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A GOAL ATTAINMENT MODEL FOR TRANSMISSION EXPANSION PLANNING USING A META HEURISTIC TECHNIQUE*

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Abstract– Power system restructuring and deregulation introduces new functions, the so-called open access to transmission network, for transmission system providers. Transmission system operators are dealing with facilitating more room for electric power transfer. The transmission expansion problem (TEP) is a crucial issue, especially as it can help competition under a new scheme of power system reform. There is a very limited capability in controlling this natural tendency of power flows, while transmission expansion is a major task to meet the growth of demand. There has been some research in this field, however, in this paper a hybridization of a meta heuristic technique associated with a conventional method is employed. Real genetic algorithm and goal attainment are combined in order to develop a constrained multi-objective optimization for TEP. By considering the load shedding of demand as well as capital cost of installation (CCI) for new transmission lines, a cost function is proposed in this paper. Case studies and results analysis on "Garver System" and IEEE 24-bus test system show the effectiveness of the proposed methodology.

Keywords– Transmission planning, electricity deregulation, artificial intelligence, goal attainment

1. INTRODUCTION

Electric power transmission network facilitates power plants to be located in regions more economically. With the never abating growth of electricity consumption and the increased competition in the power supply market, service providers are forced to maintain a continuous supply. As the national and international power supply industry is becoming deregulated, power industry future plans for transmission lines should be able to provide alternative paths for the flow of power from generators to load centres. Within the scheme of open access to power system networks, additional transmission to serve extra load demands can only be justified if a cost effective alternative for power generation exists [1]. Due to changes in load demand over both time and space, transmission expansion has always been a rather complicated task [2]. Changes such as load demand at a node, the output of a generator or switching line equipment to any part of the network instantaneously affect other parts of the network. These changes on load demand may cause congestion in some transmission lines [3]. There is only a very limited capability in controlling this natural tendency of power flows that can be managed by some devices such as: phase shifting transformers, HVDC lines, and FACTS [4]. Deregulation and restructure of the electricity industry encourages competition. The price of electric energy is determined by a supply-demand relationship. Therefore, energy supply pricing would be a function of time and location of demand. Moreover, restructuring increases uncertainty in load demand and market clearing price (MCP) [5, 6]. The

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price of electricity depends on the transmission network facilities. In the current restructured environment, the functions of the transmission system have been expanded beyond the historical roles of system reliability enhancement and the linkage between generation and load. The interconnection that has resulted from energy market deregulation enables more generators to compete for the provision of service in a larger aggregated market [6, 7].

However, inadequate transmission capability resulting from transmission bottlenecks has enabled some generators in local/closed markets to exercise market power [8]. In a restructured environment, a transmission system can therefore help competition and mitigate market power. In such an environment, the transmission network corresponds to an independent entity that provides transmission service in a transparent way. The implementation of a market mechanism leads to the creation of wholesale electricity markets both in pool mechanisms and bilateral transactions [6]. The operation of the power system is coordinated by either an Independent System Operator (ISO) as schedule coordinator (SC) or by a Transmission System Operator (TSO) [5]. It can be concluded that the mergence of transmission provider (TP) with ISO creates TSO. In some countries the operation of several transmission companies has also been recognized in a coordinated way leading to Regional Transmission Organization (RTO) [9].

2. LITERATURE REVIEW FOR TEP

In recent years research has been conducted in the area of transmission expansion planning (TEP). For example, a method for transmission expansion planning in a deregulated market environment is proposed by Contreras *et al.* [10]. The proposed method provides an analysis of the long-term multistage planning of a transmission system. The proposed approach utilises game theory techniques for solving subsets of a more complex model [10]. Buygi *et al*. argue that as restructuring increases, uncertainty in demand increases [8]. In order to predict these uncertainties in policies and demand, they propose a probability normal distribution function based on Monte Carlo simulation. Others consider different objective functions and deal with TEP as a standard optimisation problem. These include investment costs, load shedding, transmission losses and corona losses [1], [11-13]. Efforts have also been made by researchers to find optimal access points to the existing transmission network by non-utility generators through the enforcement of open-access rules. The objective here is the provision of a more efficient and economic power supply. The solution techniques are diverse but can be classified into three groups:

- Constructive heuristic methods;
- Classic optimization techniques;
- Meta heuristics methods.

The last has been used in recent years for the reason that it has the capability to find optimal solutions in large complex interconnected networks. Algorithms such as simulated annealing (SA), Genetic Algorithm, Tabu Search (TS) and greedy randomized adaptive search procedure (GRASP) need to be mentioned [14]. In this paper, a Combined Real Genetic Algorithm and Goal Attainment method (CoRGA) is developed for the TEP as a constrained optimization problem. In the following section the two mathematical formulations of the TEP using the goal attainment method is presented. In section 4 the results obtained from different standard cases are discussed followed by the concluding remarks in section 5.

3. MODELING TRANSMISSION EXPANSION PLANNING USING GOAL ATTAINMENT METHOD

Transmission expansion planning is a multiple objective problem, where installation costs for new lines and customer load shedding are the two most important ones. The following multi-objective optimisation problem is defined when the levels of importance of constraints may either be of equal or unequal values.

$$\begin{aligned} &\text{Min} \quad \left(f_1(\vec{x}),\ f_2(\vec{x}), \ldots\right) \\ &\text{subject to} \begin{cases} \vec{g}(\vec{x}) \le 0 \\ \vec{h}(\vec{x}) = 0 \end{cases} \end{aligned} \tag{1}$$

Where: f_i represents each goal function. X is control variable, g(x) is the function that represents soft constraints, and h(x) is the function that represents hard constraints.

If the optimal value of goal $f_i(\vec{x})$ is f_i^*, this problem can be modeled as a goal attainment problem [15]; therefore the model in Eq. (1) will be rewritten as Eq. (2).

$$\begin{aligned} &\text{Min} \quad Z \\ &\text{subject to} \begin{cases} f_i(\vec{x}) - w_i z_i \le f_i^* \\ \sum w_i = 1 \\ \vec{g}(\vec{x}) \le 0 \\ \vec{h}(\vec{x}) = 0 \end{cases} \end{aligned} \tag{2}$$

Where: w_i represents the relative attainment of the goal *i*. Thus a general TEP problem can be presented as:

$$\begin{aligned} &\text{Min} \quad Z \\ &\text{subject to} \begin{cases} \sum_{(i,\ j) \in \Omega} c_{ij} n_{ij} - w_1 z_1 = 0 \\ \sum_i r_i - w_2 z_2 = 0 \\ w_1 + w_2 = 1 \\ P_{Gi} - \sum_{j=1}^{N_b} |V_i||V_j|(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}) = P_{Di} + r_i \\ Q_{Gi} - \sum_{j=1}^{N_b} |V_i||V_j|(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}) = Q_{Di} + r_i \tan\varphi_i \\ |V_i|_{min} \le |V_i| \le |V_i|_{max} \\ P_{D_i}^{min} \le P_{D_i} \le P_{D_i}^{max} \\ P_{G_{min}} \le P_{G_i} \le P_{G_{max}} \qquad i = 1, \ldots, N_G \\ Q_{G_{min}} \le Q_{G_i} \le Q_{G_{max}} \qquad i = 1, \ldots, N_G \\ S_{ij} \le 0.8 S_{ij}^{max} \\ 0 \le n_{ij} \le \overline{n}_{ij} \\ n_{ij} : \text{integer}; \qquad (i,\ j) \in \Omega. \end{cases} \end{aligned} \tag{3}$$

Where:

c_{ij}: the investment cost for a circuit that can be added between buses *i* and *j*

n_{ij}: the number of circuit that is added between buses *i* and *j*

r_i : MW load shedding at bus i

P_{Gi}: real power generation at bus i

Q_{Gi}: reactive power generation at bus i

N_b: bus number

$\left|V_i\right|$: voltage magnitude at bus i

G_{ij}: real parts of the ijth element of Y_{bus} matrix

B_{ij}: real / imaginary parts of the ijth element of Y_{bus} matrix

PD_i: real load demand at bus i

QD_i : reactive load demand at bus i

φ_i : power factor at bus i

$P_{D\,i}^{\min}$ / $P_{D\,i}^{\max}$: minimum / maximum of load demand at bus i, respectively

P_{Gmax}: maximum real power generation at bus i

P_{Gmin} : minimum real power generation at bus i

Q_{Gmax}: maximum reactive power generation at bus i

Q_{Gmin}: minimum reactive power generation at bus i

S_{ij} : apparent power flow in line ij

S_{ijmax}: thermal limit of line ij

$\overline{n}_{ij}$: maximum number of circuits that can be added between buses *i* and *j*

Ω : the set of candidates for new transmission lines

In transmission expansion planning, uncertainty in demand can be defined at each individual load bus inside the range of its minimum and maximum demand $\left[P_{D_i}^{\min}; P_{D_i}^{\max}\right]$. It can be verified that the proposed model minimises load curtailment, while achieving the minimum installation costs of transmission lines. It should be noted that the algorithm tries to serve more loads besides managing investment costs, simultaneously. Different solutions can be acquired based on different values for w_is, where they provide an appropriate environment for decision makers. The optimisation problem presented in this paper can be solved using different optimisation techniques. For example, one can approach this problem using the classical optimisation techniques such as Branch and Bound, Benders decomposition, heuristic and meta heuristics algorithms [9-14]. Genetic Algorithm (GA) technique is suitable for multi-objective optimisation problems resulting in good solutions whilst maintaining low computational costs. Similar to other meta heuristics solutions, GAs are more efficient in terms of computational time and may find a better solution than the other classical optimisation methods such as: Benders Decomposition (BD) and Branch and Bound (BB) methods. A good example that compares the BD and BB with GA is discussed in a classical example by Goldberg [16], Michalewicz [17] and Haffner et al (2001) [18]. TEP is a large and non-convex optimization problem, perhaps due to the enormous number of variable and nonlinear constraints in the model. In addition, some variables in the model are real and some variables are integer or binary which can be handled by meta heuristic techniques easily. The previous researches illustrate that the BD technique presents a great difficulty in convergence, while the BB technique finds quality solutions but does not converge due to the prohibitive processing time [16-18]. In this regard, a combinatorial of a conventional and a meta heuristic technique is developed in this paper.

4. CoRGA ALGORITHM

CoRGA, proposed as a solution algorithm in this paper, is a hybridization of the goal attainment technique and real genetic algorithm. The proposed algorithm will act as a generalized assignment problem [19] to solve TEP under uncertain demand fluctuations. CoRGA adopts fuzzy sets in fitness evaluation considering two objectives: minimum load shading and minimum CCI for new transmission lines. The reason for using fuzzy numbers is due to the modelling of uncertainties in demand [9, 22]. One of the most important issues in representing a candidate solution in the proposed method is codification. A proper codification may prevent complications in the implementation of the CoRGA algorithm. The individual is a solution proposal for the planning problem, or better, is the topology made up of all lines added to the system corresponding to an investment proposal. In TEP, the individual of CoRGA is represented by a vector size. Each vector is constructed using the number of new lines that are proposed to be added to the respective branches and system loads. Each member can vary its value from zero to the maximum number of lines. Thus, in the codification shown in Fig. 1, branch 2–6 has two new lines; branch 3–5 has one new line, etc.

1-2	1-4	3-5	2-6	4-6
0	0	1	2	1

Fig. 1. Codification proposal

In addition, this chromosome includes consumer load shedding which is selected randomly between zero and maximum load at each bus, in which loads can be selected from a normal (Gaussian) distribution function. The centre of this distribution function is assumed between $P_{D_i}^{min} = P_{D_i}^{\circ}$ and $P_{D_i}^{mzx} = 1.1 P_{D_i}^{\circ}$ with a variance equal to 0.5, where $P_{D_i}^{\circ}$ is the base load. Loads will be estimated as the means of 100 random load samples considering these conditions. The proposed method in this paper does not require that the characteristics of the lines be kept constant. The number of chromosomes in the CoRGA population depends on the dimension of the system. Similar to ordinary GA, CoRGA includes selection, recombination and mutation operators.

In CoRGA, selection is based on a ranking process where the fitness levels assigned to each individual chromosome depends only on its ranking position and not on the actual fitness value. Equation (4) can be used to calculate the rank of each individual.

$$\mathrm{Rank}(P) = 2 - SP + \frac{2(SP-1)(P-1)}{N-1} \tag{4}$$

Where: N is the number of individuals and P is the position of each individual in the population. Recombination may consist of three kinds of operators denoted by Eqs. (5-7) [20].

$$\begin{aligned} O_1 &= \lambda P_1 + (1-\lambda) P_2 \\ O_2 &= \lambda P_2 + (1-\lambda) P_1 \qquad \lambda \in \{0,1\} \end{aligned} \tag{5}$$

$$\begin{aligned} O_1 &= \lambda_1 P_1 + (1-\lambda_1) P_2 \\ O_2 &= \lambda_2 P_2 + (1-\lambda_2) P_1 \qquad \lambda_1, \lambda_2 \in [-0.25, 1.25] \end{aligned} \tag{6}$$

$$\begin{aligned} O_1 &= \lambda P_1 + (1-\lambda) P_2 \\ O_2 &= \lambda P_2 + (1-\lambda) P_1 \qquad \lambda \in [-0.25, 1.25] \end{aligned} \tag{7}$$

Where P_1, P_2 are the two parents, O_1, O_2 are their two offspring and λ_1, λ_2 are two randomly generated numbers. In order to achieve a high degree of precision in the proposed method a dynamic mutation is designed for fine-tuning [15]. If gene P_k is selected from parent P, then there is an equal chance that the resulting gene will be either of the following choices:

$$\begin{cases} O_k = P_k - r(P_k - a_k)(1 - \frac{t}{T})^c \\ O_k = P_k + r(b_k - P_k)(1 - \frac{t}{T})^c \end{cases} \tag{8}$$

Where, a_k and b_k are the lower and the upper band of P_k respectively, r is a uniform random number between (0, 1), t is the number of current generation, T is maximum number of generation, and *c* is a parameter determining the degree of non-uniformity. The flow diagram of the CoRGA algorithm is illustrated in Fig. 2.

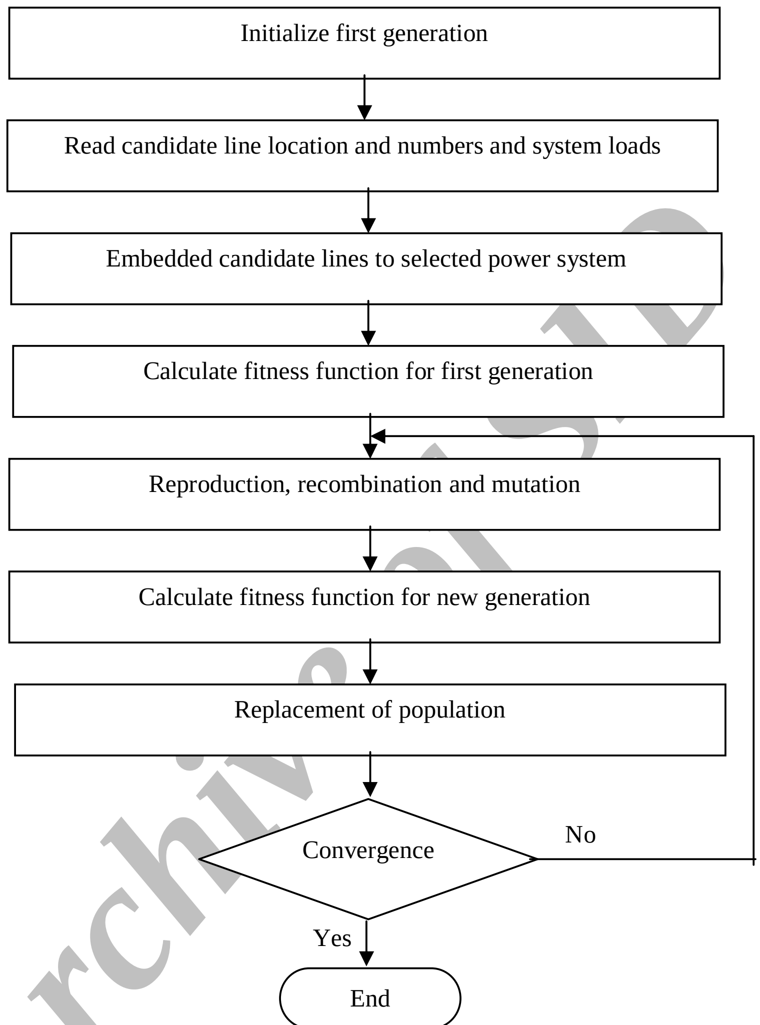

Fig. 2. CoRGA flow diagram

5. CASE STUDIES AND RESULTS ANALYSIS

The proposed method of solving the TEP problem under demand uncertainty is tested on two different power networks. The first network is the "Garver System" [14] and the second network is an IEEE 24-bus test system.

a) The Garver system

The Garver system is a six bus system with 15 branch candidates, a total demand of 760 MW, and a maximum of 3 lines can be added to each branch. The initial topology of the Garver system is shown in Fig. 3. To implement CoRGA for optimum TEP, a population with the size of 100 individual chromosomes is used, while crossover and mutation rates are 76 % and 3 % respectively. The selection process is terminated when the number of generations reaches 50. To calculate the fitness value based on a combination of the goal attainment method and fuzzy numbers appropriate membership functions are defined for each objective. A typical membership function for load shading is shown in Fig. 4, where for the base-case the total resulted load shedding with no congestion reaches 522 MW. This value is determined with the fuzzy membership “0”, whilst in an ideal condition with no load curtailment the membership would be “1”. The values between [0 1] decrease steadily in accordance with the Gaussian membership function shown in Fig. 4. The membership function for capital cost for installation (CCI) is illustrated in Fig. 5, where the optimum value [22] for CCI is proposed to be at 110000 unit. In the case described here, the fuzzy membership value of “1” assigned to the objective of minimising CCI, is assumed to be greater than 110000 units. Conversely, the fuzzy membership value of “0” are assigned to the CCIs that are more than 250000 units. The unit of cost in this example is shown to be equivalent to \$1.0 (US Dollars). The costs that lie between these [25000, 110000] can be explained as linear variations shown in Fig. 5.

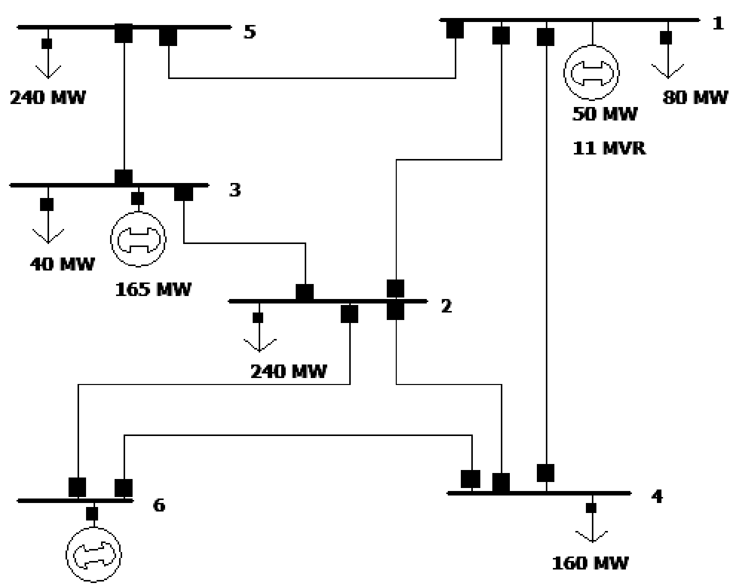

Fig. 3. A schematic view of the Garver system

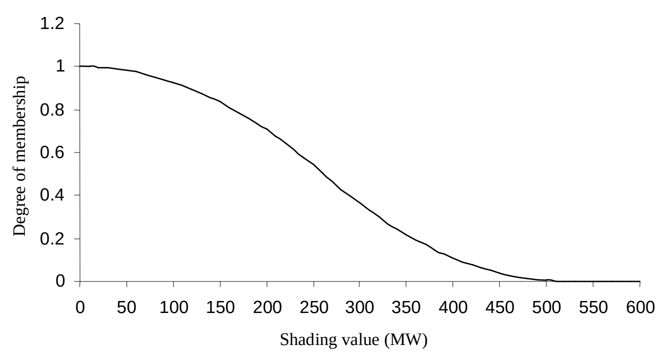

Fig. 4. Membership function for load shading

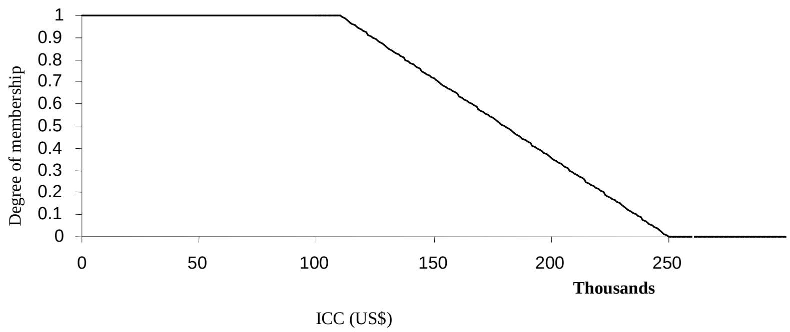

Fig. 5. CCI membership function

- **Uncertainty in Demand**

The uncertainty in demand is modeled using a normal probabilistic distribution function with increasing in all mean load values of 10% and a variance of 0.5. The uncertainty in demand is implemented for two scenarios. In the first scenario, a fuzzy statement helps to define the levels of importance for load shedding and investment costs. Table 1 presents the simulation results of two scenarios. In the first scenario the relative importance of load shedding is assumed to be higher than the investment costs. In the second scenario the statement is inverted. The optimum values for load shedding in both scenarios are reported in Table 2.

Table 1. Garver system results

Scenario	Importance		Total shedding (MW)	CCI (US$)	Candidate Lines
	Load shedding	CCI			
1	high	low	98.798	208000	$n_{1\text{-}6}=1$; $n_{2\text{-}6}=2$ $n_{3\text{-}5}=1$; $n_{4\text{-}6}=2$
2	low	high	268.1467	110000	$n_{2\text{-}3}=1$; $n_{2\text{-}6}=1$ $n_{4\text{-}6}=2$

Table 2. Load shedding results

Bus #	Active load (MW)			
	Base-case	Bas- case with Uncertainty	Scenario 1	Scenario 2
1	80	84.672	84.672	80.2811
2	240	253.99	208.159	130.4128
3	40	42.27	42.27	42.116
4	160	169	169	147.0912
5	240	252.936	199.967	134.8202
Total Loads	760	802.868	704.07	534.7213

The search process for scenarios 1 and 2 are shown in Figs. 6 and 7 respectively. It is apparent from the two graphs in Figs. 6 and 7 that by implementing the CoRGA algorithm, a reasonably good convergence can be obtained.

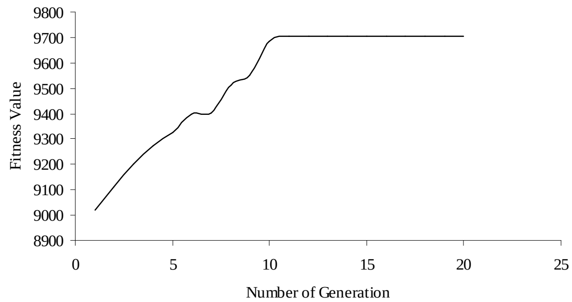

Fig. 6. Search process for scenario 1

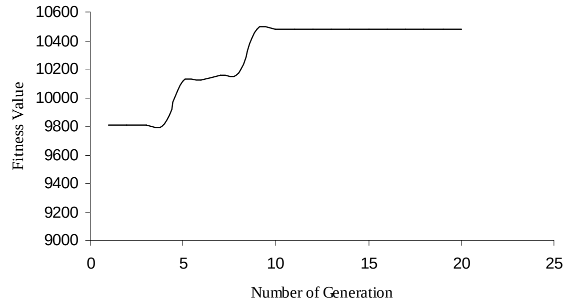

Fig. 7. Search process for scenario 2

b) IEEE 24-bus test system

This system consists of 24 buses and 41 branches with a total demand for 8550MW. It is assumed that three lines can be added to each branch. The initial topology of the IEEE 24-Bus system is shown in Fig. 8. The behaviour of the load shading membership function is assumed to conform as illustrated in Fig. 9. Simulation results for the IEEE 24-bus system shows a total of 3700 MW load shedding with no congestion. The CCI membership function is shown in Fig. 10. The optimal investment proposed in [22] stands at 1,520,000 units (US Dollars). Here, the investments less than this value are assumed to have membership "1", while the other values up to $2,500,000 are assigned with a linear membership function as shown in Fig. 10.

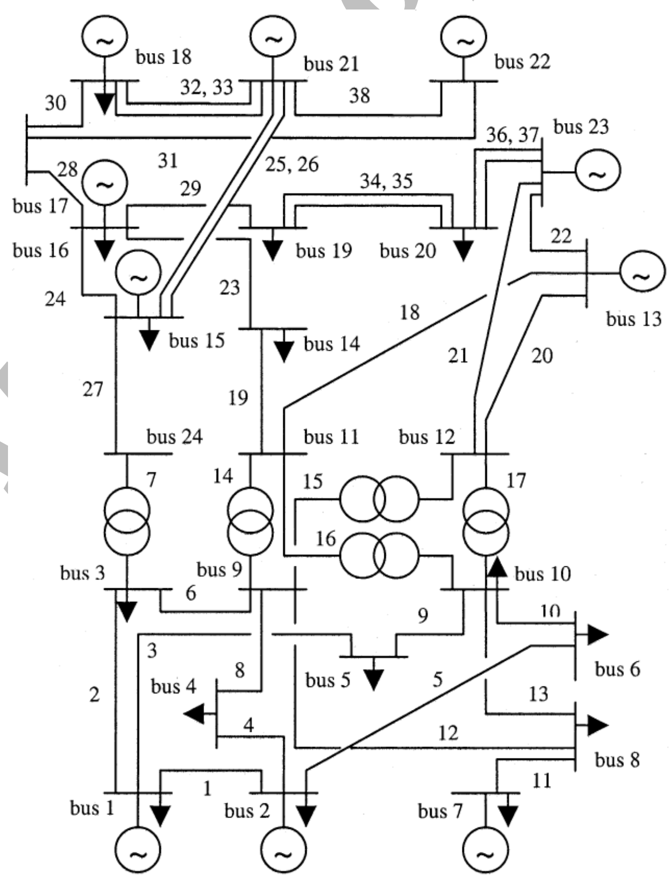

Fig. 8. IEEE 24-bus system

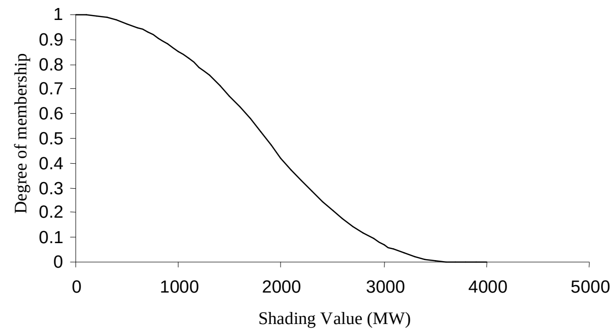

Fig. 9. Load shedding membership function

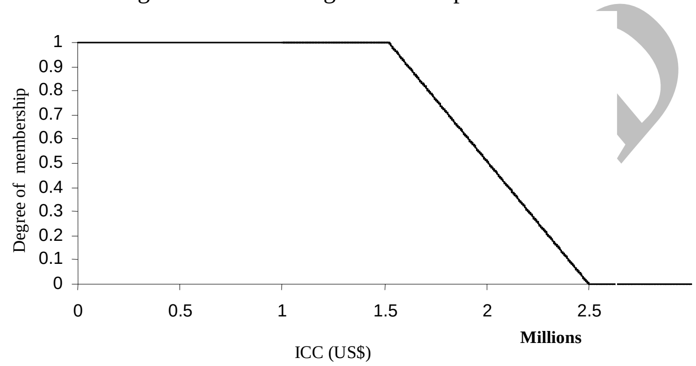

Fig. 10. CCI membership function

Table 3. IEEE 24-buses results

Case	Importance		Total shedding (MW)	CCI($)	Candidate lines
	Load shedding	CCI			
1	high	low	352.41	1660000	n_{1-2}=3; n_{7-8}=1, n_{5-10}=3; n_{16-17}=1, n_{18-21}=1
2	low	high	585.71	1000000	n_{7-8}=3; n_{6-10}=1,n_{18-21}=1

Table 3 represents the results of the optimisation process on the IEEE 24-bus system for the two different scenarios. The optimum load shedding for both scenarios is presented in Table 4.

Table 4. Load shedding results

Bus #	Active load (MW)			
	Base-case	Base-case with uncertainty	Case 1	Case 2
1	324	342.9	342.9	342.5
2	291	306.2	306.2	135.44
3	540	566.298	556.4	550.65
4	222	233.9214	167.7	168.4
5	213	224.4807	70.0	76.44
6	408	431.1336	403.5	417.5
7	375	395.3	395.3	396.23

Table 4. Continued.

8	513	541	541.0	542.39
9	525	553.7	553.7	554.14
10	585	616.4	616.4	613.49
11	0	0	0	0
12	0	0	0	0
13	0	0	0	0
14	795	836.181	822.9	823.77
15	582	615	615	616.16
16	951	1006	1006	858.73
17	300	316.8	235.9	299.63
18	999	1052.8	1052.8	1053.2
19	543	571.6	571.6	572.92
20	384	404.9	404.9	407.31
21	0	0	0	0
22	0	0	0	0
23	0	0	0	0
24	0	0	0	0
Total Load	8550MW	9014.615MW	8662.2MW	8428.9MW

Convergence trend for scenarios 1 and 2 are shown in Figs. 11 and 12 respectively. These figures show the significant search trend in terms of the fitness value versus the number of generation. Referring to Figs. 11 and 12 the fitness values for both scenarios can be obtained quickly. It can be said that the proposed method may guarantee a reasonably good convergence.

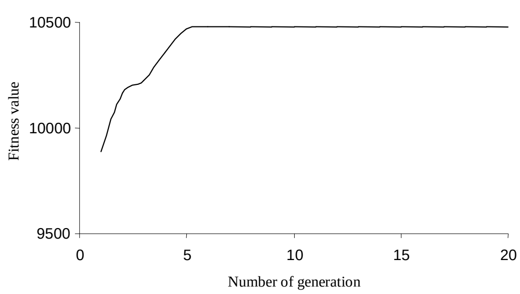

Fig. 11. Search process for case1

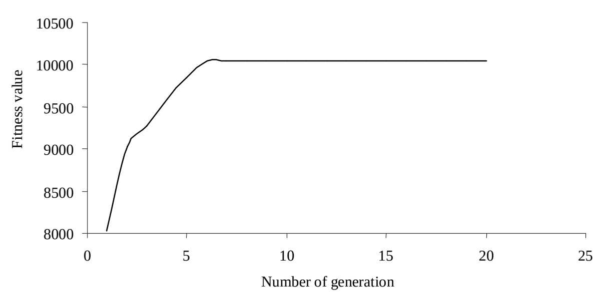

Fig. 12. Search process for case2

6. CONCLUSION

Attempts were made in this research paper to describe a novel approach in solving the transmission network expansion planning problem under uncertainties in demand. The advantage of the proposed methodology in comparison with the existing methods is that the results guarantee a minimum load shedding of demand at each bus with lesser costs of investment in new transmission lines. The solution algorithm is a combination of conventional and meta heuristic methods that take advantage of hybridization techniques in solving such a complex problem. The implementation of Real Genetic Algorithm in conjunction with Fuzzy sets and the goal attainment method has been shown to provide reasonably good solutions for TEP when there are uncertainties in demand. The convergence trend of the proposed combinatorial algorithm seems to be the significant outcome of this research work. The results obtained from the two different case studies show a promising performance for the proposed methodology. Significant savings may be made where maximum load serving with minimum transmission expansion costs is achieved. The proposed mathematical model associated with the CoRGA algorithm has been tested using both Garver and IEEE 24-bus systems, and the results seem to be promising.

Further research can be conducted to study the impacts of different weighting vectors on the decision making space, where it may offer a weighting vector dependent decision space for decision makers.

REFERENCES

1. Wu, F. F., Zheng, F. L. & Wen, F. S. (2006). Transmission investment and expansion planning in a restructured electricity market. *Energy Journal of Elsevier*, Vol. 31, pp. 954-966.
2. Escobar, A. H., Gallego, R. A. & Romero, R. (2004). Multistage and coordinated planning of the expansion of transmission systems. *IEEE Trans. Power Syst*., Vol. 9, No. 2, pp. 735–744.
3. Nayak, A. S. & Pai, M. A. (2002). Congestion management in restructured power systems using an optimal power flow framework. Master Thesis and Project Report, University of Illinois, PSERC Publication 02-23 May. 2002.
4. Gyugyi, L., Song, Y. H. & Johns, A. T. (1999). *Flexible AC transmission systems (FACTS)*. Inst.
5. Shahidehpour, M., Yamin, H. & Li, Z. (2002). *Market operations in electric power systems*. John Wiley & Sons.
6. Song, Y. H. & Wang, X. (2003). Operation of market-oriented power system. *Springer, ch.1-2*, pp. 1-48.
7. Fang, R. & Hill, D. J. (2003). A new strategy for transmission expansion in competitive electricity markets. *IEEE Trans. on Power Systems*, Vol. 18, pp. 374–380.
8. Buygi, M. O., Alzer, G. B., Shanehchi, M. H. & Shahidehpour, M. (2004). Market-based transmission planning. *IEEE Trans. On Power Systems*, Vol. 19, pp. 2060-2067.
9. Choi, J., El-Keib, A. R. A. & Tran, T. (2005). A fuzzy branch and bound-based transmission system expansion planning for the highest satisfaction level of the decision maker. *IEEE Trans. On Power Systems*, Vol. 20, No.1, pp. 475-484.
10. Contreras, J. & Wu, F. (2000). A kernel-oriented algorithm for transmission expansion planning. *IEEE Trans. Power Systems*, Vol. 15, pp. 1434–1440.
11. Latorre, G., Cruz, R. D., Areiza, J. M. & Villegas, A. (2003). Classification of publications and models on transmission expansion planning. *IEEE Trans. Power Systems*, Vol. 18, No. 2, pp. 938–946.
12. Al-Saba, T. & El-Amin, I. (2002). The application of artificial intelligent tools to the transmission expansion problem. *Electric Power Systems Research*, Vol. 62, pp. 117-126.
13. Al-Hamouz, Z. M. & Al-Faraj, A. S. (2003). Transmission expansion planning based on a non-linear programming algorithm. *Applied Energy*, Vol. 76, pp. 169-177.
14. Romero, R., Monticelli, A., Garcia, A. & Haffner, S. (2002). Test systems and mathematical models for transmission network expansion planning. *IEE Proc. Gener. Transm. Distrib.*, Vol. 149, No. 1.
15. Ching-Lai, H. & Mohammad Masud, A. S. (1979). Multiple objectives decision making methods and applications. ch.2, pp. 97-102.
16. Goldberg, D. E. (1989). *Genetics algorithms in search, optimization and machine learning*. Reading, MA: Addison–Wesley.
17. Michalewicz, Z. (1996). *Genetic algorithms + data strutures = evolution programs*. Berlin, Germany: Springer.
18. Haffner, S., Monticelli, A., Garcia, A. & Romero, R. (2001). Specialized branch and bound algorithm for

transmission network expansion planning. *Proc. Inst. Elect. Eng., Gen., Transm., Distrib*., Vol. 148, No. 5, pp. 482–488.

19. De, I., Silva, J., Rider, M. J. Romero, R. & Murari, C. A. F. (2006). Transmission network expansion planning considering uncertainty in demand. *IEEE Trans. On Power Systems*, Vol.12, No. 4 , pp. 1565-1573.
20. Holland, J. H. (1975). Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. Ann Arbor, MI: Univ. Michigan Press.
21. Gallego, R., Monticelli, A. & Romero, R. (1998). Transmission systems expansion planning by an extended genetic algorithms. *Proc. Inst. Elect. Eng., Gen., Transm., Distrib.*, Vol. 145, No. 3, pp. 329–335.
22. Wang, L. X. (1997). *A course in fuzzy systems and control*. Prentice Hall.
23. Pohlheim, H. (1994-1999). Geatbx: Genetic and Evolutionary Toolbox for Use with Matlab, www. Geatbx.com.