© 2005 - 2009 JATIT. All rights reserved.

MULTI-AREA SECURITY CONSTRAINED ECONOMIC DISPATCH BY FUZZY- STOCHASTIC ALGORITHMS

[1]PRASANNA. T.S, [2] SOMASUNDARAM. P

[1]Research Scholar, Department of Electrical and Electronics Engineering,

CEG, Anna University, Chennai, India-600025

[2]Senior Lecturer, Department of Electrical and Electronics Engineering,

CEG, Anna University, Chennai, India-600025

E-mail: tsprasanna@yahoo.com, mpsomasundaram@yahoo.com

ABSTRACT

This paper presents two new computationally efficient Fuzzy-Stochastic algorithms for solving Security Constrained Economic Dispatch (ED) in interconnected power system. The proposed algorithms are based on the combined application of Fuzzy logic strategy incorporated in both Evolutionary Programming (EP) and Tabu-Search (TS) algorithms. The main objective of the Multi Area Economic Dispatch (MAED) is to determine the generation allocation of each committed unit in the system and power exchange between areas so as to minimize the total generation cost without violating the tie-line security constraint. The proposed methods are tested on IEEE – 30 bus interconnected three area system. The investigation reveals that the proposed methods can provide accurate solution with fast convergence and has the potential to be applied to other power engineering problems.

Keywords: *Economic Dispatch , Evolutionary Programming , Tabu-Search , Fuzzy-logic.*

1. INTRODUCTION

Electric power systems are interconnected because it is a better system to operate, with maximum reliability, improved stability and less production cost than operated as isolated systems. Multi Area Economic Dispatch (MAED) is an optimization scheme to determine the best generation schedule for a given load with minimum cost, while satisfying power balance, generator limit and tie-line security constraints. Thus MAED problem is a large scale non-linear optimization problem with both linear and non-linear constraints.

In the past, many conventional optimization techniques such as equal incremental cost method [1,2] decomposition method [3], incremental network flow programme [4], Lagrangian relaxation approach [5] have emerged to solve MAED problem. For medium size power systems, the conventional methods for MAED calculations may be fast and efficient enough. However, for large scale interconnected power systems the higher dimension of possible solution space and increase of constraints result in excessive computational burden. With a view to reduce the computational burden some stochastic techniques have been developed. The recent trend is on the application of modern and improved heuristic techniques. Artificial intelligence techniques are the most widely used tool for many power system optimization problems. These methods (e.g., genetic algorithms, evolutionary programming and tabu search etc.,) seem to be promising and are still evolving. In Genetic Algorithm (GA) the solution space is discrete in nature (binary representation) and hence it is difficult to effectively apply GA to MAED problem in a continuous multi-dimensional space. Evolutionary Programming (EP) is capable of finding global or near global optimal solutions within reasonable computation time hence it has become increasingly popular in recent years in science and engineering disciplines. The ED problem with various constraints like non-smooth fuel cost function, prohibited zones and security constraints are solved using EP in [6-8]. Tabu search (TS) is a powerful optimization procedure that has been successfully applied to a number of combinatorial optimization problems. It has the ability to avoid entrapment in local minima by employing a flexible memory system. The ED problem is effectively solved using TS algorithm in [10 -12]. The major drawback of above EP and TS methods are large number of iterations and very large computation time.

© 2005 - 2009 JATIT. All rights reserved.

In the present trend, there has been an increasing interest in the application of Fuzzy model [9]. Fuzzy logic has been applied in combination with EP [14,15,17] and with TS algorithm [16]. This gives promising results especially in cases where the processes are too complex to be analyzed by conventional techniques or where the available information is inexact or uncertain. Hence in this paper an amendment based on fuzzy logic is incorporated in both EP and TS technique for solving the MAED problem. The fuzzy logic is implemented in these effective stochastic algorithms (EP and TS) for obtaining a much better (faster) convergence.

2. FORMULATION OF MAED PROBLEM

The objective of multi-area economic dispatch is to determine the generation levels and the interchange power between areas that minimise the system operation cost F_m.

The basic model of solving MAED problem with security constraint is as follows

Objective function:

$$\min\ F_m = \min \sum_{m=1}^{M}\sum_{n=1}^{N_k}\left(a_{mn}P_{mn}^2 + b_{mn}P_{mn} + c_{mn}\right) \quad (1)$$

Subject to

(i) Area Power Balance Constraint

$$APBC = \sum_{m=1}^{M}\sum_{n=1}^{N_k} P_{mn} - \sum_{m=1}^{M}\sum_{n=1}^{N_d} P_{Dmn} - P_L = 0 \quad (2)$$

(ii) Generator capacity limit constraint

$$P_{mn,\min} \le P_{mn} \le P_{mn,\max} \quad (3)$$

(iii) Tie-line power flow limit

$$\left|P_t\right| \le P_{t,\max}\ ; \quad t = 1........Nt \quad (4)$$

where

P_{mn} : The power output of generator n in area m.
a_{mn}, b_{mn} ,c_{mn} : Fuel cost co-efficients.
N_k : The number of on-line units for the area m.
P_{Dmn} : The active load at node n in the area m.
P_L : Total real power loss of multi area system.
N_d : Number of loads in area m.
P_t : The active power flow on the tie-line t.
N_t : Number of tie lines.

3. METHODOLOGY

3.1 EVOLUTIONARY PROGRAMMING (EP) BASED MAED

EP searches for the optimum value by evolving a population of feasible solutions over a number of generations or iterations. The evolution of solutions is carried out through mutation by Gaussian distribution and competitive selection. The sequential steps involved in EP approach are discussed as follows,

i) *Initialization*:- An initial population of parent individuals I_{pi} (pi = 1, 2, 3…..N_p) are generated randomly within the feasibility range. And the distributions of initial trial parents are uniform. N_p is the number of population size. The fitness function for each parent individual is computed as,

$$f_{pi} = F_m^{pi} + k_1 \mid APBC^{pi} \mid + k_2 \sum_{t=1}^{N_t} P_t^{pi\ \lim} \quad (5)$$

where

$$P_t^{pi\ \lim} = \begin{cases} |P_t^{pi}| - P_{t,\max} & if\ \ |P_t^{pi}| > P_{t,\max} \\ 0 & otherwise. \end{cases} \quad (6)$$

The values of penalty factors k_1 and k_2 are chosen such that if there is any constraint violations the fitness function value corresponding to that parent will be ineffective. The maximum fitness function value among the parent population is stored as f_{max}.

ii) *Mutation*:- Each parent I_{pi} vector generates an offspring vector I_{oi} by adding a Gaussian random variable with zero mean and pre-selected standard deviation to each individual within its feasible range.

$$I_{oi} = \left[P_{m1}^{oi}, P_{m2}^{oi}, P_{m3}^{oi}, ...P_{mn}^{oi}\right];\ \ oi=pi+N_p \quad (7)$$

$$P_{mn}^{oi} = P_{mn}^{pi} + N\left(0, \sigma_{P_{mn}}^2\right) \quad (8)$$

$N\left(0,\sigma_{P_{mn}}^2\right)$ represents a normal random variable with mean zero and variance $\sigma_{P_{mn}}^2$. The variance $\sigma_{P_{mn}}^2$ decides the width of the normal distribution curve corresponding to each variable of the individuals and it is computed as,

$$\sigma_{P_{mn}}^2 = \beta \times \frac{f_{pi}}{f_{\max}}\left(P_{mn,\max} - P_{mn,\min}\right) \quad (9)$$

Where β is the scaling factor, f_{pi} is the value of the fitness function corresponding to I_{pi} and f_{max} is the maximum fitness function value among the parent population. The value of $\sigma_{P_{mn}}^2$ depends on the relative value of f_{pi}, hence the width of the normal distribution curve is small if f_{pi} is low and vice versa. Calculate the fitness of offspring.

iii) *Competition and Selection*:- The competing pool comprises of $2N_p$ individuals obtained by the combination of parent and offspring populations.

© 2005 - 2009 JATIT. All rights reserved.

All individuals compete with each other for probabilistic selection. The first N_p individuals with minimum fitness values are retained to be the parents of the next generation. The mutation and selection process are repeated until a specified count of maximum generation or iteration is reached. There is no specific standard stopping criteria for Evolutionary Algorithms. The maximum number of iteration for the stopping criteria is identified as the one for which, if the maximum number of iteration is decreased below that value, then there would not be a convergence (reasonable minimum cost without any constraint limit violation) at least in any one or more of the 100 trial studies.

3.2. TABU SEARCH ALGORITHM BASED MAED

The tabu search technique comprises of the two basic strategies namely, diversification (Mutation) and intensification (Recombination). Whereas EP comprises of mutation process only, hence it might loose some precise information. TS also incorporate an adaptable number of mutation and recombination in every generation, thus ensuring a better convergence. The selection process in TS involves the concept of distance, which helps to prevent it from reaching a local optimum. The minimum fitness value corresponding to each iteration will be stored in tabu list. The sequential steps involved in TS approach are described as follows:

i) *Initialization*:- The initialization process is similar to that of EP as explained in section 3.1.

ii) *Mutation*:- It is a diversification strategy. Initially N_m parents (generally half of N_p) indulge in mutation. The mutation process is similar to that of EP as explained in section 3.1.

iii) *Recombination*:- It is an intensification strategy where N_r parents generates I^r_{oi} ; $oi = N_p + N_m + 1 \ldots\ldots 2N_p$ offspring.

Recombination process generates an offspring by using the parameters from two randomly selected parent individuals I_{pi1} and I_{pi2} , thereby it generates an individual with certain qualities inherited from its parents.

$$I^r_{oi} = I_{pi1} + \gamma \left(I_{pi2} - I_{pi1}\right) \tag{10}$$

where γ is the recombination factor. Calculate the fitness function value of each offspring.

iv) *Determination of* N_m and N_r:- Initially both N_m and N_r are initialized to half of the population size N_p. For the next generation or iteration either N_m or N_r is increased if the best solution in the previous iteration corresponds to the mutation or recombination process respectively. If there is an increases in N_m then a corresponding decrease in N_r is executed and vice versa, thus ensuring that $N_m + N_r = N_p$.

v) *Evaluation and Selection*:-Each individual is assigned a rank according to its fitness value. The concept of distance was added to the weight value of each individual to prevent it from being trapped in the local optimum. A far away point needs a higher rank to be selected, even if the fitness is slightly worse. The weight for each individual in the combined population decides the survival of the individual. Individuals will be ranked in the ascending order to their weight. The first N_p individuals are transcribed along with their fitness value for the next generation. The best individual along with its fitness function value is stored in the tabu list. If tabu list is filled completely then the worst solution is replaced by the best solution of the current iteration. The mutation, recombination, determination of N_m and N_r along with evaluation and selection processes are repeated until a specified count of maximum generation is reached. The maximum number of iteration is selected as explained in section 3.1.

3.3. FUZZY MUTATED EVOLUTIONARY PROGRAMMING (FMEP)

The value of variance $\sigma^2_{P_{mn}}$ in the mutation process depends on three factors. The first factor is the relative fitness function value f_{pi} / f_{max} . It is an essential factor which has a major influence on the value of variance. If the relative fitness value f_{pi} / f_{max} is low then the width of the normal distribution curve is small and vice versa. The second factor is the mutation scaling factor β . Generally β is fixed throughout the whole search process. However, for practical applications a small fixed mutation scaling factor may result in premature convergence while a large fixed mutation scaling factor may not converge. Hence there is a need for an adaptive scaling factor. The third factor is the search range ($P_{mn,max} - P_{mn,min}$) which is a constant throughout the whole search process. But actually the search range varies for each generation or iteration. Hence there is a need for an effective search range. Thus the last two factors need a certain control to obtain a better convergence. Moreover the relationship between them seems arbitrary, complex and ambiguous to determine, hence fuzzy logic strategy where the

© 2005 - 2009 JATIT. All rights reserved.

search criteria are not precisely bounded would be more appropriate than a crisp relation. Thus either an adaptive scaling factor or the variance can be obtained from the fuzzy logic strategy thereby leading to an improved EP technique termed as Fuzzy Mutated Evolutionary Programming (FMEP). The various sequential steps involved in the fuzzy implemented mutation process of EP based algorithm are as follows:

(i) The fuzzy logic inputs and output are decided and their feasible ranges are declared. The two fuzzy inputs are as follows:

Input 1 = $f_{pi} \ / \ f_{\max}$ (11)

$$INPUT\ 2 = Max\left\{ (P_{mn,\max} - P_{mn}^{pi})\ ;\ (P_{mn}^{pi} - P_{mn,\min}) \right\} \quad (12)$$

The *Input1* is the first essential factor and *Input 2* is an active search range determined as the maximum search distance or range pertaining to each element P_{mn} of parent individual I_{pi} in the present iteration from any of its corresponding limits (maximum or minimum). The mutation scaling factor β is resolved into the fuzzy control logic. The output of the fuzzy logic strategy is the variance $\sigma_{P_{mn}}^{2\ pi}$.

(ii) Fuzzification of inputs and output using triangular membership function. Five fuzzy linguistic sets have been used for each of the inputs and output as shown in Figure.1.

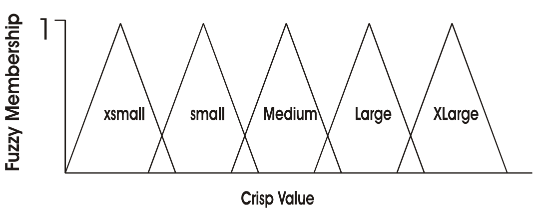

Figure.1. Fuzzy Membership function

(iii) The mutation scaling factor β is resolved into the fuzzy control logic or fuzzy rule base. The fuzzy rule base is formulated for all combinations of fuzzy inputs based on their ranges.

(iv) Defuzzification of output using Centroid method.

$$C = \sum_{i=1}^{5} x_i y_i \Big/ \sum_{i=1}^{5} y_i \quad (13)$$

Where x_i the mid-point of each fuzzy output set and y_i is its corresponding membership function value. The Centroid *C* is scaled (multiplied by its range) to obtain variance $\sigma_{P_{mn}}^2$ value of each element in the parent population.

3.4. FUZZY GUIDED TABU-SEARCH

For the tabu search algorithm the fuzzy logic is applied to Mutation and Recombination process. The fuzzy logic implementation for mutation process is same as given in section 3.3. In TS the recombination factor γ is an arbitrary variable. The fuzzy logic can be implemented to obtain a better intensification strategy. Since recombination process deals with a search process among the existing boundary or it depends on the parent population search range, the fuzzy logic system can be implemented with the following inputs,

i) Fuzzy *input 3* = $I_{pi2} - I_{pi1}$ (14)

ii) Fuzzy *input 4* = $I_{pi1} - I_{TS}^{\min}$ (15)

Fuzzy input 4 is a relative indication of the individual with the best individual in the Tabu list. And the corresponding fuzzy logic system output is the recombination factor γ. Thus leading to an amendment in the TS algorithm by using the fuzzy logic strategy, termed as Fuzzy Guided Tabu Search (FGTS).

3.5. COMPUTATIONAL PROCEDURE

The pseudo code for the proposed FMEP and FGTS methods are described as follows:

3.5.1 FMEP

Step1: Read the system data from the input file.
Step2: Initialize the population.
Step3: Evaluate the fitness function value.
Step4: Create offsprings by fuzzy Mutation.
Step5: Calculate the fitness function value for mutated off springs.
Step6: Competition and selection.
Step7: If termination is not reached goto step4.

3.5.2 FGTS

Step1: Read the system data from the input file.
Step2: Initialize the population.
Step3: Evaluate the fitness function value.
Step4: Create offsprings by fuzzy Mutation.
Step5: Create offsprings by fuzzy Recombination.
Step6: Calculate the fitness function value for both mutated and recombined off springs.
Step7: Selection of the best population based on weight factor with distance approach.
Step8: If termination is not reached goto step4.
Step9: Get the best solution from tabu-list and quit the program.

4. SIMULATION RESULTS

For examining the proposed methods, a network of three interconnected areas are constructed as

© 2005 - 2009 JATIT. All rights reserved.

shown in Figure 2. This test system is same as that was used in [13]. Area A1 is an IEEE 30-bus system. It is extended to 32 bus system by connecting two more buses at area 2 and area 3. Fuel cost function ($), generators power upper and lower limits (p.u.) and load of area 2 and area 3 are

Area 2 : $F_{31} = 650P_{31}^2 + 325P_{31}$, $0.1 \le P_{31} \le 0.9$ and Load = 0.5

Area 3 : $F_{32} = 30P_{32}^2 + 100P_{32}$, $0.1 \le P_{32} \le 0.9$ and Load = 0.4

The tie line (p.u.) constraints of the system considered are

$P_{2\text{-}31max} = 0.6$ $P_{8\text{-}32max} = 0.5$ $P_{31\text{-}27max} = 0.6$ $P_{32\text{-}21max} = 0.25$

$P_{31\text{-}32max} = 0.5$

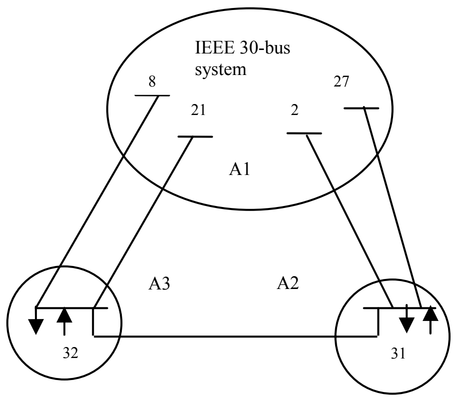

Figure.2. Three area 32 –bus system

The number of individuals N_p is chosen as 10 and the scaling factor in the mutation process of EP and TS is 0.03.The recombination and distance weight factors are 0.04 and 0.01 respectively. The penalty factors k_1 and k_2 are chosen by trial and error. Initially a small value between 10 and 100 will be chosen. After the investigation, if the constraint violated individuals have not been effectively eliminated then, the penalty factor values will be increased until a converged solution is reached with no constraint violations. Convergence is tested for 100 trial runs. The simulations were carried out on Pentium IV, 2.5 GHz processor.

The fuzzy logic data for mutation and recombination are presented in Table I and II respectively.

Table I

Data for Fuzzy Mutation

Fuzzy Set	Input 1	Input 2	Output
XSmall	0.00001 to 0.00004	10 to 30	0.001 to 0.005
Small	0.00003 to 0.006	25 to 50	0.004 to 0.06
Medium	0.005 to 0.05	40 to 80	0.04 to 0.08
Large	0.03 to 0.5	70 to 150	0.075 to 0.09
XLarge	0.4 to 1	140 to190	0.085 to 0.1

Table II

Data for Fuzzy Recombination

Fuzzy Set	Input 3	Input 4	Output
XSmall	10 to 30	10 to 30	0.001 to 0.006
Small	25 to 50	25 to 50	0.004 to 0.08
Medium	40 to 80	40 to 80	0.07 to 0.09
Large	70 to 150	70 to 150	0.085 to 0.2
XLarge	140 to 190	140 to 190	0.15 to 0.3

The convergence characteristics of security constrained MAED of test system using EP,TS, FMEP and FGTS techniques are shown in Figures 3, 4 and 5. The convergence characteristics are drawn by plotting the minimum fitness value from the combined population across iteration or generation.

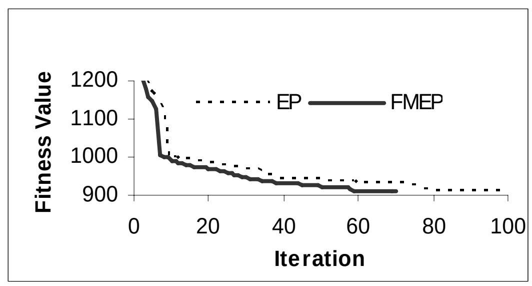

Figure.3 Convergence characteristic of EP and FMEP

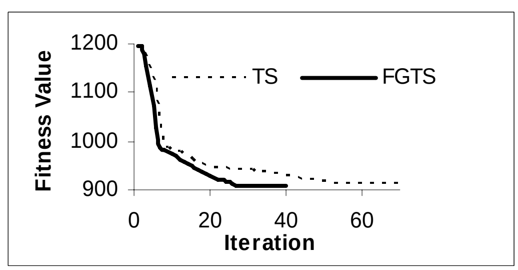

Figure.4 Convergence characteristic of TS and FGTS

From Figures 3, 4 and 5 it is observed that the fitness function converges smoothly to the optimum value without any abrupt oscillations, thus ensuring convergence reliability of the proposed algorithms. The proposed FMEP and FGTS algorithms have much better convergence than EP and TS techniques. From Figure 5 it is inferred that the FGTS has a faster convergence than FMEP.

© 2005 - 2009 JATIT. All rights reserved.

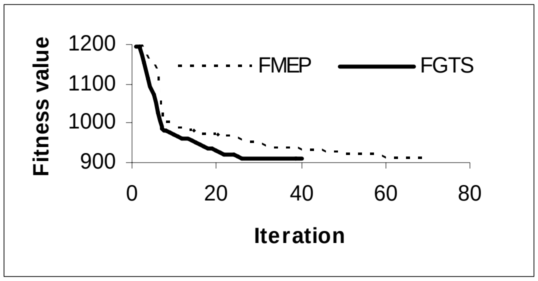

Figure.5. Convergence characteristic of FMEP and FGTS

Table III

Optimum generation schedule for MAED without security constraints				
Algorithm	**EP (P.U)**	**FMEP (P.U)**	**TS (P.U)**	**FGTS (P.U)**
Area 1				
PG1	1.64	1.64	1.63	1.63
PG2	0.41	0.41	0.42	0.41
PG3	0.19	0.19	0.18	0.18
PG4	0.23	0.22	0.22	0.22
PG5	0.16	0.16	0.16	0.16
PG6	0.15	0.15	0.15	0.14
Area 2				
PG31	0.1	0.1	0.1	0.1
Area 3				
PG32	0.9	0.9	0.9	0.9
Total Gen Power	3.78	3.77	3.76	3.74
Losses	0.083	0.083	0.082	0.082
Total Fuel Cost $/hr	921.65	921.33	920.45	920.33
Tie-line Power				
P_{32-8}	0.25	0.26	0.26	0.26
P_{32-21}	0.28	0.28	0.28	0.28
P_{2-31}	0.49	0.49	0.49	0.49
P_{27-31}	-0.17	-0.17	-0.17	-0.17
P_{32-31}	0.11	0.11	0.11	0.11
Number of Iterations	90	60	50	40

Optimum generation schedule for MAED without security constraints

The optimum solutions are given in Table III and IV for MAED without and with security constraints respectively. The results of security constrained MAED are compared with the results obtained by Artificial Neural Network (ANN) approach [13]. The tie line flows corresponding to the optimum schedule are also given in Table III and IV . The important observation is that there is no tie-line flow limit violation corresponding to the optimal schedule obtained with security constraints.

Table IV
Optimum generation schedule for MAED with security constraints

Optimum generation schedule for MAED with Security constraint					
Algorithm	**ANN [13] (P.U)**	**EP (P.U)**	**FMEP (P.U)**	**TS (P.U)**	**FGTS (P.U)**
Area 1					
PG1	1.60	1.65	1.64	1.64	1.64
PG2	0.43	0.46	0.46	0.46	0.46
PG3	0.20	0.16	0.16	0.16	0.16
PG4	0.29	0.16	0.16	0.16	0.16
PG5	0.14	0.20	0.20	0.20	0.20
PG6	0.13	0.16	0.16	0.16	0.16
Area 2					
PG31	0.1	0.1	0.1	0.1	0.1
Area 3					
PG32	0.9	0.9	0.9	0.9	0.9
Total Gen Power	3.79	3.79	3.78	3.78	3.78
Losses	0.083	0.083	0.083	0.082	0.082
Total Fuel Cost $/hr	923.03	923.02	923.02	922.83	922.8
Tie Line Power					
P_{32-8}	0.18	0.17	0.17	0.17	0.17
P_{32-21}	0.23	0.24	0.24	0.24	0.24
P_{2-31}	0.46	0.48	0.48	0.47	0.47
P_{27-31}	-0.14	-0.13	-0.13	-0.14	-0.14
P_{32-31}	0.08	0.08	0.08	0.08	0.08
Number of Iterations	-----	110	95	75	55

The optimal solutions obtained from proposed methods are same as that of obtained from ANN but with less number of iterations. From Table III and IV it is observed that the FGTS algorithm converges with less number of iterations than the other techniques for base case and security constrained MAED.

5. CONCLUSION

This paper presents two simple, efficient and reliable stochastic algorithms (FMEP and FGTS) for solving security constrained MAED problem. An interconnected 3-area, 32-bus system is tested by applying these proposed algorithms and the results are compared with that obtained from neural network approach, EP, TS techniques. The analysis reveals that TS based algorithm converges faster than EP based algorithm and in both techniques the fuzzy implemented algorithms are much faster in convergence. The proposed algorithms have the potential to be applied to other power engineering

© 2005 - 2009 JATIT. All rights reserved.

problems such as optimal power flow, dynamic economic dispatch with several essential constraints because of accurate optimum value with fast convergence.

REFERENCES

[1] Shoults R.R, Chang S.K, Helmick.S and Grady W.M. " A Practical Approach to unit commitment, economic dispatch and savings allocation for Multi-Area pool operation with Import / Export constraints". *IEEE Transactions on Power Apparatus and systems*, 1980.Vol. 99. PP625- 635.

[2] C.E.Lin and C.Y.Chou. " Hierarchical Economic Dispatch for multi-area Power Systems" *Electric power system Research,* 1991.Vol. 10. PP193 -203.

[3] Wang.C. and Shahidehpour.S.M. " A decomposition approach to non-linear multi area generation scheduling with tie line constrains using expert systems". *IEEE Trans on Power systems*, 1992. Vol. 7. PP1409-1418.

[4] Streiffert. D. "Multi-area economic dispatch with tie-line constraints". *IEEE Trans on Power systems*, 1995. Vol. 10. No.4. PP1946 - 1951

[5] Tseng, C.L.Guan, X. Svoboda. A.J. "Multi-area unit commitment for large-scale power systems". *Generation, Transmission and Distribution. IEE Proceedings*, 1998. Vol. 4. PP415 – 421.

[6] K.P.Wong, J.Yureyevich. "Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions".*IEEE trans. Power systems*, 1998. Vol. 11. PP301-306.

[7] T. Jayaharathi, G.sadasivam, Ramachandran. " Evolutionary programming based economic dispatch of generators with prohibited operating zones". *Electric power system research*, 1999. Vol. 52, PP261- 266.

[8] Somasundaram.P, K.Kuppusamy. "Application of evolutionary programming to security constrained economic dispatch". *Electrical Energy systems*, 2005. Vol. 27. PP343-351.

[9]Mauriozio, Denna, Giancarlo Mauri, Anna Maria Zanaboni. "Learning fuzzy rules with Tabu- search an application to control". *IEEE Transactions on fuzzy systems*, 1999. Vol. 7. No.2. PP295- 318.

[10]S.Khansawang, S.Pothiya, C.Boonseng. "Solving the Economic Dispatch Problem with Tabu Search Algorithm". *IEEE Conference , CIT*, 2002.Thailand. PP274-278.

[11] W.Ongsakul, S.Dechanupaprittha and I.Ngamroo. "Parallel Tabu Search Algorithm for constrained economic dispatch". *IEE Proc- Generation - transmission – distribution*, 2004. Vol. 151. No.2. PP157-165.

[12] S.Khansawang, S.Pothiya,C. Boonseng. "Distributed Tabu Search Algorithm for Solving the Economic Dispatch Problem". 2004 *IEEE Transactions on Power systems*, PP484-487.

[13] J.Z.Zhu. " Multi-Area Power systems economic power Dispatch Using a Non linear Optimization Neural Network Approach". 2003. *Taylor and Francis*. PP553-563.

[14] M.Y.El-sharkh, A.A.El-Keib,H.Chen. "A fuzzy evolutionary programming based solution methodology for security-constrained generation maintenance scheduling". *Electric Power system Research,* 2003. Vol. 67. PP67-72.

[15] M Basu. "An interactive fuzzy satisfying method based on evolutionary programming technique for multi objective short-term hydro thermal scheduling". *Electric Power system Research*, 2004.Vol. 69. PP277-285.

[16] T.Aruldoss Albert Victoire, A Ebenezer Jeyakumar. "A tabu search based hybrid optimization approach for a fuzzy modeled unit commitment problem". *Electric Power system Research*, 2006. Vol. 76. PP413-425.

[17] T.S.Prasanna, P.Somasundaram, "Fuzzy Mutated Evolutionary Programming based algorithm for combined economic and emission dispatch". *IEEE international Conference, TENCON-2008*, November 2008 ,in press.