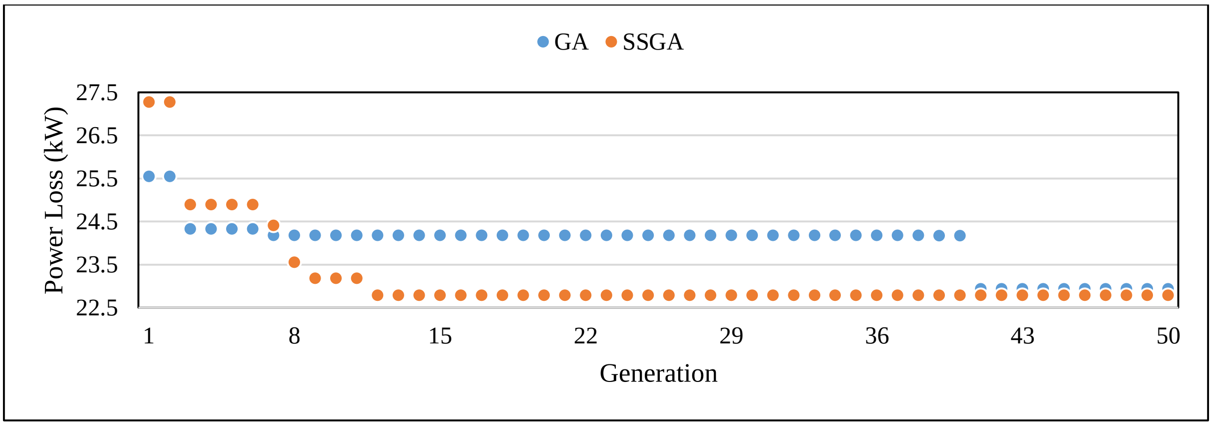
3.6.1 Case study 1: 33-bus test distribution system

For this case study the IEEE 33-bus test distribution system is assumed to be well equipped with DGs and SCs as shown in Table 3.6. The table shows that the system is integrated with total installed capacity of 1680kWp, 1540kWp, 800 kW, 1200 kVAr of SPVs, WTs, MTs and SCs, respectively. The load flow result for the state 15, keeping network in the base configuration shows feeder losses and minimum node voltage as 26.15 kW and 0.9878 p.u., respectively. A comparison of these results with that shown in Table 3.1 reveals that both power losses and node voltage profile have been significantly enhanced by the placement of DRs.

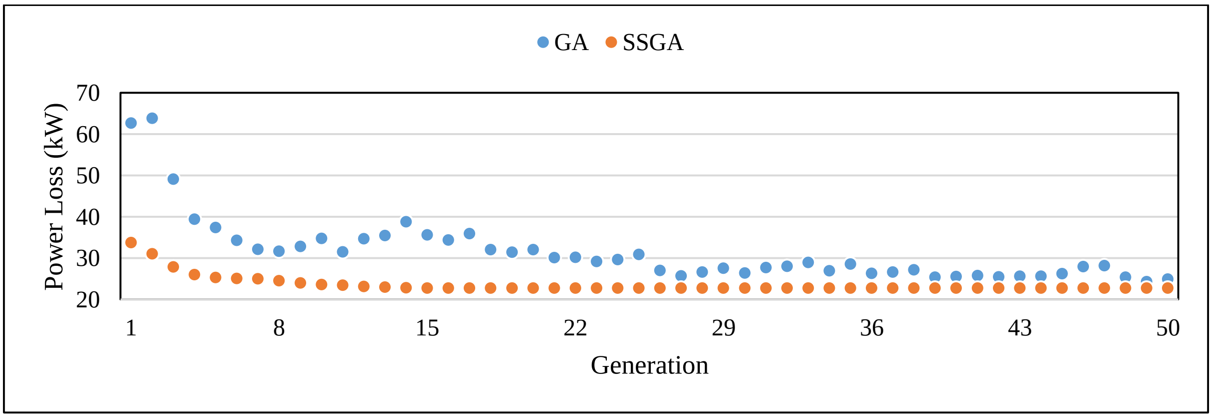
TABLE 3.6
ALLOCATION OF DRS IN IEEE 33-BUS TEST DISTRIBUTION SYSTEM

SPV (Capacity in kWp/Node)	WT (Capacity in kWp/Node)	MT (Capacity in kW/Node)	SC (Capacity in kVAr/Node)
280/14, 840/24, 560/30	420/14, 700/24, 420/30	800/24	300/12, 300/25, 600/30

The NR problem for this active distribution system is solved independently by applying GA, SSGA, PSO and SSPSO techniques. The population size and maximum generation/iteration count is kept uniformly at 20 and 50, respectively for each of these techniques. The best result obtained after 100 trial runs is found to be identical using all these techniques and suggests the optimal topology by opening of lines 7, 9, 14, 32, 37. For this topology, the feeder power loss and minimum node voltage is 139.55 kW and 0.9378 p. u., respectively which were 202.5 kW and 0.9131 p.u. respectively before network reconfiguration.



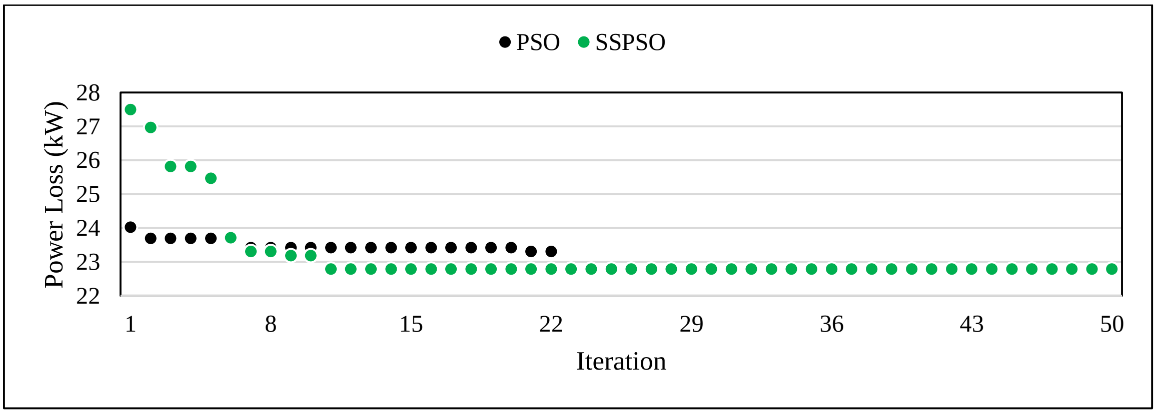
(a)



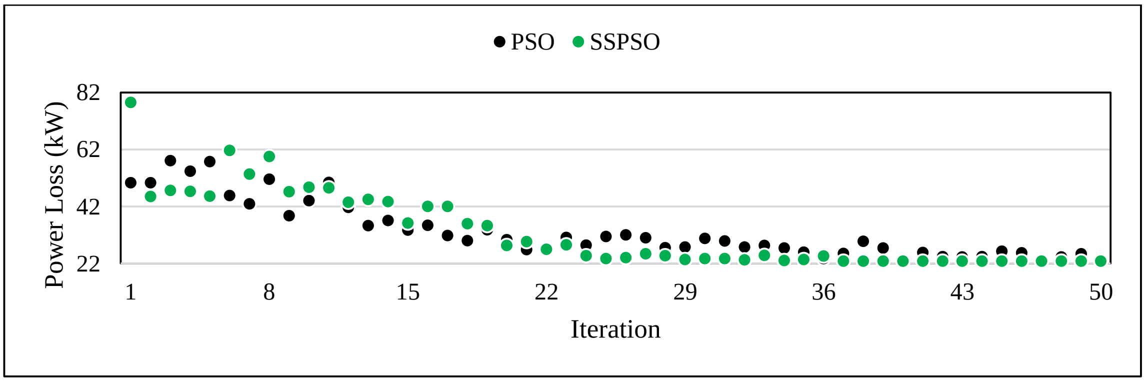
(b)

Fig. 3.6 Comparison of convergence of GA and SSGA for (a) best fitness (b) mean fitness

It is important to compare the convergence of these techniques. For this purpose the convergence for best and mean fitness are studied. The convergence for the best fitness shows the movement of best individual in the problem search whereas the convergence for the mean fitness depict the average movement of the population during the computational process. The comparison of these convergence characteristics for SSGA with GA, and for SSPSO with PSO are presented in Fig. 3.6 and Fig. 3.7, respectively. It can be observed from the Fig. 3.6 (a) that the convergence is significantly improved in SSGA, the fitness of the best individual improves at much faster rate than in GA. Similarly, Fig. 3.6 (b) shows that the mean fitness of the population is remarkably improved in SSGA. This is noteworthy because not only the best fit individual but all individuals of the population are improving their genetic information throughout the evolutionary process by virtue of super sense proposed in SSGA. Almost similar conclusions may be drawn from Fig. 3.7 which compares the convergences obtained using PSO and SSPSO for this system.

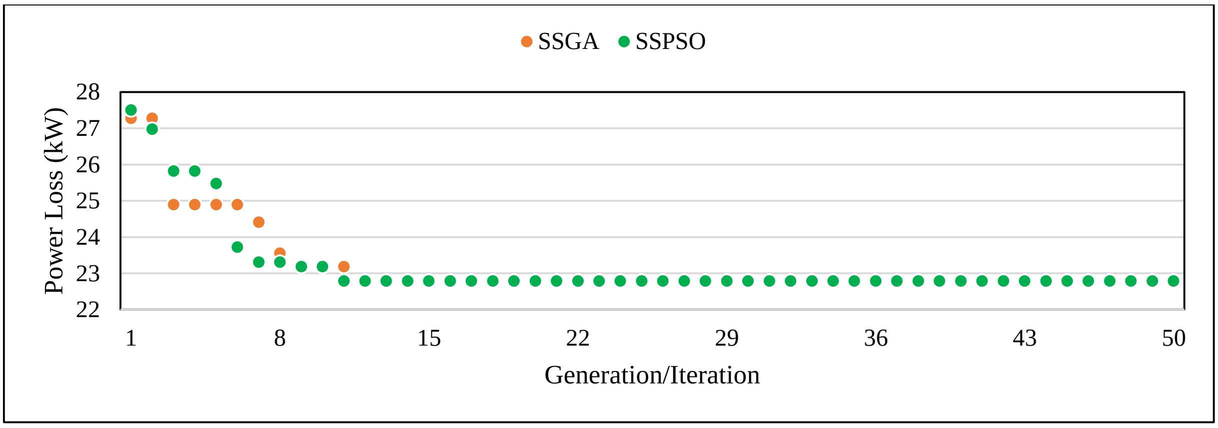


(a)

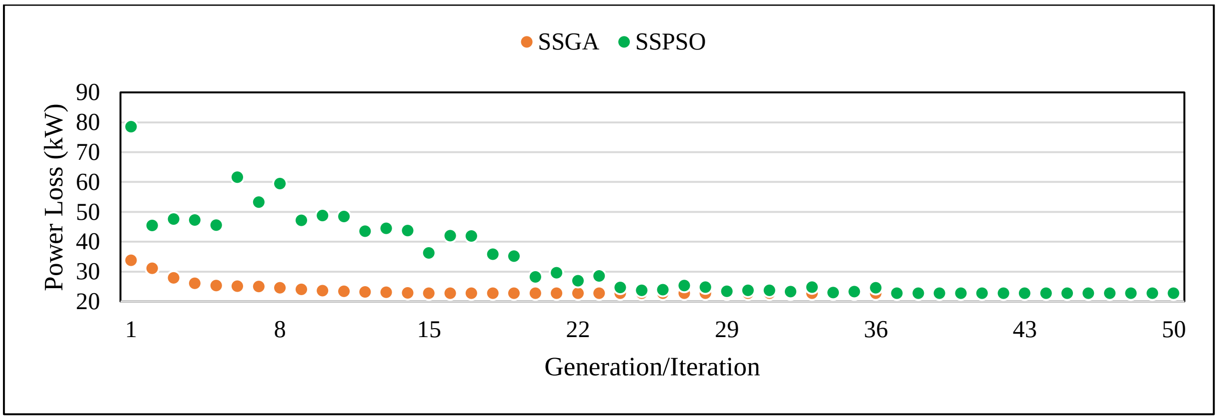


(b)

Fig. 3.7 Comparison of convergence of PSO and SSPSO for (a) best fitness (b) mean fitness



(a)



(b)

Fig. 3.8 Comparison of convergence of SSGA and SSPSO for (a) best fitness (b) mean fitness

It is interesting to compare the convergences of SSGA and SSPSO. For this purpose Fig. 3.8 is presented. The Fig. 3.8 (a) shows that the best convergences of these two algorithms are quite comparable, however, there is a marked difference while comparing their mean convergences as presented in Fig. 3.8 (b). The figure shows that the mean fitness improves much smoothly in SSGA than that in SSPSO. This indicates that SSGA provides better guided search. It probably happens on account of better communication in SSGA that maintains adequate diversity during the evolutionary process. However, the same happens in SSPSO during later half run because the velocity of particles remains uncontrolled during initial iterations in PSO owing to higher values assigned to the inertia weight parameter. Nevertheless, the comparison of the solution quality obtained after definite trial runs of these algorithms is vital before commenting upon the relative performance of these algorithms. For this purpose the statistical error analysis is performed on the sampled solutions obtained during their respective trial runs. The results of this analysis are presented in Table 3.7. On the prima-facie, the comparison of mean, best and worst fitness shows that both SSGA and

SSPSO perform better than their respective standard models. However, while considering the worst fitness, it is the SSPSO which seems to be slightly better than SSGA. The same is true as the frequency of obtaining best solution is 64 for SSPSO which is 55 for SSGA. But, SSGA is found to be better than SSPSO while comparing quality indices SD, COV_m and COV_b. Moreover, SSGA demands less CPU time than SSPSO. Therefore, it may be concluded that both SSGA and SSPSO have improved significantly than their respective standard forms, but SSGA is performing slightly better than SSPSO for this system.

TABLE 3.7
STATISTICAL ERROR ANALYSIS FOR CASE STUDY 1

Technique	Mean fitness (kW)	Best fitness (kW)	Worst fitness (kW)	SD (kW)	COV_m	COV_b	Frequency	CPU Time (s)
GA	23.65	22.79	25.33	0.6118	2.5866	4.6220	11	8.81
Proposed GA	22.97	22.79	23.80	0.2180	0.9490	1.2362	55	13.16
PSO	23.21	22.79	24.75	0.4973	2.1428	2.8466	45	8.91
Proposed PSO	22.97	22.79	23.77	0.2637	1.1484	1.3843	64	16.40

SD: standard deviation; COV_m/COV_b: coefficient of variation for mean/best fitness

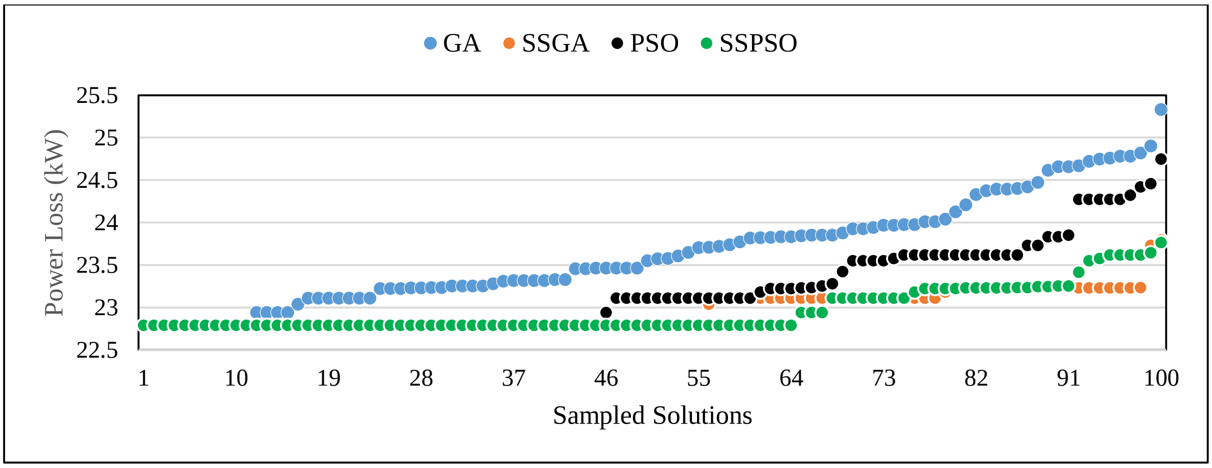


Fig. 3.9 Comparison of the spread of sampled solutions for 33-bus system

For better visualization of the relative performance of these algorithms, the spread of sampled solutions obtained are compared in Fig. 3.9. The figure shows a sample of 100 solutions which are being arranged in the order of increasing fitness. The figure clearly shows by what extent both SSGA and SSPSO have been improved than their respective standard models. It can also be seen that both SSGA and SSPSO generate good quality solutions, but SSGA is found to be slightly better. Thus the concept of "super sense" works well for both evolutionary and swarm intelligence-based metaheuristics techniques.

The behavior of the meta-heuristic techniques may vary with the size of the optimization problem, some techniques may show better performance on both small-scale and large-scale optimization problems whereas some others may behave differently. Therefore, proposed SSGA and SSPSO are investigated to solve NR problem of a large-scale distribution system in the following section.

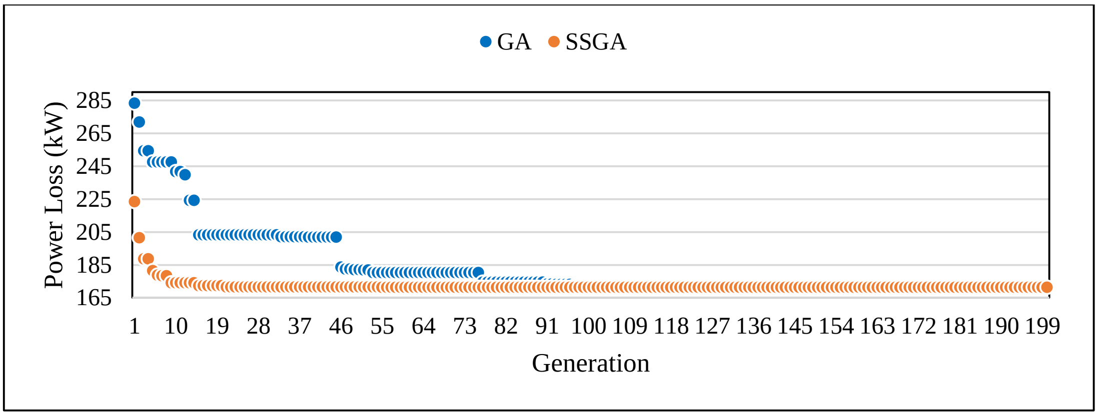
3.6.2 Case study 2: 83-bus TPC real distribution system

For this case study the 83-bus TPC real distribution system modified by installing SPVs, WTs, MT units and SCs as shown in Table 3.8. The table shows that the installed capacities of these components are 15300 kWp, 14600 kWp, 1500 kW and 7800 kVAr, respectively. For base configuration, the feeder power loss and minimum node voltage are obtained as 311.13 kW and 0.9697 p.u. while considering state 15. Thus system performance has been improved significantly by placement of these DRs, when compared with the results given in Table 3.1. The NR problem is solved using GA, SSGA, PSO and SSPSO with population size maximum generation/iteration count of 40 and 200, respectively. Each algorithm has been run independently for 100 trial runs. It has been observed that all algorithms provide identical solution that suggests opening of lines 7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92 for the most optimal radial topology of the distribution network. For this topology the power loss and minimum node voltage are 469.87 kW and 0.9532 pu, respectively which were 531.99 kW and 0.9285 pu respectively before network reconfiguration.

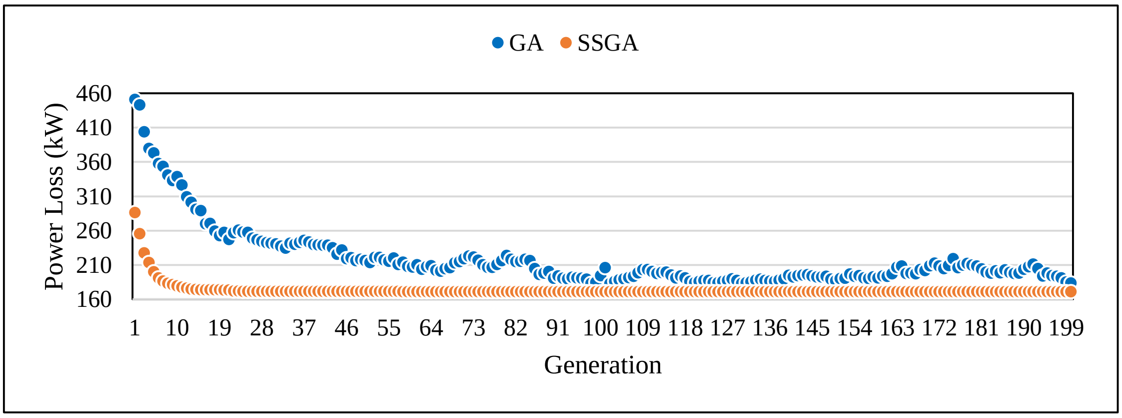
TABLE 3.8
ALLOCATION OF DRs ASSUMED IN EXISTING DISTRIBUTION SYSTEM

SPV (Capacity in kWp/Node)	**WT (Capacity in kWp/Node)**	**MT (Capacity in kW/Node)**	**SC (Capacity in kVAr/Node)**
3000/6, 3800/12, 3000/28, 2500/71, 3000/79	2800/6, 3300/12, 2800/28, 2200/71, 3500/79	290/6, 360/12, 290/28, 230/71, 330/79	1500/6, 1800/12, 1800/31, 1200/71, 1500/79
15300	14600	1500	7800

Fig. 3.10 shows the comparison of convergence characteristics obtained for these algorithms. It can be observed from the figure that SSGA still works well for this large-scale optimization problem. The convergences of SSGA, for both best and mean fitness, are found to be improved than that of GA and the amount of improvement is almost same as in case study 1.



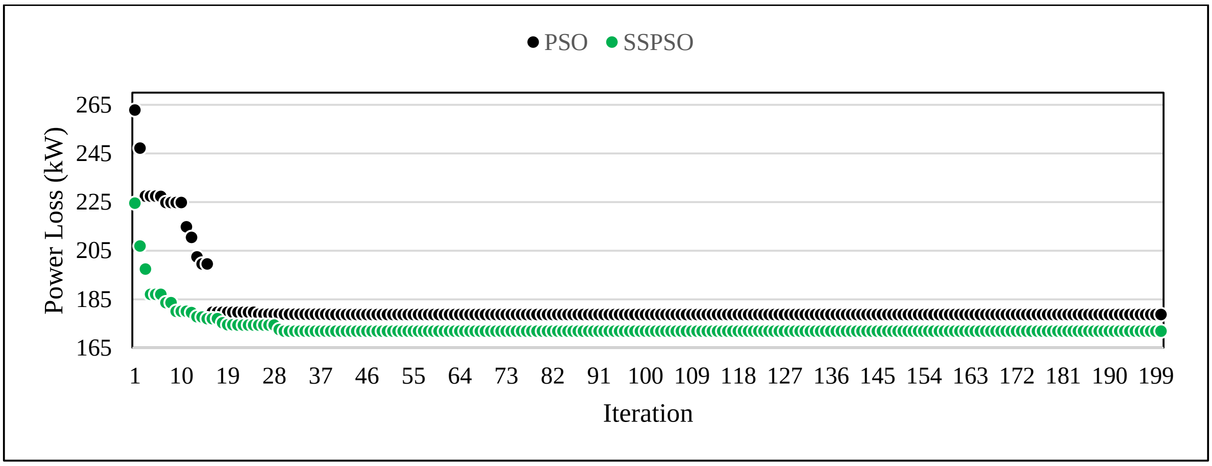
(a)



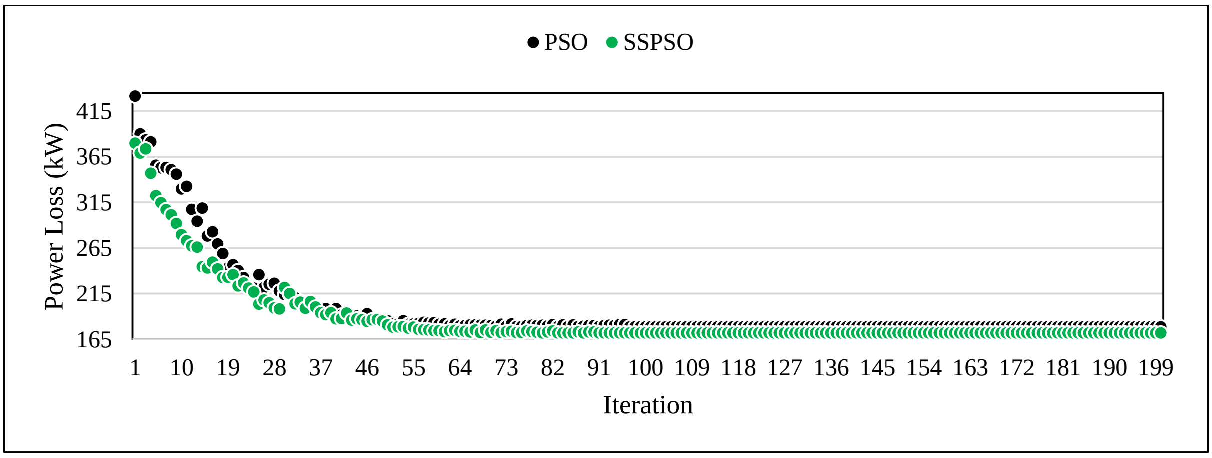
(b)

Fig. 3.10 Comparison of convergence of GA and SSGA for (a) best fitness (b) mean fitness

However, while considering Fig. 3.11 this inference cannot be developed for PSO and SSPSO. Fig. 3.11 (a) clearly shows local trapping phenomenon in PSO which has been overcome in SSPSO. Moreover, Fig. 3.11 (b) shows that the swarm is not able to reach in the promising region in PSO, as in case of SSPSO. Therefore, SSPSO is also significantly enhanced. The comparison of SSGA and SSPSO is presented in Fig. 3.12. It can be observed from the Fig. 3.12 (a) that both SSGA and SSPSO are comparable for this system also as far as the convergence of the best fitness is concerned. But, Fig. 3.12 (b) throws some light while comparing their mean convergence. The figure shows that the initial movement of individuals is much better in SSGA than in SSPSO, though their finally convergences are comparable. This shows that both SSGA and SSPSO have shown significant improvement than their respective standard models even when applied to large-scale optimization problem. However, the deviation in initial convergence may lead to different overall performance of these algorithms. This can be evaluated by conducting the statistical error test on the sampled results obtained using these algorithms.

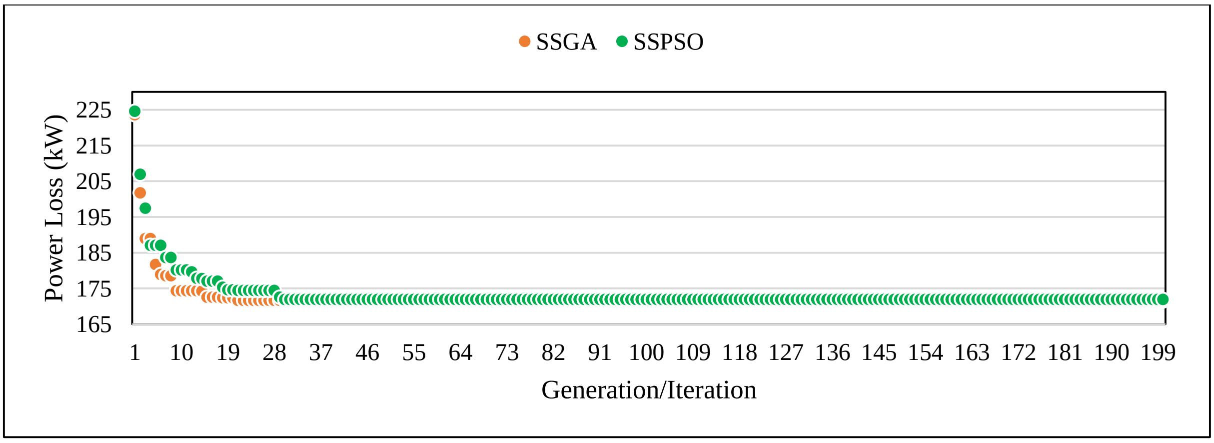


(a)

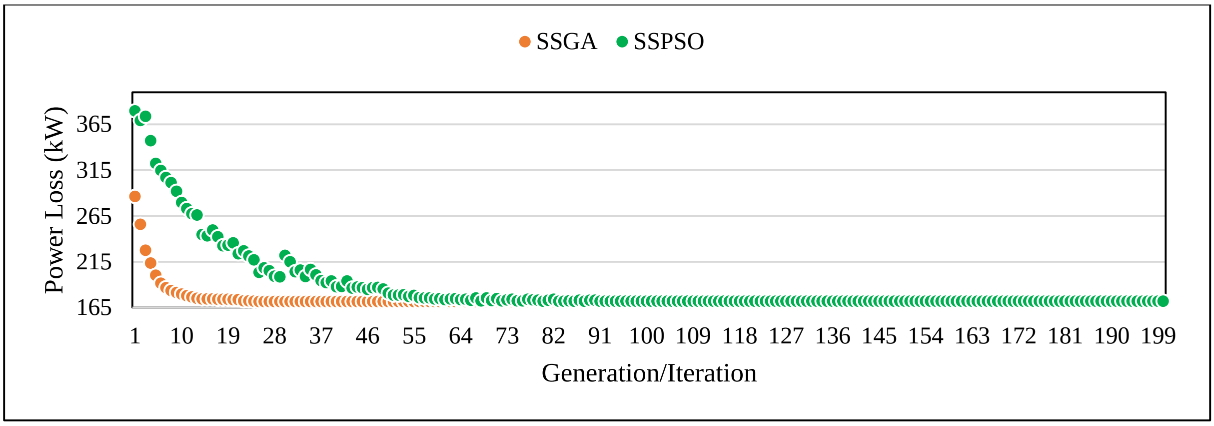


(b)

Fig. 3.11 Comparison of convergence of PSO and SSPSO for (a) best fitness (b) mean fitness



(a)



(b)

Fig. 3.12 Comparison of convergence of SSGA and SSPSO for (a) best fitness (b) mean fitness

TABLE 3.9
STATISTICAL ERROR ANALYSIS FOR CASE STUDY 2

Technique	Mean fitness (kW)	Best fitness (kW)	Worst fitness (kW)	SD (kW)	COV_m	COV_b	Frequency best fitness	CPU Time (s)
GA	173.67	171.43	180.26	2.4548	1.4135	1.9376	15	442.61
SSGA	171.66	171.43	177.19	1.1288	0.6576	0.6721	96	520.56
PSO	177.45	171.43	189.31	4.58	2.5801	4.4089	4	460.77
SSPSO	174.96	171.43	183.40	2.9577	1.6905	2.6853	7	489.73

The statistical error analysis performed for these algorithms is presented in Table 3.9. The table shows a marked improvement in the performance of SSGA in comparison to GA; not only the mean and worst fitness have been improved using SSGA but also the frequency of obtaining the best solution is remarkably improved from 15 to 96. This shows the potential of SSGA to efficiently solve large-scale optimization problems. However, SSGA is little bit more computationally demanding which is acceptable on account of better results so produced. While considering the performance of SSPSO, it has been observed that it has also improved significantly than PSO, but not as much as that of SSGA. SSPSO is not performing so well for this large-scale problem as that in case study 1. The reason is that PSO is not doing so well as that of GA for this case study. This fact can be observed from the table while comparing the values of SD, COV_m and COV_b. Therefore, it may be concluded that both SSGA and SSPSO have improved significantly than their respective standard forms, but SSGA is performing much better than SSPSO for large-scale optimization problems.

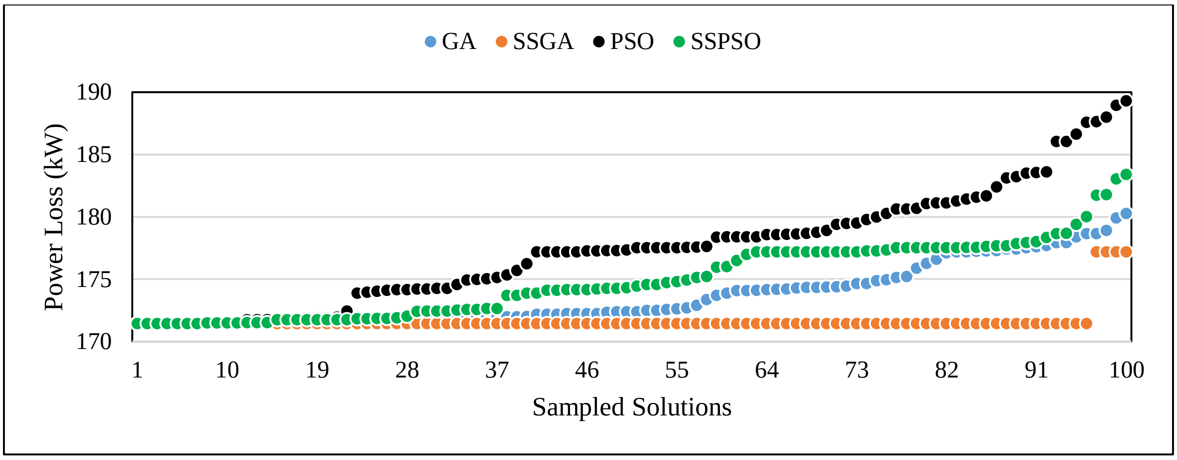


Fig. 3.13 Comparison of the spread of sampled solutions for 83-bus system

Finally, the spread of sampled solutions obtained for this system using GA, SSGA, PSO and SSPAO are compared in Fig. 3.13. The figure shows a sample of 100 solutions which are being arranged in the order of increasing fitness. The figure clearly shows by what extent both SSGA and SSPSO have been improved than their respective standard models. It can also be seen that both SSGA and SSPSO generate good quality solutions, but SSGA is much better. Interestingly, SSPSO is found to be less promising even than GA. It happens because PSO has shown very poor performance in comparison of GA. Therefore, SSPSO cannot be enhanced up to the level of SSGA. However, the concept of "super sense" works well with both evolutionary and swarm intelligence-based metaheuristics techniques, but is found to be more suitable for evolutionary-based techniques.

3.7 Discussion

The proposed SSGA and SSPSO algorithms utilize the identical element of proposed human intelligence called "super sense" without affecting the internal working of their standard models. With this single proposed modification, both SSGA and SSPSO have been improved significantly than their respective standard counterparts. However, SSGA outperforms than SSPSO, especially for large-scale optimization problems. This shows that the proposed concept of "super sense" is more suitable for evolutionary-based algorithms than the swarm intelligence based algorithms. It probably happened because of the fundamental difference between the search mechanisms employed by these algorithms. This can be discussed in detail as follows.

In GA, better fit offspring are produced by virtue of the natural selection that obeys the Darwian's principle, i.e. "Survival of the fittest". However, the rate of obtaining better fit offspring is primarily governed by the crossover operator which works very well initially and loses effectiveness as GA progresses. It happened because of the greediness associated with natural selection that gradually reduces diversity in population so the algorithm stagnates and even mutation is not sufficient as it provides limited diversity, not the local random walk around the current best individual. These limitations of GA are overcome in SSGA by replenishing population from proposed archives. The population generated from Archive-A provides local random walk around the current best individual whereas that generated from Archive-X maintains adequate diversity in population. Since the crossover operator of GA provides sufficient communication among individuals, the genetic information injected through archives is swiftly transmitted in population. This not only leads to maintain adequate diversity in each generation but also provides dedicated search for the global optima. Thus the performance of SSGA enhances significantly even for large-scale optimization problems.

On the contrary, PSO possesses very weak communication among particles and works on the philosophy, i.e. “To follow the leader”. In PSO, each particle communicate with only two particles on account of cognitive and social behavior that restricts the communication of a particle with itself and the current best particle the swarm, respectively. Though, the control equation of PSO provides diversity in population but it loses its effectiveness as the algorithm advances, same as did by the crossover operator of GA. But, SSPSO cannot enhance the performance as that of SSGA because no information exchange is possible in LS, SS or between LS and SS, as in SSGA, due to the inheritance of restricted communication in PSO. Therefore, the new information injected into the population by SS cannot be transmitted in the swarm from one to next iteration so diversity is not maintained at the desired level during the whole computational process. This leads to inadequate exploration of large problem search space so the best particle may not improve its fitness, especially during anaphase of the algorithm. The movement of the swarm therefore stagnates and eventually the algorithm converges to local optima. However, a small diversity and local random walk is provided by the population generated from the Archive-X and Archive-A, respectively. Therefore, SSPSO has shown comparable performance with that of SSGA only for small-scale problems whereas SSGA performs much better than SSPSO for large-scale optimization problems.

3.8 Summary

An attempt has been made for the coalition of human intelligence with artificial intelligence while considering the performance improvement of evolutionary and swarm intelligence based meta-heuristic techniques. The well-known metaheuristics, namely GA and PSO are selected for investigation and are applied to solve the network reconfiguration problem of active distribution systems. The human intelligence incorporated in these algorithms is called super sense because the quality of each decision variable that involved in the computational process of proposed SSGA and SSPSO is assessed and kept in memory to produce future populations based upon the accumulated information. The application results on the benchmark small test distribution system reveal that the proposed super sense feature alone is sufficient to enhance the overall performance of the standard models of both GA and PSO. This is interesting as only selection rules are modified in SSGA and SSPSO without affecting the internal mechanisms of the standard algorithms. However, When SSGA and SSPSO are applied to a large-scale real distribution system, both SSGA and SSPSO are found to improve significantly, but SSGA performs better than SSPSO. In fact, the SSGA has shown outstanding performance for large-scale optimization. The possible reason is that the genetic evolution in organisms employs variations that have been accumulated from previous generations. This important feature, however, was missing in the standard GA though it is the basis for better future generations. It is because the accumulated variations from previous generations are assured to be really good as they are being originated from those living organisms who had survived. However, SSPSO is not able to exploit the benefits of super sense feature on account of it legacy in lack of communication among particles so the new variations created are not well transmitted within the swarm.

In this chapter, improved variants of existing GA and PSO have been developed and their potentials have been investigated. The application results of the developed method to solve small and large-scale NR problems of contemporary distribution systems have been presented and discussed. In the following chapter a multi-objective formulation for optimal NR problem of contemporary distribution systems to simultaneously optimize reliability and power quality objectives while considering practical feeder power flow constraints and stochastic variation in load demand and power generation from renewable DGs is proposed.

CHAPTER 4

NETWORK RECONFIGURATION FOR RELIABILITY ENHANCEMENT AND SERVICE RESTORATION

4.1 INTRODUCTION

Reliability of power supply to end users is the most important factor in operation and planning of distribution systems. Over the past decades distribution systems have received considerably less attention regarding reliability enhancement through network operation than devoted to generating systems. The main reason for this is that loss of generating unit has a larger impact on the power supply and society as a whole than the loss of distribution system feeder. However, the analysis of customer failure statistics shows that distribution systems make the greatest individual contribution to the unavailability of customer supply. According to an estimate a typical distribution system accounts for 40% of the cost to deliver power and 80% of customers' reliability problems [13].

The reliability has assumed significant importance in recent years due to deregulation of electric utilities with consequent competitive business environment. In contemporary distribution systems with renewable DGs and stochastic nature of load demands reliability of distribution system may further deteriorate if not taken care off. Owing to higher request on reliability for customers incurred by sustainable economic growth of the world, system reliability draws more and more attentions, and thus becomes an important technical and economic indicator to distribution companies [186]. It is important to plan and maintain reliable power supply to end users as the cost of interruptions and power outages can have severe economic impact on distribution utility and its customers. This fact clearly shows the importance and necessity of reliability enhancement in the area of distribution systems. Reliability evaluation aims to assess customer annual outage frequency and duration which may assist in power system planning and operation. The reliability of distribution system is characterized by different reliability indices based on the failure rate of its components. Failure rates of different system components are the most crucial data for reliability analysis. Since accurate information of these failure rates is not available, most of the existing methods rely on average values of failure rates available in the literature. However, in real life, components would have different failure rates due to exposure to different factors such as loading level. If a component is over loaded for longer duration its failure rate will increase due to increased Joule's heating. In this context, the existing failure rates and related reliability indices need modifications.

The network reconfiguration has been successfully used to optimize multiple conflicting objectives of distribution systems performance [28, 40-41]. Therefore, NR can be used for reliability enhancement also. However, the addition of reliability objective to the NR problem makes this problem more complex and it needs to be solved with an accurate algorithm [13]. Moreover, in the event of a fault with consequent loss of a line, NR can be used to restore power supply to the consumers by providing alternative minimum loss path. In contemporary distribution systems having adequate penetration of DRs including renewable DGs, the reliability enhancement and service restoration through optimal network reconfiguration is a very complex optimization problems.

The NR inherently performs load balancing among distribution feeders whether the distribution system is passive or active. Eventually, NR can be used as a new strategy for active distribution systems to maintain reliability indices below the continuity limits imposed by regulators [139]. Thus, in addition to the classical aim of reconfiguring the distribution networks for service restoration, power loss reduction and voltage profile enhancement, it is also possible to optimally reconfigure it in order to get additional guarantee for a reliable operation. Contemporary distribution systems are well equipped with adequate penetration of DRs and remote-operated line switches. The network topology therefore may be altered to achieve desired objectives. The present trends towards deregulation and competitive business environment are forcing electric utilities to improve their efficiency and reduce cost while consumers are becoming more sensitive to reliability and power quality. Therefore, NR becomes an effective approach to increase the worth of distribution systems' reliability without extra costs, providing customers quality and financial benefits [187]. Reliability indices are calculated as the function of the failure rate and the restoration time of the system components. The frequency and duration of the interruptions experienced by users can be directly related to the system's topology [188]. The reliability indices are also greatly affected by the presence of DRs in distribution systems as their presence changes the power flow among distribution feeders.

In this chapter, a new multi-objective NR method is proposed for reliability enhancement and service restoration. Some of the existing reliability indices are modified and proposed by considering practical issues of Joule's heating of distribution feeders. Moreover, reconfiguration strategy is developed for service restoration via NR maintaining better energy efficiency. The problem is formulated by considering more practical scenarios of contemporary distribution systems having adequate penetration of DRs including renewable DGs with stochastic nature of load demand. The feasibility and the efficiency of the proposed method are investigated by a standard distribution test system. The application results on standard test distribution system demonstrate the importance of proposed methodologies.

4.2 PROPOSED RELIABILITY INDICES

The reliability of the distribution systems can be expressed in term of existing reliability indices such as system's average interruption frequency index (F), system's average interruption unavailability index (T), system's average duration interruption index (D) and energy not supplied (ENS). For a distribution network with N_c feeding nodes, the reliability indices as adopted by the Chilean law are defined by the Inter-American Committee of Regional Electricity-CIER [15] and are given as under for i^{th} topology:

$$F(i) = \frac{\sum_{j=1}^{N_c} KVA(j)\lambda(j)}{\sum_{j=1}^{N_c} KVA(j)} \tag{4.1}$$

$$T(i) = \frac{\sum_{j=1}^{N_c} KVA(j)\lambda(j)r(j)}{\sum_{j=1}^{N_c} KVA(j)} \tag{4.2}$$

$$ENS(i) = \sum_{j=1}^{N_c} KW(j)\lambda(j)r(j) \tag{4.3}$$

$$D(i) = \frac{T(i)}{F(i)} \tag{4.4}$$

$$U(j) = \lambda(j)r(j) \tag{4.5}$$

where, $F(i)$ is system's average interruption frequency index, $T(i)$ is system's average interruption unavailability index, $D(i)$ is system's average duration interruption index and $ENS(i)$ is the energy not supplied for the ith candidate topology. These objectives are the function of active load demand $kW(j)$ and apparent load demand $kVA(j)$ of the N_c system load points as well as of the failure rate $\lambda(j)$ repair time $r(j)$ and the unavailability $U(j)$ for each load point.

The reliability indices have been defined in literature [15,132] are based upon the average failure rate and average duration of interruption that might occur for a system or its components in general. However, with the penetration of DRs and due to frequent reconfiguration of distribution systems, the dynamics of power flow is changed and therefore the use of average failure rate will provide erroneous results of different reliability indices. The distribution system consists of various components such as distribution transformers, distribution feeders, switchgears, etc. The useful life of each of these components depends upon, the amount of current flows during operation of distribution systems. Higher the magnitude of current more will be the heat produced on account of Joule's heating so more wear and tear occur causing increase in failure rate. Therefore, failure rates of distribution components may be taken proportional to the amount of Joule's heating produced. Therefore, the failure rates need to be modified to take into account heating effect of the actual feeder currents. In the present work, the failure rates are proposed to be redefined by considering Joule's heating of distribution feeders. The Joule's heating is proportional to the magnitude of current flowing through the given feeder. Since current flowing through the distribution feeders varies with the dynamically changing states, the failure rates of distribution feeders shall be made dynamic. Therefore, in the present work dynamic failure rate of distribution feeders are proposed as

$$\zeta(i, j, n) = \lambda_i \left(I(i, j, n) / I(b, j, nom) \right)^2 \tag{4.6}$$

where $\zeta(i, j, n)$ and $I(i, j, n)$ denotes the failure rate and current in the jth distribution feeder during nth system state respectively while the distribution system is operating in ith radial topology and $I(b, j, nom)$ denotes the current in the jth distribution feeder during nominal load conditions for the base topology of the distribution system. Proposed failure rate becomes dynamic with reference to the load demand/power generation among distribution buses and also with the varying network topology.

The reliability index *ENS* is of prime importance for distribution system operator as it directly affects their margin of profits. In the present scenario of deregulated environment of power industries, the energy pricing to customers become dynamic owing to dynamic electricity markets. In dynamic electricity market, the electricity price depends upon the magnitude of system loading in somewhat proportional manner. In such scenario, the same amount of energy may have different costs during different hours of a day. In this context, the existing reliability index ENS may not be a useful index in terms of economy. The existing reliability index *ENS* thus needs modification, otherwise a wrong signal may be communicated while assessing monetary values of existing ENS. Therefore, reliability indices for the ith radial topology during nth system state are proposed as

$$F(i,n)=\frac{\sum_{j=1}^{N_c} KVA(j,n)\zeta\left(i,\ j,n\right)}{\sum_{j=1}^{N_c} KVA(j,n)};\forall j\in N_c,\ \forall\ n\in N \tag{4.7}$$

$$T(i,n)=\frac{\sum_{j=1}^{N_c} KVA(j,n)\zeta\left(i,\ j,n\right)r(j)}{\sum_{j=1}^{N_c} KVA(j,n)};\forall j\in N_c,\ \forall\ n\in N \tag{4.8}$$

$$ENS(i,n)=k_e\left(n\right)\sum_{j=1}^{N_c} KW(j,n)\zeta\left(i,\ j,n\right)r(j);\forall j\in N_c,\ \forall\ n\in N \tag{4.9}$$

$$D(i,n)=\frac{T(i,n)}{F(i,n)};\forall n\in N \tag{4.10}$$

$$U(i,j,n)=\zeta\left(i,\ j,n\right)r(j);\forall j\in N_c,\forall n\in N \tag{4.11}$$

In fact, from a practical point of view, the index D is not a good index to be used as an objective function because, its minimization is also possible with maximization of F [15]. The maximization of F is not a desirable attribute. Therefore, in the present study, minimization of the index D is not considered as an objective. However, power quality indices to represent energy losses and node voltage deviations are considered which may be formulated as

$$EL(i,n)=ke(n)LD(n)\sum_{j=1}^{N_c} I^2(i,j,n)R_j\ ;\ \forall j\in N_c,\forall n\in N \tag{4.12}$$

$$DV(i,n)\ =Max\Big(abs\Big(abs\left(V_s\right)-abs\left(V_{jn}\right)\Big)\Big);\forall j\in N_c,\forall n\in N \tag{4.13}$$

where, $LD(n)$ and $ke(n)$ denote the load duration and energy price prevailed for the nth system state.

4.2.1 Application Results

The effectiveness of the proposed reliability indices has been investigated using IEEE 33-bus test distribution system [144]. This system is a 33 node, 37 lines distribution system where the base configuration is obtained by opening the tie-lines 33-37. The nominal system data considered for this system may be referred from Table 3.1 of Chapter 3. In order to highlights the difference between existing and proposed reliability indices, the distribution system is first assumed in the base configuration. The existing and proposed reliability indices are determined for the distribution system at three different loading conditions, i.e. at nominal and ±10% of this loading. A comparison of the results obtained is shown in Table 4.1.

TABLE 4.1
COMPARISON OF EXISTING AND PROPOSED RELIABILITY INDICES WITHOUT DRS BEFORE NR

Reliability Index per year	Load Levels								
	1.0			1.1			0.9		
	Existing	Proposed	Diff(%)	Existing	Proposed	Diff(%)	Existing	Proposed	Diff(%)
F	3.18	3.18	0	3.18	3.91	22.97	3.18	2.53	–20.26
T	1.86	1.86	0	1.86	2.29	22.89	1.86	1.49	–20.20
ENS	437.67	437.67	0	481.43	591.41	22.84	393.90	314.41	–20.18

It can be observed from the table that proposed indices are exactly the same as existing indices under normal conditions. For other load conditions the proposed indices are different. For peak load condition, all proposed indices are larger whereas they are smaller for light load condition, which clearly reflects that if the system is overloaded the proposed reliability indices are adversely affected and vice versa. Whereas the existing reliability indices are not affected by loading conditions and therefore they are not true indicators of systems reliability under different operating conditions. The table also shows that the percent variation in proposed indices is about twice to that of percentage change in loading factor. This is true because Joule's heating varies in proportional to the square of the change in percent loading of distribution feeders. The results clearly highlights that proposed reliability indices are promising in dealing with dynamically changing network conditions. Interestingly, the index D remains almost unchanged. It happened because the index $D(i, n)$ is the ratio of indices $F(i, n)$ and $T(i, n)$, so nullify the impact of proposed dynamic failure rates. The proposed reliability indices have been used in the following section

4.3 PROPOSED NETWORK RECONFIGURATION METHOD FOR RELIABILITY ENHANCEMENT

The distribution network reconfiguration may be used to enhance the reliability distribution systems. In general, several different objectives can be included in multi-objective distribution system reconfiguration problem. Apart from the reliability indices, the feeder power loss and node voltage deviation are the other two important power performance objectives which should also be addressed. Therefore, a multi-objective formulation of NR problem is proposed. The reliability and performance objectives can be simultaneously optimized to obtain the best operating radial topology of the distribution network. However, different objectives have different units and there is difficulty in formulating a single objective function which is to be optimized to achieve most compromising solution for this multi-objective optimization problem. Keeping this in view the multi-objective NR problem is formulated in fuzzy framework. While formulating multi-objective optimization problem in fuzzy framework, the objectives considered needs to be scaled about their respective minimum and maximum bounds to obtain fuzzy membership values using suitable fuzzy membership function for each of the objective so that they can be incorporated in a single objective function. These fuzzy membership values can be combined into a single fuzzy membership value using the conventional way of addition of the objectives using weighted sums approach [11, 189]. Since this fuzzy membership value acts as the fitness function of the overall objective function to be optimized, such formulations leads to an optimal solution which may be dominated by one or more objectives thus the determination of the most compromising solution remains doubtful. In order to avoid this, the fuzzy membership values are combined by taking their geometric mean [30]. This eventually results in the rejection of those candidate topologies which possess poor degree of fuzzy satisfaction for even one objective considered. In this chapter, following objectives are considered for NR optimization problem.

1. system's average interruption frequency index $F(i, n)$
2. system's average interruption unavailability index $T(i, n)$, and
3. energy not supplied $ENS(i, n)$
4. feeder power loss $EL(i, n)$
5. system's node voltage deviation $DV(i, n)$

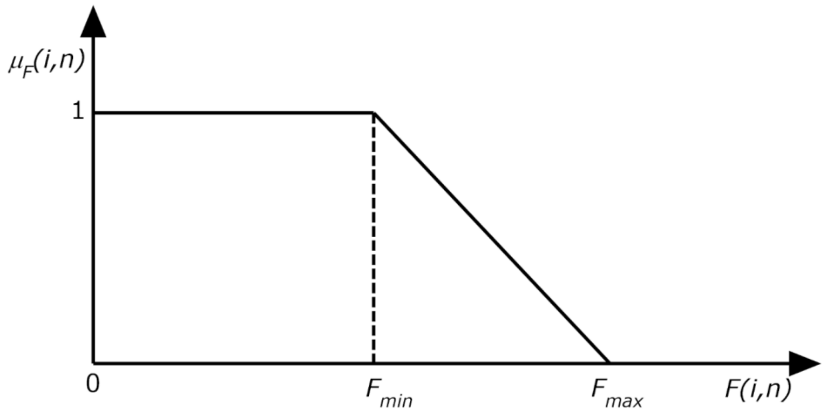


Fig. 4.1 Fuzzy membership function

Linear fuzzy membership function is considered for each of the objectives as shown in Fig. 4.1.

The multi-objective problem formulation in fuzzy framework to solve NR problem is therefore formulated as below.

$$Max\ \mu(i, n) = (\mu_F(i, n)\ \mu_T(i, n)\ \mu_{ENS}(i, n)\ \mu_{EL}(i, n)\ \mu_{DV}(i, n))^{1/5} \tag{4.14}$$

where *i* stands for the *i*th radial topology of the distribution network and *n* stands for the *n*th system state, whereas μ refers to fuzzy membership functions of various objectives considered. Where,

$$\mu_F(i,n) = \begin{cases} 1.0 & ; F(i,\ n) \le F_{min} \\ -\dfrac{F(i,\ n)}{(F_{max} - F_{min})} + \dfrac{F_{max}}{(F_{max} - F_{min})} & ; F_{min} < F(i,\ n) < F_{max} \\ 0.0 & ; F(i,\ n) \ge F_{max} \end{cases} \tag{4.15}$$

$$\mu_T(i,n) = \begin{cases} 1.0 & ; T(i,\ n) \le T_{\min} \\ -\dfrac{T(i,\ n)}{(T_{\max} - T_{\min})} + \dfrac{T_{\max}}{(T_{\max} - T_{\min})} & ; T_{\min} < T(i,\ n) < T_{\max} \\ 0.0 & ; T(i,\ n) \ge T_{\max} \end{cases} \tag{4.16}$$

$$\mu_{ENS}(i,n) = \begin{cases} 1.0 & ; ENS(i,\ n) \le ENS_{\min} \\ -\dfrac{ENS(i,\ n)}{(ENS_{\max} - ENS_{\min})} + \dfrac{ENS_{\max}}{(ENS_{\max} - ENS_{\min})} & ; ENS_{\min} < ENS(i,\ n) < ENS_{\max} \\ 0.0 & ; ENS(i,\ n) \ge ENS_{\max} \end{cases} \tag{4.17}$$

$$\mu_{EL}(i,n) = \begin{cases} 1.0 & ; EL(i,\ n) \le EL_{\min} \\ -\dfrac{EL(i,\ n)}{(EL_{\max} - EL_{\min})} + \dfrac{EL_{\max}}{(EL_{\max} - EL_{\min})} & ; EL_{\min} < EL(i,\ n) < EL_{\max} \\ 0.0 & ; EL(i,\ n) \ge EL_{\max} \end{cases} \tag{4.18}$$

$$\mu_{DV}(i,n) = \begin{cases} 1.0 & ; DV(i,\ n) \le DV_{\min} \\ -\dfrac{DV(i,\ n)}{(DV_{\max} - DV_{\min})} + \dfrac{DV_{\max}}{(DV_{\max} - DV_{\min})} & ; DV_{\min} < DV(i,\ n) < DV_{\max} \\ 0.0 & ; DV(i,\ n) \ge DV_{\max} \end{cases} \tag{4.19}$$

Subjected to the following constraints:

Power flow constraint

$$g_j(i) = 0;\ \forall j \in N_c \tag{4.20}$$

Node voltage constraint

$$V_{\min} \leq V_{jn} \leq V_{\max};\ \forall n \in N; \forall j \in N_c \qquad (4.21)$$

Feeder current limit constraint

$$I_{jn} \leq I_j^{\max};\ \forall n \in N, \forall j \in N_c \qquad (4.22)$$

Radial topology constraint

$$\Phi_n(i) = 0; \forall n \in N \qquad (4.23)$$

Calculation of indices

For the base configuration, the fuzzy membership functions of proposed reliability and power quality indices are determined separately for each system state. Thereafter, the aggregate fuzzy memberships are determined as defined below.

$$\mu_F{}^M(o) = \text{Mean}\ (\mu_F(o, n)) \qquad (4.24)$$

$$\mu_T{}^M(o) = \text{Mean}\ (\mu_T(o, n)) \qquad (4.25)$$

$$\mu_{ENS}{}^M(o) = \text{Mean}\ (\mu_E(o, n)) \qquad (4.26)$$

$$\mu_{EL}{}^M(o) = \text{Mean}(\mu_{EL}(o, n)) \qquad (4.27)$$

$$\mu_{DV}{}^{MIN}(o) = \text{Min}(\mu_{DV}(o, n)) \qquad (4.28)$$

It is noteworthy that the aggregate fuzzy membership for node voltage deviations is determined by taking the minimum, not the mean, of the *n* system states. In a similar way, the aggregate fuzzy memberships are determined for the optimal topologies obtained for all *n* system states of the distribution network while replacing the letter "*b*" by the letter "*o*". Finally, the aggregate fuzzy memberships are de-fuzzified using the following general relation.

$$X = X_{max} - \mu_X\,(X_{max} - X_{min}) \qquad (4.29)$$

Except for EL, where

$$X = (X_{max} - \mu_X\,(X_{max} - X_{min}))*8760 \qquad (4.30)$$

4.3.1 Simulation Results and Discussion

The application of proposed network reconfiguration method has been investigated using IEEE 33-bus test distribution system [30]. This system is a 33 node, 37 lines distribution system where the base configuration is obtained by opening the tie-lines 33-37. In order to investigate the proposed method the standard IEEE 33-bus test distribution system is assumed to be modified by deploying DGs and SCs as shown in Table 4.2. The table shows the assumed sizing and siting of SPVs, WTs, MT and SCs in the system. The spinning reserve is assumed to be 0.1 MW for MT unit. The generation factors and load factors for SPV and WT units considered for the sample day are shown in Table 3.2 of Chapter 3. The table also shows corresponding load factors for distribution loads which have been considered throughout the simulations. The dynamic energy charges in US$/kWh assumed for different time slots is shown in Table 4.3. SSGA proposed in Chapter 3 is used as an optimization tool to solve this multi-objective NR problem. The coding of the algorithm is developed in MATLAB® Version 7.

TABLE 4.2
ALLOCATION OF DGS AND SCS

WT	SPV	MT	SC
420 (14), 700 (24), 420 (30)	280 (14), 840 (24), 560 (30)	800 (24)	300 (12), 300 (25), 600 (30)

TABLE 4.3
DYNAMIC ELECTRICITY CHARGES

00AM- 6AM	6AM-5PM	5PM-9PM	9PM-00AM
0.02	0.06	0.12	0.09

The application of the proposed method requires the determination of values of lower and upper bounds of fuzzy membership function of each indices. The lower bound of these indices can be safely assumed to zero; however, their upper bounds depend upon the particular network topology of the distribution network. To determine upper bound of each membership function the proposed NR method is run as a single objective optimization problem for each of the objectives. The maximum value of reliability indices so obtained are rounded-off to higher side as shown in Table 4.4. With these upper bounds, the multi-objective NR problem can be formulated in fuzzy framework.

TABLE 4.4
MAXIMUM VALUE OF RELIABILITY INDICES OBTAINED USING OPTIMAL NR

F_{max} (Failure/yr)	T_{max}(h/yr)	ENS_{max} (US$/yr)	EL_{max} (US$)	DV_{max} (p.u.)
5	3	800	70	0.10

In order to investigate the effect of network reconfiguration two cases of studies have been carried out.

Scenario 1: Distribution system without DRs

Scenario 2: Distribution system with DRs

For the application of the proposed method the population size and maximum iterations are taken as 50 and 100, respectively and the best solutions obtained after 100 trial runs are shown. The results obtained for each case is compared to that obtained with base topology.

A. Distribution systems without DRs

The distribution network is first assumed to be in base configuration without DR allocation. The load profile considered for 24 system states are taken as given in Table 3.2. The fuzzy membership functions of various reliability and power quality objectives are determined for each system state which may be referred from Table 4.5.

TABLE 4.5
FUZZY MEMBERSHIP FUNCTIONS AND THE OVERALL MEMBERSHIP FUNCTION FOR BASE TOPOLOGY

State	$\mu_F^*(b, n)$	$\mu_T^*(b, n)$	$\mu_{ENS}^*(b, n)$	$\mu_{EL}^*(b, n)$	$\mu_{DV}^*(b, n)$	$\mu^*(b, n)$
1	0.8256	0.8291	0.9744	0.9841	0.5461	0.8145
2	0.8256	0.8291	0.9744	0.9841	0.5461	0.8145
3	0.8256	0.8291	0.9744	0.9841	0.5461	0.8145
4	0.8256	0.8291	0.9744	0.9841	0.5461	0.8145
5	0.8256	0.8291	0.9744	0.9841	0.5461	0.8145
6	0.7746	0.7792	0.9625	0.9794	0.4837	0.7726
7	0.7176	0.7234	0.8433	0.9228	0.4218	0.7019
8	0.7176	0.7234	0.8433	0.9228	0.4218	0.7019
9	0.7176	0.7234	0.8433	0.9228	0.4218	0.7019
10	0.6637	0.6707	0.7972	0.9080	0.3687	0.6531
11	0.6637	0.6707	0.7972	0.9080	0.3687	0.6531
12	0.6637	0.6707	0.7972	0.9080	0.3687	0.6531
13	0.5275	0.5377	0.6660	0.8708	0.2511	0.5287
14	0.6057	0.6141	0.7439	0.8922	0.3163	0.6005
15	0.5275	0.5377	0.6660	0.8708	0.2511	0.5287
16	0.5275	0.5377	0.6660	0.8708	0.2511	0.5287
17	0.5275	0.5377	0.6660	0.8708	0.2511	0.5287
18	0.5275	0.5377	0.3320	0.7416	0.2511	0.4454
19	0.4561	0.4681	0.1793	0.7025	0.1963	0.3504
20	0.3646	0.3789	0.0452	0.6526	0.1309	0.2215
21	0.3646	0.3789	0.0452	0.6526	0.1309	0.2215
22	0.6548	0.6620	0.6840	0.8584	0.3604	0.6202
23	0.8256	0.8291	0.8846	0.9284	0.5461	0.7896
24	0.8256	0.8291	0.8846	0.9284	0.5461	0.7896

The table also shows the value of overall membership function for each system state. From this table the aggregate fuzzy membership functions are determined using (24)-(28) which are then de-fuzzified using (29)-(30) to get the mean value of objectives as presented in Table 4.6. It may be observed that system's average interruption frequency index *F* is 1.7123 per year, system's average interruption unavailability index *T* is 1.0055 hr per year, average value of energy not supplied *ENS* is 229.0578 $ per year and feeder power loss *EL* is 70722.9896 $ per year. These values of indices will serve the basis for comparison for the forthcoming investigations.

TABLE 4.6
MEAN FUZZY MEMBERSHIP FUNCTIONS AND RELIABILITY INDICES FOR BASE TOPOLOGY

μF*M(b)	***μT*M(b)***	***μENS*M(b)***	***μEL*M(b)***	***μDV*MIN(b)***
0.6575	*0.6648*	*0.7137*	*0.8847*	*0.1309*
F(b) (failure/yr)	*T(b) (hr/yr)*	*ENS(b) (US $/yr)*	*EL(b)(US $/yr)*	*DV(b) (p.u.)*
1.7123	*1.0055*	*229.0578*	*70722.9896*	*0.0869*

The base configuration is now optimally reconfigured for all the 24 operating state of the distribution system using proposed method. The application results obtained of each state after 100 trial runs of the algorithm are shown in Table 4.7. The table shows optimal configuration corresponding to the best solution. The corresponding fuzzy membership functions pertaining to various objectives and their overall fuzzy membership function are also shown in this table. The comparison of Table 4.5 and Table 4.7 clearly shows that the proposed reliability enhancement method causes an improvement in overall fuzzy membership function of each system state.

The mean fuzzy membership functions of objectives and their de-fuzzyfied values are shown in Table 4.8. The comparison of this table with Table 4.6 shows that system's average interruption frequency index *F* is decreased from 1.7123 per year to 1.5300 per year, system's average interruption unavailability index *T* is decreased from 1.0055 hr per year to 0.9123 per year, the cost of average value of energy not supplied *ENS is* decreased from 229.0578 $ per year to 207.9202 $ per year and, the cost of feeder power loss *EL is* also reduced from 70722.9896 $ per year to 66282.7841 $ per year. Thus proposed NR method improves all the objectives considered. This is interesting because reliability and power quality objectives are conflicting in nature.

TABLE 4.7
OPTIMAL TOPOLOGY, FUZZY MEMBERSHIP FUNCTIONS AND THE OVERALL MEMBERSHIP FUNCTION AFTER NR

State	Optimal configuration	$\mu_F(o, n)$	$\mu_T(o, n)$	$\mu_{ENS}(o, n)$	$\mu_{EL}(o, n)$	$\mu_{DV}(o, n)$	$\mu(o, n)$
1	33-37-11-13-32	0.8315	0.8283	0.9736	0.9857	0.5924	0.8290
2	33-37-11-13-32	0.8315	0.8283	0.9736	0.9857	0.5924	0.8290
3	33-37-11-13-32	0.8315	0.8283	0.9736	0.9857	0.5924	0.8290
4	33-37-11-13-32	0.8315	0.8283	0.9736	0.9857	0.5924	0.8290
5	33-37-11-13-32	0.8315	0.8283	0.9736	0.9857	0.5924	0.8290
6	33-37-11-13-32	0.7828	0.7787	0.9616	0.9815	0.5367	0.7905
7	33-37-10-12-32	0.7319	0.7277	0.8424	0.9296	0.4791	0.7247
8	33-37-10-12-32	0.7319	0.7277	0.8424	0.9296	0.4791	0.7247
9	33-37-10-12-32	0.7319	0.7277	0.8424	0.9296	0.4791	0.7247
10	33-37-10-12-32	0.6813	0.6763	0.7964	0.9163	0.4315	0.6797
11	33-37-10-12-32	0.6813	0.6763	0.7964	0.9163	0.4315	0.6797
12	33-37-10-12-32	0.6813	0.6763	0.7964	0.9163	0.4315	0.6797
13	33-37-10-12-32	0.5540	0.5475	0.6661	0.8826	0.3262	0.5662
14	33-37-10-12-32	0.6270	0.6214	0.7434	0.9019	0.3845	0.6315
15	33-37-10-12-32	0.5540	0.5475	0.6661	0.8826	0.3262	0.5662
16	33-37-10-12-32	0.5540	0.5475	0.6661	0.8826	0.3262	0.5662
17	33-37-10-12-32	0.5540	0.5475	0.6661	0.8826	0.3262	0.5662
18	33-37-35-14-32	0.5755	0.5781	0.3844	0.7505	0.3079	0.4944
19	33-37-35-14-32	0.5117	0.5149	0.2443	0.7130	0.2573	0.4116
20	33-37-35-14-32	0.4301	0.4340	0.0524	0.6649	0.1972	0.2640
21	33-37-35-14-32	0.4301	0.4340	0.0524	0.6649	0.1972	0.2640
22	33-37-35-14-32	0.6895	0.6912	0.7084	0.8631	0.4086	0.6534
23	33-37-10-12-32	0.8338	0.8310	0.8834	0.9347	0.5906	0.8049
24	33-37-10-12-32	0.8338	0.8310	0.8834	0.9347	0.5906	0.8049

TABLE 4.8
MEAN FUZZY MEMBERSHIP FUNCTIONS AND RELIABILITY INDICES AFTER NR

$\mu_F^M(o)$	$\mu_T^M(o)$	$\mu_{ENS}^M(o)$	$\mu_{EL}^M(o)$	$\mu_{DV}^{MIN}(o)$
0.6940	0.6959	0.7401	0.8919	0.1972
$F(o)$ (failure/yr)	$T(o)$ (hr/yr)	$ENS(o)$ (US $/yr)	$EL^A(o)$ (US $/yr)	$DV(o)$ (p.u.)
1.5300	0.9123	207.9202	66282.7841	0.0803

B. Distribution systems with DRs

The distribution network is now assumed to be equipped with DRs as given in Table 3.6. Simulations are carried to determine fuzzy membership functions of the objectives considered keeping distribution network in base configuration. The results obtained for all 24 operating state are presented in Table 4.9. The table also shows overall fuzzy membership functions for each system state which is found to be improved significantly for each system state while comparing with Table 4.5. This shows that both reliability and power quality indices are sufficiently improved by deploying DRs in the distribution system. The mean fuzzy membership functions of objectives and their de-fuzzyfied values are shown in Table 4.10. The comparison of Table 4.6 and Table 4.10 clearly highlights that optimal deployment of DGs and SCs alone causes significant improvement in all reliability indices and power loss reduction.

TABLE 4.9
FUZZY MEMBERSHIP FUNCTIONS AND OVERALL MEMBERSHIP FUNCTION BEFORE NR

State	Configuration	$\mu_F^*(b, n)$	$\mu_T^*(b, n)$	$\mu_{ENS}^*(b, n)$	$\mu_{EL}^*(b, n)$	$\mu_{DV}^*(b, n)$	$\mu^*(b, n)$
1	33-34-35-36-37	0.9377	0.9234	0.9881	0.9964	0.8786	0.9438
2	33-34-35-36-37	0.9370	0.9236	0.9882	0.9962	0.8643	0.9406
3	33-34-35-36-37	0.9362	0.9233	0.9882	0.9961	0.8577	0.9389
4	33-34-35-36-37	0.9348	0.9225	0.9881	0.9960	0.8489	0.9365
5	33-34-35-36-37	0.9347	0.9225	0.9881	0.9960	0.8477	0.9362
6	33-34-35-36-37	0.9222	0.9103	0.9845	0.9951	0.8005	0.9198
7	33-34-35-36-37	0.8969	0.8877	0.9361	0.9782	0.7166	0.8782
8	33-34-35-36-37	0.9101	0.8956	0.9396	0.9839	0.7769	0.8985
9	33-34-35-36-37	0.9119	0.8878	0.9333	0.9869	0.8829	0.9198
10	33-34-35-36-37	0.8952	0.8664	0.9136	0.9845	0.8930	0.9097
11	33-34-35-36-37	0.8785	0.8412	0.8963	0.9798	0.8674	0.8914
12	33-34-35-36-37	0.8639	0.8203	0.8817	0.9744	0.8442	0.8754
13	33-34-35-36-37	0.8386	0.7933	0.8422	0.9725	0.8618	0.8597
14	33-34-35-36-37	0.8515	0.8067	0.8633	0.9733	0.8497	0.8672
15	33-34-35-36-37	0.8554	0.8179	0.8625	0.9776	0.8784	0.8768
16	33-34-35-36-37	0.8686	0.8396	0.8803	0.9797	0.7988	0.8714
17	33-34-35-36-37	0.8709	0.8476	0.8877	0.9784	0.7472	0.8631
18	33-34-35-36-37	0.8656	0.8479	0.7789	0.9488	0.6940	0.8225
19	33-34-35-36-37	0.8334	0.8192	0.7236	0.9273	0.6137	0.7759
20	33-34-35-36-37	0.8021	0.7879	0.6535	0.9088	0.5598	0.7320
21	33-34-35-36-37	0.8041	0.7895	0.6558	0.9108	0.5666	0.7352
22	33-34-35-36-37	0.9013	0.8843	0.8899	0.9746	0.7822	0.8843
23	33-34-35-36-37	0.9338	0.9133	0.9380	0.9842	0.9036	0.9341
24	33-34-35-36-37	0.9325	0.9114	0.9366	0.9838	0.9001	0.9324

TABLE 4.10

MEAN VALUES OF OBJECTIVES BEFORE NR

$\boldsymbol{\mu_F^{*M}(b)}$	$\boldsymbol{\mu_T^{*M}(b)}$	$\boldsymbol{\mu_{ENS}^{*M}(b)}$	$\boldsymbol{\mu_{EL}^{*M}(b)}$	$\boldsymbol{\mu_{DV}^{*MIN}(b)}$
0.8882	0.8660	0.8891	0.9743	0.5598
$F(b)$ (failure/yr)	$T(b)$ (hr/yr)	$ENS(b)$ (US \$/yr)	$EL(b)$ (US \$/yr)	$DV(b)$ (p.u.)
0.5590	0.4021	88.7287	15757.7700	0.0440

TABLE 4.11

FUZZY MEMBERSHIP FUNCTIONS AND OVERALL MEMBERSHIP FUNCTION AFTER NR

State	Optimal configuration	$\mu_F(o, n)$	$\mu_T(o, n)$	$\mu_{ENS}(o, n)$	$\mu_{EL}(o, n)$	$\mu_{DV}(o, n)$	$\mu(o, n)$
1	33-37-35-13-36	0.9396	0.9249	0.9883	0.9963	0.8890	0.9468
2	33-37-35-13-36	0.9395	0.9256	0.9885	0.9961	0.8769	0.9443
3	33-37-35-13-36	0.9391	0.9257	0.9886	0.9960	0.8713	0.9430
4	33-37-35-13-36	0.9385	0.9256	0.9886	0.9959	0.8639	0.9413
5	33-37-35-13-36	0.9385	0.9257	0.9886	0.9959	0.8629	0.9410
6	33-37-35-13-36	0.9272	0.9144	0.9853	0.9951	0.8189	0.9260
7	33-37-35-14-36	0.9067	0.8962	0.9414	0.9785	0.7439	0.8895
8	33-37-35-13-36	0.9156	0.9001	0.9424	0.9837	0.8006	0.9064
9	33-37-35-13-36	0.9120	0.8873	0.9330	0.9862	0.8923	0.9215
10	20-37-11-34-36	0.9053	0.8760	0.9205	0.9827	0.8725	0.9105
11	20-37-8-12-36	0.8921	0.8548	0.9058	0.9785	0.8725	0.8998
12	20-37-8-12-36	0.8797	0.8356	0.8922	0.9737	0.8493	0.8848
13	20-37-35-13-8	0.8693	0.8179	0.8588	0.9696	0.8679	0.8753
14	20-37-33-10-34	0.8739	0.8268	0.8760	0.9728	0.8552	0.8796
15	33-37-35-9-34	0.8651	0.8245	0.8645	0.9774	0.8915	0.8832
16	33-37-35-11-34	0.8674	0.8354	0.8748	0.9792	0.8331	0.8764
17	33-37-35-12-36	0.8750	0.8508	0.8902	0.9778	0.7598	0.8679
18	33-37-35-12-36	0.8725	0.8536	0.7880	0.9481	0.7042	0.8291
19	33-37-35-14-36	0.8455	0.8300	0.7418	0.9269	0.6229	0.7863
20	33-37-35-14-36	0.8163	0.8006	0.6767	0.9088	0.5699	0.7447
21	33-37-35-14-36	0.8187	0.8025	0.6793	0.9105	0.5749	0.7477
22	33-37-35-12-36	0.9045	0.8868	0.8924	0.9738	0.7821	0.8858
23	20-37-35-34-36	0.9392	0.9190	0.9425	0.9833	0.9073	0.9379
24	20-37-35-34-36	0.9382	0.9174	0.9413	0.9831	0.9037	0.9363

TABLE 4.12

MEAN VALUES OF OBJECTIVES AFTER NR

$\mu_F^{M}(o)$	$\mu_T^{M}(o)$	$\mu_{ENS}^{M}(o)$	$\mu_{EL}^{M}(o)$	$\mu_{DV}^{MIN}(o)$
0.8967	0.8732	0.8954	0.9812	0.5899
$F(o)$ (failure/yr)	$T(o)$ (hr/yr)	$ENS(o)$ (US \$/yr)	$EL(o)$ (US \$/yr)	$DV(o)$ (p.u.)
0.5167	0.3804	83.6887	13122.48	0.0316

The distribution system with DRs is now optimally reconfigured to solve multi-objective NR problem for each system state using SSGA and the best result obtained after 100 trial runs are presented in Table 4.11. The table shows optimal configuration corresponding to the best solution. For this solution, the fuzzy membership functions pertaining to various objectives and their overall fuzzy membership function is also shown in the table. While comparing with Table 4.7, it has been seen that optimal network configuration depends upon the presence of DRs in the system. A close look of the Table 4.11 with Table 4.7 shows that there is a small but definite improvement in the overall fuzzy membership function using NR. However, the comparison of Table 4.12 with Table 4.8 shows that the improvement in all objectives is satisfactory. Thus DRs improve reliability and power quality of the distribution system by good margins which can be further enhanced using NR.

In the present study, two scenarios of distribution system, i.e. without and with DRs have been investigated before and after NR. Therefore, it is important to see the consolidated results as shown in Table 4.13 before deducing any concluding remarks. It is important to note that reliability and power quality parameters are the reflections of networks operating conditions. From the table it may be observed that NR strategy is relatively more effective in the distribution network without DRs. In case where distribution system is equipped with optimally placed DRs, the effect of NR on the power quality and reliability attributes is marginal. This is perhaps due to the fact that optimally placed DRs optimizes the flow of power in all the lines and very small scope is left for further improvement. That is why the NR strategy is causing only marginal improvement in system reliability and power quality parameters. For more clear differentiation, the percentage enhancements in objectives are determined with respect to base condition of the distribution network and results obtained are presented in Table 4.14. It can be observed from the table that an enhancement of about 10% is obtained using NR in distribution systems without DRs. After DR placement the effectiveness of NR is found to be increased marginally by about 2-3%.

TABLE 4.13
COMPARISON RESULTS BEFORE AND AFTER NR

Scenario	Network Topology	*F* (failure/yr)	*T* (h/yr)	*Energy Not Supplied* (US$/yr)	*Energy Loss* (US$/yr)	*Maximum Node Voltage Deviation* (p.u.)
1	Before NR	1.7123	1.0055	229.0578	70722.99	0.0869
	After NR	1.5300	0.9123	207.92	66282.78	0.0803
2	Before NR	0.5590	0.4021	88.7287	15757.77	0.0440
	After NR	0.5167	0.3804	83.6887	13122.48	0.0316

TABLE 4.14
COMPARISON OF PERCENTAGE ENHANCEMENT IN OBJECTIVES WITH BASE CONFIGURATION

	F (failure/yr)	*T* (hr/yr)	*ENS* (US $/yr)	*EL* (US $/yr)	*DV* (p.u.)
Scenario 1 after NR	10.65	9.27	9.23	6.28	7.59
Scenario 2 before NR	67.35	60.01	61.26	77.72	49.37
Scenario 2 after NR	69.82	62.17	63.46	81.45	63.64

4.4 SERVICE RESTORATION THROUGH NETWORK RECONFIGURATION

In contemporary distribution systems, there is increasing concern about service restoration on account of two most important aspects of distribution system operation namely, reliability and economy. With significant extension and complexity of modern power systems, possibility of fault occurrence has increased many folds. This may lead to possible loss of economy and loss to customers' satisfaction. Therefore service restoration has become one of the important attributes of smart distribution operation. It evaluates loss caused by the fault, identifies solutions to restore the outage area, and indicates new configurations of the distribution network, as well as the new operation status of the distribution system's equipment, from the time when the fault was isolated to the time when the fault was repaired[136]. Distribution networks are structured in mesh configuration but operated in radial topology. Therefore, whenever a fault occurs in any line, islanding takes place. To avoid this some other line is connected to the islanded node by tie switch. However, the new radial topology obtained by randomly closing adjacent tie switch may not be optimal in terms of power quality attributes. In fact, NR was initially devised for service restoration, so whenever fault occurs at any line, some alternate route is to be provided by NR to restore the affected loads. The NR can be used to improve the operation of distribution systems in case of contingencies, considering RES in electrical networks [15]. It happened because power generations from renewable provide self-sustainability to distribution systems during contingencies. Since power generation from renewable is uncertain, the stochastic nature of load demand has to be considered while formulating NR problem. Thus service restoration assumes new dimensions for active distribution system operations. In the following section the NR is addressed from the view point of optimal service restoration

4.4.1 Proposed Methodology

Service restoration in distribution systems can be formulated as a constrained multi-objective optimization problem [191, 192]. Normally, the main objectives are to minimize either the load curtailment, the number of switching operations, or the system's power loss, with the constraints being any number of factors, including branch power flow, nodal voltage, and radial configuration [14]. Due to several technical reasons such as low cost operation, simplicity of analysis and coordination, and reduction of short circuit current, distribution systems must operate with a radial topology [190]. With increasing penetration rates of DRs, it is important to take the advantage of these components during the service restoration. The single-period model with constant load and DER power generation and the multi-period model with varying load and DR power generation during the restoration period are frequently employed to formulate service restoration problem. Usually, studies that have adopted the single-period model [193] focus on improving the optimization algorithm to get better calculating performance, whereas in other studies [194-195] that use the multi-period model, the focus is on improving the optimization model to better represent the practical operating situations of DRs and distribution systems [136]. In the present study single-period model is considered, but it can be extended to multi-period model. The solution algorithm used for optimal NR therefore needs modification. For this purpose proposed GA of Chapter 3 is modified. In proposed GA, the genetic information is in the form of line switches which should be open to obtain desired radial topology of the distribution network. Therefore, the switch corresponding to the faulted line must remain intact as the genetic information among all individuals of the population throughout the genetic evolutions. It is noteworthy that this genetic information should not be swept away during the evolutionary process otherwise the whole computational process will be in vain. Fortunately, it will not happen in GA once the genetic information about the faulted line is being assigned to all individuals during initialization, as the crossover operator is not able to hinder the genetic information. However, care has to be taken during mutation. The process of restricting the faulted line during crossover and mutation is explained in Fig. 4.2 and 4.3

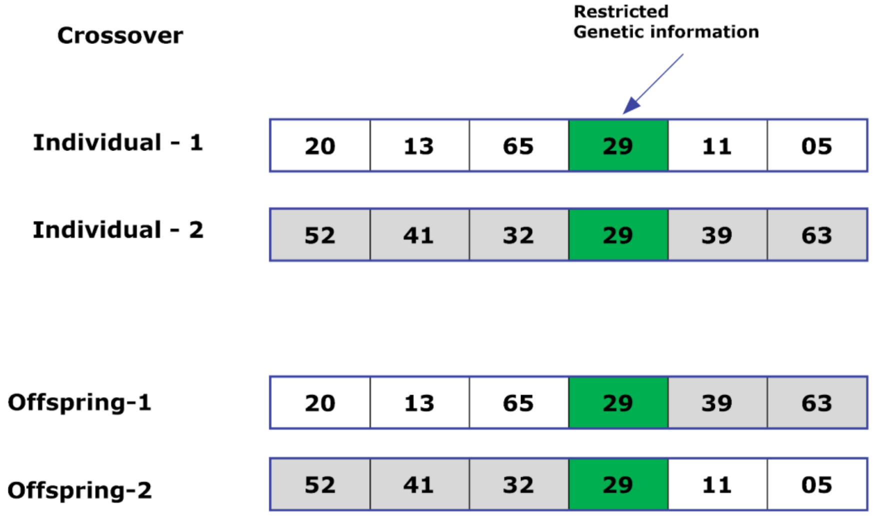


Fig. 4.2 Proposed crossover to intact genetic information of the faulted line during evolutionary process

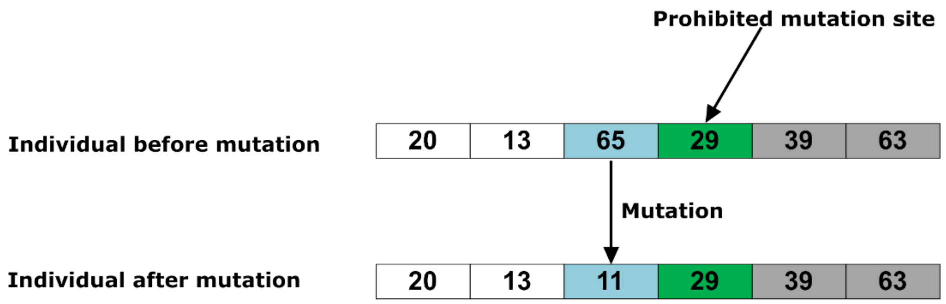


Fig. 4.3 Proposed mutation to intact genetic information of the faulted line during evolutionary process

Fortunately, in the proposed GA the structure of the individual is such that each gene is associated with one loop vector. While applying GA, the loop corresponding to the faulted line is identified so that this genetic information may remain intact among all individuals during initialization. The site corresponding to this genetic information is kept abandoned while mutating individuals. With these two modifications the GA proposed in Chapter 3 is modified to solve service restoration problem of distribution systems using optimal NR.

4.4.2 Problem Formulation

The objective of the problem may be formulated as to restore service to the isolated portions of a distribution system through network reconfiguration which minimizes power loss of the given system state keeping node voltages within prescribed limits. The problem constraints regarding to power flow, node voltage limits, thermal limits of feeders, etc. are considered as it is. However, the radiality constraints is redefined by the restriction of keeping the line to remain essentially open where the contingency is being considered. The objective function for the NR problem is defined as to

$$\text{Max. } F_{in} = \left(PLoss_{bn} - PLoss_{an}\right); \forall n \in N \tag{4.31}$$

subject to the system operational constraints defined below.

The sum of the power supplied from the utility grid and the total power generated by the different DRs being installed in the distribution system must be balanced by the local load demand and feeder power losses. For a radial network, a set of recursive equations are used to model the power flow in the network as given by (32)-(36).

$$P_{j+1} = P_j - R_j \frac{P_j^2 + Q_j^2}{V_j^2} - p_{j+1};\ \forall j \in N_c \tag{4.32}$$

$$Q_{j+1} = Q_j - X_j \frac{P_j^2 + Q_j^2}{V_j^2} - q_{j+1};\ \forall j \in N_c \tag{4.33}$$

$$V_{j+1}^2 = V_j^2 - 2\left(R_j P_j + X_j Q_j\right) + \left(R_j^2 + X_j^2\right)\frac{P_j^2 + Q_j^2}{V_j^2};\ \forall j \in N_c \tag{4.34}$$

$$p_{j+1} = p_{j+1}^{L} - p_{j+1}^{\mathrm{DG}};\ \forall j \in N_c \tag{4.35}$$

$$q_{j+1} = q_{j+1}^{L} - q_{j+1}^{\mathrm{SC}};\ \forall j \in N_c \tag{4.36}$$

4. Node voltage constraint

All node voltages V_{jn} of the nodes at state n must be maintained within the minimum and maximum permissible limits *i.e.* $V_{\min}$ and $V_{\max}$, respectively as defined below

$$V_{\min} \le V_{jn} \le V_{\max};\ \forall n \in N; \forall j \in N_c \tag{4.37}$$

5. Feeder current constraint

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

$$I_{jn} \le I_j^{\max};\ \forall n \in N, \forall j \in N_c \tag{4.38}$$

6. Radial topology constraint

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

$$\Phi_n(i) = 0; \forall n \in N \tag{4.39}$$

s.t. N_b=0 for the contingency considered on line N_b

4.4.3 Simulation Results

The proposed method is applied to 33-bus test distribution system as detailed in section 4.3 assuming that only one contingency occurred at a time in the distribution systems. The main objective is service restoration even during contingencies without any loss of load. The contingencies are considered on line 8, 12, 16, and 27, being the longest lines of the system having maximum probability of fault occurrence. The network loads and generations are assumed to be corresponding to state 18. This state is considered because the peak load condition and solar generation is moderate during this state of the distribution system. Using proposed GA method the distribution systems is reconfigured for all assumed contingency one by one. The population size and maximum generation are taken as 30 and 50, respectively. The crossover and mutation rates of GA are fixed at 0.9 and 0.05, respectively. The best result obtained after 100 independent trials of GA is used for analysis. The algorithm has been developed using MATLAB and the simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM. In order to show the importance of NR in the presence of DRs, the service restoration problem is solved for the following scenarios:

Scenario 1: Distribution system without DRs

Scenario 2: Distribution system with DRs

A. Scenario 1: Distribution system without DRs

Under given operating state the optimal topology requires opening of lines 7, 9, 14, 32 and 37 the corresponding losses are 139.51 kW with minimum node voltage as 0.9378 p.u. The service restoration problems under four different contingencies as stated above are considered. It is important to note that for each contingency, the corresponding sectionalizing switch automatically opens due to the operation of associated circuit breakers. The proposed method is then applied to determine number of remaining switching operations needed to restore service to network loads that are isolated due to forced outages with minimum possible loss. The application results for different contingencies are summarized in Table 4.15. The table also shows the results of the service restoration problem when the contingencies are considered for lines 8, 12, 16, and 27. Each of these contingency may cause islanding of many loads if not taken care off. It can be observed from the table that for each contingency, the proposed method provides the best possible optimal configuration with service restoration and acceptable node voltages. From the table it may be observed that for a fault on line 12 and 27, only two switching operation is required that is closing of one line with only 2 to 5 % increase in loss compared to normal pre-fault condition. The minimum node voltage nearly remains the same. For all other contingencies, the required switching operations are 4 with increase in power loss from 8 to 19 % with acceptable node voltages. It is also important to mention that the time taken for service restoration depends on the number of switching operations and so, lesser is the required number of switching operations lesser will be the time in service restoration.

TABLE 4.15
RESULTS OF SERVICE RESTORATION (WITHOUT DRS)

Configuration/ contingency	**Network configuration**	**Switching required**	**Power loss**	**Increase in loss (%)**	**Vmin**	**Vmax**
Nominal configuration	7, 9, 14, 32, 37	-	139.51	-	0.9378	1.0
Fault on line 8	**6**, **8,** 9, 14, 37	4	165.97	18.96638	0.9107	1.0
Fault on line 12	7, 9, **12**, 32, 37	2	145.97	4.630492	0.9371	1.0
Fault on line 16	**6**, 9, 14, **16,** 37	4	150.11	7.598022	0.9271	1.0
Fault on line 27	7, 9, 14, **27,** 32	2	143.27	2.695147	0.9398	1.0

B. Scenario 2: Distribution system with DRs

The Distribution is assumed to be equipped with mix-DG model and SCs as given in Table 3.6. With this DR placement, the optimal configuration obtained is 7, 9, 17, 28 and 34. With this configuration the losses are found to be significantly reduced by about 86% with adequate enhancement in node voltage profile as that in the base case condition. Therefore, this DR placement enhances performance of the system to good margins. The distribution network is optimally reconfigured for service restoration while considering each of the contingencies and the results obtained are presented Table 4.16. The table shows that the results of service restoration problem for the state 18 while contingencies are considered for lines 8, 12, 16 and 27. It can be observed from the table that the increase in loss is marginal using proposed method. However, the results obtained are better to that obtained without DRs. This can be compared from Fig. 4.4 It can be observed from the figure that proposed NR strategy is very effective in maintaining the performance of distribution systems in terms of loss reduction and voltage profile enhancement during contingencies, the increase in loss reduction is small enough and all node voltages are within prescribed limits. However, the performance of the network is found to be further enhanced during contingencies while considering the presence of DRs. More specifically, NR causes almost same loss reduction during contingencies as during normal operating conditions with adequate DRs in the system.

A similar conclusion can be made while observing node voltages. Therefore, optimal NR has significant importance during contingency conditions of active distribution systems.

TABLE 4.16
RESULTS OF SERVICE RESTORATION (WITH DRS)

Case	Network configuration	Switching required	Power loss	Increase in loss (%)	*Vmin*	*Vmax*
Normal reconfigured case	7, 9, 17, 28, 34	-	28.44	-	0.97716	1.0
Fault on line 8	7, **8, 14**, 28, **35**	6	32.76	15.18987	0.97716	1.0
Fault on line 12	7, **8**, **12,** 17,28	4	29.07	2.21519	0.97716	1.0
Fault on line 16	7, **8**, **16,** 28, 34	4	28.99	1.933896	0.973836	1.0
Fault on line 27	7, 9, 17,**27,**34	2	28.72	0.984529	0.97580	1.0

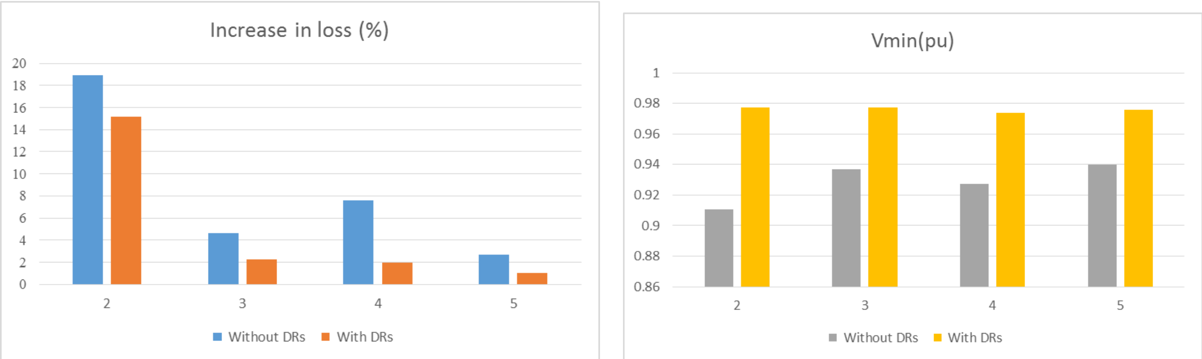


Fig. 4.4 Comparison of network performance during contingencies without and with DRs

4.5 NETWORK RECONFIGURATION WITH LOAD SHADING

With increasing penetration rates of DGs in distribution systems, an important issue to study is how to take advantage of DGs during the service restoration process [136]. DGs can play crucial role during fault and more specifically during grid failure to maintain supply of some important loads through optimal load shedding which is essentially the function of demand side management (DSM). In contemporary distribution systems, service restoration during grid failure is one of the most common issues. The problem of supply restoration has been handled by islanding certain area(s) of active distribution systems [193-196], without or with reconfiguring the network topology. However, such strategies to curtail critical loads whereas certain noncritical load(s) may remained live in service area. The load shading using network reconfiguration instead of the network islanding seems to be more attractive option for service restoration in active distribution systems. In this section, the problem of service restoration is extended to take into account the presence of DG and the use of optimal load shedding through network reconfiguration. The goal in this case is to find the optimal network configuration that allows minimum load shedding. In the presented approach, load shedding is activated when the total power demand of the network exceeds available generation either due to fault or forced outage. The problem is formulated by considering mix-DR model consists of SPVs, WTs, MT, and SCs to provide a more realistic scenario and the system operation is observed under grid failure mode. Moreover, the effectiveness of network reconfiguration on loss reduction and voltage profile enhancement is also investigated. A simple method is developed for load shading so that critical loads remains energized during grid failure. To formulate this problem all the loads are ranked according to their priorities and importance. The performance of distribution system is observed, both before and after NR. It has been assumed that system loads can be remotely controlled. The application result on modified standard test distribution system highlights the importance of proposed methodology.

4.5.1 Proposed Methodology

The active distribution systems are usually equipped with renewable DGs, mostly with SPVs and WTs. These renewable energy sources (RESs) are characterized by their intermittency in power generation and are non-dispatchable. Therefore, distribution planners suggest some alternative energy sources (AESs) such as micro turbines (MTs), fuel cells, small hydro turbines, etc. to make the combined sources dispatchable. The integration of such mix-DG model provides more reliable operation of distribution systems under normal conditions and may be very useful under grid failure condition as they can supply to critical loads of the systems. During grid failure, power output of DGs is usually not sufficient to meet out the current load demand of the system and so load shedding is inevitable. However, critical loads should not be shed. Therefore the model of service restoration of active distribution system requires defining priorities of system loads with following objectives:

1. Minimum load shedding and making sure that high priority loads are served in order of priority
2. Maintaining load and generation balance
3. Maintaining connectivity and radial topology of the system.
4. Network losses are as small as possible while satisfying the constraints of distribution system.

The overall methodology of proposed method involves the following steps:

Fixing Load Priority

In the present work all system loads are arranged in the order of their relative importance. The highest ranked node is the most critical one and the last one is the one which is least critical. This ranking will be helpful in framing load shedding strategy during the period of power shortage on account of planned or forced outage of some generation or grid failure.

Load Shading and DG Power Control

Several works have reported islanding for service restoration in active distribution systems by suggesting different strategies [194-196] where mainly the distribution network usually islanded into as many number as the number of DGs. These strategies have several shortcomings. For instance, certain loads/area remains energized even when they may have non-critical load(s) or certain de-energized area may contain some critical load. These problems may be overcome to some extent using optimal NR provided that all line switches are remotely operated, but is highly challenging task. However, the service restoration in distribution systems may be provided by load shading, instead of islanding the distribution network, if the distribution network is equipped with remotely controlled load switches. The load shading overcomes the general problems associated with islanded operation of distribution systems as the graph of the distribution system remains connected during load shading. In this view, load shading seems to be a better alternative of system operation during grid failure events.

In load shading, the loads are curtailed by considering their order of priority in order to match power balance within distribution network. The power balance is essential to keep the system in normal state. However, it is not easy to achieve this task in grid-disconnected distribution systems equipped with high penetration of renewable DGs. It happen because, in the prevailing system state, the forecasted generations from the renewable DG units may be assumed as the only known set of random variables whereas the loads to be shaded constitutes the set of unknown variables. In addition, network power loss remains unknown till the load flow is carried. While doing load flow, the source node cannot be taken as the slack bus for the grid-off distribution system. The renewable DGs cannot do the same job as have intermittent power generation. Therefore, MT is the only choice for the selection of the slack bus during load flow. Therefore, the power output of this MT unit needs control to meet out the system losses and uncertainty in the power generation from renewable DGs.

A simple algorithm is proposed to simultaneously determine the set of shaded loads and power control of MT unit. According to this algorithm, the load flow is carried while selecting suitable MT unit as the slack bus. The algorithm initiates with all loads assumed to be energized. The power supplied by the slack bus is then measured. If the slack bus power is found to be more than the pre-specified maximum limit of the MT unit, a load with least priority is curtailed and another load flow is carried. In this way, loads are curtailed in sequence and load flows are executed till the slack bus power becomes equal or less than the maximum limit of the MT unit. The results after final load flow simultaneously provides DG power control of the MT unit, the set of loads to be shaded and system losses.

Pre-Estimated Load Demand

Modern distribution systems are large and complex as they may consists of several lines and hundreds or even thousands of nodes. The proposed algorithm may be computationally demanding for such large-scale distribution systems. The computational time of the algorithm can be significantly reduced if it is initiated with a pre-estimated load demand, instead that of total demand of the system. For this purpose, the possible generation from all dispatchable and non-dispatchable DGs is known and then the amount of load and corresponding losses are determined using proposed algorithm while keeping the pre-estimated load demand always just higher than the difference of total generation and power losses. With this pre-estimation of load demand, the algorithm converges within few iterations. The pre-estimated load demand is given by the following relation:

$$P_D^{pre} \geq \sum P_{SPV}^{for} + \sum P_{WT}^{for} + \sum P_{MT} - Ploss \tag{4.40}$$

Some forecasted error is always associated with the stochastic load demand and the power generation from renewable DGs. Therefore, a suitable reserve is required for MT unit being selected as the slack bus otherwise the solution provided for DG power control may not be able to cater excess load demand or the shortage of power generation from renewables as per their forecasted values. The reserve proposed for the MT unit therefore should be selected with care and wisdom. The pre-estimated load demand is therefore redefined by the following relation:

$$P_D^{pre} \geq \sum P_{SPV}^{for} + \sum P_{WT}^{for} + \sum \left(P_{MT} - P_{MT}^{res} \right) - Ploss \tag{4.41}$$

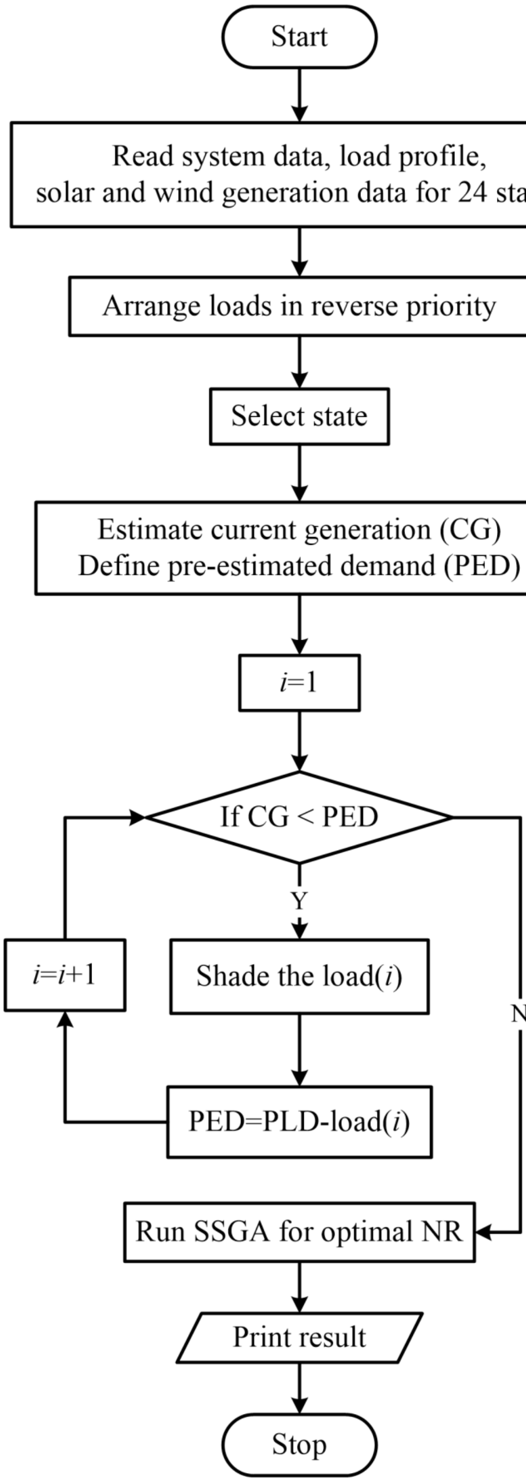


Fig.4.5 Flow Chart for load shading

Network Reconfiguration

After obtaining the set of de-energized loads, MT power control, the distribution network is optimally reconfigured to minimize power losses and to enhance node voltage profile while considering available power generations from renewable DGs for the concerned state of the system. The distribution network remains disconnected from the grid, therefore the MT is used as the slack bus having a pre-specified maximum power generation limit as determined by DG power control. This time the power control of MT absorbs the change in loss due to NR so provides its final optimal dispatch for the state considered. In case the failure duration extends for more than one state, the network is optimally reconfigured for each of the concerned state separately. The GA developed in Chapter 3 can be applied without any change to solve NR problem.

The flow chart of the proposed method for service restoration of active distribution system during grid failure is shown in Fig. 4.5.

The mathematical formulation of the proposed method is as under.

4.5.2 Problem Formulation

Objective 1: To determine minimum load shading keeping load priority in to account under grid failure for the available power from renewable DGs and MTs.

$$Max\ P_{DR} = \sum p_{Dq};\ \forall q \in LP \tag{4.42}$$

where, p_{Dq} is the load demand of the qth priority and P_{DR} is the amount of load remains energized during grid failure condition.

s. t. constraints

Node voltage constraint

$$V_{\min} \le V_{jn} \le V_{\max};\ \forall n \in N; \forall j \in N_c \tag{4.43}$$

Feeder current constraint

$$I_{jn} \le I_j^{\max};\ \forall n \in N, \forall j \in N_c \tag{4.44}$$

power balance inequality constraint

$$P_{DR} + Ploss \ \le\ \sum P_{SPV} + \ \sum P_{WT} + \ P_{MT}{}^{gen} \tag{4.45}$$

MT generation limit constraint

$$0 \ \le P_{MT}{}^{gen} \le\ P_{MT} - P_{MT}{}^{res} \tag{4.46}$$

Objective 2: To operate distribution system in minimum loss configuration during grid failure for the available power from renewable DGs and MTs.

$$\text{Max. } F_{in} = \left(PLoss_{bn} - PLoss_{an}\right); \forall n \in N \tag{4.47}$$

s. t. constraints

power balance constraint

$$P_{MT}{}^{gen} = P_{DR} + Ploss - \sum P_{SPV} - \sum P_{WT} \tag{4.48}$$

MT generation limit constraint

$$0 \le P_{MT}{}^{gen} \le \left(P_{MT} - P_{MT}{}^{res}\right) \tag{4.49}$$

In addition, the constraints related to node voltage, feeder current and radial topology are taken as considered before.

4.5.3 Simulation Results

The simulations are carried on IEEE 33-bus test distribution system [30]. The base configuration of the distribution network is obtained by opening lines 33-37. The power loss for this system in base configuration is found to be 202.50 kW. The distribution system is equipped with DRs as shown in Table 3.6. The priority of all system loads are assumed as shown in the Table 4.17

TABLE 4.17
PRIORITIES OF LOADS

Load Priority	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Nodes	24	32	7	31	11	12	3	2	15	14	29	30	4	17	16	21
Load Priority	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
Nodes	26	28	10	23	22	6	5	18	33	13	20	8	27	9	19	25

The simulation is carried only for few selected system states, viz. 3, 7, 13, 19 and 22. These states are considered to cover possible combinations of variety in power generation from SPVs and WTs, and the variation in load demand of the system. The reserve capacity for MT unit is taken as 100 kW. The proposed methodology is applied to this system with network topology in base configuration. The distribution network is then optimally reconfigured using SSGA of Chapter 3. The results obtained are presented and compared. The population size and maximum generation for SSGA are taken as 50 and 100. The best result obtained after 100 trial runs is considered for analysis.

The proposed algorithm runs with base configuration and the results obtained are presented in Table 4.18. The table shows the MT power and the set of loads to be shaded during grid failure for each state considered. The table shows the power generation from renewable DGs and MT unit, total load demand available after load shading and the power loss incurred. It can be observed that the power balance is maintained in each state using proposed method while keeping MT generation within limits. The table also shows the nodes being de-energized on account of load shading and the percentage load to be shaded as suggested using proposed algorithm. It can be seen from the table that the percentage load shading varies from about 0 to 49% during different system states considered which is mainly governed by the power generation from renewable DGs. However, the self-sustainability of the system is about 50% with the given DG placement. Thus proposed algorithm can maintains supply to almost all important loads during grid failure. The table also shows that the distribution network remains efficient and also the node voltage profiles are maintained well within limits during grid failure events.

TABLE 4.18
DISTRIBUTION SYSTEM WITH BASE CASE

State	**Power generation (kW)**				**Available load demand (kW)**	***Ploss* (kW)**	**Nodes de-energized**	**Shaded load (%)**	**Loss reduction (%)**	***Vmin* (p.u.)**	***Vmax* (p.u.)**
	SPV	**WT**	**MT**	**Total**							
3	0	745.36	666.08	1411.44	1401.20	10.20	22, 6, 5, 18, 33, 13, 20, 8, 27, 9, 19, 25	36.07	94.96	0.99	1.00
7	13.44	611.38	690.50	1315.32	1305.11	10.22	26, 28, 10, 23, 22, 6, 5, 18, 33, 13, 20, 8, 27, 9, 19, 25	43.31	94.95	0.99	1.00
13	1624.56	1379.84	441.69	3446.10	3417.80	28.29	Nil	0	86.03	0.97	1.00
19	0	1175.02	707.38	1882.4	1866.57	15.83	17, 16, 21, 26, 28, 10, 23, 22, 6, 5, 18, 33, 13, 20, 8, 27, 9, 19, 25	48.99	92.19	0.97	1.00
22	0	1267.42	690.11	1957.53	1942.25	15.28	21, 26, 28, 10, 23, 22, 6, 5, 18, 33, 13, 20, 8, 27, 9, 19, 25	38.49	92.45	0.97	1.00

TABLE 4.19
DISTRIBUTION SYSTEM WITH OPTIMAL RADIAL TOPOLOGY

State	Optimal Configuration	MT (kW)	*Ploss* (kW)	Loss reduction (%)	*Vmin* (p.u.)	*Vmax* (p.u.)
3	5, 8, 9, 17,33	661.21	5.316	97.37	0.9944	1.00
7	5, 7, 17,33, 34	685.46	5.183	97.44	0.9952	1.00
13	5, 9, 16,21,33	430.44	17.04	91.58	0.9828	1.00
19	17, 19, 27,34, 35	697.46	5.903	97.08	0.9917	1.00
22	16, 21,25, 33,34	681.51	6.680	96.70	0.9914	1.00

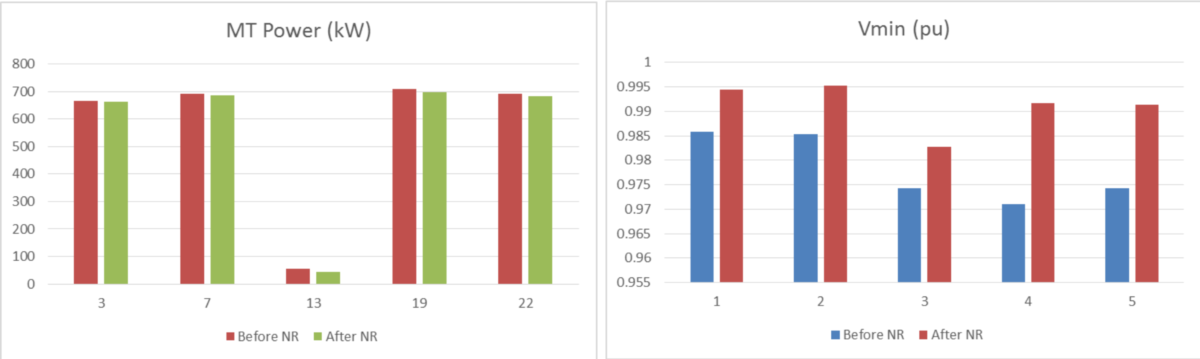


Fig. 4.6 Comparison of MT power, loss reduction and V_{min} before and after NR

Now the proposed SSGA is applied to operate the distribution system with optimal radial topology to minimize losses and to enhance node voltage profile. The best result obtained after 100 independent runs is presented in Table 4.19. The table shows optimal radial topology and MT power and power losses for each system state. It can be observed from the table that after NR the system become more efficient with better node voltage profiles and with less power generation from MT units. This is quite obvious because NR provides load balancing among distribution feeders thus reduces power losses and enhances node voltage profiles. The amount of benefit obtained using NR can be observed from Fig 4.6. It can be observed from the figure that MT power generation is marginally reduced after NR because NR causes marginal loss reduction in each system state. This fact can be verified from Fig 4.6 showing small but definite increase in loss reduction using NR. However, an important role is played by NR while comparing enhancement in node voltage profiles as shown in Fig 4.6. This enhancement is small but may be called significant as the minimum node voltages are found to be improved from say 0.9711 p.u. to 0.9917 p.u. during peak load condition (state 19). This shows the importance of NR in distribution systems equipped with adequate DRs.

The proposed method efficiently provides the optimal set of loads to be de-energized by maintaining priority of each and every load, and also provides the corresponding power control of dispatchable DG whether the distribution network is going to operate in base configuration or optimal radial topology during grid failure. The distribution network operator has a choice to operate the network in either of the topologies by considering the benefits of optimal NR. Though, simulation results validate power balance during grid failure, in practice it may not match on account of error present in the forecasted data of load demand and power generation from renewable DGs. Such errors can be taken in to account using suggested reserve capacity of the MT unit which has been considered here as 100 kW. The selection of this reserve capacity depends upon uncertainty in the power generation from renewables on account of geographical conditions, seasonal variations, etc., variability in load demand and system losses so may be taken with care to avoid further curtailment of certain other system load (s).

4.6 SUMMARY

Contemporary distribution systems are with high penetration of diverse distributed resources which effectively manage power flow among distribution system so enhances performance and reliability to good extent. In this chapter, the issues of reliability enhancement and service restoration of distribution system have been addressed using proper network reconfiguration strategies. Existing reliability indices have been modified to take into account the changing dynamics of contemporary distribution systems. New reliability indices gives due consideration to Joule's heating in actual operating conditions of the distribution systems. NR is a well-known operational strategy of radial distribution systems to enhance system performance and reliability by optimally managing power flow among distribution feeders. Attempts have been made in this chapter to investigate the applicability of NR to enhance system reliability and performance of contemporary active distribution systems. A multi-objective problem is framed in fuzzy framework to simultaneous optimize various power quality and reliability objectives while considering more realistic scenario pertaining to the variability and uncertainty in power generation and load demand among distribution buses. Moreover, new NR strategies are developed to enhance energy efficiency of radial distribution system while facing service restoration against on-grid and off-grid contingencies. Proposed methodologies are applied to standard test distribution system and the results on investigation are presented. The study reveals the importance of proposed methodologies, NR strategies and reliability indices proposed for contemporary distribution systems, that they reduce feeder power losses and enhances node voltage profiles by very good margins. In this context it is important to investigate the effectiveness of conventional network reconfiguration strategy where the network topology is expected to vary with every predetermined changing state of the distribution system. In this chapter, a detailed investigation has been carried about CNR while considering different scenarios pertaining to the diversity in load demand and power dispatches from DGs. In addition, day-ahead network reconfiguration strategy is proposed where the distribution network reconfigured only once during 24 hours. A detailed comparison of CNR and DNR is provided while considering all scenarios and it has been observed that DNR strategy causes a marked reduction in switching operation of line switches, but at the cost of marginal increased energy losses, however, node voltage profiles not affected from practical point of view. This is true only when distribution system is equipped with adequate DRs. So DNR strategy may be an attractive alternative for DNOs to simultaneously provide simplicity and effectiveness in the operation and control of distribution systems while maintaining promising levels in both maintaining the network efficiency and quality power delivered to customers.

CHAPTER 5

DAY-AHEAD NETWORK RECONFIGURATION STRATEGY FOR ACTIVE DISTRIBUTION SYSTEMS

In contemporary distribution system are moving towards complete system automation for effective on line monitoring and control of distribution systems. One of the most important aspects the automation of contemporary distribution system is to cope up with uncertain generations from renewables DGs. The automated distribution systems adopt to changing generations and loads for optimal performance through network reconfiguration. For accurate implementation of distribution system reconfiguration proper modeling of renewable generations and loads are very important. Among renewable DGs, SPVs and WTs are preferred on account of the access of better and economic DG technologies. However, renewable DGs are characterized by intermittency in power generation. Similarly loads on distribution system are stochastic in nature. Moreover, there exists a diversity in loads among distribution buses on account of different class of customers, i.e. residential, industrial, commercial customers, each having its characteristic load profile [8]. For so much diversity in generations and loads, the optimal operation of distribution systems demands frequent network reconfigurations in a day. However, frequent NR is neither advisable nor feasible in practice due to switching costs, over use of switches and prospective switching transients. Therefore, there is a need to develop planned network reconfiguration strategy based on forecasted load and generation data so as to optimize the number of switching. This leads to the idea of day-ahead network reconfiguration (DNR) strategy where the distribution network is to be operated in optimal number of topologies in a given time frame for optimal performance of distribution system. In this chapter, a comprehensive comparative study is carried for conventional NR (CNR) and DNR while considering various scenarios pertaining to the presence of DRs in distribution system, their power control, and diversity and variability of load and power generation among distribution buses. The application results on a benchmark test distribution system show the importance of proposed DNR for contemporary distribution systems.

5.1 PROPOSED DAY-AHEAD NETWORK RECONFIGURATION (DNR) STRATEGY

The competitive deregulated environment and smart grid initiatives have imposed intense pressure on DNOs to achieve optimum efficiency and performance of distribution systems. The optimal NR is one of the operational strategies which can help to improve efficiency and performance of distribution systems to great extent and relief to DNOs. However, the distribution network cannot be frequently reconfigured with each and every varying state of the distribution system in the view of switching cost involved and the prospective switching transients. The later become crucial on shunt capacitors present to provide necessary reactive support.

In recent there is a growing trends towards vast deployment of DGs in distribution systems on account of environmental, economic and social concerns. The SCs have also been deployed along with DGs as they are relatively cheap energy sources as they are essential to supply reactive power support to several renewable DGs, which are the exclusive source of active power. These components have been usually placed optimally in the distribution system thus significantly affects power flow among distribution feeders. Several works [85-97,102] have reported that these components can optimize the feeder power flows to such an extent that a power loss reduction of about 80-90% could be achieved. The presence of DGs and SCs have significantly reduced the effectiveness of network reconfiguration as far as system losses and voltage profile are concerned. However, NR is indispensable as it serves many purpose in addition to loss reduction and voltage profile improvement such as load balancing, congestion management, service restoration, load shedding etc. In view of this, it is necessary to review the NR strategy for contemporary active distribution system.

The operating states of contemporary distribution systems changes dynamically on account of inconsistency in power generation from renewable DGs and stochastic nature of load demand. For such system, the conventional network reconfiguration (CNR) suggests as many network topologies as the number of operating states. However, frequent NR for small reduction in losses and marginal improvement in load profile is neither advisable nor feasible on account of cost involved. Under such conditions day-ahead NR (DNR) strategy provides better alternative for DNOs. The DNR strategy is based upon the fact that the benefits of NR in contemporary distribution systems with high DG penetration are much less compared to that achieved in legacy passive distribution systems.

In DNR strategy the forecasted data of loads and generation is analyzed for the next 24 hours and on the basis of this analysis, an optimal look up table for switching of tie/sectionalizing switches is prepared for the next day. For formulation of DNR, stochastic nature of load demand, diversity of loads among buses and uncertain nature of the power generation from renewable DGs are taken into consideration. The variability and uncertainty in load demand and power generation from renewable DG units can be handled effectively using deterministic approach as discussed in Chapter 3. However, distribution buses possess definite load diversity due to different category of customers. To handles the diversity in load profiles of the buses, proper load modeling is required.

The modeling of load profile is one of the important issues while dealing with any distribution system optimization problem. Earlier efforts [197-200], and many others, have addressed these problems by modeling load profile of the system using piecewise multiple load levels. This provides probably the simplest modeling, but is not accurate as all loads are assumed to vary in unison that in practice occurs seldom. Distribution systems generally have a load class mix of various types of customers, i.e. residential, industrial, and commercial in which every bus of the system has a different type of load connected to it [164]. The distribution planners usually provide dedicated feeders to supply their particular class of customers. Since each customer has characteristic stochastic load pattern so the stochastic load demand pattern remains more or less same along particular feeders but differ from one feeder to another feeder. A sample daily load profiles for the residential, industrial and commercial customers are shown in Fig. 5.1. The figure shows diversity of load that exists among these customers. The load profile of the system is determined by the sum of these profiles as shown in figure. The figure reveals that the shape of system load profile would be different if load diversity is ignored. Therefore in the proposed formulation of DNR, the diversity of loads among feeders is considered.

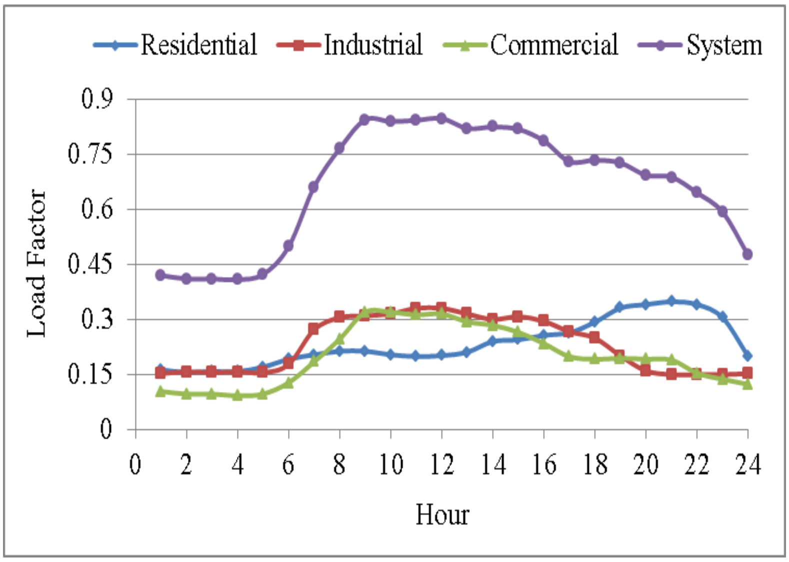


Fig. 5.1 Daily load profile of (a) residential customers (b) industrial customers (c) commercial customers and (d) load profile of the system

5.2 FORMULATION OF DNR

Distribution networks are conventionally reconfigured to minimize feeder power losses for the particular system states. Therefore, the objective function for the CNR strategy is formulated as

$$\min\ P_{Loss}^{n} = \sum_{r=1}^{N_r} R_r \frac{P_{r,n}^2 + Q_{r,n}^2}{\left|V_{r,n}\right|^2} + \sum_{i=1}^{N_i} R_i \frac{P_{i,n}^2 + Q_{i,n}^2}{\left|V_{i,n}\right|^2} + \sum_{c=1}^{N_c} R_c \frac{P_{c,n}^2 + Q_{c,n}^2}{\left|V_{c,n}\right|^2} \tag{5.1}$$

where the subscripts *r*, *i* and *c* refers to residential, industrial and commercial loads respectively. However, for proposed DNR strategy, all the system states pertaining to the typical day have to be taken into account. Therefore, the objective function is formulated to minimize energy loss incurred during the day, and is formulated as

$$\min E_{Loss} = \sum_{n=1}^{N} LD_n P_{Loss}^{n} \tag{5.2}$$

where, N denotes total system states considered for the typical day.

Subject to the following network operation constraints:

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 (3)-(7).

$$P_{j+1} = P_j - R_j \frac{P_j^2 + Q_j^2}{V_j^2} - p_{j+1};\ \forall j \in N_c \tag{5.3}$$

$$Q_{j+1} = Q_j - X_j \frac{P_j^2 + Q_j^2}{V_j^2} - q_{j+1};\ \forall j \in N_c \tag{5.4}$$

$$V_{j+1}^2 = V_j^2 - 2\left(R_j P_j + X_j Q_j\right) + \left(R_j^2 + X_j^2\right)\frac{P_j^2 + Q_j^2}{V_j^2};\ \forall j \in N_c \tag{5.5}$$

$$p_{j+1} = p_{j+1}^{L} - p_{j+1}^{\mathrm{DG}};\ \forall j \in N_c \tag{5.6}$$

$$q_{j+1} = q_{j+1}^{L} - q_{j+1}^{\mathrm{SC}};\ \forall j \in N_c \tag{5.7}$$

2. Node voltage constraint

All node voltages V_{jn} of the nodes at state $j$must be maintained within the minimum and maximum permissible limits *i.e.* $V_{\min}$ and $V_{\max}$, respectively as defined below

$$V_{\min} \le V_{jn} \le V_{\max};\ \forall n \in N; \forall j \in N_c \tag{5.8}$$

3. 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

$$I_{jn} \le I_j^{\max};\ \forall n \in N, \forall j \in N_c \tag{5.9}$$

4. Radial topology constraint

The reconfigured network topology must be radial, i.e. with no closed path. Therefore, the radiality constraint for the *i*th radial topology at *n*th system state is defined as

$$\Phi_n(i) = 0; \forall n \in N \tag{5.10}$$

Eq. (3.10) of Chapter 3 is used to model uncertainty in load demand and power generation from SPVs and WTs. The stochastic nature of residential, commercial and industrial load demand can also be modeled separately using similar equations. The synthetic data so produced for power generation and load demand among various distribution buses is used for simulation.

5.3 Simulation Results

The proposed method is applied to IEEE 33-bus test distribution system [30]. This is a 12.66 kV radial distribution system with 32 sectionalizing lines (normally closed) and 5 tie-lines (normally open). In base case the network configuration is made radial by opening all tie-lines which are numbered as 33-37 as shown in Table 5.1. The line voltage, active and reactive loading of the system are also shown in the table. The table also shows the classification of system feeders as residential, industrial and commercial and corresponding nodes, as in [156]. The unitized load factors of residential, industrial and commercial loads and the corresponding load durations considered for the daily load profile of the system is presented in Table 5.2. The data is based upon the aggregate daily load pattern as taken in [156]. Further it has been assumed that renewable DGs such as wind turbines (WTs) and solar photovoltaic (SPVs), micro turbines (MTs), and shunt capacitors (SCs) exist in this system. The allocation of these distributed resources in the system is presented in Table 5.3. It can be observed from the table that WTs of capacity 1540kWp, SPVs of capacity 1880kWp and MTs of capacity 800 kW are installed in the distribution system and the total reactive power injection by SCs is 1200kVAr.

TABLE 5.1
INITIAL DATA OF IEEE 33-BUS SYSTEM

Particular	**Value**	**Feeder**	**Nodes**
Line Voltage (kV)	12.66	Residential	1-15
Nominal Active Demand (kW)	3715	Industrial	22-29
Nominal Reactive Demand (kVAr)	2300	Commercial	16-21, 30-33
Base Configuration	33 to 37	-	-

TABLE 5.2
LOAD FACTORS AND LOAD DURATION FOR DAILY LOAD PROFILE

State	Residential	Industrial	Commercial	State	Residential	Industrial	Commercial
1	0.4	0.8	0.4	13	0.8	1	0.8
2	0.4	0.8	0.4	14	0.8	0.8	0.8
3	0.4	0.8	0.4	15	0.8	1	0.8
4	0.4	0.8	0.4	16	0.8	1	0.8
5	0.4	0.8	0.4	17	0.8	1	0.8
6	0.4	1	0.4	18	0.8	1	0.8
7	0.6	1	0.4	19	0.8	1	1
8	0.6	1	0.4	20	1	1	1
9	0.6	1	0.4	21	1	1	1
10	0.6	1	0.6	22	1	0.8	0.4
11	0.6	1	0.6	23	0.4	0.8	0.4
12	0.6	1	0.6	24	0.4	0.8	0.4

TABLE 5.3
ALLOCATION OF DRS ASSUMED IN EXISTING DISTRIBUTION SYSTEM

SPV		**WT**		**MT**		**SC**	
Node	**Capacity (kWp)**	**Node**	**Capacity (kWp)**	**Node**	**Capacity (kW)**	**Node**	**Capacity (kVAr)**
14	280	14	420	24	800	12	300
24	840	24	700	-	-	25	300
30	560	30	420	-	-	30	600

Following four scenarios are considered to investigate the impact of day-ahead network reconfiguration while considering the effect of load diversity among distribution buses and power dispatches from renewable DGs:

Scenario 1: NR without considering load diversity with intermittent power DGs

Scenario 2: NR without considering load diversity and with fixed power DGs

Scenario 3: NR considering load diversity and with intermittent power DGs

Scenario 4: NR considering load diversity and with fixed power DGs

In scenarios 2 and 4, it has been assumed that the distribution system is equipped with adequate distributed storages (DSs) so that fixed power can be injected into the system using renewable DGs. Moreover, while load diversity among distribution buses is ignored, as in scenarios 1 and 2, the load factor for each bus is taken as the mean of load factors of various types of loads while diversity is considered. This provides identical daily load profiles of the system whether the diversity in load is considered or ignored. This measure is essential to provide valid comparison of results. The load profile therefore obtained is shown in Fig. 5.2. This load profile is considered for all scenarios.

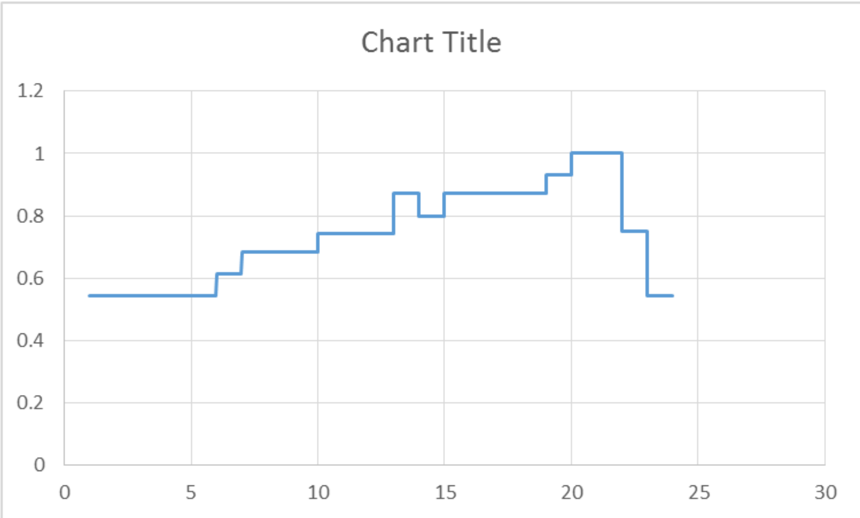


Fig. 5.2 Load profile considered for the system

For each of the scenarios considered, the distribution network is optimally reconfigured to minimize power losses using both CNR and DNR strategies. While employing CNR strategy, the distribution network is independently optimally reconfigured for each system state. The results obtained using CNR and DNR strategies are compared and investigated.

SSGA developed in Chapter 3 is employed to solve NR problem. The population size and maximum generation are set at 20 and 200, respectively after usual tradeoff. The crossover and mutation rates are taken as 0.9 and 0.1, respectively and the selection rate is 0.5 and selection ratio is in the range of [1-4]. The best result obtained after 100 independent trials is used for investigation. Details of the platform used for computation is Intel(R) i5, 3.2 GHz, 4GB RAM.

5.3.1 Scenario 1: NR without Considering Load Diversity and with Intermittent Power DGs

Since load diversity among distribution buses is ignored, the load factors shown in Table 5.2 are valid for each system bus. The power generation factors for SPVs and WTs considered for a typical day are shown in Fig. 5.3. The capacity of MTs and SCs is taken as given in Table 5.3. The distribution network is optimally reconfigured using SSGA for each hour separately while employing CNR strategy. The best result obtained after 100 independent trials of SSGA for each hour of the day are presented in Table 5.4.

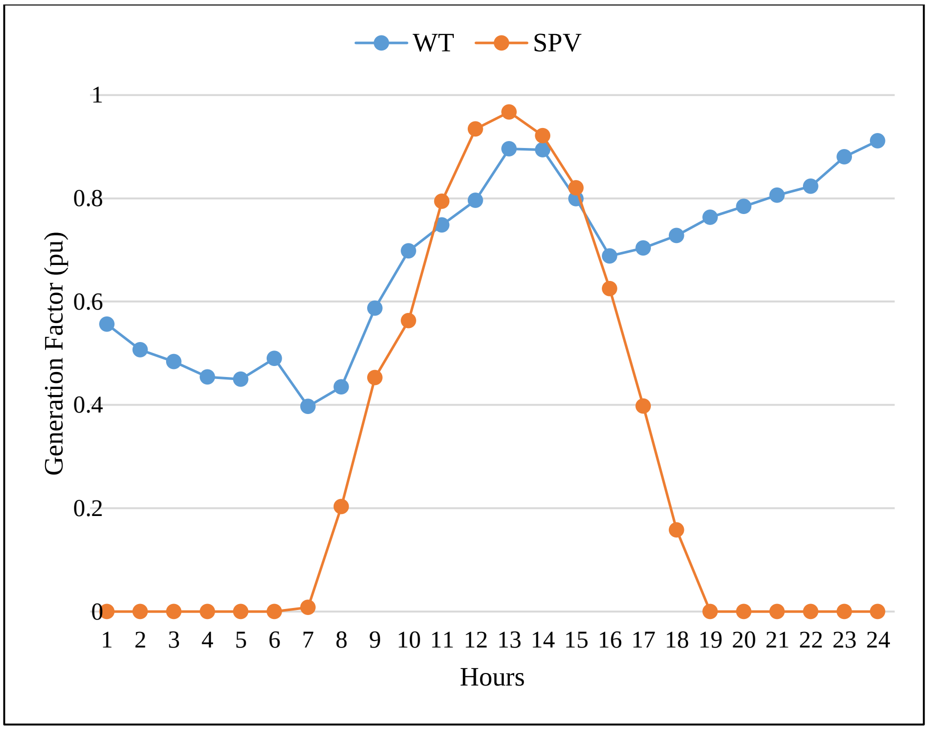


Fig. 5.3 Power generation factor data from renewable DGs for a day

The table shows power losses before network reconfiguration are 2621.34 kWh, i.e. without DRs. These losses are found to be 576.37 kWh by placement of DRs. It implies that about 78% energy losses have been reduced by DR placement so very little margin is available for NR to further reduce the feeder power losses. The table also shows optimal feeder power loss and the corresponding network topology while reconfiguring distribution network using CNR strategy. It can be observed from the table that the daily energy losses are reduced from 576.37 kWh to 394.33 kWh using this NR strategy, but it require total 84 switching operations. Therefore, total 84 switching operations are required to reduce about 182 kW energy losses if CNR strategy is employed.

TABLE 5.4
SIMULATION RESULTS USING CNR STRATEGY FOR SCENARIO 1

State	**Power loss (kW)**			**Configuration**
	Base Case	**With DRs before NR**	**With DRs after NR**	
1.	55.65	12.68	7.29	2, 8, 17, 25, 34
2.	55.65	13.27	7.59	8, 17, 25, **33**, 34
3	55.65	13.60	7.67	8, 17, 25, 33, 34
4	55.65	14.08	7.88	8, **16**, 25, 33, 34
5	55.65	14.15	7.85	8, **17**, 25, 33, 34
6	71.92	17.11	9.33	8, 17, 25, 33, 34
7.	90.09	25.43	13.67	**7, 9, 22, 28**, 34
8.	90.09	18.77	10.61	**8, 17, 25, 33**, 34
9.	90.09	15.33	11.45	**16,** 25, 33, 34, **35**
10.	107.30	18.13	14.80	**9, 21**, 25, **29, 33**
11.	107.30	23.60	20.70	**5**, 9, **16**, 21, 33
12.	107.30	29.82	26.85	5, 9, 16, **20**, 33
13.	150.68	32.06	29.41	5, **7**, 9, 16, **21**
14.	125.76	31.16	28.50	5, 9, 16, **20, 33**
15.	150.68	26.15	22.79	**7**, 9, **21, 25, 29**
16.	150.68	23.73	17.22	**8**, 9, 25, **33, 35**
17.	150.68	25.24	16.60	8, **17**, 25, 33, **34**
18.	150.68	29.85	17.83	**7**, 8, 17, **27**, 34
19.	173.40	42.41	24.46	7, **9**, 17, **28**, 34
20.	202.50	53.17	31.02	7, 9, 17, 28, 34
21.	202.50	52.01	30.41	7, 9, 17, 28, 34
22.	110.12	19.73	11.77	7, **8**, 17, **26**, 34
23.	55.65	12.30	9.17	**5,** 7, **9, 16, 33**
24.	55.65	12.58	9.46	5, 7, 9, 16, 33
Total	**2621.34**	**576.37**	**394.33**	Total switching operations = 84

Next, simulations are carried for day-ahead NR to obtain that single optimal topology which prevails throughout the day yet minimizes daily energy losses of the system. The best result obtained after 100 trial runs of SSGA shows optimal network topology by opening the lines 7, 8, 9, 25 and 16 that provides daily energy loss of 426.11 kWh. The comparison results of CNR and proposed DNR strategies are presented in Table 5.5.

TABLE 5.5
COMPARISON RESULTS OF CNR AND DNR STRATEGIES FOR SCENARIO 1

Particular	**CNR**	**DNR**
Daily energy loss (kWh)	394.33	426.11
Daily energy loss reduction (kWh)	182.04	150.26
Daily energy loss reduction (%)	31.58	26.07
Minimum node voltage (p.u.)	0.9744	0.9667
Daily switching operations	84	4

It can be observed from the table that daily energy losses are reduced by about 26% using DNR strategy which is about 32% using CNR strategy, but total switching operations are drastically reduced from 84 to 4 using DNR strategy. However, 6% additional energy losses accounts to 32 kWh for 80 additional switching operations which is quite small for this system having peak demand of 3715 kW. It is important to note that cost of 80 switching operation is much higher than the cost of additional saving of 32 kWh by even the most economic means of switching. It can also be observed from the table that DNR is capable to maintain nearly the same node voltage profiles as CNR as the minimum voltage obtained are 0.9744 p.u. and 0.9667 p.u., respectively. Therefore, proposed DNR strategy seems to be promising for modern distribution systems well equipped with DGs and SCs.

5.3.2 Scenario 2: NR without Considering Load Diversity and with Fixed Power DGs

Modern distribution systems have renewable power sources having intermittency in power generations. The load demand is also stochastic in nature. Therefore, alternative energy sources such as MTs and battery storages are also installed in the system. The advantage of battery storages over MTs is that they can charge during off-peak hours and discharge during peak load hours thus also absorbs variations in the generations from renewables in a better way. In this study, the distribution system is assumed to be equipped with sufficient battery storage so that fixed power can be taken from intermittent power generation sources such as SPVs and WTs. In this way, fixed power may be extracted from renewable DGs. For this scenario, the load demand and load profile, both are considered as in scenario 1 but it has been assumed that the system is well equipped with sufficient storages and control strategies to make time-invariant power injection during the day among distribution buses having SPVs and WTs. The power generation from MTs and SCs is also assumed to be constant during the day. The fixed power dispatches from these energy resources considered are presented in Table 5.6.

TABLE 5.6
FIXED POWER DISPATCHES CONSIDERED FROM DRS

SPV		WT		MT		SC	
Node	**Power (kW)**	**Node**	**Power (kW)**	**Node**	**Power (kW)**	**Node**	**Power (kVAr)**
14	110	14	220	24	600	12	300
24	300	24	360	-	-	25	300
30	200	30	220	-	-	30	600

TABLE 5.7
SIMULATION RESULTS USING CNR STRATEGY FOR SCENARIO 2

State	**Power loss (kW)**		**Configuration**
	With DRs before NR	**With DRs after NR**	
1.	9.69	7.7	5 7 8 9 16
2.	9.69	7.7	5 7 8 9 16
3	9.69	7.7	5 7 8 9 16
4	9.69	7.7	5 7 8 9 16
5	9.69	7.7	5 7 8 9 16
6	10.54	7.5	16 **25 33 34 35**
7.	13.16	8.74	**17** 25 33 34 35
8.	13.16	8.7	17 25 33 34 35
9.	13.16	8.7	17 25 33 34 35
10.	16.81	10.8	**8** 17 25 33 34
11.	16.81	10.8	8 17 25 33 34
12.	16.81	10.8	8 17 25 33 34
13.	29.47	18.2	**7 9** 17 **27** 34
14.	21.69	13.65	7 **8** 17 27 34
15.	29.47	18.2	**7 9** 17 27 34
16.	29.47	18.2	7 9 17 27 34
17.	29.47	18.2	7 9 17 27 34
18.	29.47	18.2	7 9 17 27 34
19.	37.52	23	7 9 17 **28** 34
20.	48.85	29.9	7 9 17 28 34
21.	48.85	29.9	7 9 17 28 34
22.	17.50	11.2	**8** 17 **25 33** 34
23.	9.69	7.7	**5 7** 8 **9 16**
24.	9.69	7.7	5 7 8 9 16
Total	490.08	318.54	Total switching operations = 40

The distribution network is optimally reconfigured using CNR strategy and the results obtained after 100 independent trials of SSGA are presented in Table 5.7. The table shows optimal network configuration and power losses before and after NR. It can be observed from the table that CNR strategy reduces daily energy losses from 490.08 kWh to 318.54 kWh, i.e. of about 172 kWh. When the distribution network is reconfigured using DNR strategy, the energy losses are found to be reduced from 490.08 kWh to 332.09 via optimal network configuration obtained by opening the lines 7, 8, 34, 26 and 17. This causes an energy loss reduction of about 158 kWh. A comparison between these two reconfiguration strategies is presented in Table 5.8. It can be observed from the table that DNR strategy for NR is looking more attractive alternative than the CNR strategy for this scenario also as it reduces 34 switching operations against about 14 kWh additional daily energy losses in the system without much affecting the node voltage profiles. It is noteworthy that CNR strategy requires 40 switching operations for the sample day which was 84 for scenario1. It happened because constant power is being tapped from DGs in this scenario so intermittency in power generation among distribution buses is not present. This shows that higher the variability in load and generation, more frequent switching operations are required to maintain network in optimal topologies under varying system states.

TABLE 5.8
COMPARISON RESULTS OF CNR AND DNR STRATEGIES FOR SCENARIO 2

Particular	**CNR**	**DNR**
Daily energy loss (kWh)	318.54	332.09
Daily energy loss reduction (kWh)	171.54	157.99
Daily energy loss reduction (%)	35.00	32.24
Minimum node voltage (p.u.)	0.9755	0.9727
Daily switching operations	40	6

5.3.3 Scenario 3: NR Considering Load Diversity and with Intermittent Power DGs

In order to consider load diversity among distribution buses, the system nodes are considered to be divided into residential, industrial and commercial categories as shown in Table5.1 and the load factors assigned to these loads during the typical day are taken as presented in Table5.2.The table also shows the load duration corresponding to each load factor for different types of loads. The daily load profile so obtained for this system is presented in Fig. 5.1, and is used for simulations. The sizing and siting of DRs is considered same as in previous scenarios and the power generation profiles considered for SPVs and

WTs is taken same as in Fig. 5.3. The distribution network is optimally reconfigured using CNR strategy and the results obtained after 100 trial runs of SSGA are presented in Table 5.9.The table shows that base case losses incurred in the day is found to be 2388.40 kWh which were 2621.34 kWh in the previous scenarios while load diversity was ignored. This shows a reduction in feeder power losses while load diversity is considered. Therefore, ignoring load diversity results in pessimistic feeder power loss which is of the order of about 10% for this system. This shows the importance of considering load diversity among distribution buses. The table also shows that daily energy losses are reduced from 2388.40 kWh to 483.43 kWh by DR placement and then further reduced to 351.77 kWh using CNR strategy. Therefore, a loss reduction of about 132 kWh can be achieved using CNR strategy, but it requires 90 switching operations during the typical day. It is interesting to observe from the table that minimum switching operations are required either during the off-peak hours or during peak hours of the day. It happened due to zero/negligible solar insolation and lack in load diversity among distribution buses, respectively. However, more switching operations are required for rest of the hours, where variability in load and solar insolation exist.

When DNR strategy is employed, the losses are reduced to 383.74 kWh using optimal network configuration 7, 8, 9, 17 and 25.The comparison results for CNR and DNR strategies is presented in Table 5.10.The table shows that DNR strategy requires only 4 switching operations. Thus DNR strategy saves 86 switching operations against 32 kWh additional energy losses as compared to CNR strategy without much affecting node voltage profiles. An important observation has been made that the number of switching operations are not much affected by the variability in load and generation among distribution buses while employing DNR strategy though the same is not true for CNR strategy.

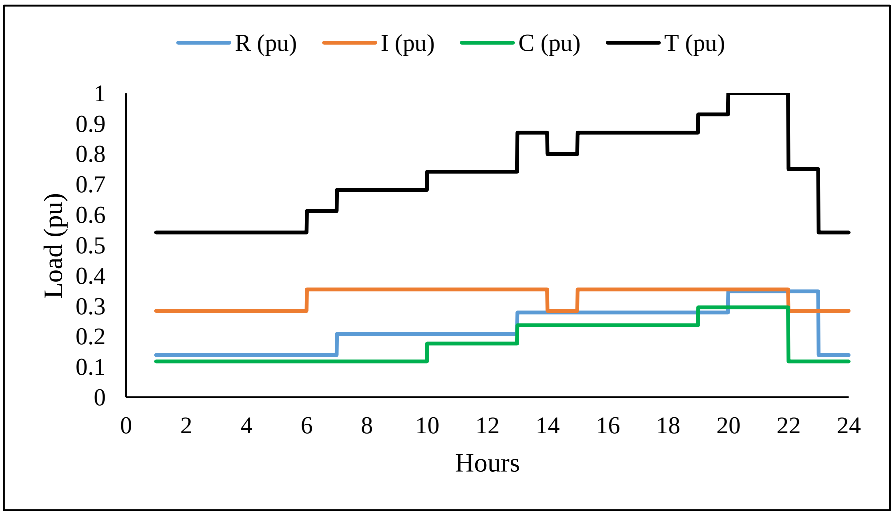


Fig. 5.4 Load profiles for different type of loads and load profile of the system

TABLE 5.9
SIMULATION RESULTS USING CNR STRATEGY FOR SCENARIO 3

State	**Power loss (kW)**			**Configuration**
	Base Case	**With DRs before NR**	**With DRs after NR**	
1.	46.72	8.87	6.13	7, 8, 9, 17, 26
2.	46.72	9.28	6.13	7, 8, 9, 17, 26
3	46.72	9.52	6.13	7, 8, 9, 17, 26
4	46.72	9.89	6.13	7, 8, 9, 17, 26
5	46.72	9.94	6.13	7, 8, 9, 17, 26
6	57.63	10.37	7.13	7, 8, 22, 34, 36
7.	71.90	17.01	10.90	7, 9, 17, 23, 34
8.	71.90	11.47	8.15	7, 8, 9, 16, 26
9.	71.90	9.86	8.58	7, 9, 15, 25, 33
10.	93.49	12.56	11.43	7, 9, 16, 25, 33
11.	93.49	18.77	17.12	5, 9, 16, 20, 33
12.	93.49	25.47	23.03	5, 10, 16, 19, 33
13.	141.42	28.49	26.86	5, 7, 9, 16, 21
14.	125.76	31.16	28.50	5, 9, 16, 20, 33
15.	141.42	22.21	20.58	9, 16, 21, 25, 33
16.	141.42	19.30	15.14	9, 25, 29, 33, 35
17.	141.42	20.49	14.59	7, 8, 9, 26, 35
18.	141.42	24.77	16.03	7, 8, 17, 27, 34
19.	175.23	41.98	25.32	7, 9, 28, 34, 36
20.	202.50	53.17	31.02	7, 9, 17, 28, 34
21.	202.50	52.01	30.41	7, 9, 17, 28, 34
22.	94.43	17.19	11.44	7, 8, 14, 25, 34
23.	46.72	9.63	7.30	7, 9, 17, 25, 33
24.	46.72	10.02	7.59	5, 7, 9, 17, 33
Total	2388.40	483.43	351.77 0.9744	Total switching operations = 90

TABLE 5.10
COMPARISON RESULTS OF CNR AND DNR STRATEGIES FOR SCENARIO 3

Particular	CNR	DNR
Daily energy loss (kWh)	351.77	383.74
Daily energy loss reduction (kWh)	131.66	99.69
Daily energy loss reduction (%)	35.00	32.24
Minimum node voltage (p.u.)	0.9744	0.9701
Daily switching operations	90	4

5.4.4 Scenario 4: NR considering load diversity and with fixed power DGs

For this scenario, the load factors at various distribution buses and the fixed power dispatches from various energy sources are taken from Table 5.2 and Table5.6, respectively. The distribution network is optimally reconfigured using CNR strategy and the best result obtained after 100 independent trials of SSGA are presented in Table 5.11. It can be observed from the table that energy losses for the typical day are reduced from 410.29 kWh to 283.36 kWh using CNR strategy thus saves about 127 kWh.

TABLE 5.11

SIMULATION RESULTS USING CNR STRATEGY FOR SCENARIO 4

State	Power loss (kW)		Configuration
	With DRs before NR	With DRs after NR	
1.	7.42	5.9190	7 9 16 25 33
2.	7.42	5.9190	7 9 16 25 33
3	7.42	5.9190	7 9 16 25 33
4	7.42	5.9190	7 9 16 25 33
5	7.42	5.9190	7 9 16 25 33
6	6.55	5.3622	7 9 **17** **26** 33
7.	7.98	6.6169	7 8 9 17 **25**
8.	7.98	6.6169	7 8 9 17 25
9.	7.98	6.6169	7 8 9 17 25
10.	10.81	8.5179	7 8 9 17 **27**
11.	10.81	8.5179	7 8 9 17 27
12.	10.81	8.5179	7 8 9 17 27
13.	24.66	16.5805	7 8 17 **28** **34**
14.	21.69	13.6451	7 8 17 **27** 34
15.	24.66	16.5805	7 8 17 **28** 34
16.	24.66	16.5805	7 8 17 28 34
17.	24.66	16.5805	7 8 17 28 34
18.	24.66	16.5805	7 8 17 28 34
19.	37.04	23.8666	7 **9** 28 34 **36**
20.	48.85	29.8510	7 9 **17** 28 34
21.	48.85	29.8510	7 9 17 28 34
22.	15.74	10.9442	7 **8** **14** **25** 28
23.	7.42	5.9190	7 **9** **16** 25 **33**
24.	7.42	5.9190	7 9 16 25 33
Total	410.29	283.26	Total switching operations = 36

For this saving total 36 switching operations have to be performed during the day. Now the distribution network is reconfigured using DNR strategy and the optimal configuration obtained is 7, 8, 34, 26 and 17. The comparison results of CNR and DNR strategies are presented in Table 5.12. The table shows that for this scenario also both CNR and DNR strategies are producing quite comparable results. The DNR saves 28 switching operations at the cost of 14 kWh additional daily energy loses without much affecting node voltage profiles of the system.

TABLE 5.12
COMPARISON RESULTS OF CNR AND DNR STRATEGIES FOR SCENARIO 4

Particular	CNR	DNR
Daily energy loss (kWh)	283.26	297.58
Daily energy loss reduction (kWh)	127.03	112.71
Daily energy loss reduction (%)	30.96	27.96
Minimum node voltage (p.u.)	0.9755	0.9727
Daily switching operations	36	8

5.4 DISCUSSION

In the present study, investigations have been made to operate distribution network in optimal radial topology by employing CNR and proposed DNR strategies while fully considering variability and intermittency in load and power generation from renewable DGs through four scenarios. The comparisons of consolidated results are presented in Table 5.13 and Fig 5.5.

TABLE 5.13
COMPARISON OF VARIOUS SCENARIOS

Scenario	Load diversity	DG's Power	Daily energy loss reduction by NR (%)		Energy loss reduction by NR (kWh/day)			*Vmin* (p.u.)		Total switching operations	
			X	Y	X	Y	X-Y	X	Y	X	Y
a	Not considered	Intermittent	31.58	26.07	182.04	150.26	31.78	0.9744	0.9667	84	4
b	Not considered	Fixed	35.00	32.24	171.54	157.99	13.55	0.9755	0.9727	40	6
c	Considered	Intermittent	27.23	20.62	131.66	99.69	31.97	0.9744	0.9701	90	4
d	Considered	Fixed	30.96	27.47	127.03	112.71	14.32	0.9755	0.9727	36	8

X: CNR, Y: DNR

(a) Intermittent power DGs (b) Fixed power DGs

Fig. 5.5 Comparison of CNR and DNR strategies while considering load diversity in the presence of (a) intermittent power DGs (b) fixed power DGs

Fig. 5.5 (a_1) shows that proposed DNR strategy causes slightly less daily energy loss reduction when compared with CNR. The figure also shows that the consideration of load diversity causes reduced energy losses, which is due to the fact that power flow among distribution feeders is reduced while load diversity among distribution buses is taken into account. Conversely, ignoring load diversity will leads to wrong signals for power loss calculation. The comparison with Fig. 5.5 (b_1) reveals that fixed DG power results in marginal reduction in feeder power loss which is attributed to the optimal control setting of DGs. Similar conclusions may be drawn from Fig. 5.5 (a_2) and (b_2) showing comparison for the percentage daily energy loss reduction. The minimum node voltage occurred during the typical day are compared in Fig. 5.5 (a_3) and (b_3) which reflects the comparison of worst node voltage profile that prevailed during the day. The comparison reveals that node voltage profiles remains more or less same using CNR or DNR strategies and have no significant impact of considering load diversity or the type of power generation from DGs.

This probably happen because of high penetration of DRs in the distribution systems which have already contributed a lot for node voltage profile enhancement. However, the type of DG power generation has a great impact on the number of switching operations as can be seen by comparing Fig. 5.5 (a_4) and (b_4) while considering CNR. It can be observed that the number of switching operations is almost halved using fixed power DGs, though the effect of load diversity is not perceptible. This leads to an important conclusion that variability of power generation is much more effective than load diversity while considering switching operations to achieve desired topology of distribution networks. Another marked observation is that total switching operations are drastically reduced using DNR strategy, especially while considering intermittent nature of DGs. Therefore, proposed DNR strategy seems to be superior to the CNR strategy as the energy loss reduction is marginally higher and node voltage profiles being maintained within permissible limits.

Finally, in order to show the importance of proposed DNR in modern distribution systems, simulations are carried for the same distribution system without any DR integration. However, the load profile is considered as shown in Fig. 5.4 where load diversity is considered. SSGA is applied for CNR strategy and the best results obtained after 100 trial runs of SSGA are presented in Table 5.14. It can be observed from the table that optimal configuration obtained is 7, 9, 14, 32 and 37, except for the states 1-12 and 23-24 where it is 7, 9, 14, 31, 37. Now DNR strategy is applied that provides optimal configuration 7, 9, 14, 32 and 37. This shows that variability of load not causes insignificant variations in the optimal topology of the distribution networks. While comparing with previous studies, an important conclusion can be drawn that intermittency in renewable sources leads to variation in optimal network topologies.

TABLE 5.14
SIMULATION RESULTS FOR CNR STRATEGY WITHOUT CONSIDERING DRS

State	Power loss (kW)	Configuration
1.	35.3102	7 9 14 37 31
2.	35.3102	7 9 14 37 31
3	35.3102	7 9 14 37 31
4	35.3102	7 9 14 37 31
5	35.3102	7 9 14 37 31
6	44.5807	7 9 14 37 31
7.	52.9346	7 9 14 37 31
8.	52.9346	7 9 14 37 31
9.	52.9346	7 9 14 37 31
10.	68.9130	7 9 14 37 31
11.	68.9130	7 9 14 37 31
12.	68.9130	7 9 14 37 31
13.	100.4416	7 9 14 37 **32**
14.	87.5798	7 9 14 37 32
15.	100.4416	7 9 14 37 32
16.	100.4416	7 9 14 37 32
17.	100.4416	7 9 14 37 32
18.	100.4416	7 9 14 37 32
19.	125.1101	7 9 14 37 32
20.	139.5165	7 9 14 37 32
21.	139.5165	7 9 14 37 32
22.	62.0681	7 9 14 37 32
23.	35.3102	7 9 14 37 **31**
24.	35.3102	7 9 14 37 31
Sum	1713.30	Total switching operations = 4

TABLE 5.15
COMPARISON RESULTS FOR CNR AND DNR STRATEGY WITHOUT CONSIDERING DRS

Particular	CNR without DRs	DNR without DRs
Daily energy loss (kWh)	1713.30	1718.53
Daily energy loss reduction (kWh)	675.13	669.90
Daily energy loss reduction (%)	28.27	28.05
Minimum node voltage (p.u.)	0.9378	0.9378
Daily switching operations	4	0

This fact can be observed from Table 5.15 showing comparison results for CNR and DNR strategies. The table reveals that CNR strategy demands total 4 switching operations for the typical day whereas it is zero for DNR strategy, but it causes marginal additional energy losses of about 5 kWh for this system. In this view, CNR strategy may looks better than DNR strategy. However, in case the distribution system having high DG penetration the reverse may be very useful for DSOs. This shows the importance of proposed DNR strategy over the conventional CNR strategy for modern active distribution systems well-equipped with renewable DGs.

5.5 SUMMARY

Contemporary distribution systems are with high penetration of diverse distributed resources such as SPVs, WTs along with MTs and SCs. These DRs can effectively manage power flow among distribution system so reduce feeder power losses and enhances node voltage profiles by very good margins. In this context it is important to investigate the effectiveness of conventional network reconfiguration strategy where the network topology is expected to vary with every changing state of the distribution system. In this chapter, a comprehensive comparative study is carried for conventional NR (CNR) and DNR while considering various scenarios pertaining to the presence of DRs in distribution system, their power control, and diversity and variability of load and power generation among distribution buses. In addition, day-ahead network reconfiguration strategy is proposed where the distribution network reconfigured only once during 24 hours. A detailed comparison of CNR and DNR is provided while considering all scenarios and it has been observed that DNR strategy causes a marked reduction in switching operation of line switches at the cost of marginal increased energy losses with acceptable voltage profiles. It is important to note the additional switching cost of CNR strategy is much higher than the additional energy loss cost as switching involves the operation of associated circuit breakers. The extensive simulation on a benchmark test distribution system shows the importance of proposed DNR for contemporary distribution systems. Therefore DNR strategy may be an attractive alternative in contemporary distribution system for DNOs to simultaneously provide simplicity and effectiveness in the operation and control of distribution systems while maintaining promising levels in both maintaining the network efficiency and quality power delivered to customers.

CHAPTER 6

CONCLUSIONS

The electric power industries have witnessed many reforms in recent years. There is a paradigm shift in the electric power generated, transmitted and distributed. At distribution level, the concept of smart distribution system is evolving with wide spread deployment of renewable DGs and shunt capacitors. The major emphasis of distribution systems operators is on reliability efficiency, optimum assets utilization and quality of power delivery to the end users. The Distribution System Network Reconfiguration (NR) is a well-known operational strategy that can help to improve the overall performance of distribution systems. In fact, distribution network reconfiguration has played vital role in service restoration, reliability and network performance improvement of distribution systems. However, the integration of uncertain renewable power generating sources with necessary dispatchable DGs at distribution level has changed the dimension of conventional distribution network reconfiguration problem. Therefore this thesis attempts to reinvestigate the problem of multi-objective network reconfiguration for contemporary distribution systems. It aims to analyze the effect of reconfiguration on the overall performance of contemporary and future distribution systems and to reinvestigate solutions methodologies for network reconfiguration of contemporary and future distribution systems. This thesis addresses three crucial aspects of network reconfiguration for active distribution systems namely, reliability and power quality enhancement, service restoration and system performance improvement. New formulations and strategies are proposed for NR while considering realities and facts of existing distribution systems by duly addressing the variability, diversity and uncertainty in load demand and power generation among distribution buses. A detailed literature survey pertaining to distribution system reconfiguration is presented in chapter 2 of the thesis.

In Chapter 3, different variants of GA and PSO (super sense GA) SSGA and (super sense PSO) SSPSO respectively have been developed by incorporating the human intelligence element in their basic models. Proposed SSGA and SSPSO incorporate human intelligence by sensing the quality of decision variables before they will participate in the computational process of the algorithms. This super sense feature intends well-guided search by providing a better balance between exploration and exploitation of the problem search space. It is noteworthy that only selection rules are modified in SSGA and SSPSO without affecting the internal mechanism of standard algorithms. Developed SSGA and SSPSO are applied to solve the NR problem for loss minimization. The application results are investigated on standard test distribution as well as real distribution systems. The application results reveal the effectiveness of SSGA and SSPSO algorithms for large-scale optimization. Following conclusions are drawn from this chapter.

1. The proposed SSGA and SSPSO are capable to efficiently solve the distribution reconfiguration problem of contemporary distribution systems and are found to be superior to the conventional GA and PSO respectively.
2. For large scale complex optimization problem the performance of proposed SSGA is found to be superior to SSPSO. However, the performances of the two for small-scale optimization problems are comparable.
3. The super sense element is found to be more beneficial for evolutionary algorithms than swarm intelligence algorithms.

In Chapter 4, the reliability enhancement and service restoration aspects of contemporary distribution systems have been addressed through NR. Some new reliability indices are proposed by giving due consideration to the current flowing in distribution feeders. Since NR balances feeder currents, the proposed reliability indices provides better signal for system reliability than existing indices. The NR problem is solved by suggesting multi-objective formulation in fuzzy frame work to satisfy reliability and power quality indices of active distribution systems while considering the stochastic nature of load demand and power generation from renewable DGs. The application results obtained on standard test distribution system using proposed method are presented and compared with existing method. In addition, both on-grid and off-grid service restoration problems are solved by suggesting optimal NR. The NR problem is solved to enhance system performance during fault period. Separate algorithms are developed to efficiently handle optimal NR problems. The power balance constraint is satisfied by determining optimum critical load by suggesting iterative algorithm and proposing suitable spinning reserve of MT unit. The results of study are presented. Following conclusions are drawn from this chapter.

1. The proposed reliability indices dynamically changes with the magnitude of system loading. It has been observed that proposed reliability indices are squarely related with system loading, thus truly reflects system reliability.
2. Proposed multi-objective NR optimization methodology provides satisfactory compromising solution while dealing with conflicting objectives of reliability and power quality improvement
3. There is substantial improvement in reliability and power quality through NR in passive distribution systems. However, in active distribution system the effect of NR on power quality and reliability attributes is comparatively less. This is due to the fact

that optimally placed DGs and SCs optimizes the power flow in distribution line and consequently improves power quality and reliability attributes. There is little scope left for further improvement through NR.

NR enhances system reliability and power quality by about 10%, whereas optimally placed DGs and SCs contribute by about 60%, while investigating independently.

4. For on-grid service restoration, NR maintains almost same performance of the distribution system, with adequate DRs, during contingencies as that during normal operating conditions.
5. The proposed off-grid service restoration using load shading, instead of the conventional area shading, is found to be more attractive strategy for active distribution systems.
6. The proposed strategy for load shading, MT power control and provision of spinning reserve on MT unit effectively manages to restore optimum critical loads by maintaining power balance during abnormal conditions.
7. Proposed NR for the off-grid service restoration significantly reduces power losses and node voltage deviations in distribution systems.

In Chapter 5, a new day-ahead NR (DNR) strategy is proposed for active distribution systems. More realistic framework is suggested by considering load diversity on distribution buses on account of the load diversity exist among residential, industrial and commercial loads, besides considering the stochastic nature of load demand and power generation from renewable DGs. A detailed investigation is made on standard test distribution system to compare proposed DNR strategy with conventional NR (CNR) strategy while considering different scenarios pertaining to diversity in load demand and nature of power dispatches from DGs. Following conclusions are drawn from this chapter.

1. The consideration of load diversity is an important issue in the formulation of NR problem. The ignorance of load diversity among distribution buses shows optimistic performance of distribution systems. This may mislead the planning and operation of distribution systems.
2. The system operation is found to be better with fixed power dispatches from DGs, but requires optimum installation of energy storage systems in distribution systems.
3. Contemporary distribution systems are with high and optimal penetration of diverse distributed resources such as SPVs, WTs along with MTs and SCs can effectively manage power flow among distribution system thereby reduce feeder power losses and enhances node voltage profiles by very good margins.

4. DNR strategy seems to be an attractive alternative for DNOs for simplified but effective operation and control of distribution systems via minimal switching operations and associated switching transients while maintaining promising levels in both network efficiency and node voltage deviations.
5. In active distribution system DNR strategy causes a marked reduction in switching operation of line switches at the cost of marginal increased energy losses with acceptable voltage profiles. It is important to note the additional switching cost of CNR strategy is much higher than the additional energy loss cost as switching involves the operation of associated circuit breakers. Therefore in contemporary distribution system DNR provides a promising and economic tool to improve the performance of distribution systems.

Salient Contributions

Salient contributions of the thesis may be summarized as under:

1. Proposed modified reliability indices by incorporating the effect of system loading to reflect actual operating condition of distribution system
2. Developed and proposed SSGA for complex and large-scale NR optimization problems of distribution systems.
3. Developed and proposed SSPSO for complex and large-scale NR optimization problems of distribution systems.
4. Proposed multi-objective NR optimization methodology in fuzzy framework for simultaneous optimization of reliability and power quality objectives of active distribution systems
5. Proposed both on-grid and off-grid service restoration strategies to enhance network performance using NR by suggesting load shading, DG power control and spinning reserve.
6. Proposed day-ahead NR (DNR) strategy for active distribution systems by suggesting more realistic formulation while considering load diversity among distribution buses owing to different types of customers and the stochastic nature of load demand and power generation from renewable DGs.

Future Scope

1. In the present work, it has been assumed that renewable DGs are the source of active power alone and no energy storage devices are equipped in the distribution system. This work can be extended by considering other types of DGs which are also capable to

generate reactive power, and energy storage devices. The NR problem can also be extended by considering issues related to carbon footprints, demand response, smart meter data, DG constraint management, and other more approaches to manage active distribution systems.

2. The present work may be extended to include other aspects of distribution system performance such as congestion of management distribution network, voltage stability, micro-grid management overload management of Distributed Energy Resources (DERs), optimal switching of shunt capacitors, OLTC management etc.
3. The present work can also be extended to develop a comprehensive methodology for multi-objective day ahead scheduling in distribution networks with high penetration of distributed renewable energy sources including energy storage taking into account the demand response, peak shaving and pricing aspects.

APPENDIX A

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 [30]. 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.

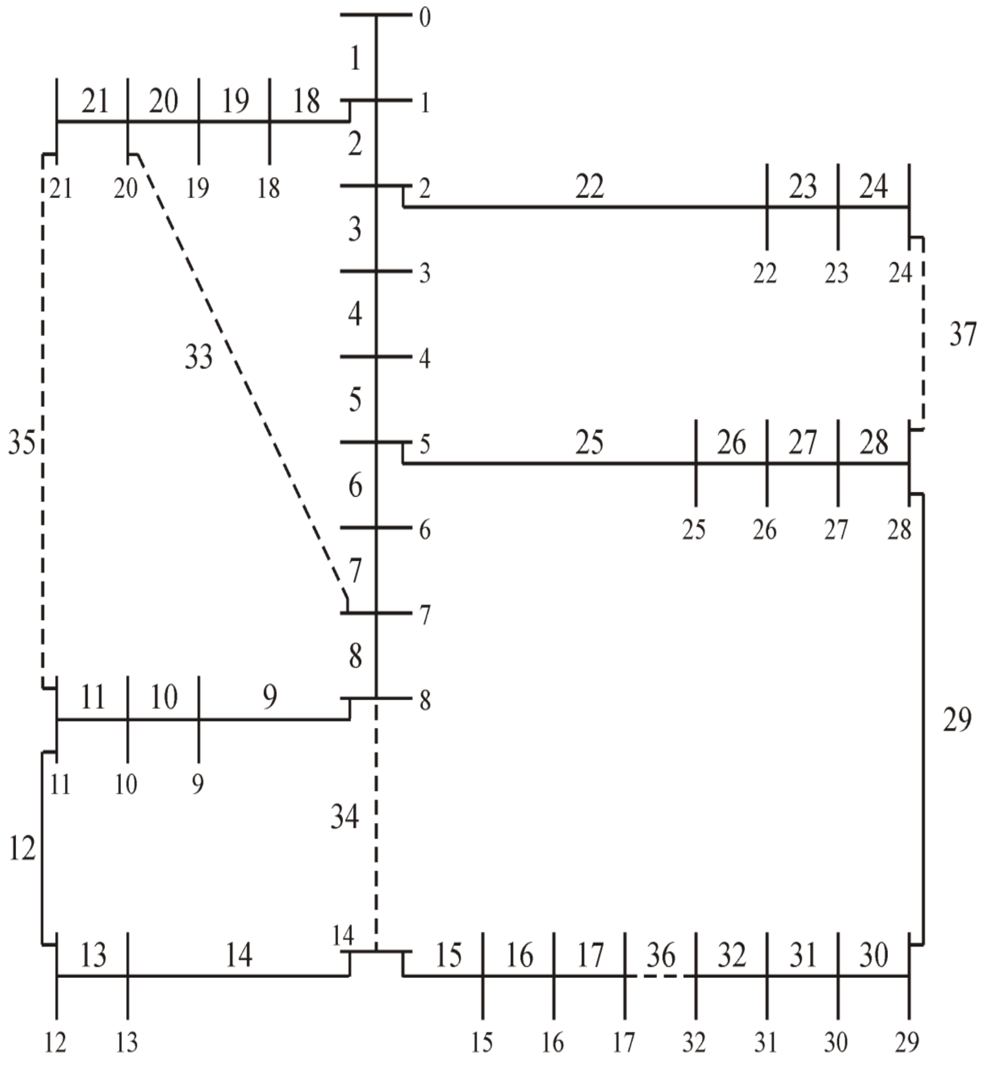


Fig. A.1 Single line diagram of 33-bus system

TABLE A.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 A.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 A.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 [68]. 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.

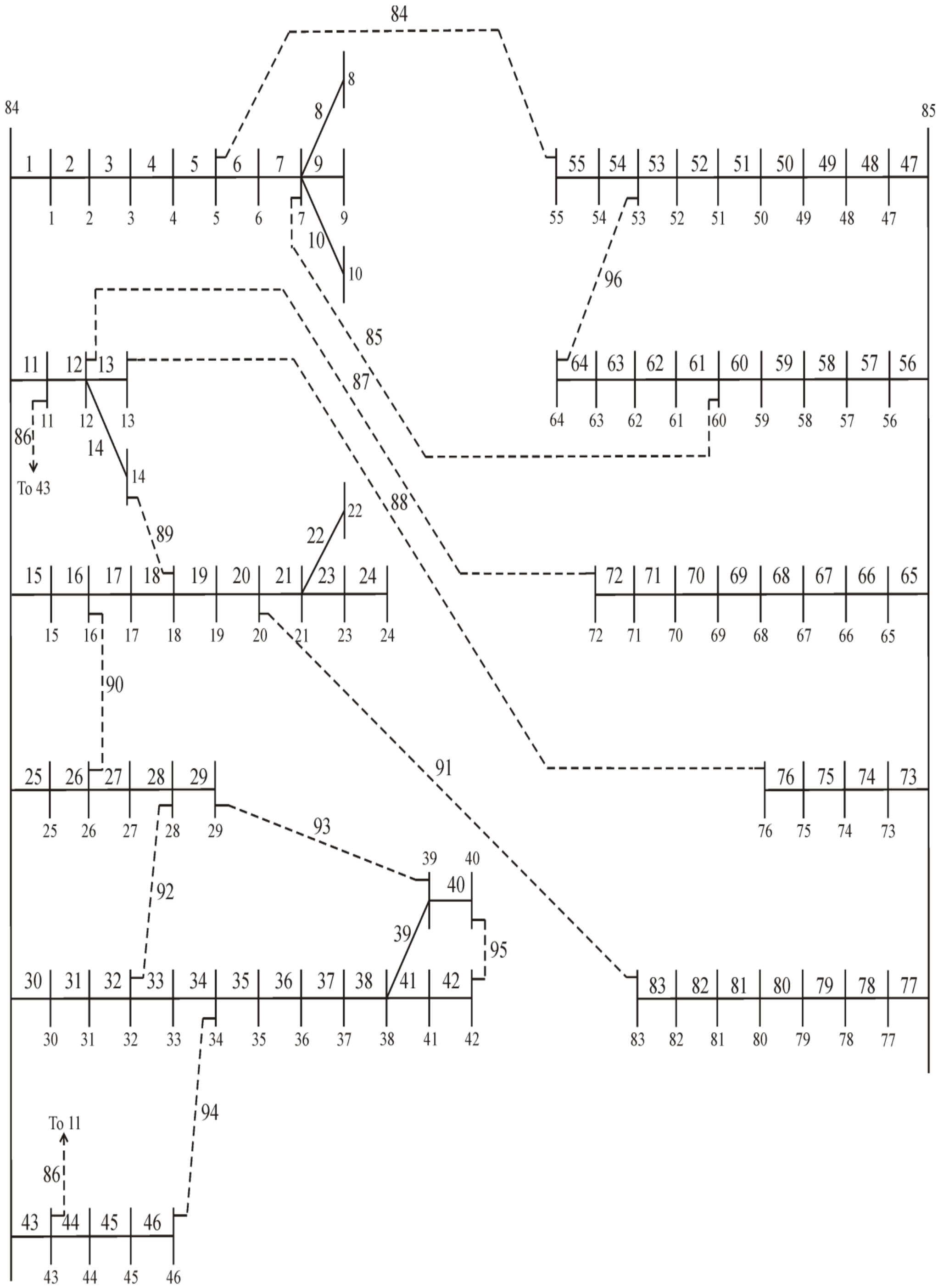


Fig. A.2 Single line diagram of 83-bus system

TABLE A.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 A.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 A.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 A.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

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PUBLICATIONS

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

International Journal:

Published:

1. Praveen Kumar, *et al.*, "Prospectives of Day-Ahead Network Reconfiguration for Smart Distribution Systems Considering Load Diversity," *International Journal of Electrical Energy*, vol. 4, no. 3, pp. 184-188, September 2016.

Communicated:

1. Praveen Kumar, *et al.*, “Metaheuristics with super sense for distribution network reconfiguration under uncertain environment”, *IET Generation, Transmission & Distribution*.
2. Praveen Kumar, *et al.*, “Reliability and power quality enhancement in contemporary distribution systems via optimal network reconfiguration,” *IET Renewable Power Generation*.
3. Praveen Kumar, *et al.*, “Service restoration of microgrids using super sense genetic algorithm,” *International Journal of Electrical Power & Energy Systems* (Elsevier).
4. Praveen Kumar, *et al.*, “Optimal day-ahead network reconfiguration for active distribution networks,” *Arabian Journal for Science and Engineering* (Springer).

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