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Synergism of Genetic Algorithms and Fuzzy Systems for Power System Applications

11.1 Introduction

The power system of today is a complex interconnected network having four major components – generation, transmission, distribution and loads. Electricity is being generated in large hydro, thermal and nuclear power stations, which are normally located far away from the load centers. Large and long transmission networks are wheeling the generated power from these generating stations to different distribution systems, which ultimately supply the load. The distribution system is that part of the power system which connects the distribution substations to the consumers' service-entrance.

Earlier the utilities were mainly concerned about the optimal dispatch of active power only, but evolvement of competition has also resulted in the optimal dispatch of reactive power. When only total cost is minimized by real power scheduling of available generator in a system, the optimal power flow (OPF) corresponds to *Active Power Dispatch*. Some of the solution techniques successfully used for active power dispatch include classical co-ordination methods based on Lagrangian multiplier approach (Chowdhury and Rahman 1990), Linear programming (LP) based methods (Stott and Hibson 1978; Stott and Marinho 1979), quadratic programming (QP) approach (Nanda et al. 1989), Gradient method using steepest descent technique (Dommel and Tinney 1968) and Newton's methods (Sun et al. 1984; Maria and Findlay 1987). A comprehensive review of various optimization techniques available in the literature is reported in references (Happ 1977; Sasson and Merril 1974; Carpantier 1985). The classical method of optimization is relatively simple, fast and requires less memory space but sometimes it is unable to handle the system constraints effectively and sometimes convergence is not obtained. The LP based method involves approximation in linearizing the objective function and constraints and may result in zigzagging of the solution. Gradient based methods compute the derivative of the function at each step. They require a close initial guess and in general suffer from convergence difficulties and may stuck to local minima.

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The GAs (genetic algorithms) have been applied to solve unit commitment problem (Kazarlis et al. 1996), Optimal reactive power dispatch (ORPD) problem (Singh et al. 1993; Swarup et al. 1996; Lee et al. 1997) and for economic load dispatch problem (Walters and Sheble 1993; Sheble and Britigg 1995; Chen and Chang 1995; Orero and Irving 1996; Achyuthakan 1997). Miranda et al. (1996) have provided a survey of three branches of evolutionary programming (EP), genetic algorithms (GAs) and discusses their relative merits and demerits.

The superiority of GA methods in handling continuously non-differentiable objective has been given in (Walters and Sheble 1993; Achyuthakan 1997). For better results and faster convergence, conventional GA models have been modified by including new operators such as elitism, shuffle in reproduction, multi-point or uniform crossover and creep mutation. Considering three added features, a refined GA is used to solve economic load dispatch (ELD).

A pyramid genetic algorithm (PGA) has been used in Lee et al. (1997) for voltage profile optimization. The PGA can analytically determine the bound values of mutation and crossover probabilities, which are otherwise, chosen by experience. The GA-Fuzzy approach presented in this paper is developed to get above mentioned advantages by varying crossover and mutation probabilities throughout the generations by fuzzy-rule base.

11.2 Transmission Planning, Pricing and Structure/Models of Indian Power Sector

A bibliographical survey of power system wheeling under deregulated environment is presented by Sood et al. (2002). A lot of literature is available for the issue of transmission open access. Christie and Anjan Bose (1996) discussed the complete deregulation scenarios and technical issues related to operation and control of the system. Various aspects of pricing of transactions in open access are discussed by Silva et al. (1998), David (1998), Arriaga et al. (1995b) and Vojdani et al. (1996).

1. *Transmission planning*

A genetic algorithm based dynamic transmission planning methodologies are formulated by Rudnick et al. (1996) and Lima et al. (1998) to determine the economically adapted transmission system in open access. But since the transmission planning is a complex, nonlinear and dynamic problem, a simple GA method is not suitable. Object oriented software for transmission planning in open access is proposed by Handschim et al. (1998). Raga et al. (2005) have presented a multi-criteria formulation (i.e. investment costs, operational cost and the expected energy not supplied) for multiyear dynamic transmission expansion planning problems. The solution algorithm adapts an interactive decision-making approach that starts at a non dominated solution of the problem.

2. *Transmission pricing methods*

Transmission pricing has been discussed in a detail in the literature. Happ (1994) has presented computational procedure and data requirements for embedded cost methods, incremental cost methods and marginal costs methods.

Caramanis et al. (1986) has presented new wheeling rates for buying and selling. A computer program WRATES is developed by Caramanis et al. (1989) is used to provide the practical means of computing the marginal cost of wheeling. This analysis requires a load flow program integrated with constraints and economic load dispatch simulation.

First extensive computations of marginal cost of wheeling and rates based on marginal costs are carried out by Merrill and Erickson (1989). Different methodologies for costing of transmission services have been developed and are reported by Shirmohammadi and Thomas (1991) and Shirmohammadi et al. (1991). The theory to evaluate optimal wheeling rates for the case of bus to bus wheeling is developed in (Lo and Zhu 1993). It is based on the marginal cost theory which has been used for electricity pricing. On the basis of the equitable sharing of the benefits arising from wheeling transactions among the wheeler, the power seller and the buyer, this approach has the advantage over others. It avoids the direct evaluation of the network maintenance cost and the quality of supply cost components.

Several methodologies have been reported for cost of wheeling. A nonlinear optimization program with linear constraints is developed by Li et al. (Li and David 1993) to calculate the amount of wheeled energy and wheeling price solved by gradient projection method.

The principles and practices of a new methodology for wheeling rate evaluation without assuming the existence of the spot price based market place is describe by Lo and Zhu (1994). Li et al. (1994) have used a wheeling rate based on marginal cost pricing and implemented using the modification of the optimal power flow.

A load flow based model for calculating the various cost components is presented by Kovacs and Leverett (1994). A separate pricing of transmission and distribution services is proposed by Farmer et al. (1995). SRMC and LRMC based models are proposed by Lima and Pereira et al. (1995) for allocating transmission cost among users of centralized transmission service. A novel approach that alleviates the inherent shortcomings of SRMC based pricing and maintains the economic efficiency of the price signals are proposed by Farmer et al. (1995). But the effect of security analysis has not been taken care while considering the optimal conditions.

Lima (1996) has proposed load-flow based Megawatt-mile, Modulus, Zero counter complex calculations and greater data and provides no incentive to users.

Pereira et al. (1996) have presented a method for evaluating an optimal set of transmission prices to be charged for use of a transmission system on a time-of-use basis. Prices are calculated by maximizing the global benefit of using the transmission system that allocates both capacity and operational cost.

A methodology to allocate the cost of transmission network facilities to wheeling transactions in decentralized power systems using Game theory is proposed by Tsukamoto et al. (1996) and Ferrero et al. (1998). The concept of game theory is employed to deal with the conflicts in a deregulated power system.

Wakefield et al. (1997) have presented transmission costing framework and its application for analyzing the transmission costing issues. Zobian and Illic (1997) have proposed a methodology for allocating transmission cost among users of a centralized transmission service. The share of each participant is proportional to its impact on system transmission investment requirements. This allocation rule provides incentives for all participants to remain in the pool and ensures revenue reconciliation. Yu and David (1997) have proposed an approach which distinguishes between operating and embedded costs and have developed separate methods in respect of each of these components.

In (1999) a method for long run marginal cost (LRMC) based pricing in multi-area interconnected system, based on the incremental use of each area's transmission network at times of peak flow, is proposed.

In (Muchayi Maxwell and El-Hawary 1999) unlike other methods which use only the variation of fuel cost for generation to estimate the rate structures, the proposed pricing algorithm incorporates the optimal allocation of transmission system operating costs based on time-of-use pricing. The transmission costs are obtained by assigning a price k to each unit of power flow in the network.

In (Moya 2002), a model of marginal adequacy costs is developed in order to reflect the influence that any nodal load has on system static security. An adequacy cost function is defined, making use of the load that must be theoretically withdrawn at each node in order to re-establish power flows on transmission elements, after any static contingency of a predefined set occurs.

Chen et al. (2002) have presented a method to provide a detailed description of each nodal price, by breaking down each nodal price into a variety of parts corresponding to the concerned factors, such as generations, transmission congestion, voltage limitations and other constraints or elements.

Gang et al. (2005) have proposed a transmission and wheeling pricing method based on the monetary flow tracing along power flow paths: the monetary flow–monetary path method. Active and reactive power flows are converted into monetary flows by using nodal prices. The method introduces an uniform measurement for transmission service usages by active and reactive powers.

Gil et al. (2006) presents an approach for the allocation of transmission network costs by controlling the nodal electricity prices. The proposed approach introduces generation and nodal injection penalties into the traditional economic dispatch so as to create nodal price differences that recover the required transmission revenue from the resulting congestion rent.

Galetovic and Montecinos (2006) describes the new method used in Chile to allocate transmission charges among generating companies and customers. They show that the new Chilean transmission charge scheme is a hybrid based on marginal cost pricing, identification of use through economic benefits and flow identification methods, and last, a postage stamp to redistribute almost all the charges that customers have to pay.

Sedaghati (2006) has proposed a novel method for allocation of the fixed cost of the transmission systems to agents using facilities. In (Verma and Gupta 2006), a nonlinear optimization problem has been formulated to maximize the social welfare in the open power market using a unified power flow controller (UPFC).

3. *Market structures/models*

A Poolco model suitable for power system planning and decomposing spot prices to reveal components caused by congestion is presented by Finny et al. (1997).

Illic and Prasad et al. (2003) provided simulation-based demonstrations of hybrid electricity market that combines the distributed competitive advantages of centralized markets.

Ren et al. (2004, 2004a) compared the quantitative behavior of the two markets, i.e. pay as bid and marginal pricing, assuming that generators submit the best strategic offers that correspond to the specified pricing method. In Part I of their two-part study, assuming that the system marginal costs for pay-as-bid (PAB) and marginal pricing (MP) are random with known probability density functions, they develop generator strategic offers by maximizing the corresponding expected values of the generator profits over the offer parameters. In Part II relations are established between the system marginal costs (SMCs) for each market type and a common random demand, thus allowing the two markets to be compared through the expected values and variances of the individual generation profits and of the consumer payments.

Competitive markets for electricity determine either a uniform marginal price (UMP), a set of nodal marginal prices (NMPs), or a smaller set of zonal marginal prices (ZMPs). Ding and David (2005) prove that, the UMP or ZMP models (a) do not affect the total economic surplus, (b) redistribute the surplus among generators and loads at the different nodes, and (c) give perverse incentives for generation expansion.

Fleten and Erling (2005) have proposed a stochastic linear programming model for constructing piecewise-linear bidding curves to be submitted to Nord Pool, which is the Nordic power exchanger. They have considered the case of a price-taking power marketer who supplier electricity to price-sensitive end users.

Plazas et al. (2005) considers a profit-maximizing thermal producer that participates in a sequence of spot markets, namely, day-ahead, automatic generation control (AGC), and balancing markets. The producer behaves as a price-taker in both the day-ahead market and the AGC market but as a potential price-maker in the volatile balancing market.

Li and Mohammad (2005) describes a method for analyzing the competition among transmission-constrained generating companies (GENCOs) with incomplete information. Each of GENCO models and its opponents' unknown information with specific types for transforming the incomplete game into a complete game with imperfect information.

Ongasakul and Chayakulkheeree (2006) have proposed a coordinated fuzzy constrained optimal power dispatch (CFCOPD) algorithm for bilateral contract, balancing electricity and ancillary services markets.

Bompard et al. (2006) has presented comprehensive approach to evaluate the performance of the electricity markets with network representation in presence of bidding behavior of the producers in a pool system. A supply function strategic bidding model for the producers is introduced, and then different scenarios in terms of bidding behavior and network constraints are studied and compared on the basis of a set of microeconomic metrics.

Philpot and Erling (2006), present a model of a purchaser of electricity in Norway, bidding into a wholesale electricity pool market that operates a day ahead of dispatch.

Olmos and Neuhoff (2006) have proposed an algorithm and apply it to the European electricity network to identify a balancing point that reduces market power of generation companies and is well connected. Market-level data or detailed information about demand is not required.

4. *Congestion management*

Congestion management is one of the major tasks performed by system operators (SOs) to ensure the operation of transmission system within operating limits. In the emerging electric power market, the congestion management becomes extremely important and it can impose a barrier to the electricity trading. Kumar et al. (2005) presented bibliographical survey of papers/literature on congestion management issues in the deregulated electricity markets.

A study of congestion management based on congestion pricing is proposed by Glavitsch and Fernando (1998).

Singh et al. (1998) studied the management of costs associated with transmission constraints (i.e. transmission congestion costs) in a competitive electricity market. The paper examines two approaches for dealing with these costs. The first approach is based on a nodal pricing framework and forms the basis of the so-called pool model. The second approach is based on cost allocation procedures proposed for the so-called *bilateral* model. An advanced analytical method for secure and efficient operation of power system is proposed by Shirmohammadi et al. (1998).

A congestion problem formulation should take into consideration interactions between intra-zonal and inter-zonal flows and their effects on power systems. It is perceived that phase-shifters and tap transformers play vital preventive and corrective roles in congestion management. These control devices help the ISO mitigate congestion without re-dispatching generation away from preferred schedules. In Ref. (2000) a procedure is introduced for minimizing the number of adjustments of preferred schedules to alleviate congestion and apply control schemes to minimize interactions between zones while taking contingency-constrained limits into consideration.

Service identification and congestion management are important functions of the ISO in maintaining system security and reliability. In Fu and John et al. (2001), a combined framework for service identification and congestion management is proposed. Verma et al. (2001) presents the development of simple and efficient models for suitable location of unified power flow controller (UPFC), with static point of view, for congestion management.

Gan and Donald et al. (2002) briefly review the New England power system (NEPOOL) locational pricing proposal being implemented. Two new approaches for locational market power screening are presented. The first one is based on a zonal network model and the second is based on a nodal transmission model.

The paper by Bompard et al. (2003) briefly reviews the congestion management (CM) schemes and the associated pricing mechanism used by the independent grid operators (IGOs) in five representative schemes. These are selected to illustrate the various CM approaches in use: England and Wales, Norway, Sweden, PJM, and California. They develop a unified framework for the mathematical representation of the market dispatch and redispatch problems that the IGO must solve in CM.

Kristiansen (2004) gives an overview of the current practice for congestion management, transmission pricing, and area price hedging in the Nordic region. Transmission congestion in the Nordic region is managed by using the area price model and counter trade. In Kumar et al. (2004), a new zonal/cluster-based congestion management approach has been proposed. The zones have been determined based on lines real and reactive power flow sensitivity indexes also called as real and reactive transmission congestion distribution factors. The generators in the most sensitive zones, with strongest and nonuniform distribution of sensitivity indexes, are identified for rescheduling their real power output for congestion management.

A new congestion management system is proposed in Mendez and Hugh (2004), applied under nodal and zonal dispatches with implementation of fixed transmission rights (FTR) and flow gate rights (FGR). The FTR model proves to be especially suitable for congestion management in deregulated centralized market structures with nodal dispatch, while the FGR is suitable for decentralized markets.

In the paper (Aguado et al. 2004), authors deal with the operation of power systems consisting of several interconnected electricity markets. They proposed an alternative approach to inter-regional trade that avoids the flaws of forward markets with explicit auctioning of interconnections capacities. They proposed the integration of a forward market with a balancing (spot) market for inter-regional exchanges based on nodal pricing.

Alomoush (2005) presents some performance indices to compare different dispatch options, where it proposes to use some congestion and system utilization measures. These measures are used in the paper to indicate level of system usage and congestion severity under different dispatch scenarios, and may enable the system operator or the qualified dispatch decision-making entity to decide which dispatch, among different dispatch scenarios, is the optimal.

The paper by Conejo et al. (2006) addresses the congestion management problem avoiding offline transmission capacity limits related to stability. These limits on line power flows are replaced by optimal power flow-related constraints that ensure an appropriate level of security, mainly targeting voltage instabilities, which are the most common source of stability problems.

11.3 GA-Fuzzy System Approach for Optimal Power Flow Solution

The present day power system is a very large and integrated power system comprising of several generators and buses. Recent trends of deregulation of power system have resulted in increased competition in the area of generation, transmission and distribution of power. The problem of economic operation of power system had emerged when it was required to operate two or more units to meet economically the demand when net generation exceeds the demand.

In the recent past, methods using genetic algorithms (GAs) (Goldberg 1989) have become popular to solve the optimization problems mainly because of its robustness in finding optimal solution and ability to provide near optimal solutions close to global minima. GAs are search algorithms based on the mechanics of natural selection and natural genetics. The performance of GA can also be improved by introducing new problem specific genetic operators. In Maha et al. (2006) a new genetic operator named *pluck* is introduced that incorporates a problem specific knowledge in population generation and leads to a better channel utilization in mobile computing problem. GAs are different from other optimization methods in the following ways:

- GAs search from population of several points, not a single individual point in the population.
- GAs have inherent parallel computation ability.
- GAs use pay off information (objective function) and not derivatives or auxiliary knowledge.
- GAs use probabilistic transition rules, so they can search a complicated and uncertain area to find the global optimum.

The basic idea in GA is to maintain a population of chromosomes that evolves through a process of competition and controlled variation. Simple forms of GAs performance largely depend on the appropriate setting of genetic parameters namely crossover probability and mutation probability. It has been observed that after few generations, the fitness value of each chromosome becomes almost equal to other chromosomes from the same population. The effect of crossover beyond this stage becomes insignificant due to very small variation in the chromosomes in a particular population. Therefore, it is difficult to find optimal settings for these parameters.

The techniques developed to set these parameters are classified by Eiben and Smith (2003) as parameter tuning and parameter control. For parameter tuning, the parameter values are set in advance (before the run) and are kept constant during the whole execution of the algorithm. In parameter control techniques, parameters are initialized at the start of execution and are allowed to change during the run. Parameter control techniques are classified mainly into three groups based on the type of change they introduce:

- *Deterministic*: the parameter value is updated according to some deterministic rule without using any feedback from the population. The deterministic mutation rate schedule implementation proposed in Smith and Fogarty, (1997) has successful results for hard combinatorial problems.
- *Self adaptive*: the parameter is evaluated and updated by the evolutionary algorithm itself by encoding the parameters into the chromosomes and undergo mutation and recombination. The basic idea is that better parameter values will survive in the population since they belong to the surviving individuals. Bäck (1993) refers to this approach as on-line learning. In their work, they propose a self adaptation mechanism of a single mutation rate per individual.
- *Individually adaptive*: the parameter value is updated based on some feedback (usually fitness values of individuals) from the population. Srinivas and Patnaik. (1994) has proposed this approach by giving mutation rate adaptation rule in the form of following equations:

$$p_m = k_2(f_{\max} - f)/(f_{\max} - f_{avg}), \; f \geq f_{avg}$$
$$p_m = k_4, \; f < f_{avg}$$

where

f = fitness value of the individual,
$f_{\max}$ = best fitness value of the current generation,
f_{avg} = average fitness value of the current generation,
constants k_2 and $k_4 = 0.5$.

In an adaptive GA-Fuzzy algorithm developed in present research work has two important parameters namely, crossover probability ($\mathrm{P_c}$) and mutation probability ($\mathrm{P_m}$). They are varied dynamically during the execution of the program according to a fuzzy knowledge base which has been developed from experience to maximize the efficiency of GA.

11.3.1 OPF Problem

The optimal power flow problem is concerned with optimization of steady state power system performance with respect to an objective function f, subject to numerous constraints. For optimal active power dispatch, the objective function f is the total generation cost as expressed below:

$$\min\ f = \sum_{i=1}^{N_g}(a_i + b_i P_{gi} + c_i P_{gi}^2) \tag{11.1}$$

where

N_g = total number of generation units,
$a_i,\ b_i$ and c_i = cost coefficients of generating unit,
P_{gi} = real power generation of i$^{\text{th}}$ unit i $= 1, 2, \ldots . N_g$

subject to following constraints:

Equality constraints as

$$P_{gi} - P_{di} - \sum_{j=1}^{N} |V_i||V_j||Y_{ij}| \cos(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{11.2}$$

and

$$Q_{gi} - Q_{di} - \sum_{j=1}^{N} |V_i||V_j||Y_{ij}| \sin(\delta_i - \delta_j - \theta_{ij}) = 0 \tag{11.3}$$

Inequality constraints as

$$P_{gi}{}^{min} \le P_{gi} \le p_{gi}{}^{max} \tag{11.4}$$
$$Q_{gi}{}^{min} \le Q_{gi} \le Q_{gi}{}^{max} \tag{11.5}$$
$$V_i^{min} \le V_i \le V_i^{max} \tag{11.6}$$
$$t_k{}^{min} \le t_k \le t_k{}^{max} \tag{11.7}$$
$$\delta_{gi}{}^{min} \le \delta_{gi} \le \delta_{gi}{}^{max} \tag{11.8}$$
$$line\_flow_1 \le line\_flow_1^{max} \tag{11.9}$$
$$Q_{cm}{}^{min} \le Q_{cm} \le Q_{cm}{}^{max} \tag{11.10}$$

where, N = Total number of buses,
N_T = Total number of tap changing transformers,
$Q_{cm} = m^{th}$ shunt capacitor/reactor compensations,
N_l = Total number of lines,
N_c = Total number of shunt capacitors
i and $j = 1, 2, \ldots .\ N$,
$k = 1, 2, \ldots ..\ N_T$,
$l = 1, 2, \ldots .\ N_l$,
$m = 1, 2, \ldots .\ N_c$,
P_{gi} and Q_{gi} = real and reactive power generation at bus i,
P_{di} and Q_{di} = real and reactive power demands at bus i,
$|V_i|$ and $|V_j|$ = voltage magnitudes at bus i and j respectively,
δ_i and δj = voltage angles at bus i and j,

$Y_{ij} = |Y_{ij}|\angle\theta_{ij}$ = admittance matrix,
t_k = tap setting of k^{th} transformer,
$line\_flow_l$ = line flow at l^{th} line

11.3.2 Synergism of GA-Fuzzy System Approach

At the starting stage, high crossover probability and low mutation probability yield good results, because a large number of crossover operations produce better chromosomes for a finite number of generations, after that the fitness value of each chromosome vector becomes almost equal. Beyond this the effect of crossover is insignificant due to little variation in the chromosome vectors in that particular population. At later stages, increasing the mutation rate of the chromosomes inculcates new characteristics in the existing population and therefore diversifies the population.

Therefore, philosophy behind varying Pc and Pm is that the response of the optimization procedure depends largely on the stage of optimization, i.e. a high fitness value may require relatively low crossover and high mutation probabilities for further improvement, alternatively, at low fitness values the response would be better with relatively high crossover and low mutation probabilities.

Schuster (1985) proposed heuristics for optimal setting of the mutation probability (Pm). Fogarty, (1981) and Booker (1987) investigated time dependencies on the mutation and crossover probabilities respectively. Grefenstette, (1981) and Schaffer (1981) found optimal settings for all these parameters of the GA by experiment.

In this work, a GA-Fuzzy approach is used in which ranges of parameters – crossover probability (Pc) and mutation probability (Pm) have been divided into LOW, MEDIUM and HIGH membership functions.

The GA parameters (Pc and Pm) are varied based on the fitness function values as per the following logic:

The value of the best fitness for each generation (BF) is expected to change over a number of generations, but if it does not change significantly over a number of generations (UN) then this information is considered to cause changes in both Pc and Pm.

The diversity of a population is one of the factors, which influences the search for a true optimum. The variance of the fitness values of objective function (VF) of a population is a measure of its diversity. Hence, it is also considered as another factor on which both Pc and Pm may be changed.

The membership functions and membership values for these three variables (BF, UN and VF) are selected after several trials to get optimum results.

11.3.3 GA-Fuzzy System Approach for OPF Solution (GAF-OPF)

Figure 11.1 is a diagrammatic representation of an approach to incorporate fuzzy logic to find GA based OPF solution.

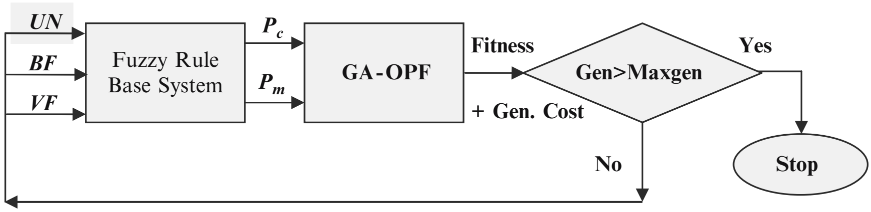

Fig. 11.1. Implementation of fuzzy system to GA for OPF solution

Therefore, this approach may be divided broadly in two parts namely GA-OPF and fuzzy rule base system (for controlling the GA parameters Pc and Pm dynamically during execution).

(A) GA technique for OPF

In GA-OPF, GA is used as a search technique for optimization of power flow in different lines of the power system. The GA requires the evaluation of the so-called fitness function (FF) to assign a quality value to every solution produced. Movement in a GA is accomplished using three primary operations: Parent reproduction, crossover and mutation. The details of important operations during solution of GA-OPF are as follows:

1. *Encoding*

Binary coded strings having 1s and 0s are used for building chromosomes through random process. The randomly generated chromosomes represent binary coded values of controllable variables e.g. power generation at all generator (PV) buses other than slack bus, the voltage magnitude at all PV buses, tap settings of variable tap transformers and shunt capacitor/reactor compensations.

The bits of each chromosome are separated out for different control variables and are converted into equivalent decimal values by the following formula:

$$X_i = X_i^{min} + dec_i(b_1 b_2 \ldots\ldots)_2 \times ((X_i^{max} - X_i^{min})/(2^{bits\_reqd}i - 1)) \quad (11.11)$$

where,

$dec_i(b_1\ \ b_2 \ldots\ldots)_2$ =decimal values of bits corresponding to *ith* control variable,
X_i^{min} = minimum generation value of *ith* control variable,
X_i^{max} = maximum generation value of *ith* control variable,
$bits\_reqd$ = Total number of bits required to represent *ith* control variable.

Load flow using Newton–Raphson method is run for set of control variables values belonging to each chromosome. If load flow converges and slack bus generation obtained from load flow solution is within specified limits then chromosome is included to complete initial population. Otherwise, a new chromosome is generated according to same procedure and checked again.

2. *Fitness function evaluation*

GAs are usually designed so as to maximize the fitness function (FF), which is a measure of quality of each candidate solution. The objective of the OPF problem is to minimize the total generation cost including power flow constraint for each line and other equality and inequality constraints stated above. In proposed GA-Fuzzy approach, penalty index (pen_index_i) for each generated chromosome is calculated for lines having power overflows ($over\_flow_l$), based on respective penalty factors (p_l) as follows:

$$pen\_index_i = \sum_{l=i}^{n_i} p_l * overflow_1 \tag{11.12}$$

and fitness function is modified to keep line flows under limits as:

$$FF_{i=}\{A/(1 + cost_i)\}e^{-(k^* pen\_index)_i} \tag{11.13}$$

Where as

$i = 1$ to population size,
$n_l =$ total number of lines in system,
$l = 1$ to n_l,
$over\_flow_l =$ overflow in l^{th} line, if any otherwise zero,
$pen\_index_i =$ penalty index for i^{th} chromosome,
$FF_i =$ fitness value of function for i^{th} chromosome,
$A\ and\ k =$ large numerical constant,
$cost_i =$ cost corresponding to i^{th} chromosome.

3. *GA operators*

As a next step in solution finding process, GA operators – *Reproduction, Crossover* and *Mutation* are applied in above sequence for each generation. The reproduction operator selects a chromosome string from the previous generation based on the string's fitness and its probability of propagation to the next generation. In the reproduction operator a stochastic remainder selection is used instead of simple Roulette wheel. In simple Roulette wheel selection, there is no guarantee that the best strings would be selected. To overcome this problem the stochastic selection is used in this work. Selection continues until the population of the next generation is filled. The crossover and mutation operators work in conjunction with selection similarly as in simple GA. The values for P_c and P_m are assigned respectively for first generation, then after these values are determined by fuzzy rule base for the successive generations.

After crossover and mutation, load flow using Newton-Raphson method is run. If load flow converges and slack bus generation obtained from load flow solution is within specified limits then chromosome is included to valid population. For any generation, the minimum generation cost amongst all valid chromosome and corresponding generation pattern is stored in variable C_{min}.

For first generation, value of C_{min} is stored in another variable C_{min_gen} representing generation minimum cost, and for successive generations if $C_{min} < C_{min\_gen}$ then C_{min_gen} is replaced by C_{min} otherwise C_{min_gen} of previous generation is reconsidered. The process continues till last generation.

11.3.3.1 Fuzzy System for Controlling Crossover and Mutation Probability

The best fitness (*BF*) for each generation, number of generations for unchanged BF (*UN*) and variance of fitness values of objective functions (*VF*) for population of each generation are computed. These variables values are fed as input to fuzzy rule base system, as shown in Fig. 11.1.

Fuzzy rule base for GA-fuzzy approach

The GA parameters (PC, Pm) in GA-Fuzzy algorithm are varied based on fuzzy rules base as mentioned in earlier chapter for the solution of optimal power flow (OPF).

11.3.4 Test Results

GA-OPF and GA-Fuzzy OPF proposed here are tested by solving various test systems. These systems are 26-bus system (Saadat 2002), 6-bus system (Osman et al. 2004), IEEE 30-bus system and modified IEEE 30-bus system (Lee et al. 1985; Lai et al. 1997). The data for all the above systems are given in Appendix C, D, E, F respectively. The test examples have been run on 1.7 GHz Celeron with 128 MB RAM PC.

11.3.4.1 6-Bus System

Osman et al., (2004) have developed a modified co-evolutionary genetic algorithm (M-COGA) and compared the results with classical economic dispatch and standard flow (ED+LF), Weber (1997) and simulated annealing (OPFSA) (2003) on a 6-bus system. The proposed GA-Fuzzy OPF and GA-OPF are tested using the GA parameters given below:

Population size:	50,
Maximum no. of Generations:	200,
Selection operator:	Stochastic remainder,
Initial crossover probability:	0.9,
Initial mutation probability:	0.01

The voltage magnitude limits, active and reactive power limits and line flows limits are taken same as in references (Osman et al. 2004; Web 1997). All the lines have power flow limit of 100 MVA, except line 4–5 whose limit is 50 MVA. The values of P_c and P_m changes from 35th generation and remain constant after 71st generation ($P_c \approx 0.5676$ and $P_m \approx 0.0665$), as shown in Fig. 11.2b. It is observed that convergence of GA-Fuzzy OPF is better than GA-OPF as shown in Fig. 11.2a. The results are tabulated in Table 11.1. The results highlight the goodness of this solution technique having minimum generation cost while satisfying all constraints. Load flow solution and lines flows are given in Table 11.2.

In ED + LF method though the cost is low but losses are more as compare to GA-Fuzzy OPF and also there are certain limit violations.

11.3.4.2 26 Bus System

The 26 bus system has 46 branches, 6 generators and 7 variable tap transformers (Saadat 2002). The OPF problem has been solved GA-OPF and GA-Fuzzy OPF. The performance of the method proposed by Sadaat (2002) and GA-OPF are compared with GA-Fuzzy OPF. GA-OPF and GA-Fuzzy OPF are compared for same initial population and following GA parameters in Table 11.3.

In GA-Fuzzy OPF approach, P_c and P_m are dynamically changed during execution and governed by fuzzy rules as shown in Fig. 11.3b.

For GA-OPF and GA-Fuzzy OPF, transformers tap settings are assumed to vary within a range of ±10% of rated values. The lower voltage magnitude limits for all buses are 0.9 p.u. whereas the upper limits for PV buses are 1.1 p.u. and for remaining buses including the slack bus the limit is 1.025 p.u..

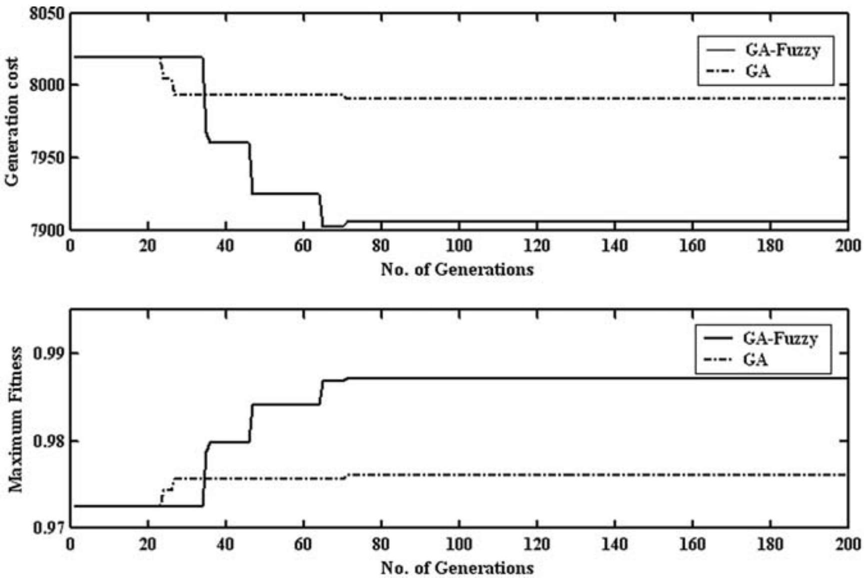

Fig. 11.2a. Convergence of generation cost & max. fitness for GA-OPF & GA-Fuzzy OPF for 6-bus. Generation cost is in \$/h

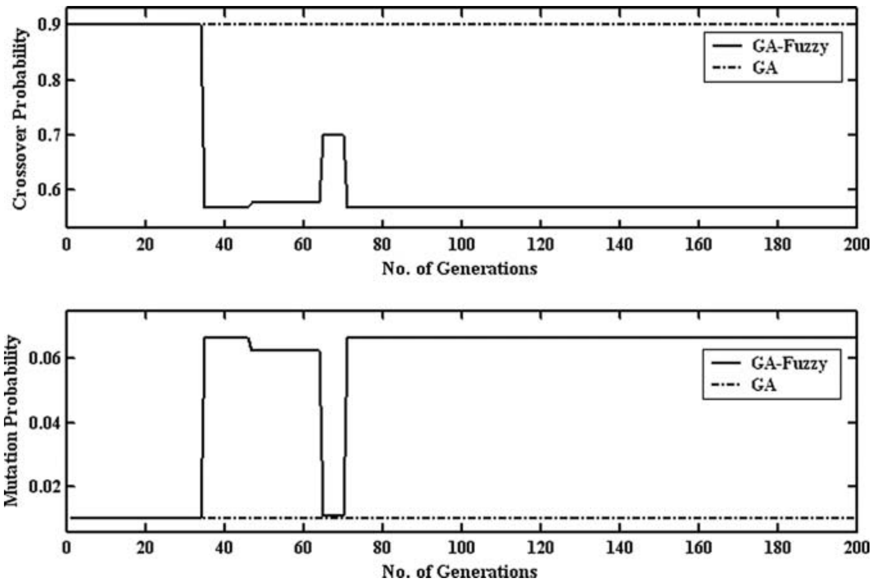

Fig. 11.2b. Crossover and mutation probabilities variations for GA-OPF & GA-Fuzzy OPF for 6-bus system

Table 11.1. Comparison of different OPF methods for 6-bus system

	Classical optimization methods		Non-classical optimization methods			
	ED + LF	Weber [23]	OPFSA [24]	M-COGA [22]	GA-OPF	GA-Fuzzy OPF
Unit 1 (MW)	99.74	160.39	131.80	152.3252	108.466	140.865
Unit 2 (MW)	216.17	133.39	190.98	151.6563	235.337	188.025
Unit 3 (MW)	50.00	143.00	109.15	118.0913	130.938	100.244
Unit 4 (MW)	250.00	169.00	178.24	187.0893	134.262	180.205
Cost ($/h)	7,860	8,062	7,938	7,987.1764	7,990.2795	7,905.9163
Losses (MW)	15.91	5.38	6.33	9.2088	9.003	9.33
Violating quantities	2	0	0	0	0	0

As shown in Fig. 11.3b, the values of P_c and P_m in GA-Fuzzy OPF change from 8th generation and remain constant after 14th generation ($P_c. \approx 0.56759$ and $P_m \approx 0.06654882$). It is evident from Fig. 11.3a and comparison of methods tabulated in Table 11.4, that GA-Fuzzy OPF has better convergence rate and results least generation cost amongst the three methods. Transformer tapings and voltage magnitudes (Table 11.5) are also found to be within limits.

Table 11.2. Load flow solution and lines flows of 6-bus system using GA-Fuzzy OPF

Bus	Voltage (pu)	Angle(degrees)	Load		Generation	
			MW	MVAr	MW	MVAr
1	1.001	0.000	100	20	140.856	8.357
2	1.017	1.338	100	20	188.025	15.495
3	1.01	−5.495	100	20	100.244	95.456
4	1.00	−1.300	100	20	180.205	11.556
5	0.977	−3.489	100	50	0.0	0.0
6	0.981	−5.664	100	10	0.0	0.0

From bus	To bus	Line flow (MVA)
1	2	32.176
2	4	56.43
1	5	72.725
3	5	52.314
4	5	49.347
3	6	31.607
4	6	87.413

Table 11.3. GA parameters

Population size	30
Maximum generation	100
Initial crossover probability	0.9
Initial mutation probability	0.01
Selection operator	Stochastic remainder

11.3.4.3 IEEE 30-Bus System

The proposed GA-Fuzzy OPF is also applied to IEEE 30 bus system. Two sets of generator cost curves are used to illustrate the robustness of the technique. In case (i) a quadratic cost curve (Alsac and Stott 1974; Yuryevich and Wong 1999) is taken. In case (ii), some of the cost curves are replaced with quadratics plus sine components [YUR99]. Therefore in case (ii), there are many local optimum solutions for the dispatch problem and as a result steepest descent (SD) method cannot determine the global optimum solution. The problem is therefore well suitable for validating the proposed algorithm. The GA-OPF and GA-Fuzzy OPF are compared for IEEE 30-bus system for same parameters as 26 bus system discussed earlier except a mutation probability (= 0.005), population size (= 50) and maximum number of generations (= 50).

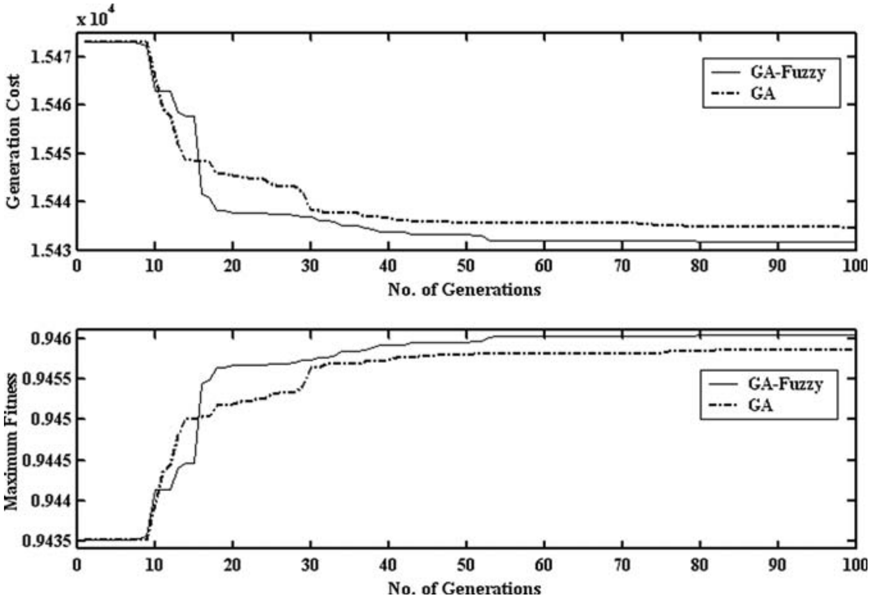

Fig. 11.3a. Convergence of generation cost and max. fitness for GA-OPF & GA-Fuzzy OPF for 26 Bus system. Generation cost is in \$/h

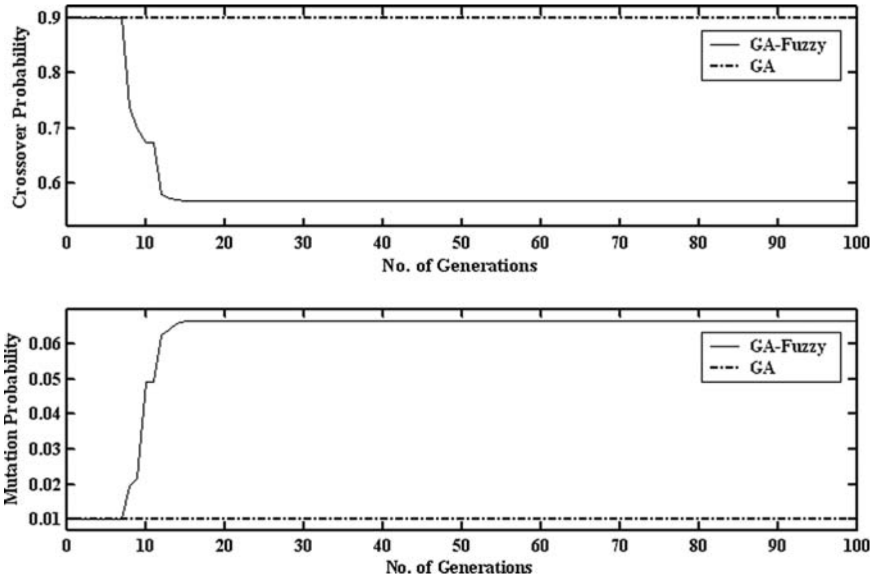

Fig. 11.3b. Crossover and mutation probabilities variations for GA-OPF & GA-Fuzzy OPF for 26 bus system

Table 11.4. Comparison of different OPF methods for 26 bus system

	Generation		
	Sadaat-OPF (in MW)	GA-OPF (in MW)	GA-Fuzzy OPF (in MW)
Bus no. 1	447.611	444.703	449.642
Bus no. 2	173.087	170.968	162.317
Bus no. 3	263.363	258.495	264.086
Bus no. 4	138.716	135.239	139.932
Bus no. 5	166.099	181.525	173.9
Bus no. 26	86.939	83.939	85.924
Gen.Cost ($/h)	15447.72	15434.67	15431.69
Losses (MW)	12.8	11.869	12.8

Table 11.5. Load flow solution and transformer tap settings of 26 bus system using GA-Fuzzy OPF

Bus no.	Voltage magnitude (in p.u.)	Angle (in degrees)	Load	
			MW	MVAr
1	1.025	0	51	41
2	1.025	−0.239	22	15
3	1.074	−0.47	64	50
4	0.91	−2.138	25	10
5	1.026	−1	50	30
6	0.994	−2.771	76	29
7	0.992	−2.388	0	0
8	0.992	−2.258	0	0
9	0.979	−4.476	89	50
10	0.976	−4.334	0	0
11	0.992	−2.798	25	15
12	0.987	−3.325	89	48
13	0.991	−1.12	31	15
14	0.984	−2.338	24	12
15	0.978	−3.156	70	31
16	0.97	−3.907	55	27
17	0.974	−4.563	78	38
18	1.004	−1.872	153	67
19	0.976	−6.075	75	15
20	0.967	−4.777	48	27
21	0.965	−5.452	46	23
22	0.963	−5.363	45	22
23	0.956	−6.428	25	12
24	0.949	−6.726	54	27
25	0.955	−6.329	28	13
26	1.015	−0.324	40	20
Total			1263.00	637.00

Table 11.5. (*Continued*)

Transformer tap settings						
Line 2–3	Line 2–13	Line 3–13	Line 4–8	Line 4–12	Line 6–19	Line 7–9
0.98	1.000	1.080	0.932	0.90	0.983	0.9903

Table 11.6. Best and worst solutions for GA-Fuzzy OPF for IEEE 30 bus system (quadratic cost curve)

	Worst solution ($/h)	Best solution ($/h)	% Difference
EP [36]	805.61	802.62	0.371147
GA-Fuzzy OPF	802.32054	802.00031	0.03991

Case (i) Quadratic Cost Curve

In this case the unit cost curves are represented by quadratic functions. The program is tested for 100 different runs. The generation costs of 802.32054 $/h and 802.00031 $/h are obtained for worst and best solutions, respectively (0.03991% difference), through GA-Fuzzy OPF. It shows the consistency in the results and better performance of the proposed method than evolutionary programming (EP) OPF for the same number of runs (Table 11.6).

As shown in Fig. 11.4b, the values of P_c and P_m change from 2nd generation and remain constant after 15th generation ($P_c. \approx 0.5676$ and $P_m \approx 0.0666$) for the best solution. The solutions obtained from other GA and non-GA techniques available in literature (Roa and Pavez-lazo 2003; Alsac and Stott 1974; Abido 2002; Paranjothi and Anburaja 2002; Yuryevich and Wong 1999) are compared in Table 11.7. The load flow and transformer tap settings for best solution are provided in Table 11.10. It is observed that in GA-Fuzzy OPF a better convergence rate is obtained (as in Fig. 11.4a) and a minimum generation cost is also achieved in GA-Fuzzy OPF (as in Table 11.7).

Case (ii) Quadratic Cost Curve with Sine Components

In this case, a sine component is added to the quadratic equation cost of the generators at buses 1 and 2 to reflect the valve-point loading effects. The values of cost coefficients are given in Table 11.8.

The cost curves of other generators are taken same as in case (i). The algorithm is tested for 100 different runs. The generation costs of the worst and the best solutions are 924.3387 and 921.3506 $/h, respectively (0.323% difference). As per Table 11.9, percentage difference between worst and best solution for GA-Fuzzy OPF is less than evolutionary programming (EP) based OPF. Therefore, GA-Fuzzy approach is found to be superior in solving OPF for cost curve with sine components for same number of runs.

As per Fig. 11.6b values of P_c and P_m vary from 4th generation onwards till 50th generation ($P_c. \approx 0.57292$ and $P_m \approx 0.06392$) for best solution. The

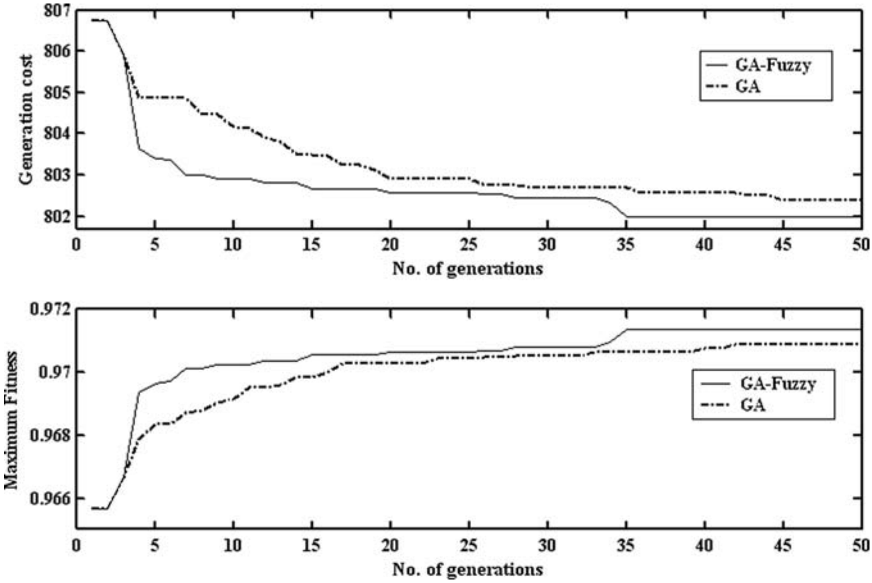

Fig. 11.4a. Convergence of generation cost and max. fitness for GA-OPF & GA-Fuzzy OPF for IEEE 30 bus system (case i). Generation cost is in \$/h

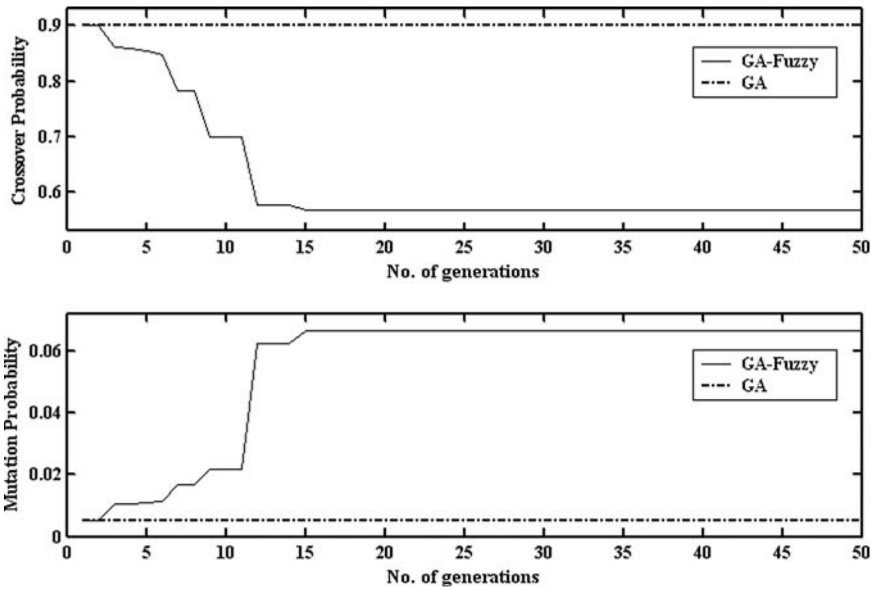

Fig. 11.4b. Crossover and mutation probabilities variations for GA-OPF & GA-Fuzzy OPF for IEEE 30 bus system (case ii)

Table 11.7. Comparison of different OPF methods for IEEE 30 bus system

Quantity	Proj. Gradient [33]	OPFSA [31]	Tabu-Search [34]	GA [35]	RGA [35]	Decoupled OPF by RGA [35]	EP [36]	EGA [37]	GA OPF	GA-Fuzzy OPF
P_1	138.56	173.15	176.04	170.1	174.4	173	173.848	176.2	175.6439	174.9664
P_2	57.56	48.54	48.76	53.9	46.8	48.7	49.998	48.75	48.941	50.35294
P_5	24.56	19.23	21.56	20.6	22.0	26.8	21.386	21.44	21.1765	21.45098
P_8	35.00	12.81	22.05	18.8	23.9	17.7	22.630	21.95	22.647	21.17647
P_{11}	17.93	11.64	12.44	12.0	11.0	10.5	12.928	12.42	12.431	12.66667
P_{13} (in MW)	16.91	13.21	12.00	17.7	14.5	16.3	12.000	12.02	12.00	12.10980
Gen.Cost ($/h)	813.74	799.45	802.29	805.94	804.02	806.86	802.62	802.06	802.3841	802.0003

Table 11.8. Generator cost coefficients for case (ii)

Bus	$P_G{}^{min}$ (in MW)	$P_G{}^{max}$ (in MW)	Cost coefficients				
			a	b	c	d	e
1	50	200	150	2.00	0.0016	50.00	0.0630
2	20	80	25	2.50	0.0100	40.00	0.09890

Generation cost function: $\cos t_i = a_i + b_i P_{g_i} +_i c_i P_{g_i}^2 + |d_i \sin(e_i(P_{g_i}^{\min} - P_{g_i}))|$

Table 11.9. Best and worst solutions for GA-Fuzzy OPF for IEEE 30 bus (quadratic cost curves with sine components)

	Worst solution ($/h)	Best solution ($/h)	% Difference
EP [36]	926.68	919.89	0.7327
GA-Fuzzy	924.336729	921.350629	0.323

solution details including load flow, transformer tap settings and line flows are provided for best solution in Table 11.10.

The line flows obtained in this case are within the limits and other constraints are also satisfied. Again GA-Fuzzy OPF proves to be consistently superior to GA-OPF due to faster convergence and lesser generation cost, as shown in Fig. 11.5a.

11.3.4.4 Modified IEEE 30-Bus System

The original IEEE 30-bus network consists of 6 generator buses, 21 load buses and 41 lines, of which 4 lines (6, 9),(6, 10),(4, 12) and (28, 27) are under-load-tap-setting transformer lines. In modified IEEE 30-bus system buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 have been selected as shunt capacitor/reactor compensation buses. The apparent power flow limit in line (8, 28) is taken as 12 MVA.

The GA-OPF and GA-Fuzzy OPF are compared as shown in Fig. 11.6. for this system for same parameters as for 6-bus system discussed earlier except crossover probability (= 0.95), mutation probability (= 0.005), population size (= 50) and maximum number of generations (= 50).

Hence for best case solution, the changes in values of P_c and P_m start from 4th generation and till 50th generation (P_c. $\approx$ 0.67479 and $P_m \approx$ 0.04901), as shown in Fig. 11.7a, and b. The OPF solutions obtained from other GA technique based on dynamical hierarchy of the coding system and non-GA technique based on gradient projection method (GPM) are available in literature (Lee et al. 1985), respectively. These results are compared along with other methods in Table 11.11.

It indicates minimum generation cost obtained due to optimal values of controllable variables, i.e. active power generations, generator bus voltages,

Table 11.10. Load flow solution and transformer tap settings of IEEE 30 bus system using GA-Fuzzy OPF

Bus	Voltage in p.u.		Angle in degrees		Generation				Load	
	Case (i)	Case (ii)	Case (i)	Case (ii)	MW Case (i)	MW Case (ii)	MVAr Case (i)	MVAr Case (ii)	MW	MVAr
1	1.05	1.05	0	0	174.9664	199.672	−6.562	−9.126	0	0
2	1.034	1.034	−3.608	−4.335	50.35294	20	22.356	39.212	21.7	12.7
3	1.022	1.016	−5.675	−5.875	0	0	0	0	2.4	1.2
4	1.016	1.008	−6.817	−7.062	0	0	0	0	7.6	1.6
5	1.006	1.006	−10.509	−11.007	21.45098	22.275	30.372	31.548	94.2	19
6	1.008	1.005	−7.944	−8.232	0	0	0	0	0	0
7	0.999	0.998	−9.529	−9.904	0	0	0	0	22.8	10.9
8	1.003	1.003	−8.154	−8.431	21.17647	23.725	18.89	25.987	30	30
9	1.029	1.018	−10.152	−10.121	0	0	0	0	0	0
10	1.021	1.027	−12.059	−11.951	0	0	0	0	5.8	2
11	1.071	1.051	−8.783	−8.483	12.66667	14.706	21.737	16.89	0	0
12	1.018	1.038	−11.139	−11.135	0	0	0	0	11.2	7.5
13	1.048	1.048	−10.228	−10.144	12.1098	13.427	22.635	8.075	0	0
14	1.005	1.023	−12.096	−12.07	0	0	0	0	6.2	1.6
15	1.002	1.019	−12.242	−12.188	0	0	0	0	8.2	2.5
16	1.012	1.026	−11.832	−11.764	0	0	0	0	3.5	1.8
17	1.013	1.021	−12.214	−12.111	0	0	0	0	9	5.8
18	0.997	1.009	−12.917	−12.825	0	0	0	0	3.2	0.9
19	0.996	1.007	−13.113	−13.005	0	0	0	0	9.5	3.4
20	1.002	1.011	−12.911	−12.801	0	0	0	0	2.2	0.7
21	1.009	1.015	−12.535	−12.43	0	0	0	0	17.5	11.2
22	1.009	1.016	−12.524	−12.422	0	0	0	0	0	0
23	0.996	1.01	−12.707	−12.652	0	0	0	0	3.2	1.6
24	0.997	1.008	−12.956	−12.913	0	0	0	0	8.7	6.7
25	1.001	1.015	−12.759	−12.826	0	0	0	0	0	0
26	0.983	0.997	−13.193	−13.248	0	0	0	0	3.5	2.3
27	1.012	1.028	−12.361	−12.5	0	0	0	0	0	0
28	1.002	0.999	−8.433	−8.71	0	0	0	0	0	0
29	0.992	1.008	−13.619	−13.72	0	0	0	0	2.4	0.9
30	0.98	0.996	−14.522	−14.595	0	0	0	0	10.6	1.9
Total					292.7233	293.806	109.43	112.585	283.4	126.20

	Gen. Cost ($/h)	Losses (MW)	Transformer tap setting			
			Line 6–9	Line 6–10	Line 4–12	Line 28–27
Case (i)	802.0003	9.494	1.0032	0.9645	1.0161	0.9645
Case (ii)	921.3506	10.406	1.0355	0.9129	0.9452	0.9452
1–2	117.211	139.6258				
1–3	58.3995	61.0022				
2–4	34.0758	30.7947				
2–5	63.7783	61.7539				
2–6	45.3399	41.6185				
3–4	54.5622	56.8812				
4–6	50.2703	48.6008				
4–12	30.5889	33.3706				
5–7	14.1355	16.1981				
6–7	33.9924	35.221				

Table 11.10. (*Continued*)

Lines	Line flow (in MVA)	
	Case (i)	Case (ii)
6–8	13.6882	9.2172
6–9	22.4033	27.0031
6–10	14.6187	20.0154
6–28	16.5409	16.0689
8–28	3.3685	3.0049
9–11	24.1764	21.6919
9–10	32.7929	31.3223
10–20	11.0315	9.8192
10–17	9.861616	7.33966
10–21	18.96153	18.074
10–22	9.0741	8.5101
12–13	24.9376	15.5102
12–14	7.6911	8.1147
12–15	17.4525	18.8445
12–16	6.34027	7.723838
14–15	1.2313	1.5983
15–18	5.4066	6.18
15–23	4.5343	5.358
16–17	3.2983	3.756
18–19	2.3627	2.8022
19–20	8.5117	7.3363
21–22	2.0887	3.1629
22–24	6.9397	5.7964
23–24	1.4447	1.8148
24–25	1.3934	1.8788
25–26	4.2647	4.2626
25–27	5.633	6.1149
27–29	6.4154	6.4095
27–30	7.2897	7.2825
28–27	19.7428	20.07
29–30	3.7542	3.7525

transformer taps and shunt capacitors/reactive compensations. The convergence of GA-Fuzzy OPF is better than GA-OPF as evident from Fig. 11.7a. The apparent power flows at line (8, 28) is 3.034 MVA and 3.317 MVA for GA-OPF and GAF-OPF respectively. The load flow solution for best solution is provided in Table 11.12.

GA-Fuzzy OPF is run for 100 different runs with different initial populations on above system. The convergence graphs for generation costs and maximum fitness in best and worst cases are shown in Fig. 11.8, which are converging very close to each other. The total generation cost obtained in worst case is 801.1601 \$/h. Therefore, GA-Fuzzy OPF gives consistently good results as percentage deviation between best case and worst case generation costs is $\approx 0.089\%$, which is a very small variation.

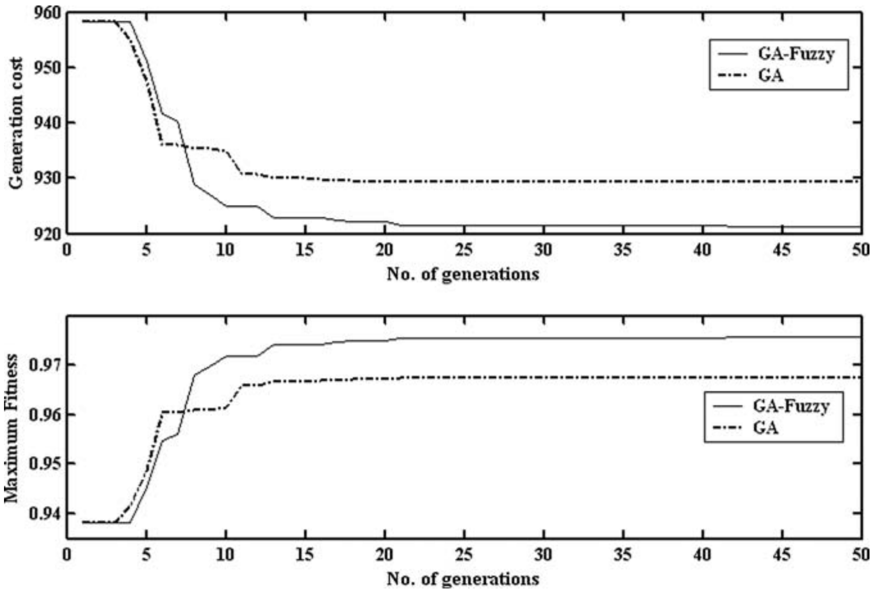

Fig. 11.5a. Convergence of generation cost and Max. fitness for GA-OPF & GA-Fuzzy OPF for IEEE 30 bus system (case ii). Generation cost is in \$/h

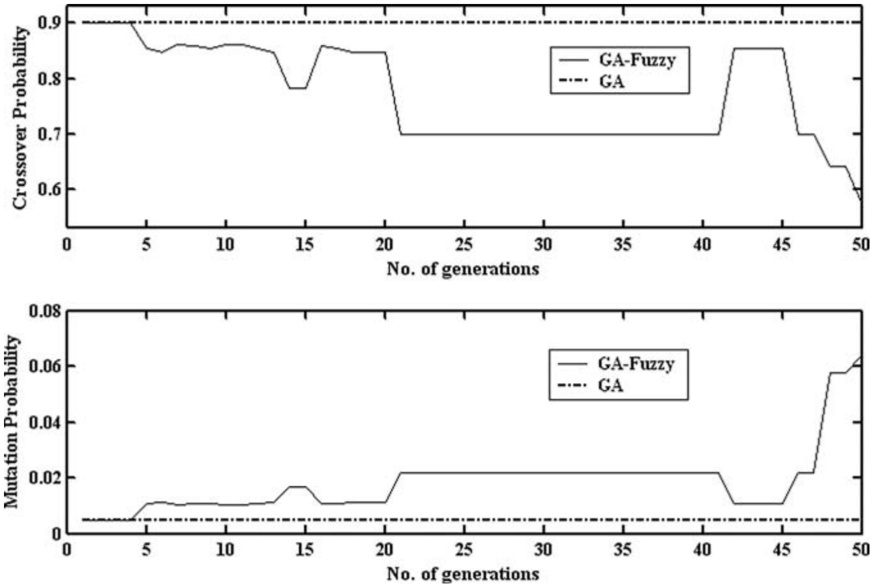

Fig. 11.5b. Crossover and mutation probabilities variations for GA-OPF & GA-Fuzzy OPF for IEEE 30 bus system (case ii)

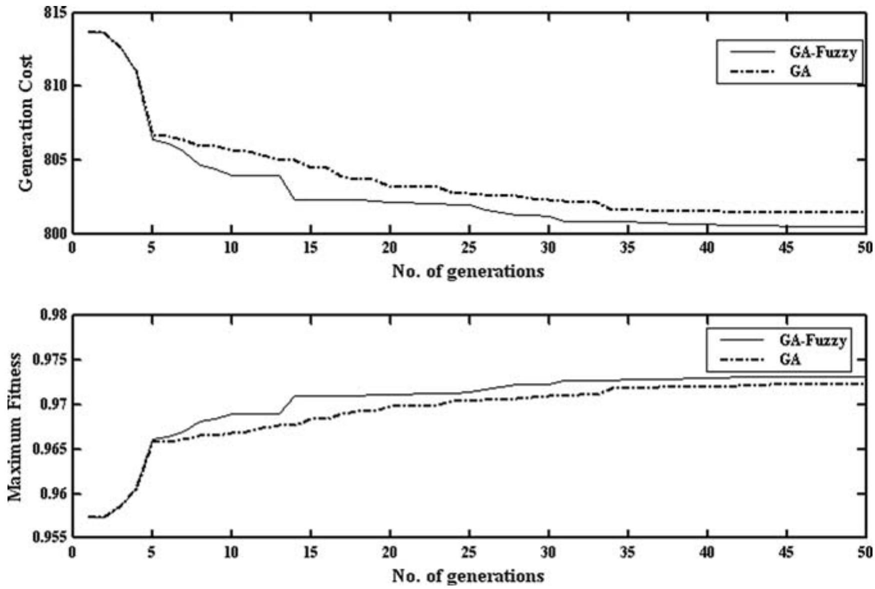

Fig. 11.6a. Convergence of generation cost & max. fitness for GA-OPF & GA-Fuzzy OPF for modified IEEE 30-bus system

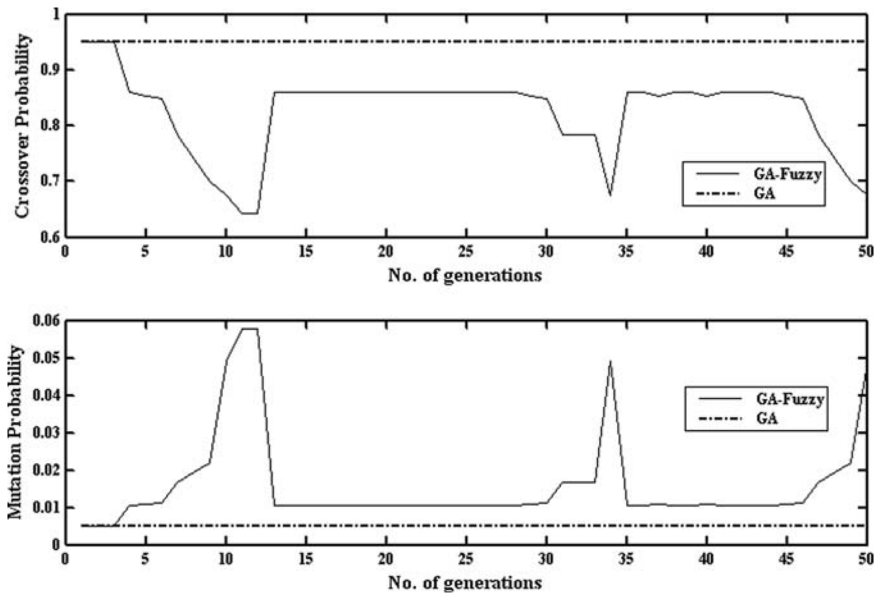

Fig. 11.6b. Crossover and mutation probabilities variations for GA-OPF & GA-Fuzzy OPF for modified IEEE 30-bus system

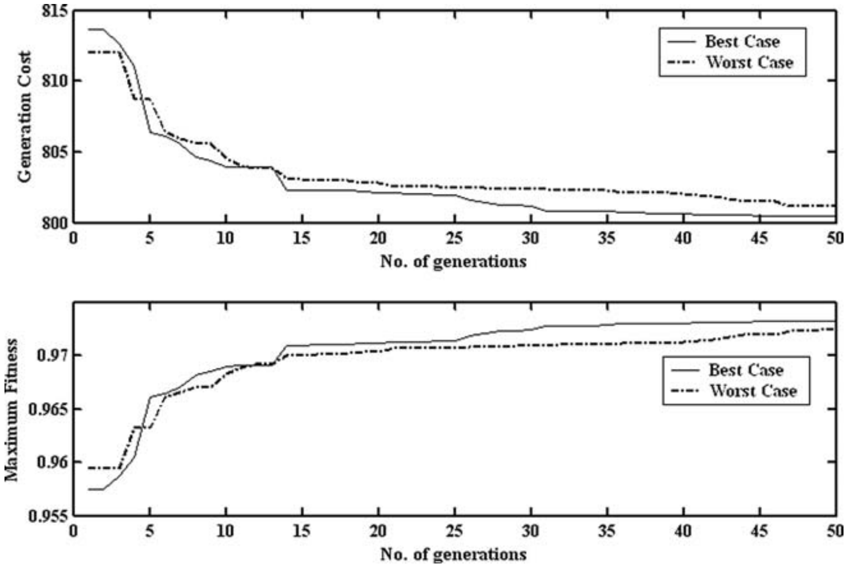

Fig. 11.7. Convergence of generation cost & max. fitness for best and worst cases for modified IEEE 30-bus system using GA-Fuzzy OPF

Table 11.11. Comparison of different OPF methods for modified IEEE 30-bus system

Bus	Active power generations (in MW)						Generation cost ($/h)	Real power losses (MW)
	1	2	5	8	11	13		
Lee et al. [25]	187.219	53.781	16.955	11.288	11.287	13.355	804.853	10.485
Lai et al. [26]	177.7594	48.722	21.454	20.954	11.768	12.052	800.805	9.309
GA-OPF	175.462	50.118	22.000	20.686	11.882	12.439	801.447	9.187
GA-Fuzzy OPF	174.886	48.941	21.176	22.647	12.588	12.000	800.442	8.838

Bus	Generator bus voltages (in p.u.)					
	1	2	5	8	11	13
Lee et al. [25]	1.1	1.08	1.03	1.04	1.08	1.08
Lai et al. [26]	1.081	1.063	1.034	1.038	1.1	1.055
GA-OPF	1.073	1.052	1.03	1.04	1.076	1.061
GA-Fuzzy OPF	1.081	1.063	1.031	1.039	1.095	1.07

Table 11.11. (*Continued*)

Line	Transformer tap settings			
	(6,9)	(6,10)	(4,12)	(28,27)
Lee et al. [25]	1.072	1.07	1.032	1.068
Lai et al. [26]	1.0	0.975	0.975	1.0
GA-OPF	1.016	1.0419	1.087	1.0097
GA-Fuzzy OPF	0.99032	0.98387	0.99032	0.96451

Bus	Shunt capacitor/reactor compensations (in MVAr)								
	10	12	15	17	20	21	23	24	29
Lee et al [25]	0.692	0.046	0.285	0.287	0.208	0.000	0.330	0.938	0.269
Lai et al. [26]	0.1	0.7	1.9	2.4	1.5	2.2	4.7	4.7	2.4
GA-OPF	3.033	2.544	4.618	4.266	4.736	0.528	2.476	4.442	4.194
GA-Fuzzy OPF	3.982	0.02	4.149	4.99	4.432	4.354	4.54	4.687	2.097

11.3.5 Conclusions

The proposed GA-Fuzzy OPF has also been tested in different test systems as indicated earlier. It has shown better results in terms of convergence, consistency in different runs and minimum generation cost as compared to simple GA-OPF and the other techniques. These advantages are mainly due to the changes in crossover and mutation probabilities values which are governed by a set of fuzzy rule base, although they are stochastic in nature. The variations in above GA parameters governed by fuzzy rule base have resulted in lesser generation costs with high convergence rates than other GA and non GA-OPF variants tested for 26-bus, 6-bus, IEEE 30-bus and modified IEEE 30-bus systems (Figs. 11.9–11.12).

In order to demonstrate the real potential of such technique, the proposed GAF-OPF is successfully tested on IEEE 30 bus system for quadratic cost curve with sine components also. The results obtained are compared with EP based OPF with greater satisfaction. This proves the superiority of the proposed GA-Fuzzy OPF method to the gradient-based conventional and other GA variants for finding OPF solution.

11.4 Transmission Pricing Model Under Deregulated Environment

11.4.1 Introduction

Several methods are developed for allocation of the costs embedded in the system to various transactions (embedded cost based pricing) and those incurred by system from one additional transaction (incremental

Table 11.12. Load flow solution for modified IEEE 30-bus system using GA-Fuzzy OPF

Bus	Voltage in p.u.	Angle in degrees	Generation		Load	
			MW	MVAr	MW	MVAr
1	1.081	0	174.886	5.021	0	0
2	1.063	−3.279	48.941	30.435	21.7	12.7
3	1.05	−5.273	0	0	2.4	1.2
4	1.05	−6.347	0	0	7.6	1.6
5	1.034	−9.588	21.176	29.221	94.2	19
6	1.041	−7.361	0	0	0	0
7	1.03	−8.761	0	0	22.8	10.9
8	1.039	−7.568	22.647	36.845	30	30
9	1.049	−9.574	0	0	0	0
10	1.025	−11.429	0	0	5.8	2
11	1.095	−8.414	12.588	17.344	0	0
12	1.032	−10.671	0	0	11.2	7.5
13	1.07	−9.736	12	10.337	0	0
14	1.021	−11.649	0	0	6.2	1.6
15	1.02	−11.883	0	0	8.2	2.5
16	1.023	−11.319	0	0	3.5	1.8
17	1.022	−11.673	0	0	9	5.8
18	1.012	−12.495	0	0	3.2	0.9
19	1.01	−12.661	0	0	9.5	3.4
20	1.014	−12.451	0	0	2.2	0.7
21	1.016	−11.968	0	0	17.5	11.2
22	1.016	−11.95	0	0	0	0
23	1.015	−12.378	0	0	3.2	1.6
24	1.007	−12.42	0	0	8.7	6.7
25	1.014	−12.173	0	0	0	0
26	0.996	−12.596	0	0	3.5	2.3
27	1.026	−11.749	0	0	0	0
28	1.035	−7.814	0	0	0	0
29	1.008	−13.027	0	0	2.4	0.9
30	0.996	−13.878	0	0	10.6	1.9

cost based pricing). In (Sood 2003), an evolutionary programming based SRMC method is proposed and several embedded cost based methods in (Uttar Pradesh 2004) are proposed for Indian system. But their results are obtained for different transmission subsystems. The methodologies for determination of transmission pricing should be so designed that basic goals of transmission pricing can be achieved. Therefore, the methodology can be designed on the basis of marginal cost or embedded cost or a composite cost, i.e. the combination of marginal and embedded cost.

In this chapter, marginal cost method is used and tested on modified IEEE-30 bus system. Embedded cost allocation methods, e.g. Postage Stamp and

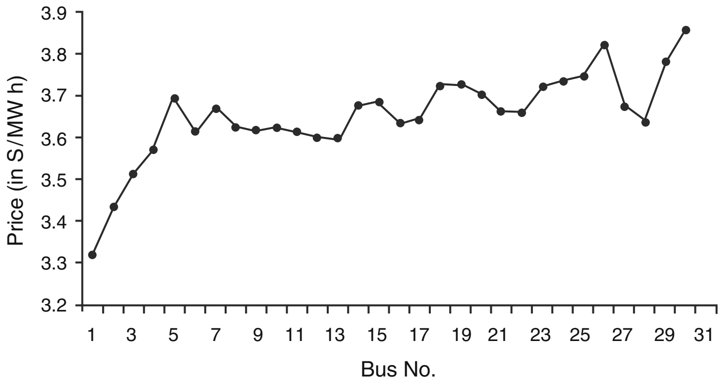

Fig. 11.8. Real marginal prices for modified IEEE 30 Bus System

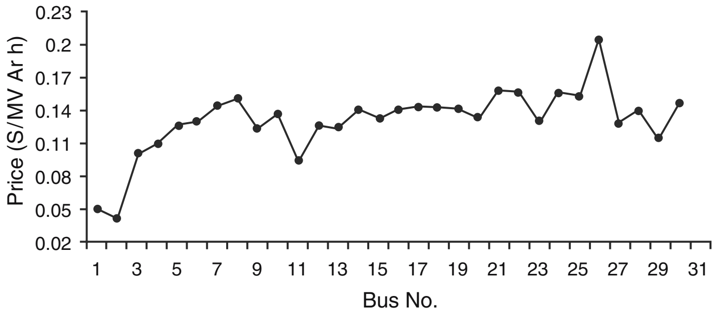

Fig. 11.9. Reactive marginal prices for modified IEEE 30 Bus System

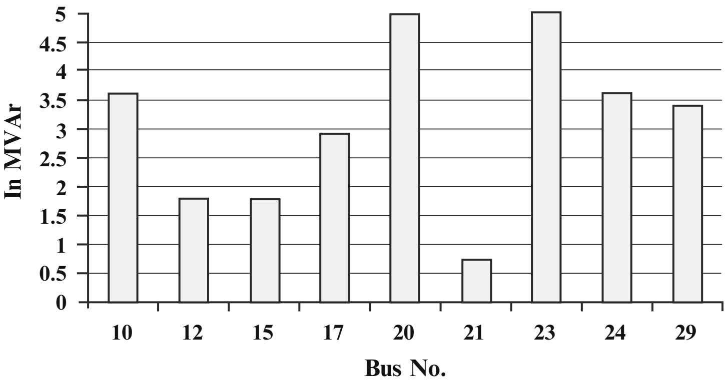

Fig. 11.10. Optimal value of shunt capacitor value for modified IEEE 30 – bus system

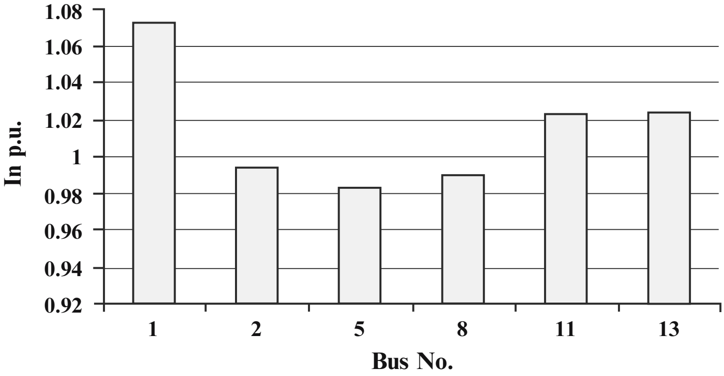

Fig. 11.11. Generator bus voltages for modified IEEE 30 – bus system

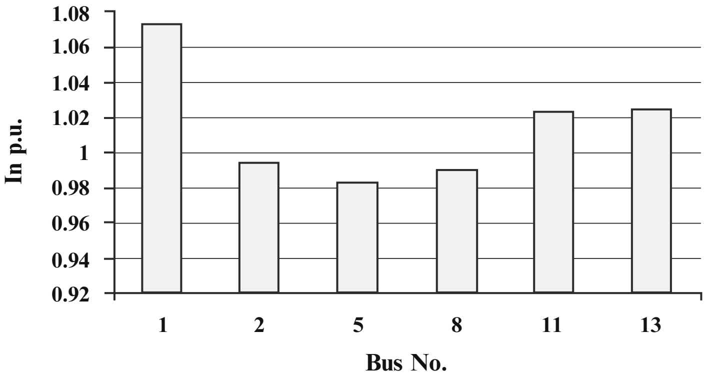

Fig. 11.12. Optimal real power generation for modified IEEE 30 – bus system

MW-Mile methods are also tested and analyzed on Indian UPSEB 75 bus system. A new variant of MW-Mile is proposed and analyzed. Finally, a hybrid type marginal cost based transmission pricing model is proposed for Indian transmission system with pool, bilateral and multilateral transactions. In this model, supplementary/complementary charges left as unrealized revenue after applying marginal cost method are allocated using the MW-Mile methods. This model is tested on Indian UPSEB 75 bus system.

11.4.2 Marginal Cost Based Transmission Pricing Method

In this section the marginal cost based transmission pricing method is analyzed and tested, which dispatches the pool in combination with privately negotiated bilateral and multilateral wheeling contracts, with maximization of social benefit with all system constraints. In the method, all scheduled firm transactions are considered to be added to the system. The method is based on GA-Fuzzy optimization technique, which has been described earlier. The losses taking place in transmission network due to transactions as well as pool are considered to be supplied from the pool itself. They are not supplied by transactions generators or cope up with transaction loss supply contracts which are complex to setup and coordinate.

As the process of developing suitable transmission pricing methodologies in India is in initial stages, hence following facts are considered for application of pricing method to modified IEEE 30 bus system and Indian UPSEB 75 bus system.

1. All the pool generators are required to bid their generation cost characteristics to the pool along with maximum generation.
2. There are no non-firm bilateral transactions.
3. The active and reactive power of pool loads are known from load forecasting and kept constant during optimization. Therefore, there is no bidding from pool demands.
4. The other costs of system like maintenance and different overheads, etc. are not being included in proposed model, which should be considered independently.

1. *Mathematical formulation*

Let n = number of buses in a system
$nfbt$ = number of schedule firm bilateral transactions
$nfmt$ = Groups of schedule firm multilateral transactions

$$\text{Firm bilateral transaction load component at } jth \text{ bus } (Pd_j^{fb}) = \sum_{i=1}^{n} FBT_{ij} \tag{11.14}$$

where FBT_{ij} = Firm bilateral transactions delivered at the jth load bus from the ith generator bus.

$$\text{Generation at ith bus for firm bilateral transactions } (Pg_j^{fb}) = \sum_{j=1}^{n} FBT_{ij} \tag{11.15}$$

For a firm bilateral transaction *fbt* from *ith* to a *jth* bus

$$Pg_i^{fbt} = Pd_j^{fbt} \tag{11.16}$$

where, Pg_i^{fbt} and Pd_j^{fbt} are real power generation and demand for a firm bilateral transaction *fbt*, at i^{th} and j^{th} bus, respectively.

Vector of real power demand from firm bilateral transactions may be written as

$$Pd^{fb} = FBT^T \times U = \left\{ Pd_j^{fb}; j = 1, 2, \ldots\ldots, n \right\} \tag{11.17}$$

where FBT = matrix of firm bilateral transactions delivered at the jth load bus from the ith generator bus.

U = Unity vector of dimension n.

Vector of real power generation from firm bilateral transactions also be written as

$$Pg^{fb} = FBT^T \times U = \left\{ Pd_i^{fb}; i = 1, 2, \ldots\ldots, n \right\} \tag{11.18}$$

In case of a multilateral transaction, there are many generation points (at least more than one), similarly there are many load points (at least more than one).

Let PMT^k = size of *kth* group of multilateral transaction, i.e. total power that has to be transferred from generation points to the load points of a *kth* group of multilateral transaction.

ngk = number of generation points for a *kth* group
ndk = number of demand points for a *kth* group

Real power demand of kth multilateral transaction = Pd_j^{mk} where $k = 1, 2, \ldots .n$.

Real power generation from *kth* multilateral transaction = Pg_i^{mk} where $i = 1, 2, \ldots .n$.

For k^{th} group of multilateral transaction with total power transfer PMT^k is

$$\sum_{i=1}^{n} Pg_i^{mk} \sum_{j=1}^{n} Pd_j^{mk} = PMT^k \tag{11.19}$$

Total generation at *ith* bus due to *nfmt* groups of multilateral transactions is

$$Pg_i^m = \sum_{k=1}^{nfmt} Pg_i^{mk} \tag{11.20}$$

Total demand at jth bus due to *nfmt* groups of multilateral transactions is

$$Pd_j^m = \sum_{k=1}^{nfmt} Pd_j^{mk} \tag{11.21}$$

Generation vector of all firm multilateral transaction groups may be written as

$$Pg^m = \{Pg_i^m; i = 1, 2, \ldots.., n\} \tag{11.22}$$

Demand vector of all firm multilateral transaction groups may be written as

$$Pd^m = \{Pd_j^m; j = 1, 2, \ldots.., n\} \tag{11.23}$$

The gencos participating in the pool bid their cost function and maximum generation, which they want to deliver to the pool. After optimization of social benefit generations at power pool generation buses are known.

Let the vector of pool real power generation

$$Pg^p = \{Pg_i^p; i = 1, 2, \ldots\ldots.., n\} \tag{11.24}$$

Vector of pool real power demand

$$Pd^p = \{Pd_j^p; j = 1, 2, \ldots\ldots.., n\} \tag{11.25}$$

Let the vectors of the total real power demand and generation be

$$Pd^T = \{Pd_j^T; j = 1, 2, \ldots\ldots\ldots., n\} \tag{11.26}$$

$$Pg^T = \{Pg_i^T; i = 1, 2, \ldots\ldots\ldots., n\} \tag{11.27}$$

From equations (11.21), (11.23) and (11.25)

$$Pd^T = Pd^p + Pd^{fb} + Pd^m \tag{11.28}$$

Similarly, from equations (11.18), (11.22) and (11.24)

$$Pg^T = Pg^p + Pg^{fb} + Pg^m \tag{11.29}$$

All firm transactions are ready to pay the system marginal price and they do not bid.

The load point of the transaction and pool may have reactive power component in addition to real power.

Let Qd^p and Qd^{fb} be the vector of the reactive power demand due to pool and firm bilateral transaction, respectively.

$$Qd^p = \{Qd_j^p; j = 1, 2, \ldots.n\} \tag{11.30}$$

$$Qd^{fb} = \{Qd_j^{fb}; j = 1, 2, \ldots.n\} \tag{11.31}$$

In the combined power pool transaction dispatched, gencos supplying the loads by transactions may also participate in the pool. Therefore, all such gencos in combinations may meet the reactive power requirements at all the buses of the system. It means that the power balance equation (11.16) for bilateral transactions and (11.19) for multilateral transaction is not necessary for reactive power. However for specific situation when a genco is not participating in pool and it is supplying loads by a transaction and the reactive power requirement of the load is to be supplied by the genco of the transaction only, then these equations for reactive power are also valid.

It is better to supply the reactive power as per requirement of the system, rather than supplying the reactive power at the generation point of a transaction equal to reactive power of load at the load point of the transaction. All generators are paid and loads are charged for the reactive power accordingly.

2. *Objective function and constraints*

The objective function for the optimization problem is to minimize the overall costs of active and reactive power generation with the capital investment of capacitor. Based on the assumption of constant loads, to minimize the total cost is equivalent to maximize the social benefits. Therefore, suggested objective function to maximize social benefit is given as follows:

$$\min \sum_{j=1}^{ng} [C_i(Pg_i) + C_i(Qg_i)] \sum_{j=1}^{ncap} C_{cj}(Qc_j) \tag{11.32}$$

Let the active power generation cost curve bid of the generator at *ith* bus = $C_i(Pg_i)$

Reactive power generation cost of generator at *ith* bus = $C_i(Qg_i)$

Equivalent production cost of *jth* capacitor = $C_{cj}(Qc_j)$

where, $j = 1, 2, \ldots\ldots ncap$, as $ncap$ = Total number of capacitors operating in the system

ng = Total number of pool generators.

It is seen that GA-Fuzzy OPF technique works successfully for non-linear active generation cost curves. Therefore, proposed model is also capable of handling all types functions such as linear, quadratic, non-linear, convex or non-convex, continuous or discontinuous, etc. used for representing active power generation cost curve bids function in (11.32). For sake of simplicity cost curves for active power generation are modeled by following quadratic function:

$$C_i(Pg_i) = a + Pg_i + cPg_i^2 \tag{11.33}$$

Guo et al. (2004) have used equation for reactive power generation cost of the same form of quadratic equation as (11.33) but with different a, b and c coefficients. Another form introduced in (Lamont and Fu 1999) and used in (Dai et al. 2001) is based on opportunity cost.

The equivalent production cost for capital investment return of capacitors in (11.32) can be expressed as their depreciated rate (the life span of capacitors is 15 years) as follows:

$$\begin{aligned} C_{cj}(Qc_j) &= Qc_j \times \$11600/MVAr \div (15 \times 365 \times 24 \times h)\text{h} \\ &= Qc_j \times \$13.24/(100\ MVArh) \end{aligned} \tag{11.34}$$

where h represents the average usage rate of capacitors taken as 2/3. Qc_j is in per unit on 100 MVA base. Equation (11.34) is a linear cost function with the slope of $dC_{cj}(Qc_j)/dQc_j = \$13.24/(100\,MVArh)$ representing approximately the capacitor investment impacts on reactive pricing.

The equality constraints are load flow equations:

$$g(V, \delta) = 0 \tag{11.35}$$

where

$$g(V, \delta) = \left\{ \begin{matrix} Pg_i - Pd_i - P_i(V, \delta) \Rightarrow For\ each\ PV\ and\ PQ\ bus\ except\ slack\ bus \\ Qg_i - Qd_i - Q(V, \delta) \Rightarrow For\ each\ PQ\ bus\ only \end{matrix} \right\}$$

where

P_i = active power injection into *ith* bus
Q_i = reactive power injection into *ith* bus
Pd_i = active load on *ith* bus
Qd_i = reactive load on *ith* bus
Pg_i = active generation on *ith* bus
Qg_i = reactive generation on *ith* bus

The inequality constraints are:

- Active power generation Pg_i at PV buses

$$Pg_i^{\min} \leq Pg_i \leq Pg_i^{\max} \tag{11.36}$$

  where $Pg_i^{\min}$ and $Pg_i^{\max}$ are respectively minimum and maximum value of active power generation at *ith* PV bus.
- Reactive power generation Qg_i at PV buses

$$Qg_i^{\min} \leq Qg_i \leq Qg_i^{\max} \tag{11.37}$$

  where $Qg_i^{\min}$ and $Qg_i^{\max}$ are respectively minimum and maximum value of reactive power generation at *ith* PV bus.
- Reactive power output limit of capacitor

$$0 \leq Qc_j \leq Qc_j^{\max} \tag{11.38}$$

  where $Qc_j^{\max}$ is maximum value of output of capacitor at *jth* bus.
- Voltage magnitude V of each PV and PQ bus

$$V_i^{\min} \leq V_i \leq V_i^{\max} \tag{11.39}$$

  where, $V_i^{\min}$ and $V_i^{\max}$ are respectively minimum and maximum voltage at *ith* bus
- Phase angle δ of voltage at all the buses.

$$\delta_i^{\min} \leq \delta_i \leq \delta_i^{\max} \tag{11.40}$$

  where, $\delta_i^{\min}$ and $\delta_i^{\max}$ are respectively minimum and maximum allowed value of voltage phase angle at *ith* bus

- Transmission power limit

$$S_{ij} \leq S_{ij}^{\max} \tag{11.41}$$

where, $S_{ij}^{\max}$ is the maximum rating of transmission line connecting bus i and j.

Based on the above mathematical model the corresponding Lagrangian function of this optimization problem takes the form:

$$\begin{aligned}
L = &\sum_{i=1}^{ng}[C_i(Pg_i) + C_i(Qg_i)] + \sum_{j=1}^{ncap} C_{cj}(Qc_j) - \sum_{i=1}^{n} \lambda_{pi}[Pg_i - Pd_i - P_i(V,\delta)] \\
&- \sum_{i=1}^{n} \lambda_{qi}[Qg_i - Qd_i - Q_i(V,\delta)] + \sum_{i=1}^{ng} \mu_{pi,\min}(Pg_i^{\min} - Pg_i) \\
&+ \sum_{i=1}^{ng} \mu_{pi,\max}(Pg_i - Pg_i^{\max}) + \sum_{i=1}^{ng} \mu_{qi,\min}(Qg_i^{\min} - Qg_i) \\
&+ \sum_{i=1}^{ng} \mu_{qi,\max}(Qg_i - Qg_i^{\max}) + \sum_{j=1}^{ncap} \mu_{cj,\max}(Qc_j - Qc_j^{\max}) \\
&+ \sum_{i=1}^{n} \sum_{\substack{i=1 \\ j\neq 1}}^{n} \eta_{ij}(S_{ij} - S_{ij}^{\max}) + \sum_{i=1}^{n} \upsilon_{i,\min}(V_i^{\min} - V_i) + \sum_{i=1}^{n} \upsilon_{i,\max}(V_i - V_i^{\max})
\end{aligned}$$

According to the theory of microeconomics, the marginal prices for active and reactive power on *ith* bus are λ_{pi} and λ_{qi}, respectively, in the above Lagrangian function and are taken as the corresponding spot prices in electricity markets. Similar to vector λ, the vectors μ, η and υ contain marginal change in cost with respect to the corresponding constraints. The elements of vectors μ, η and υ respectively are different than zero only in case that the corresponding constraints are active.

Optimization of (11.32), with power flow relations included as equality constraints (11.35), inequality constraints (11.36) to (11.41) along with generation bidding constraints GA-Fuzzy approach. All the control variables, e.g. V at PV bus and tap ratio of tap setting transformers are also taken care in this optimization process. GA-Fuzzy approach does not provide Lagrange multipliers required for determination of SRMC (short run marginal cost) during optimization process directly. Therefore, in the proposed model method used to determine LMP (locational marginal prices) and hence SRMC is explained in the next section. A solution to this optimization problem provides the pool demands Pd_i^p and pool generations Pg_i^p.

1. *Method for determination of LMP and SRMC*

The optimization problem is solved, if the following equations of optimality are satisfied.

$$\frac{\partial L}{\partial Pg_i} = \frac{\partial C_i(Pg_i)}{\partial Pg_i} - \lambda_{pi} = 0 \quad i = 1, \ldots\ldots ng \tag{11.42}$$

$$\frac{\partial L}{\partial Qg_i} = \frac{\partial C_i(Qg_i)}{\partial Qg_i} - \lambda_{qi} = 0 \qquad i = 1, \ldots\ldots., ng \tag{11.43}$$

$$\begin{aligned}
\frac{\partial L}{\partial \delta_i} &= \sum_{j=1}^{n}\left[\lambda_{pj}\frac{\partial P_j}{\partial \delta_i}\right] + \sum_{j=1}^{n}\left[\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\right] = 0 \\
&= \left(\lambda_{ps}\frac{\partial P_s}{\partial \delta_i} + \sum_{j=1_{j\neq s}}^{ng+nload}\lambda_{pj}\frac{\partial P_j}{\partial \delta_i}\right) \\
&\quad + \left(\lambda_{qs}\frac{\partial Q_s}{\partial \delta_i} + \sum_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i} + \sum_{\substack{j=1\\ j\neq s}}^{nload}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\right) \\
&= \left(\lambda_{ps}\frac{\partial P_s}{\partial \delta_i} + \lambda_{qs}\frac{\partial Q_s}{\partial \delta_i} + \sum_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\right) \\
&\quad + \left(\sum_{\substack{j=1\\ j\neq s}}^{ng+nload}\lambda_{pj}\frac{\partial P_j}{\partial \delta_i} + \sum_{\substack{j=1\\ j\neq s}}^{nload}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\right)
\end{aligned} \tag{11.44}$$

where $i = 1, 2, \ldots.(ng + nload)$ and $i \neq s$

$$\begin{aligned}
\frac{\partial L}{\partial V_i} &= \sum_{j=1}^{n}\left[\lambda_{pj}\frac{\partial P_j}{\partial V_i}\right] + \sum_{j=1}^{n}\left[\lambda_{qj}\frac{\partial Q_j}{\partial V_i}\right] = 0 \\
&= \left(\lambda_{ps}\frac{\partial P_s}{\partial V_i} + \sum_{\substack{j=1\\ j\neq s}}^{ng+nload}\lambda_{pj}\frac{\partial P_j}{\partial V_i}\right) + \left(\lambda_{qs}\frac{\partial Q_s}{\partial V_i} + \sum_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial V_i} + \sum_{j=1}^{nload}\lambda_{qj}\frac{\partial Q_j}{\partial V_i}\right) \\
&= \left(\lambda_{ps}\frac{\partial P_s}{\partial V_i} + \lambda_{qs}\frac{\partial Q_s}{\partial V_i} + \sum_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial V_i}\right) + \left(\sum_{\substack{j=1\\ j\neq s}}^{ng+nload}\lambda_{pj}\frac{\partial P_j}{\partial V_i} + \sum_{\substack{j=1\\ j\neq s}}^{nload}\lambda_{qj}\frac{\partial Q_j}{\partial V_i}\right)
\end{aligned} \tag{11.45}$$

where $i = 1, 2, \ldots..nload$ *and* $i \neq s$

$$\frac{\partial L}{\partial \lambda_{pi}} = P_i(V, \delta) - Pg_i + Pd_i = 0 \quad (i = 1, \ldots\ldots.n) \tag{11.46}$$

$$\frac{\partial L}{\partial \lambda_{qi}} = Q_i(V, \delta) - Qg_i + Qd_i = 0 \quad (i = 1, \ldots\ldots.n) \tag{11.47}$$

where n = *total no. of buses*
s = *slack bus*
ng = *total no. of generator buses*
$nload$ = *total no. of load buses*

Equations. (11.45) and (11.46) can be expressed in matrix form as follows:

$$\left[\frac{\lambda ps\frac{\partial P_s}{\partial \delta_i}+\lambda_{qs}\frac{\partial Q_s}{\partial \delta_i}+\sum\limits_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\quad i=1,\ldots(ng+nload)}{\lambda ps\frac{\partial P_s}{\partial V_i}+\lambda_{qs}\frac{\partial Q_s}{\partial V_i}+\sum\limits_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial V_i}\quad i=1,\ldots(nload)}\right]$$

$$+\left[\begin{array}{ll|l} \frac{\partial P_j}{\partial \delta_i} & \begin{array}{l} j=1,\ldots(ng+nload)\\ i=1,\ldots(ng+nload)\\ i\ and\ j\neq s\end{array} & \frac{\partial Q_j}{\partial \delta_i}\ \begin{array}{l} j=1,\ldots nload\\ i=1,\ldots(ng+nload)\\ i\ and\ j\neq s\end{array}\\ -- & ----------- & --\ -----------\\ \frac{\partial P_j}{\partial V_i} & \begin{array}{l} j=1,\ldots(ng+nload)\\ i=1,\ldots(ng+nload)\\ i\ and\ j\neq s\end{array} & \frac{\partial Q_j}{\partial V_i}\ \begin{array}{l} j=1,\ldots nload\\ i=1,\ldots(ng+nload)\\ i\ and\ j\neq s\end{array} \end{array}\right]\left[\begin{array}{l}\lambda_{pj}\\ j=1,\ldots(ng+nload)\\ j\neq s\\ -----------\\ \lambda_{qj}\\ \quad j=1,\ldots(nload)\\ \quad j\neq s\end{array}\right]$$

$$=\begin{bmatrix}0\\ \\ -\\ 0\\ \\ \end{bmatrix}$$

It can also be expressed as:

$$\left[\frac{\lambda_{ps}\frac{\partial P_s}{\partial \delta_i}+\lambda_{qs}\frac{\partial Q_s}{\partial \delta_i}+\sum\limits_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\ i=1,\ldots(ng+nload)}{\lambda_{ps}\frac{\partial P_s}{\partial V_i}+\lambda_{qs}\frac{\partial Q_s}{\partial V_i}+\sum\limits_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_i}{\partial V_i}\quad i=1,\ldots nload}\right]$$

$$+[J]^T\left[\frac{\lambda_{pj}\ \begin{array}{c} j=1,\ldots(ng+nload)\\ j\neq s\end{array}}{\lambda_{qj}\ \begin{array}{c} j=1,\ldots nload\\ j\neq s\end{array}}\right]=\left[\frac{0}{0}\right]$$

where J = *Jacobian obtained from N-R load flow method for final optimized results.*

$$\left[\frac{\lambda_{pj}\quad j=1,\ldots(ng+nload)}{\lambda_{qi}\qquad j=1,\ldots nload}\right]=-\left([J]^T\right)^{-1}$$
$$\times\left[\frac{\lambda_{ps}\frac{\partial P_s}{\partial \delta_i}+\lambda_{qs}\frac{\partial Q_s}{\partial \delta_i}+\sum\limits_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_j}{\partial \delta_i}\ i=1,\ldots(ng+nload)}{\lambda_{ps}\frac{\partial P_s}{\partial V_i}+\lambda_{qs}\frac{\partial Q_s}{\partial V_i}+\sum\limits_{\substack{j=1\\ j\neq s}}^{ng}\lambda_{qj}\frac{\partial Q_i}{\partial V_i}\quad i=1,\ldots nload}\right] \tag{11.48}$$

Equation. (5.30) can be written for slack bus as:

$$\lambda_{ps} = \frac{\partial C_s(Pg_s)}{\partial Pg_s} \tag{11.49}$$

and (11.43) can be written for slack and PV buses respectively as:

$$\lambda_{qs} = \frac{\partial C_s(Qg_s)}{\partial Qg_s} \tag{11.50}$$

$$\lambda_{qi} = \frac{\partial C_i(Qg_i)}{\partial Qg_i} \ i = 1, \ldots\ldots ng \tag{11.51}$$

Therefore, real (λ_p) and reactive (λ_q) marginal prices for slack bus, PV buses and PQ buses are obtained solving (11.48)–(11.51).

Short run marginal cost (SRMC) of real power wheeling PWC_{ij} and reactive power wheeling QWC_{ij} for transaction from bus i to j are calculated by following equations:

$$PWC_{ij} = PW_{ij}x\ (\lambda_{pj} - \lambda_{pi}) \tag{11.52}$$

$$QWC_{ij} = QW_{ij}x\ (\lambda_{qj} - \lambda_{qi}) \tag{11.53}$$

where, PWC_{ij} and QWC_{ij} are real power and reactive power to be wheeled from bus i to j, respectively.

3. *Algorithm for marginal cost transmission pricing method*

Step 1 All system voltages and pool loads are set to initial conditions. All feasible (scheduled) firm transactions are added to the system.

Step 2 For active power generation cost, reactive power generation cost of all pool generators and capacitor reactive power support cost, the optimization of objective function (11.32) is carried out satisfying all constraints (11.35)–(11.41) using GA-Fuzzy approach. The inequality constraints of tap setting transformers are also considered in this optimization process.

Step 3 After the optimization, voltages, tap settings, capacitors reactive supports and pool generations are obtained.

Step 4 Marginal costs for both real and reactive power at all buses are calculated using (11.48–11.50).

Step 5 SRMC of wheeling for bilateral transactions are calculated using (11.52) and (11.53), respectively.

Step 6 The amount to be paid by each demand and amount to be received by each genco is determined based on marginal cost. Similarly, multilateral transaction is treated.

Step 7 The Marginal network revenue is determined based on total payments and receipts.

4. *Application of marginal cost transmission pricing method*

The results of method tested for modified IEEE 30 bus system are presented here. The data and single line diagram of this system is given in Appendix F.

The calculations shown in Tables 11.13–11.17 indicates that due to implementation of marginal prices (i.e. nodal prices), marginal network revenue of 40.301905 \$/h is obtained.

Table 11.13. Revenue received from Pool demand

Bus no.	Real demand (MW)	λ_{pi} (\$/MW h)	Revenue (\$/h)	Reactive demand (MVAr)	λ_{qi} (\$/MVAr h)	Revenue (\$/h)
1	0	3.31921	0	0	0.049762	0
2	21.7	3.435997	74.56113	12.7	0.042547	0.540345
3	2.4	3.513915	8.433397	1.2	0.101652	0.121983
4	7.6	3.570239	27.13382	1.6	0.110167	0.176267
5	94.2	3.690331	347.6292	19	0.127005	2.413096
6	0	3.612632	0	0	0.129748	0
7	22.8	3.66913	83.65617	10.9	0.144936	1.579805
8	30	3.626385	108.7916	30	0.150447	4.513415
9	0	3.616505	0	0	0.123827	0
10	5.8	3.621814	21.00652	2	0.13621	0.27242
11	0	3.61415	0	0	0.094843	0
12	11.2	3.599261	40.31173	7.5	0.126418	0.948136
13	0	3.598323	0	0	0.123478	0
14	6.2	3.676129	22.792	1.6	0.141555	0.226487
15	8.2	3.685928	30.22461	2.5	0.134784	0.336961
16	3.5	3.634265	12.71993	1.8	0.141915	0.255447
17	9	3.64232	32.78088	5.8	0.143435	0.831922
18	3.2	3.723113	11.91396	0.9	0.142798	0.128519
19	9.5	3.728377	35.41958	3.4	0.142602	0.484848
20	2.2	3.704354	8.149579	0.7	0.13277	0.092939
21	17.5	3.662132	64.08731	11.2	0.159024	1.78107
22	0	3.659034	0	0	0.156488	0
23	3.2	3.722763	11.91284	1.6	0.12908	0.206529
24	8.7	3.736867	32.51075	6.7	0.158234	1.060166
25	0	3.746257	0	0	0.152652	0
26	3.5	3.822748	13.37962	2.3	0.203776	0.468684
27	0	3.674906	0	0	0.128106	0
28	0	3.640752	0	0	0.140059	0
29	2.4	3.783965	9.081516	0.9	0.116025	0.104422
30	10.6	3.858995	40.90535	1.9	0.147013	0.279325
Total			1037.401	Total		16.82278

Table 11.14. Expenditure for generation

Bus no.	Real generation (MW)	λ_{pi} (\$/MW h)	Expenditure (\$/h)	Reactive generation (MVAr)	λ_{qi} (\$/MVArh)	Expenditure (\$/h)
1	174.961	3.31921	580.7323	11.902	0.049762	0.592267
2	47.529	3.435997	163.3095	15.599	0.042547	0.663691
5	21.176	3.690331	78.14645	36.06	0.127005	4.5798
8	24.51	3.626385	88.8827	34.885	0.150447	5.248344
11	12.039	3.61415	43.51075	15.297	0.094843	1.450813
13	12.329	3.598323	44.36372	21.845	0.123478	2.697377
Total			998.9454	Total		15.23229

Table 11.15. Revenue received from Bilateral transactions

Transaction no.	From bus	To bus	Size (MW)	SRMC (\$/MW h)	Revenue Received (\$/h)
1	9	13	5	−0.018182	−0.09091
2	22	25	5	0.087223	0.436115
Total					0.345205

Table 11.16. Revenue received from multilateral transactions

Bus no.	MW	λ_{pi} (\$/MW h)	Expenditure (\$/h)	Bus no.	MW	λ_{pi} (\$/MW h)	Revenue received (\$/h)
6	4	3.612632	14.450528	11	2	3.61415	7.2283
7	2	3.66913	7.33826	13	3	3.598323	10.794969
				14	1	3.676129	3.676129
Total			21.788788	Total			21.699398

Table 11.17. Summary of results

S. no.		In (\$/h)
1	Revenue received from pool real demand	1,037.401
2	Revenue received from pool reactive demand	16.82278
3	Revenue received from bilateral transactions	0.345205
4	Revenue received from multilateral transactions	−0.08939
5	Expenditure for real generation	998.9454
6	Expenditure for reactive generation	15.23229
7	*Total revenue*	*1,054.479595*
8	*Total expenditure*	*1,014.17769*
9	*Marginal network revenue*	*40.301905*

11.4.3 Postage Stamp Method

It is a simplest method of transmission pricing and makes no distinction between transaction with regard to the power flow path, supply or delivery points, or the time when it takes place.

The results of this method tested for Indian UPSEB-75 bus system are presented in Table 11.18 in this section (Fig. 11.13–11.17). Single line diagram and transmission ARR (annual revenue requirement) data is given Appendix G.

Table 11.18. Embedded cost allocation for Indian UPSEB 75-bus system using postage stamp method

Transactions	Rs. lakh/h
Bilateral T1	0.211683854
Bilateral T2	0.190515469
Bilateral T3	0.15876289
Bilateral T4	0.105841927
Bilateral T5	0.088589693
Bilateral T6	0.034504468
Bilateral T7	0.042336771
Bilateral T8	0.02857732
Bilateral T9	0.031752578
Bilateral T10	0.148178698
Bilateral T11	0.052920963
Bilateral T12	0.465704479
Multilateral	2.937854367
Pool	1.264408828
Total ARR	5.761632306

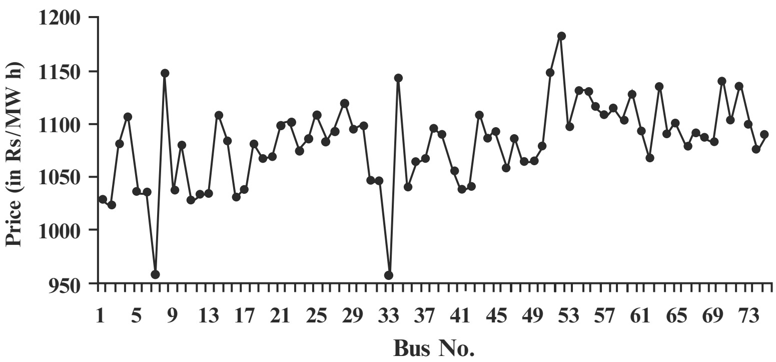

Fig. 11.13. Real marginal price for Indian UPSEB 75-bus system

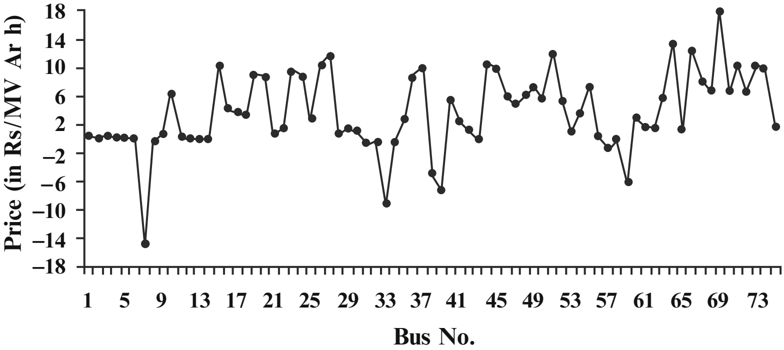

Fig. 11.14. Reactive marginal price for Indian UPSEB 75-Bus System

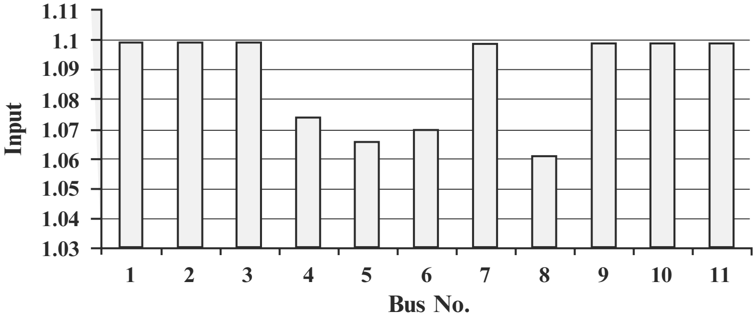

Fig. 11.15. Generator bus voltage for Indian UPSEB 75-Bus System

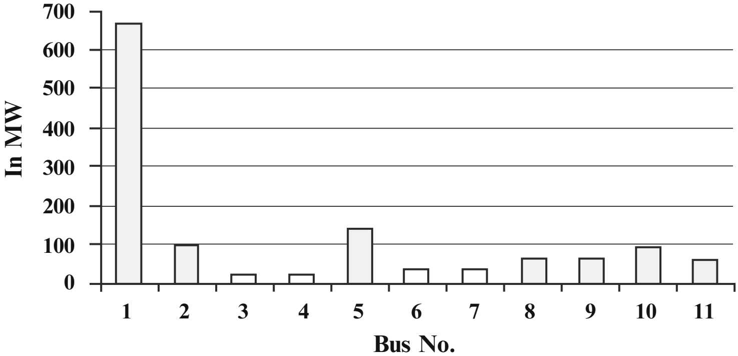

Fig. 11.16. Optimal values of real power generation for Indian UPSEB 75 Bus System

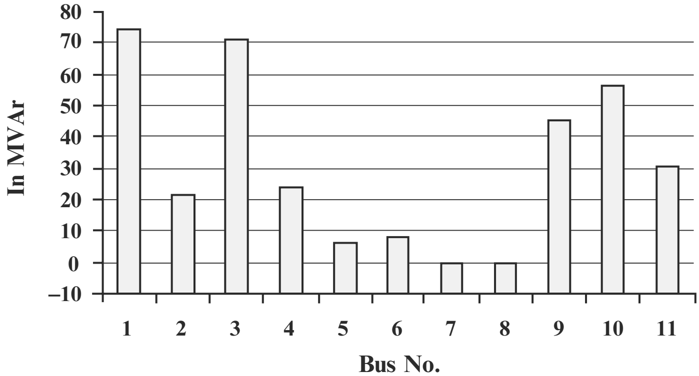

Fig. 11.17. Optimal values of reactive power generation for Indian UPSEB 75 Bus System

11.4.4 MW Mile Methods

It requires the accurate load flow results to compute the power flow in the lines. Once the power flow in each line is known, system usage index for each transaction is calculated. The transmission charge is then proportional to the transmission usage by individual transaction. The system usage index for each transaction is calculated by following relation:

$$UI_{T_i} = \sum_j \left[\frac{P_{j;T_i} * (L_j * F'_j)}{(\sum_i P_{j;T_i} + P_{j;pool})} \right] \tag{11.54}$$

UI_{T_i} = Price charged for transaction T_i in \$ (System Usage Index)
P_{j,T_i} = Incremental loading of line j due to transaction (bilateral/multilateral) T_i, MW.
$P_{j;pool}$ = Loading of line j due to pool transactions, MW.
L_j = Length of the line j, mile.
F'_j = Cost of the line per unit length, \$/Mile.

(i) *Procedure to calculate system usage index*

Step 1: Find the cost of the line by multiplying the unit cost of the line by the line lengths $(L^*_j\ F'_j)$.

Step 2: Find the base case power flow on all lines, which can be obtained using an OPF.

Step 3: Find the new load flow solution with each transaction T_i and hence the power flows on each line.

Step 4: Calculate the incremental power flows in each line caused by the transaction T_i.

Step 5: Calculate each line usage due to transaction T_i by multiplying incremental line flows obtained in Step 4 and cost of per unit length of line in Step 1, i.e. $P^*_{j,T_i}(L^*_j\ F'_j)$, where j is any line.

Step 6: Find the total system usage by transaction T_i, i.e. $\sum_j P^*_{j,T_i}(L^*_j\ F'_j)$.

Step 7: The system usage UI_{T_i} (System Usage Index) of each transaction T_i is calculated for proportional allocation of ARR given by equation (11.54).

Step 8: Calculate the proportional allocation of ARR to transaction T_i.

(ii) *Proposed methods for proportional allocation of ARR*

Let

UI_{T_i} = system usage index of any transaction T_i(bilateral/multilateral) as given by (11.54)

UI_{pool} = system usage index due to pool transactions, as given by (11.55)

$$UI_{pool} = \sum_j \left[\frac{P_{j;pool} * (L_j * F'_j)}{(\sum_i P_{j;T_i} + P_{j;pool})} \right] \tag{11.55}$$

$UI_{combined_i}$ = system usage index due to all transactions taken simultaneously, i.e. bilateral+multilateral (if any), as given by (5.44)

$$UI_{combined} = \sum_j \left[\frac{P_{j;\sum T_i} * (L_j * F'_j)}{(P_{j;\sum T_i} + P_{j;pool})} \right] \tag{11.56}$$

where $P_{j;\sum T_i}$ = Incremental loading of line j due to all transactions taken simultaneously, i.e. bilateral+multilateral (if any), MW.

The ARR allocation can be done by two possible methods discussed below:

Method-1 (When all transactions are considered independently)

$$\text{Transmission charges paid for transaction } T_i(R_{T_i})$$
$$= ARR \times \frac{UI_{T_i}}{(\sum_i UI_{T_i} + UI_{pool})} \tag{11.57}$$

Transmission charges paid for pool transactions $(R_{pool}) = ARR$ – Transmission charges paid for transactions T_i, *i.e. (Bilateral and Multilateral, if any)*

$$= ARR \times \frac{UI_{pool}}{(\sum_i UI_{T_i} + UI_{pool})} \tag{11.58}$$

In this method ARR is shared by all transactions (bilateral, multilateral and pool) on the basis of their respective system usage. The system usage is measured here in terms of system usage index. Whenever another bilateral or multilateral transaction takes place, the ARR is redistributed among all transactions according to new and lesser system usage index values. Therefore, charges paid by each transaction become less compared to earlier case (i.e. when new transaction did not take place). This method gives incentive to all old transactions whenever new transaction takes place in the system.

This method suffers from a major drawback whenever two or more than two transactions take place simultaneously. In that case it charges higher than actual values (transactions are taken simultaneously) for bilateral and multilateral transactions. Therefore, pool transactions have advantage of paying lesser amount of charges. The reason of this drawback is that combined usage index ($UI_{combined}$) of transactions, i.e. (bilateral + multilateral, if any) is less than sum of usage indexes ($\sum_i UI_{T_i}$) of transactions, i.e. (bilateral + multilateral, if any) treating each of them independently. This is due to difference in actual value of power flow in each line (considering all transactions taking place simultaneously) and algebraic sum of power flow in each line due to bilateral and multilateral transactions (if any) independently.

Method-2 (When all transaction are considered simultaneously)

Allocation of transmission charges paid for bilateral and multilateral transactions simultaneously

$$(R_{combined}) = ARR \times \frac{UI_{combined}}{(UI_{combined} + UI_{pool})} \tag{11.59}$$

$$\text{Transmission charges paid for transaction } T_i(R_{T_i}) = R_{combined} \times \frac{UI_{T_i}}{\sum_i UI_{T_i}} \tag{11.60}$$

$$\text{Transmission charges paid for pool transactions } (R_{pool}) = ARR - \sum_i R_{T_i} \tag{11.61}$$

In this method, collective charges for all bilateral and multilateral transactions (if any) are calculated. Then individual contribution to collective charges for each transaction is calculated on the basis of system indexes of transactions (while considering all transactions independently). Therefore, drawback of method-1 is rectified in this method. This method is more transparent in nature than method-1.

(iii) *Application of proposed MW-Mile methods*

The results obtained for both the methods on Indian UPSEB 75-Bus system are given in Table 11.19, whereas system data and line data are given in Appendix G. System usage indices for both the methods are given in Table 11.20. The results reveal that due to effect of all the transactions taking place simultaneously in method-2 the charges allocated to bilateral and multilateral transactions are lesser as compared to method-1.

Table 11.19. Embedded cost allocation for Indian UPSEB 75-bus system using MW-mile methods

Transactions	Method-1 (Rs. lakh/h)	Method-2 (Rs. lakh/h)
Bilateral T1	0.132874487	0.073341923
Bilateral T2	0.226654476	0.125105094
Bilateral T3	0.042219114	0.023303428
Bilateral T4	0.056802223	0.031352778
Bilateral T5	0.058398303	0.032233757
Bilateral T6	0.015925418	0.008790256
Bilateral T7	0.023775288	0.013123101
Bilateral T8	0.012272944	0.006774222
Bilateral T9	0.195182687	0.107733801
Bilateral T10	0.12254473	0.06764027
Bilateral T11	0.052171774	0.028796937
Bilateral T12	0.498692644	0.275260348
Multilateral	2.227124232	1.229292226
Pool	2.096993986	3.738884167
Total ARR	*5.761632306*	*5.761632306*

Table 11.20. System usage indexes for transactions when all transactions are taking place independently

S. no.	Transaction	System index
1	Bilateral T1	0.001286717
2	Bilateral T2	0.002194855
3	Bilateral T3	0.000408837
4	Bilateral T4	0.000550056
5	Bilateral T5	0.000565512
6	Bilateral T6	0.000154217
7	Bilateral T7	0.000230233
8	Bilateral T8	0.000118848
9	Bilateral T9	0.001890091
10	Bilateral T10	0.001186687
11	Bilateral T11	0.000505216
12	Bilateral T12	0.004829192
13	Multilateral	0.021566811
14	Pool	0.020306668
	Total (Bilateral+Multilateral+Pool)	*0.05579394*

When all bilateral and multilateral transactions are taking place simultaneously

S. No.	Transaction	System index
1	Bilateral+multilateral	0.032869084
2	Pool	0.02668025
	Total (Bilateral+Multilateral+Pool)	*0.059549334*

11.4.5 Hybrid Deregulated Transmission Pricing Model

To facilitate efficient competition in generation, the transmission utility, i.e. Transco (which shall continue to operate as monopoly) is obliged to provide full access to the transmission facilities in a non-discriminatory manner. In order for Transco to operate viably, the charges should be sufficient to cover Transco's revenue requirement. It is noted in (Tabors 1994) and findings of study team report (Echauz and Vachtsevanos 1994) discussed that in a regulated environment such as in electric transmission business, marginal cost based pricing provides an efficient economic and engineering solution to developing a tariff structure.

However, it has been observed that relying solely on this marginal pricing does not generate sufficient revenue for the transmission utility, and the common solution is to establish supplementary charges which when added to the marginal network income would equal to the total network cost. This would mean that a composite cost paradigm may be implemented, based on embedded costs and marginal costs to reflect transmission pricing based on actual costs of existing network facilities, as well as the operation cost. After identifying need of supplementary charges, a brief discussion on the method of supplementary charges allocation and application of the hybrid model to the Indian UPSEB 75-Bus system are in following section.

1. *Method of supplementary charge allocation*
   The allocation of supplementary charges creates additional challenge as how to allocate the charge among transmission users in an equitable manner and to ensure that it does not distort the economic signals provided by marginal pricing. Probably the most popular method is linking the charge with the actual use of the system by the user. In the MW-Mile methodology the actual use of transmission facilities is expressed, conceptually, by a product of power due to a particular transaction times the distance this power travels in the network. Therefore in this hybrid model supplementary charges are allocated on the basis of two MW-Mile methods already explained in earlier section.
2. *Application of proposed Hybrid transmission pricing model to Indian UPSEB 75-Bus system*
   The results of proposed model tested for Indian UPSEB 75-Bus system are presented here.

The results are obtained for marginal prices, generator bus voltages, real power generations and reactive power generations after applying algorithm for marginal cost based transmission pricing method. The calculations shown in Tables 11.21–11.25 that due to implementation of marginal prices (i.e. nodal prices), marginal network revenues of 112,954.4 Rs/h is obtained.

Table 11.21. Revenue received from pool demand

Bus no.	Real demand (MW)	λ_{pi} Case-II (Rs/MW h)	Revenue Case-II (Rs/h)	Reactive demand (MVAr)	λ_{qi} Case-II (Rs/MVAr h)	Revenue Case-II (Rs/h)
1	0	1028.018	0	0	0.558	0
2	0	1023.905	0	0	0.086	0
3	0	1082.344	0	0	0.473	0
4	0	1108.433	0	0	0.162	0
5	0	1034.929	0	0	0.013	0
6	0	1034.556	0	0	0.039	0
7	0	960.118	0	0	−14.59	0
8	0	1146.357	0	0	−0.424	0
9	0	1036.89	0	0	0.636	0
10	0	1080.348	0	0	6.428	0
11	0	1027.98	0	0	0.368	0
12	27	1033.528	27905.26	0	0	0
13	12	1034.753	12417.04	0	0	0
14	0	1109.193	0	0	0	0
15	0	1085.629	0	0	10.432	0
16	0	1030.641	0	0	3.998	0
17	0	1036.924	0	0	3.731	0
18	0	1082.531	0	0	3.335	0
19	0	1067.155	0	0	9.05	0
20	56.37	1069.194	60270.47	1.06	8.928	9.46368
21	0	1098.966	0	0	0.791	0
22	0	1102.138	0	0	1.23	0
23	0	1075.28	0	0	9.573	0
24	27.95	1086.46	30366.56	7.66	8.927	68.38082
25	0	1110.085	0	0	2.591	0
26	0	1084.315	0	0	10.519	0
27	106	1094.203	115985.5	7.83	11.769	92.15127
28	0	1118.675	0	0	0.669	0
29	0	1094.279	0	0	1.201	0
30	0	1098.456	0	0	0.944	0
31	0	1045.211	0	0	−0.742	0
32	18.11	1045.804	18939.51	11.59	−0.419	−4.85621
33	0	959.137	0	0	−9.132	0
34	0	1146.321	0	0	−0.422	0
35	0	1037.723	0	0	2.895	0
36	0	1063.1	0	0	8.97	0
37	0	1067.299	0	0	9.852	0
38	0	1096.058	0	0	−5.066	0
39	0	1089.664	0	0	−7.35	0
40	0	1055.626	0	0	5.665	0
41	0	1037.16	0	0	2.311	0
42	112.5	1039.465	116939.8	−294.7	1.173	−345.683

Table 11.21. (*Continued*)

Bus no.	Real demand (MW)	λ_{pi} Case-II (Rs/MW h)	Revenue Case-II (Rs/h)	Reactive demand (MVAr)	λ_{qi} Case-II (Rs/MVAr h)	Revenue Case-II (Rs/h)
43	0	1109.193	0	0	0	0
44	0	1087.5	0	0	10.409	0
45	0	1093.023	0	0	9.998	0
46	0	1058.116	0	0	5.942	0
47	34.55	1087.35	37567.94	4.38	4.748	20.79624
48	0	1063.089	0	0	6.057	0
49	25.72	1062.683	27332.21	15.8	7.055	111.469
50	2.1	1077.431	2262.605	9.2	5.617	51.6764
51	57.75	1149.66	66392.87	0.62	12.028	7.45736
52	14.27	1183.529	16888.96	−23.36	5.45	−127.312
53	12.63	1096.113	13843.91	0.33	1.16	0.3828
54	21.95	1131.157	24828.9	17.02	3.673	62.51446
55	14.23	1129.993	16079.8	2.81	7.392	20.77152
56	0	1114.006	0	0	0.362	0
57	52.78	1107.552	58456.59	18.53	−1.514	−28.0544
58	54.19	1112.947	60310.6	11.29	−0.335	−3.78215
59	21.89	1103.845	24163.17	11.01	−6.318	−69.5612
60	24.2	1128.782	27316.52	2.44	2.963	7.22972
61	56.5	1092.145	61706.19	6.58	1.651	10.86358
62	17.18	1067.086	18332.54	7.41	1.461	10.82601
63	58.01	1135.825	65889.21	5.31	5.95	31.5945
64	56.79	1090.578	61933.92	13.33	13.518	180.1949
65	47.84	1100.608	52653.09	12.81	1.361	17.43441
66	31.74	1077.662	34204.99	15.18	12.384	187.9891
67	0	1090.699	0	0	8.145	0
68	42.87	1087.015	46600.33	33.6	6.571	220.7856
69	55.94	1081.533	60500.96	32.53	18.014	585.9954
70	23.34	1140.459	26618.31	2.3	6.715	15.4445
71	0	1102.819	0	0	10.169	0
72	52.52	1135.953	59660.25	11.76	6.586	77.45136
73	37	1099.594	40684.98	4.46	10.297	45.92462
74	18	1074.16	19334.88	8.87	9.803	86.95261
75	0	1089.873	0	0	1.252	0
Total			*1306388*	*Total*		*1344.501*

As Transco's total revenue requirement is 576,163.2306 Rs/h, therefore supplementary charges of $(576,163.2306–112,954.4 = 463,208.8306$ Rs/h) can be realized by MW-Mile based supplementary charge allocation method.

Table 11.22. Expenditure for Generation

Bus No.	Real Generation (MW)	λ_{pi} (Rs/MW h)	Expenditure (Rs/h)	Reactive Generation (MVAr)	λ_{qi} (Rs/MVArh)	Expenditure (Rs/h)
1	669.08	1028.018	687826.3	74.39	0.558	41.50962
2	100	1023.905	102390.5	21.46	0.086	1.84556
3	20	1082.344	21646.88	70.59	0.473	33.38907
8	20	1108.433	22168.66	24.05	0.162	3.8961
5	140	1034.929	144890.1	6.36	0.013	0.08268
6	36.3	1034.556	37554.38	8.14	0.039	0.31746
7	33.72	960.118	32375.18	0	−130.59	0
8	60	1146.357	68781.42	0	−0.424	0
9	60	1036.89	62213.4	45.44	0.636	28.89984
10	90	1080.348	97231.32	56	6.428	359.968
11	60	1027.98	61678.8	30.44	0.368	11.20192
12	–	–	–	115.71	0	0
13	–	–	–	28.99	0	0
14	–	–	–	14.42	0	0
15	–	–	–	35	10.432	365.12
Total			*1338757*	*Total*		*846.2303*

Table 11.23. Revenue received from bilateral transactions

Transaction no.	From bus	To bus	Size (MW)	SRMC (Rs/MW h)	Revenue Received (Rs/h)
1	2	50	200	53.426	10, 685.2
2	3	55	180	47.649	8, 576.82
3	4	37	150	−41.134	−6, 170.1
4	5	20	100	34.265	3, 426.5
5	6	52	83.7	148.973	12, 469.04
6	7	62	32.6	106.968	3, 487.157
7	8	57	40.0	−38.805	−1, 552.2
8	9	74	27.0	37.27	1, 006.29
9	10	60	30.0	48.434	1, 453.02
10	11	54	140.0	103.177	14, 444.78
11	16	48	50.0	32.448	1, 622.4
12	75	73	440.0	9.721	4, 277.24
Total					*53, 726.15*

Allocation of supplementary charges

Finally, in order to complete realization of Transco's revenue requirement, allocation of supplementary charges by both the MW-Mile methods is tabulated in Table 11.26. Again, method-2 will be preferred over method-1

Table 11.24. Revenue received from multilateral transactions

Bus no.	MW	λ_{pi} (Rs/MW h)	Expenditure (Rs/h)	Bus No.	MW	λ_{pi} (Rs/MW h)	Revenue Received (Rs/h)
12	1,273	1,033.528	1,315,681	24	100	1,086.46	108,646
13	898.7	1,034.753	929,932.5	25	211	1,110.085	234,227.9
14	150.0	1,109.193	166,379	27	100	1,094.203	109,420.3
15	454.0	1,085.629	492,875.6	28	227	1,118.675	253,939.2
				30	126	1,098.456	138,405.5
				34	141	1,146.321	162,433.7
				39	170	1,089.664	185,242.9
				42	1,000	1,039.465	1,039,465
				46	156	1,058.116	165,066.1
				56	144	1,114.006	160,416.9
				67	200	1,090.699	218,139.8
				71	200	1,102.819	220,563.8
Total			*2,904,868*	Total			*2,995,967*

Net Revenue received = 91,099

Table 11.25. Summary of results

S. no.		(Rs/h)
1	Revenue received from pool real demand	1,306,388
2	Revenue received from pool reactive demand	1,344.501
3	Revenue received from bilateral transactions	53,726.15
4	Revenue received from multilateral transactions	91,099
5	Expenditure for real generation	1,338,757
6	Expenditure for reactive generation	846.2303
7	*Total Revenue*	*1,452,557.6*
8	*Total Expenditure*	*1,339,603.2*
9	*Marginal Network Revenue*	*112,954.4*

because it is more transparent. Moreover, in deregulated competitive business environment method-2 encourages more bilateral and multilateral transactions by charging lesser supplementary charges.

11.4.6 Conclusion

A SRMC based marginal pricing method using GA-Fuzzy technique is developed and tested on IEEE 30-bus system while optimizing real and reactive generation costs and capacitor reactive support cost. This method enables to calculate reactive power wheeling charges also. In category of embedded cost allocation methods – Postage Stamp allocation method and two MW-Mile methods are employed to determine embedded costs revealed that MW-Mile

Table 11.26. Supplementary charges allocation for Indian UPSEB 75-bus system using MW-mile methods

Transaction	Method-1 (in lakh Rs h)	Method-2 (in lakh Rs h)
Bilateral T1	0.106824984	0.058963537
Bilateral T2	0.182219829	0.100578771
Bilateral T3	0.0339422	0.01873487
Bilateral T4	0.045666393	0.025206201
Bilateral T5	0.046949571	0.025914469
Bilateral T6	0.012803304	0.007066962
Bilateral T7	0.019114255	0.010550379
Bilateral T8	0.009866922	0.005446185
Bilateral T9	0.156917909	0.086613025
Bilateral T10	0.098520359	0.054379684
Bilateral T11	0.041943715	0.023151418
Bilateral T12	0.400926047	0.221296713
Multilateral	1.790505797	0.988294604
Pool	1.685887022	3.005891488
Supplementary charges	*4.632088306*	*4.632088306*

(method-2) is best among all the three methods tested for Indian UPSEB-75 bus system.

Finally, a hybrid type marginal cost based deregulated transmission pricing model is proposed and tested for Indian UPSEB 75-bus system with pool, bilateral and multilateral transactions. In this supplementary charges are allocated by MW-mile methods. Therefore, a complete framework for transmission pricing is designed and implemented on Indian system.

11.5 Congestion Management Using GA-Fuzzy Approach

11.5.1 Introduction

Congestion is a consequence of various network constraints characterizing a finite network capacity that may limit the simultaneous delivery of power from an associated set of power transactions (Singh et al. 1998). The network constraints include thermal limits, voltage/VAR requirements and the stability considerations. Among all the constraints, thermal limits are the most frequently considered factor in determining network capacity.

In a deregulated electricity market, the task of ISO (Independent System Operator) is to ensure that contracted power transactions are carried out reliably. However, due to the large number of transactions that take place simultaneously, transmission networks may easily get congested. Congestion may result in preventing new contracts, unfeasibility in existing and new contracts, additional outages and damages to system components.

Managing congestion to minimize the restrictions of the competitive market has become the central activity of systems operators. It has been observed that the unsatisfactory management of transactions could increase the congestion cost which is an unwanted burden on customers. For different power market structures, the approach to manage congestion may vary. A number of methods dealing with congestion management in deregulated electricity markets have been discussed earlier. Hogan (1992) proposed the contract network and nodal pricing approach using the spot pricing theory for pool type market. Chao and Peck (1996) proposed an alternative approach which is based on parallel markets for link based transmission capacity rights and energy trading under a set of rules defined and administered by the System Operator (SO).

A congestion management approach after the deregulation of the Slovenian power system is presented in Grgic et al. (2001, 2002). The method is based on countertrade method where the system operator, based on technical and economic data, decides the optimal redispatch that eliminates congestion.

Singh and David (2003) has proposed dynamic security constrained congestion management in an unbundled electric power system. The different zones have been determined based on lines real and reactive transmission congestion.

Several optimal power flow (OPF) based congestion management schemes for multiple transactions also have been proposed. An approach using the minimum total modification to the desired transactions for relieving congestion is presented. A variant of this least modification approach used a weighting scheme with the weights being the surcharges paid by the transactions for transmission usage in the congestion-relieved network. Marginal cost signals were used for generators to manage congestion. A similar approach is proposed in (Singh et al. 1998), where the congestion cost is bundled with marginal cost at each bus in pool model and a congestion cost minimization is adopted in bilateral model.

Fu and Lamout (2001) has proposed the objective function consisting of congestion cost and service costs. A new mechanism of congestion management in multilateral transaction networks has been developed based on physical flows.

There are two broad paradigms that may be employed for congestion management. The first method includes actions like outage of congested lines or operation of transformer taps, phase shifters or FACTS devices. These means are termed as cost-free only because the marginal costs (and not the capital costs) involved in their usage are nominal.

The *not-cost-free* means include:

(1) *Rescheduling generation*
Here, system operator re-dispatches power generation in such a way, that resulting power flows does not overload any line. Every generation unit can bid an increase or decrease of its production in a similar manner

as this is done on a balancing market, while the responsibility of system operator is to select bids in efficient way. Somehow, counter trade approach based congestion management can be viewed as simplified optimal power flow problem, where optimization variables are re-dispatch of the active power production and criteria function is minimum of the costs related to this active power re-dispatch.

(2) *Prioritization and curtailment of loads/transactions*
A parameter termed as willingness-to-pay-to-avoid-curtailment was introduced in the objective function. This can be an effective instrument in setting the transaction curtailment strategies which may then be incorporated in the optimal power flow framework.

In this chapter, countertrade congestion management on GA-Fuzzy based OPF formulations incorporating (1) and hybrid type, i.e. both ((1) and (2)) above are presented and tested. The function of above OPF based models is to modify system dispatch to ensure secure and efficient system operation based on the existing operating condition. It would use the dispatchable resources (i.e. real and reactive power generations and capacitor reactive supports) and controls (i.e. transformer tappings) subject to their limits and determine the required curtailment of transactions to ensure uncongested operation of the power system. A new load curtailment scheme for pool loads is proposed where all connected loads are divided into three different groups depending on their *willingness to pay* up to certain load curtailment value.

11.5.2 Transmission Congestion Penalty Factors

A concept of transmission congestion penalty factors is developed and implemented to control line overflows in proposed GA-Fuzzy approach for congestion management. Transmission congestion penalty factor for each transmission line is computed which can adopt a suitable value depending upon amount of power flow (in MVA) above/below the maximum limit. Therefore, the congested line/lines and lines near to congested line/lines have higher values of transmission congestion penalty factors than other lines in the system. These transmission congestion penalty factors are helpful in deciding appropriate re-dispatchment of dispatchable resources. The procedure for determining transmission congestion penalty factors is explained in next section.

1. *Procedure to determine transmission congestion penalty factors*
   A base case situation is considered for congestion management. This base case refers to optimal settings of real power generation schedule, transformer tap settings and capacitor reactive support settings under normal state and with these settings now system is subjected to congestion (with one/more than one line limits is/are violated).

The following steps are followed to compute these penalty factors.

Step 1. Load flow solution and line flows ($S_{ij\text{-}base}$) are obtained for base case.
Step 2. Set the line limits in congestion case ($S_{ij\text{-}M}$).
Step 3. GA-Fuzzy approach as described earlier, is used to generate population of different generation schedules satisfying equality and non-equality constraints (except line flows limits).
Step 4. Line flows ($S_{ij\text{-}tr}$) are calculated for each such generation schedule and line penalty factors (P_{ij}, where i and j denote bus numbers between which transmission line is connected) are calculated according to Fig. 11.18.
Step 5. Another parameter, *line_flow_sum* representing cumulative effect of penalty factors and transmission line flows in congestion is computed as follows:

$$line\_flow\_sum = \sum_{l=1}^{n_1} P_{ij} * S_{ij-tr}$$

where n_l = no. of transmission lines.

These new types of transmission congestion penalty factors have two advantages. First, separate slope for penalty factor of each transmission line is determined depending upon power overflow above rated line flow value of that transmission line. It means that line with lesser power overflow will have lower value of slope, and thus will result small value of penalty factor. Similarly, it is understood that line with comparatively higher power overflow will have higher value of penalty factor. This adaptive feature is helpful in finding right solution (optimal values of control parameters, e.g. real power genera-

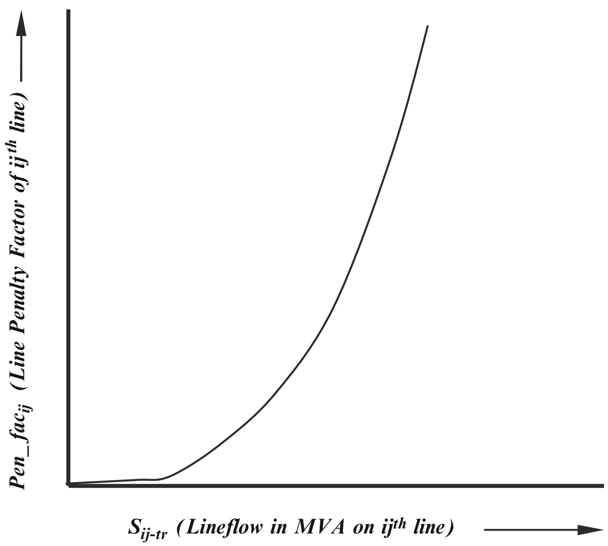

Fig. 11.18. Graphical representation of penalty factors as straight lines

tion, transformer tapping and capacitors values) by search techniques such as GA. Secondly, only single logic mentioned in step-4 works for determining these congestion penalty factors based on magnitude of power overflow in the line/lines. Therefore, no difficulty arises in choosing suitable values of penalty factors.

11.5.3 Proposed Methods for Congestion Management

Three methods are proposed with different objectives using GA-Fuzzy optimal approach and are explained below:

Method-1. Objective of minimization of line overflows only.

Method-2. Objective of minimization of line overflows along with (real power generation + reactive generation) redispatch cost and change in capacitor support cost.

Method-3. Objective of minimization of line overflows along with (real power generation + reactive generation) redispatch cost, change in capacitor support cost and load curtailment.

Mathematical functions representing redispatch cost of real power generation, reactive power generation and change in capacitor support cost are given below. The *real power redispatch cost* $C_{adj}(\Delta P_{g,k\text{-}m})$ is computed by adjusting generation of each generating unit less or more than base case value, with the help of *adjustment bids characteristics curves* shown in Fig. 11.19. These curves are decided by special *adjustment bids* $C_{adj,Pg,k\text{-}m}$ invited from all the generator units for generating power less or more than base case values. Therefore, *real power redispatch cost* ca be expressed as:

$$C_{adj}(\Delta P_{g,k\text{-}m}) - C_{adj,Pg,k\text{-}m} * \Delta P_{k\text{-}m} \ \$/hr \tag{11.62}$$

The reactive power cost of generator is also called opportunity cost Dai (2001). The reactive power output of a generator will reduce its active power generation capability which can serve at least as spinning reserve, and the corresponding implicit financial loss to generator is modeled as an opportunity cost. Therefore *reactive power redispatch cost* $C_{adj}(\Delta Q_{g,k\text{-}m})$ of generator as defined by Kumar (2004) is:

$$\begin{aligned} C_{adj}(\Delta Q_{g,k-m}) = \lfloor & C_{pg}(S_{G,\max,k-m}) \\ & - C_{pg}(\sqrt{S^2_{G,\max,k-m} - \Delta Q^2_{g,k-m}})\rfloor kprofit \ \$/h \end{aligned} \tag{11.63}$$

where $C_{pg}(P_{G,k-m}) = a_k + b_k P_{G,k-m} + c_{km} P^2_{G,k-m}$

i.e. the cost of active power generation is modeled by above quadratic function. Where a_k, b_k and c_k are costs coefficients of *kth* generator and $S_{G,\max,k-m}$ is the nominal maximum apparent power of generation and *kprofit* is the profit rate of active power generation taken between 5 and 10% [DAI01].

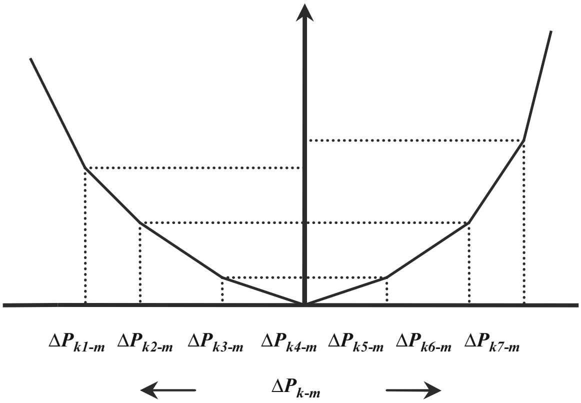

Fig. 11.19. Adjustment bid characteristic representing cost function of the change of active power production at the kth generator

The equivalent cost for return on the capital investment of the capacitors, which is expressed as their depreciation rates (the life span of capacitors is assumed as 15 years) is computed as

$$C(Q_{C,kc-m}) = Q_{C,kc-m} \frac{(\$11600/M\text{var})}{(15^*365^*24^*h)\ hour}$$
$$= Q_{C,kc-m}{}^* \$13.24/(100\,M \text{ var } hour) \qquad (11.64)$$

where h is the average usage rate of capacitors taken as 2/3. Equation (11.64) is a linear cost function with the slope of $\frac{dC_{adj,kc-m}(Q_{C,kc-m})}{dQ_{C,kc-m}} = \frac{\$13.24}{100\,M \text{ var } hour}$, which can be approximately represented as:

$$C_{adj}(\Delta Q_{C,kc-m}) = \Delta Q_{C,kc-m}{}^*(13.24/100)\$/hr \qquad (11.65)$$

Method 1 - Objective of minimization of line overflows only

Step 1. Real power generation redispatch $\Delta P_{g,k\text{-}m}$, reactive power generation redispatch $\Delta Q_{g,k\text{-}m}$ and change in capacitor reactive support $\Delta Q_{C,kl\text{-}m}$ are computed for each valid generation schedule in population, where k = generating unit no., kc = capacitor unit no. and m = no. of generation schedule in population.

Step 2. Correspondingly, redispatch costs of real power generation $C_{adj}(\Delta P_{g,k\text{-}m})$, reactive power generation $C_{adj}(\Delta Q_{g,k\text{-}m})$ and change in capacitor reactive support $C_{adj}(\Delta Q_{C,kcm})$ are computed as per expressions (11.62), (11.63), and (11.65), respectively.

Step 3. Fitness of each generation schedule in a population is calculated as:

$$Fitness = \frac{1}{A{*}line\_flow\_sum} \qquad (11.66)$$

where, A = numerical constant.

Step 4. Finally values of real and reactive power generation schedule, transformers tapping values, bus voltages, capacitor reactive support values and line flows calculated in last generation of GA-Fuzzy based optimization approach.

Method 2 - Objective of minimization of line overflows along with (real power generation + reactive generation) re-dispatch cost and change in capacitor support cost

1. Step1 and Step 2 of method-1 are followed.
2. Fitness of each generation schedule in a population is calculated as:

$$Fitness = \frac{e^{-B\times\left(\sum_{g}^{NG} C_{adj}(\Delta P_{g,k-m})+\sum_{g}^{NG} C_{adj}(\Delta Q_{g,k-m})+\sum_{c}^{NC} C_{adj}(\Delta Q_{C,kl-m})\right)}}{A \times line\_flow\_sum} \tag{11.67}$$

   where A and B are numerical constants.
3. Step 4 of method-1 is followed.

Method 3 – Objective of minimization of line overflows along with (real power generation + reactive generation) redispatch cost, change in capacitor support cost and load curtailment

1. Step1 of method-1 is followed.
2. If real loads connected on load buses under congestion are termed as base load values, then load cutailment is done by reducing base load values in three different groups (G-1, G-2 and G-3). G-1, G-2 and G-3 refer to groups of loads (consumers) which are paying fee (*willingness to pay*) for load curtailment upto 80, 60 and 40 of their base case load values respectively, in a congestion state. Load values after curtailment ($P_{d,kl\text{-}m,gr-i}$) in three different groups (G-1, G-2 and G-3) are computed.
3. Step2 of method-1 is followed.
4. Fitness of each generation schedule in a population is calculated as:

$$Fitness = \frac{\begin{array}{c} e^{-}B \times \left(\sum_{g}^{NG} C_{adj}(\Delta P_{g,k-m}) + \sum_{g}^{NG} C_{adj}(\Delta Q_{g,k-m}) + \sum_{c}^{NC} C_{adj}(\Delta Q_{C,kc-m})\right. \\ \left. + \sum_{i=1}^{3} K_i(\sum_{kl}^{NL} (P_{d,kl-m,gr-i}) - \sum_{kl}^{NL} (P_{d,kl-m,base-i}))^2\right) \end{array}}{A \times line\_flow\_sum} \tag{11.68}$$

   where A, B and K_i are numerical constants.
5. Step4 of method-1 is followed.

11.5.4 Test Results

The proposed methods are implemented on modified IEEE 30 bus system. The busdata and linedata are given in Appendix F. Line (8,28) get congested (exceeding flow limit of 12 MVA) if outage of line (6,28) is considered.

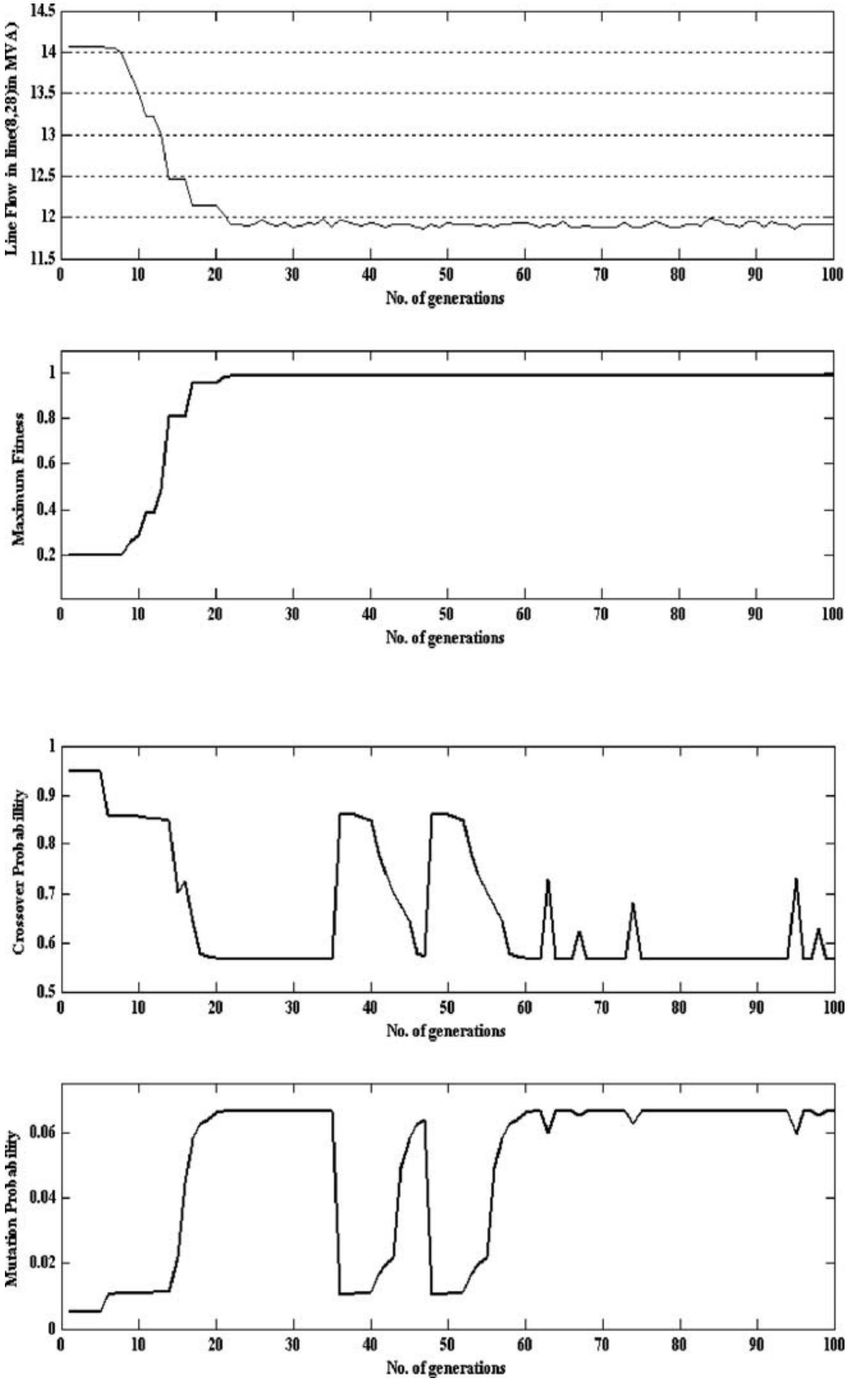

Fig. 11.20. Convergence of different parameters, crossover probability and mutation probability variations using GA-Fuzzy approach for Method-1

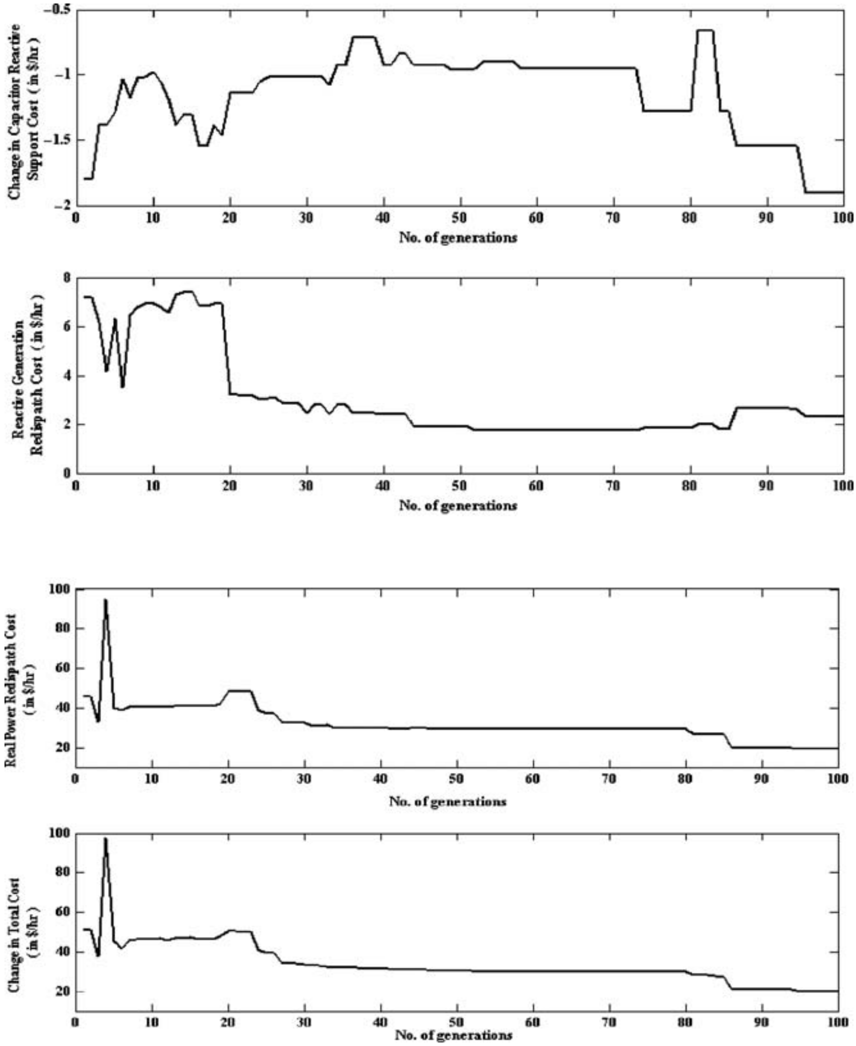

Fig. 11.21. Convergence of different parameters, crossover probability and mutation probability variations using GA-Fuzzy approach for Method-2

Figures 11.20, 11.21 and 11.22 show the convergence of different parameters along with crossover probability and mutation probability variations.

Figures 11.23–11.26 and Table 11.27 represent bus voltage profile for different methods.

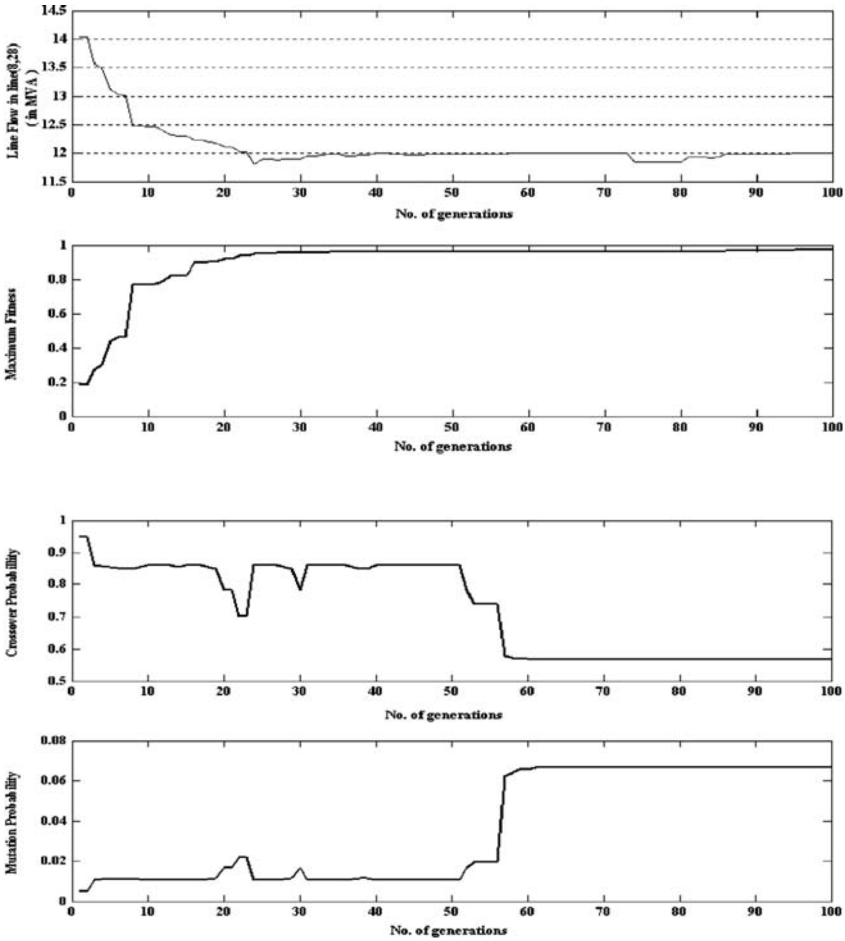

Fig. 11.21. (*Continued*)

11.5.5 Conclusions

The results tabulated in Table 11.28a shows optimal values of active power generation, reactive power generation and capacitor reactive support to avoid congestion for method-1 and method-2. Method-1 is found to be superior than method-2 so far controlling of power overflow is concerned. In table 28b method-2 seems to be more economical than method-1. The differences in performance of both the methods are due to modeling of their respective fitness function. In method-1, emphasis is only on control of power overflow on the Lines, whereas control of power overflow along with redispatch costs of (real power + reactive power) generation and change in capacitor

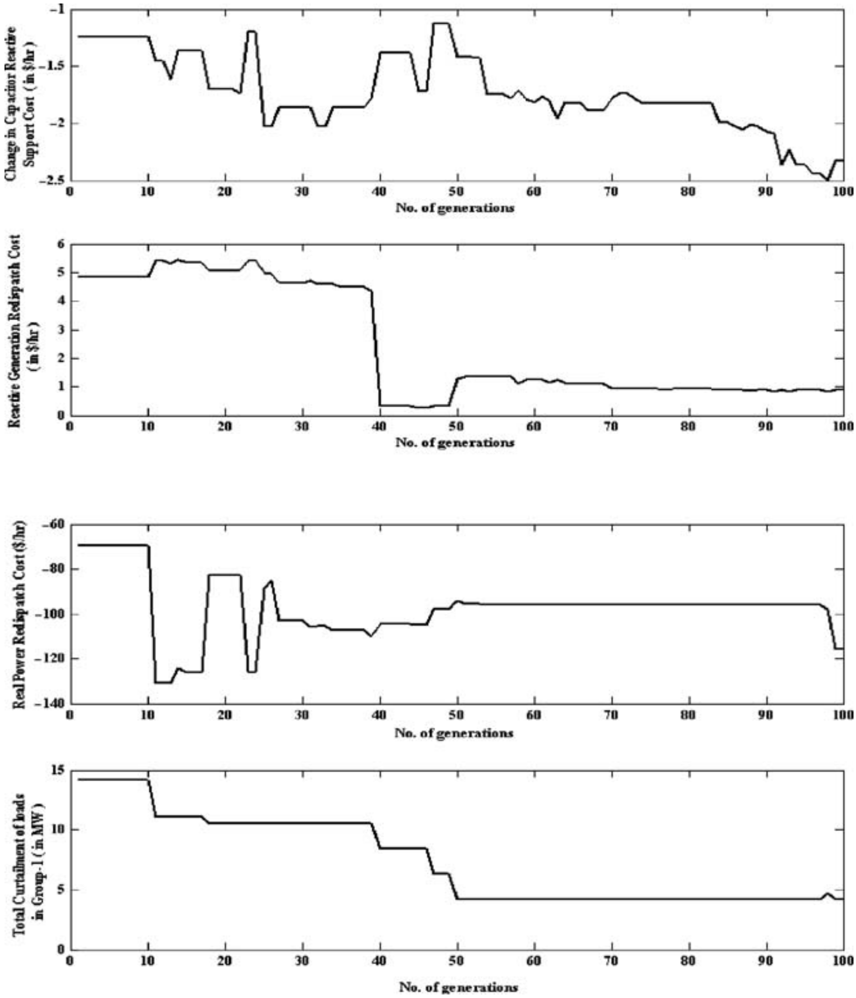

Fig. 11.22. Convergence of different parameters, crossover probability and mutation probability variations using GA-Fuzzy approach for Method-3

reactive support cost are intermingled in method-2. It is also clear from Fig. 11.21 for method-2 that a controlling action to check power overflow is dominant over economic redispatchment cost feature throughout the GA-Fuzzy based optimization procedure. From the results it is seen that slightly lesser load bus voltage variation (i.e. between maximum and minimum load bus voltages) with very small increment in average system voltage value (i.e. average of all bus voltages of the system). It means that from voltage point of view, method-2 is not inferior than method-1, although this particular aspect requires verification for other power systems also. Therefore,

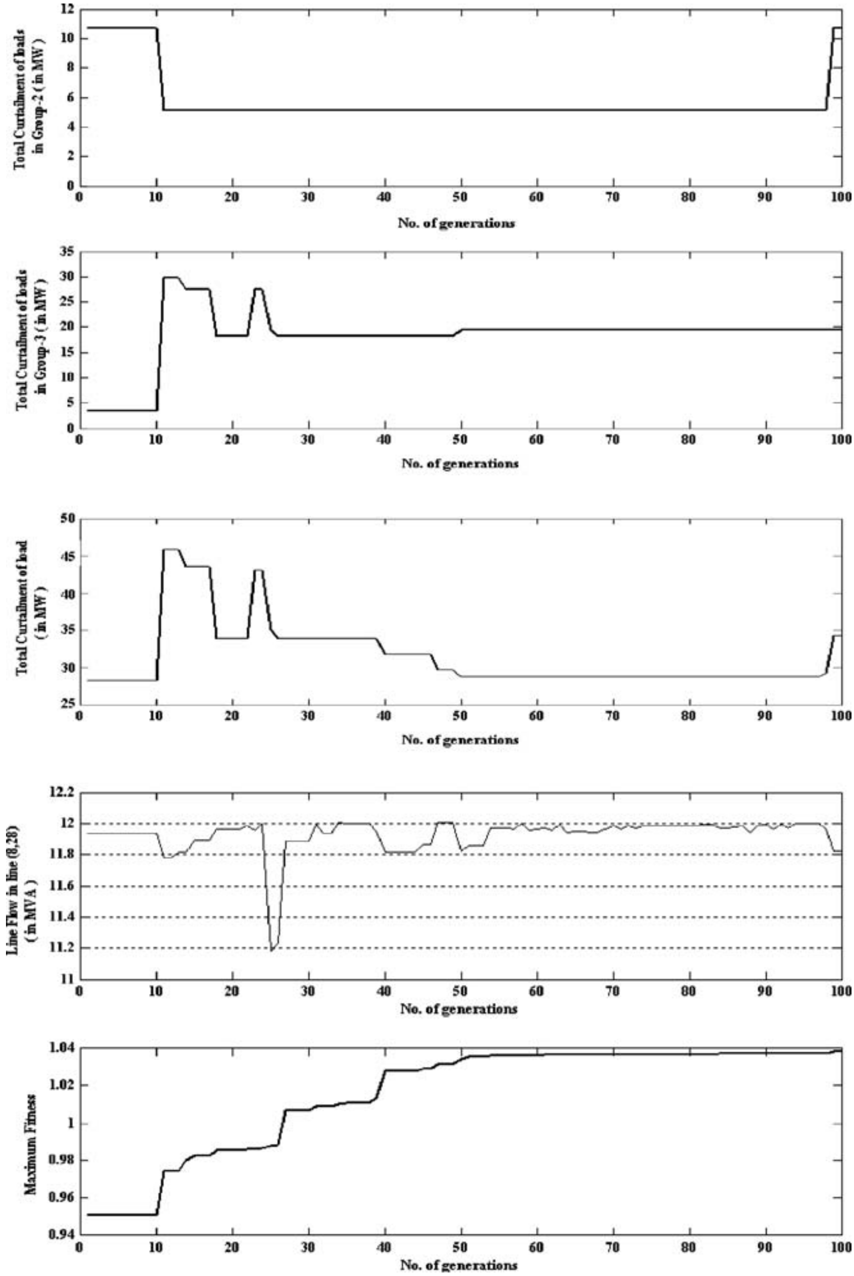

Fig. 11.22. (*Continued*)

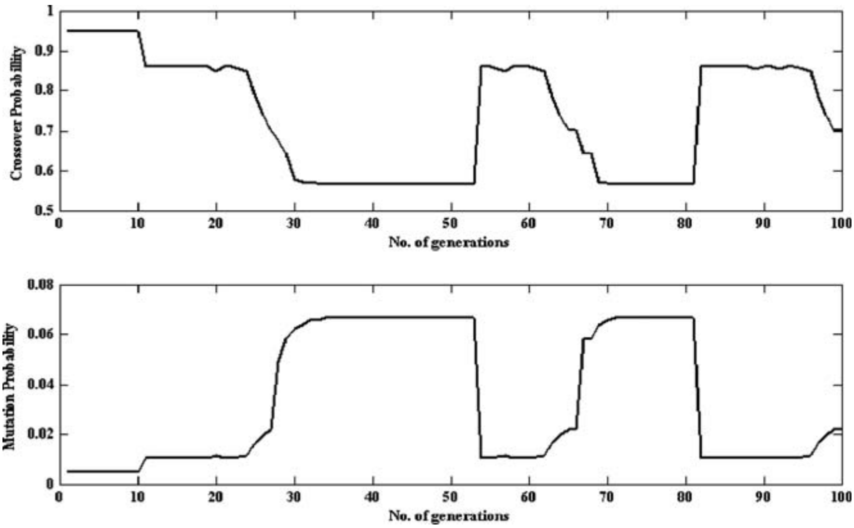

Fig. 11.22. (*Continued*)

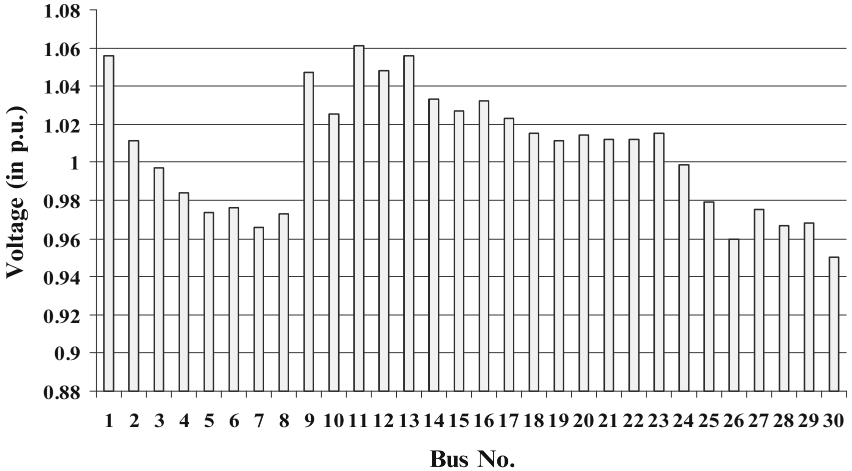

Fig. 11.23. Bus voltage profile using congestion management method-1

method-1 and method-2 both have applicability from congestion management view point.

Method-3 is developed for a scenario different from one in which method-1 and method-2 work. In this method, a load curtailment feature is also added in fitness function by mathematical modeling. This feature enables pool customers to pay extra charges in order to avoid congestion as shown in Ta-

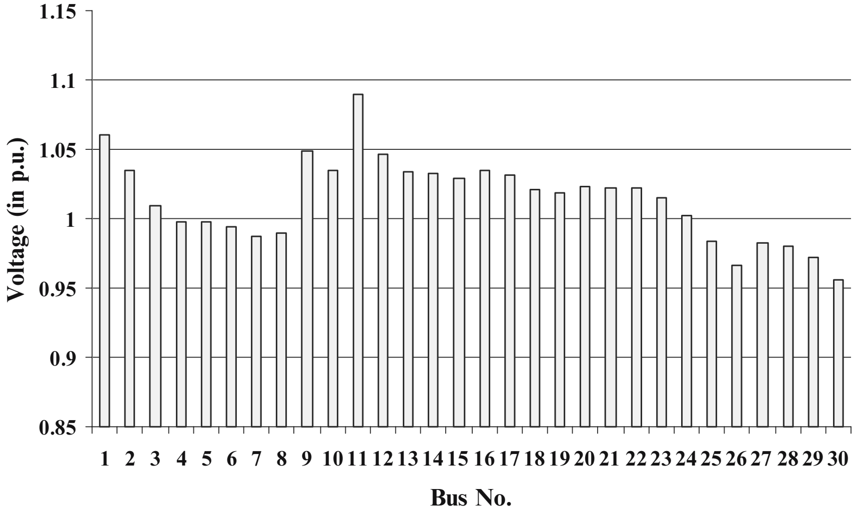

Fig. 11.24. Bus voltage profile using congestion management method-2, when kprofit = 5%

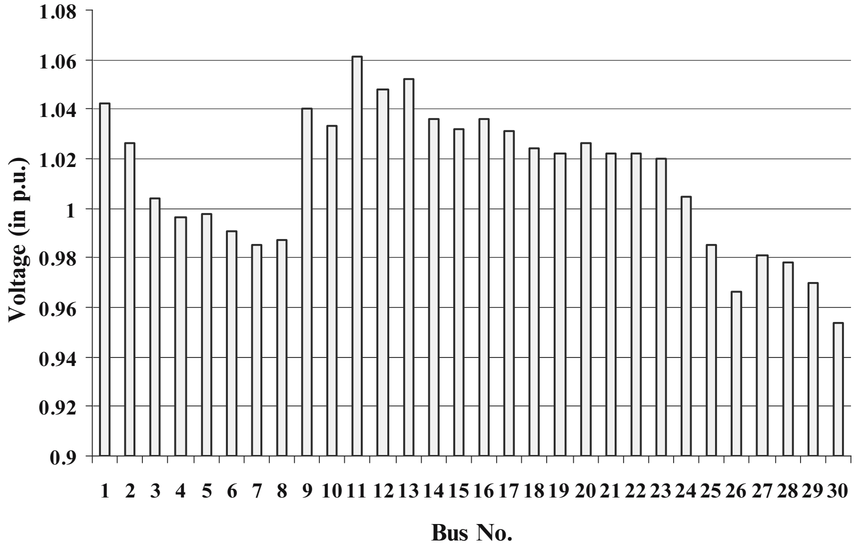

Fig. 11.25. Bus voltage profile using congestion management method-2, when kprofit = 10%

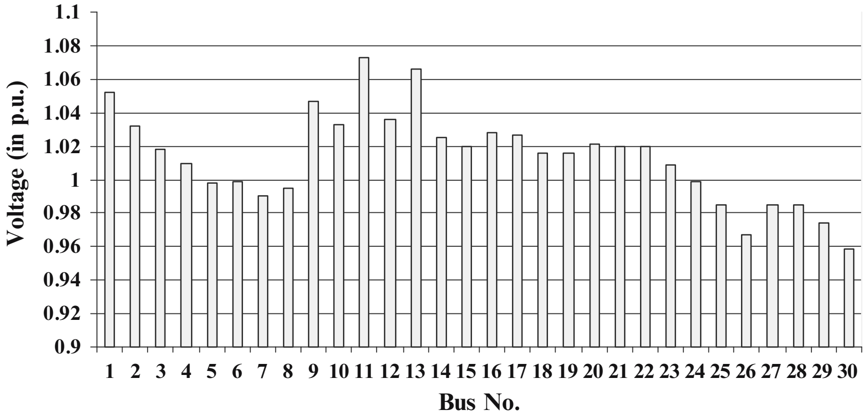

Fig. 11.26. Bus voltage profile using congestion management method-3

Table 11.27. Comparison of maximum and minimum voltage levels at Load buses and average system voltages for proposed methods of congestion management

		Method-1	Method-2		Method-3
			Kprofit = 5%	Kprofit = 10%	
load bus	Maximum	Bus 12: 1.048 p.u.	Bus 9: 1.049 p.u.	Bus 12: 1.048 p.u.	Bus 9: 1.047 p.u.
	Minimum	Bus 30: 0.95 p.u.	Bus 30: 0.956 p.u.	Bus 30: 0.954 p.u.	Bus 30: 0.959 p.u.
	Difference	0.098 p.u.	0.093 p.u.	0.094 p.u.	0.088 p.u.
Average value of system voltage		1.005533 p.u.	1.0139 p.u.	1.012433 p.u.	1.0135 p.u.

ble 11.28c. This method can be applicable in deregulated environment as it seems to be fair, transparent and consumer satisfaction to great extent.

A hybrid strategy having two stages is also formed on the basis of three methods developed and tested on modified IEEE 30 bus system. In first stage, method-1 or method-2 can be used. If congestion is still not avoidable then under second stage method-3 with load-curtailment and willingness to pay feature can be used.

11.5.6 Bibliography and Historical Notes

The application of genetic algorithms for altering membership functions of fuzzy controllers to make it adaptive Karr and Gentry 1993; Park et al. 1994).

The idea of fuzzifying genetic algorithms emerged in 1990s. Various ways of integrating fuzzy systems and genetic algorithms were proposed by Sanchez (1993), Xu and Vukovich (1993) and Buckley and Hayashi (1994a).

El-Hawary (1998) has shown various fuzzy system applications to Electric Power Applications in deregulated Environment. Iyer (2003) mentioned an integrated fuzzy-neural approach to electricity spot-price forecasting in a deregulated electricity market. Ming et al. (2004) used an ARIMA approach to forecasting electricity price. Saini et al. (2006) explained the GA-Fuzzy integrated System Approach to solve OPF problem and help in congestion management. Ravikumar et al. (2007) paper deals with the intelligent approach for fault diagnosis using support vector machines.

Table 11.28a. Comparison of redispatchment of P, Q, change in capacitor reactive power support and line flow at line (8,28) for method-1 and method-2

$$\textit{Real power generation redispatch cost (in \$h)} = \sum_{g}^{NG} C_{adj}(\Delta P_{g,k-m}) \quad Method-1\ Fitness = \frac{1}{A \times line\_flow\_sum}$$

$$\textit{Reactive power generation redispatch cost (in \$h)} = \sum_{g}^{NG} C_{adj}(\Delta Q_{g,k-m}) \quad Method-2\ fitness = \frac{e^{-B\times\left(\sum_{g}^{NG} C_{adj}(\Delta P_{g,k-m}) + \sum_{g}^{NG} C_{adj}(\Delta Q_{g,k-m}) + \sum_{c}^{NC} C_{adj}(\Delta Q_{C,kl-m})\right)}}{A \times line\ \_\ flow\ \_\ sum}$$

$$\textit{Change in capacitor support cost (in \$h)} = \sum_{c}^{NC} C_{adj}(\Delta Q_{c,kc-m}) \quad Method-3\ Fitness = \frac{e^{-B\left(\sum_{g}^{NG} C_{adj}(\Delta P_{g,k-m}) + \sum_{g}^{NG} C_{adj}(\Delta Q_{g,k-m}) + \sum_{c}^{NC} C_{adj}(\Delta Q_{C,kc-m}) + \sum_{i=1}^{3} K_i\left(\sum_{kl}^{NL}(P_{d,kl-m,gr-i}) + \sum_{kl}^{NL}(P_{d,kl-m,base-i})\right)^2\right)}}{A \times line\_flow\_sum}$$

S. no.	Generation at	In congestion state		Congestion management method					
				Method-1		Method-2			
						When kprofit = 5%		When kprofit = .10%	
		P_g(in MW)	Q_g(in MVAr)	P_g(in MW)	Q_g(in MVAr)	P_g(in MW)	Q_g(in MVAr)	P_g(in MW)	Q_g(in MVAr)
1.	Bus 1	175.165	4.624	156.568	72.914	163.962	32.23	156.348	7.958
2.	Bus 2	48.941	29.345	33.647	−4.262	41.882	39.692	48.471	41.596
3.	Bus 5	21.176	28.21	33.941	25.8	20.765	33.403	21.039	39.725
4.	Bus 8	22.647	40.559	12.549	29.386	11.667	27.073	12.451	29.301
5.	Bus 11	12.588	17.124	26.706	8.078	26.471	22.08	21.059	11.095
6.	Bus 13	12.00	10.263	28.8	6.634	28.031	−8.37	33.082	3.108
Total		292.517	130.125	292.211	138.551	292.778	146.107	292.45	132.782

Table 11.28a. (*Continued*)

S. no.	Generation at	In congestion state		Congestion management method					
				Method-1		Method-2			
						When kprofit = 5%		When kprofit = .10%	
		P_g(in MW)	Q_g(in MVAr)	P_g(in MW)	Q_g(in MVAr)	P_g(in MW)	Q_g(in MVAr)	P_g(in MW)	Q_g(in MVAr)
S.No.	Capacitor at	Q_C(in MVAr)		Q_C(in MVAr)		Q_C(in MVAr)		Q_C(in MVAr	
1.	Bus 10	3.982		1.585		2.299		4.012	
2.	Bus 12	0.02		2.916		1.037		0.02	
3.	Bus 15	4.149		0.998		4.354		3.836	
4.	Bus 17	4.99		3.043		1.937		3.562	
5.	Bus 20	4.432		1.526		2.114		4.658	
6.	Bus 21	4.354		0.802		0.773		3.748	
7.	Bus 23	4.54		3.503		1.155		3.464	
8.	Bus 24	4.687		4.237		1.791		2.485	
9.	Bus 29	2.097		4.355		3.387		2.903	
Total		33.251		22.965		18.847		28.686	
Line flow at line (8,28)(in MVA)		16.64		11.921		11.993		11.9715	

Table 11.28b. Comparison of congestion relief charges for method-1 and method-2

S. No.	Generation at	Congestion management method					
		Method-1		Method-2			
				When kprofit = 5%		When kprofit = .10%	
		$C(\Delta P_g)$(in \$ h)	$C(\Delta Q_g)$(in \$ h)	$C(\Delta P_g)$(in \$ h)	$C(\Delta Q_g)$(in \$ h)	$C(\Delta P_g)$(in \$ h)	$C(\Delta Q_g))$(in \$ h)
1.	Bus 1	−59.823	2.0764	−36.0217	0.3343	−60.5312	0.0097
2.	Bus 2	−48.4633	1.6359	−23.3393	0.1525	−1.5495	0.4278
3.	Bus 5	58.2958	0.0211	−1.3936	0.0978	−0.4239	0.9631
4.	Bus 8	−35.7547	0.3496	−38.7967	0.515	−36.0927	0.7102
5.	Bus 11	55.1735	0.3117	54.1465	0.0925	31.6587	0.2745
6.	Bus 13	67.8	0.0412	64.5317	1.1247	87.5395	0.3215
Total(in \$ h)		37.2283	4.4359	19.1269	2.3169	20.6009	2.706975
S. No.	Capacitor at	$C(\Delta Q_c)$(in \$/hr)		$C(\Delta Q_c)$(in \$/hr)		$C(\Delta Q_c)$(in \$/hr)	
1.	Bus 10	−0.3174		−0.2228		0.004	
2.	Bus 12	0.3834		0.1347		0	
3.	Bus 15	−0.4172		0.0271		−0.0414	
4.	Bus 17	−0.2578		−0.4042		−0.1891	
5.	Bus 20	−0.3848		−0.3069		0.0299	
6.	Bus 21	−0.4703		−0.4741		−0.0802	
7.	Bus 23	−0.1373		−0.4482		−0.1425	
8.	Bus 24	−0.0596		−0.3834		−0.2915	
9.	Bus 29	0.299		0.1708		0.1067	
Total(in \$ h)		−1.3619		−1.9071		−0.6041	
Grand total(in \$ h)		40.3023		19.5367		22.703775	

Table 11.28c. Redispatchment of (Real power + reactive power generation), change in capacitor reactive power support and line flow at line (8,28) for method-3

S. no.	Generation at	Method-3	
		P_g(in MW)	Q_g(in MVAr)
1.	Bus 1	150.747	13.316
2.	Bus 2	42.353	32.196
3.	Bus 5	19.529	30.004
4.	Bus 8	10.098	31.131
5.	Bus 11	15.02	13.246
6.	Bus 13	19.027	23.381
Total		256.774	143.273
S.No.	Capacitor at	Q_C(in MVAr)	
1.	Bus 10	2.329	
2.	Bus 12	2.808	
3.	Bus 15	1.693	
4.	Bus 17	0.401	
5.	Bus 20	1.986	
6.	Bus 21	1.027	
7.	Bus 23	1.115	
8.	Bus 24	1.115	
9.	Bus 29	3.16	
Total		*15.636*	

Table 11.28c. (*Continued*)

S. no.	Generation at	Method-3							
		P_g(in MW)				Q_g(in MVAr)			
S. no.	Load. Group-1	P_l(in MW)	Load Group-2		P_l(in MW)	Load Group-3		P_l(in MW)	
		In Congestion	Method-3		In Congestion	Method-3		In Congestion	Method-3
1.	Bus 7	22.8	21.6232	Bus 4	7.6	7.0116	Bus 2	21.7	14.56
2.	Bus 8	30.0	28.4516	Bus 5	94.2	86.9071	Bus 3	2.4	1.6103
3.	Bus 17	9.0	8.5355	Bus 15	8.2	7.5652	Bus 10	5.8	3.8916
4.	Bus 18	3.2	3.0348	Bus 16	3.5	3.229	Bus 12	11.2	7.5148
5.	Bus 26	3.5	3.3194	Bus 21	17.5	16.1452	Bus 14	6.2	4.16
6.	Bus 29	2.4	2.2761	Bus 23	3.2	2.9523	Bus 19	9.5	6.3742
7.	Bus 30	10.6	10.0529	Bus 24	8.7	8.0265	Bus 20	2.2	1.4761
Total		*81.5*	*77.2935*	*Total*	142.9	131.8369	*Total*	59.0	39.587
Line flow at line (8,28) (in MVA)		*11.823*							

Group G1- load group 1
Group G2- load group 2
Group G3- load group 3