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Combined Economic And Emission Dispatch Using Artificial Neural Network

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***Abstract*: -** This paper proposes an Artificial Neural Network approach for solving the Combined Economic and Emission Dispatch (CEED) problem using Radial Basis Function (RBF) based neural network. The purpose of CEED is to minimize both the operating fuel cost and emission level simultaneously while satisfying load demand and operational constraints. This multi-objective CEED problem is converted into a single objective function using a modified price penalty factor approach.

***Index Terms*: -** *economic dispatch, emission dispatch, price penalty factor, lambda iteration technique, radial basis function (RBF), clustering technique.*

I. INTRODUCTION

The purpose of the traditional Economic Dispatch (ED) problem is to find the most economical schedule of the generating units while satisfying load demand and operational constraints. This involves allocation of active power between the units, as the operating cost is insensitive to the reactive loading of a generator, the manner in which the reactive load of the station is shared among various on line generator does not affect its economy[1].

The progress of optimal dispatch goes far back as the early 1920's, when engineers were concerned with the problem of economic allocation of generation or the proper division of the load among the generating units available . Prior to 1930, various methods were in use such as: (a) the base load method where the next most efficient unit is loaded to its maximum capability, then the second most efficient unit is loaded, etc., (b). "best point loading," where units are successively loaded to their lowest heat rate point, beginning with the most efficient unit and working down to the least efficient unit, etc. It was recognized as early as 1930, that the incremental method, later known as the "equal incremental method," yielded the most economic results. In 1954, co-ordination equation was developed for solving economic dispatch problem. A break through in the mathematical formulation of the economic dispatch problem was achieved by Carpentier in the early 1960's, who treated the entire work in an exact manner (active power and reactive power dispatch). The

Solution of Carpentier's formulation is a non-linear optimization which has been the subject of much study though the present and its implementation in real time remains a challenge.

Several classical optimization techniques are used for solving economic dispatch problem. These are Lambda Iteration Method, Gradient method and Dynamic Programming (DP) method [1], etc. Among this lambda iteration method has been applied in extensively and used by power utilities due to its ease of implementation.

The conventional methods of economic dispatch are dealt with in detail by Allen J. Wood, Bruce F. Wollenberg [1], I. J. Nagrath, D.P. Kothari [2] and C. L. Wadhwa [3]. All these authors have presented algorithms for finding the solution to the economic generation scheduling by iterative methods based on exact co-ordination equation for determining the optimum plant allocations, and equal incremental cost principle for determining the allocation of different generators in a generating station.

M.R.Gentt and J.W.Lamont [4] have started the early work on minimum emission dispatch and proposed a method for on-line steam unit dispatch that results in the minimum NO_X emissions. They had used a combination of a straight line and an exponential term for the total NO_X emissions. K. Srikrishna and C.Palanichamy [5] have proposed a method for Combined Economic and Emission Dispatch (CEED) using price penalty factor. A modified price penalty factor is proposed in [6] to find economic emission fuel cost with respect to the load demand. In this the line flow constraints are computed directly from the Newton Raphson method.

Outlines of the paper

2. Problem formulation of CEED and procedure to find price penalty factor and mathematical formation of CEED using lambda iteration method

3.Radial Basis Function based Neural Networks including Clustering technique.
4 simulation results comparing with lambda method, discussions and conclusions.

II. COMBINED ECONOMIC AND EMISSION DISPATCH PROBLEM FORMULATION

The objective of Economic Dispatch (ED) is to minimize the total generation cost of a power system over some appropriate period:

$$Minimize\ F = \sum_{i=1}^{n} f_i(P_i) \quad (1)$$

where, F : total generation cost (*Rs/hr*)
n : number of generators
P_i : real power generation of i^{th} generator (*MW*)
$f_i(P_i)$: generation cost for P_i Subject to a number of power systems network equality and inequality constraints. These constraints include:

2.1 System Active Power Balance

$$\sum_{i=1}^{n} P_i = P_D + P_{loss} \quad (2)$$

where, P_D : total system demand (*MW*) P_{loss} : transmission loss of the system (*MW*)

2.2 Generation Limits

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

where, $P_{i,min}$: minimum power output limit of i^{th} generator (*MW*)
$P_{i,max}$: maximum power output limit of i^{th} generator (*MW*)

2.3 Combined Economic and Emission Dispatch

The economic dispatch and emission dispatch are considerably different. The economic dispatch deals with only minimizing the total fuel cost (operating cost) of the system violating the emission constraint. On the other hand emission dispatch deals with only minimizing the total emission of NO_X from the system violating the economic constraints. Therefore it is necessary to find out an operating point, that strikes a balance between cost and emission. This is achieved by combined economic and emission dispatch (CEED).
The multi-objective combined economic and emission dispatch problem is converted into single optimization problem by introducing price penalty factor h [12] as follows:

$$Minimize\ \Phi = F + h^* E \quad (Rs./hr) \quad (4)$$

subject to demand constraint (2) and generating capacity limits (3).
The price penalty factor h blends the emission with the normal fuel costs and Φ is the total operating cost of the system (*i.e.*, the cost of fuel + the implied cost of emission).
Once the value of price penalty factor is determined, the problem reduces to a simple economic dispatch problem. By proper scheduling of generating units, comparative reduction is achieved in both total fuel cost and NOx emission.

2.3. A Fuel Cost Objective

The classical economic dispatch problem of finding the optimal combination of power generation, which minimizes the total fuel cost while satisfying the total required demand, can be mathematically stated as follows

$$Minimize\ F = \sum_{i=1}^{n} f_i(P_i) \quad (5)$$

where
$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i$ where, a_i , b_i and c_i are fuel cost coefficients.

2.3. B Emission Objective

The minimum emission dispatch optimizes emission objective, which can be modeled using second order polynomial functions

$$Minimize\, E = \sum_{i=1}^{n} \alpha_i P_i^2 + \beta_i P_i + \gamma_i \quad (6)$$

α_i, β_i, γ_i : emission coefficients of the i^{th} generating unit

2.3. C Multi-objective Formulation

The multi-objective economic dispatch optimizes the above classical economic dispatch and emission dispatch simultaneously which can be formulated as: $Minimize\ \phi = \sum_{i=1}^{n} f_i\,(F, E)$ (7)

where $f_i(F, E) = w_1(a_iP_i^2 + b_iP_i + c_i) + w_2h_m(\alpha_iP_i^2 + \beta_iP_i + \gamma_i)$

here : h_m is modified price penalty factor

: w_1 and w_2 are weights ($w_1 + w_2 = 1$)

2.4 Procedure to Find Price Penalty Factor

The price penalty factor h_i is the ratio between the maximum fuel cost and maximum emission of corresponding generator

$$h_i = \frac{F(P_{i,\max})}{E(P_{i,\max})}\ (Rs/Kg)\ ,\ i = 1,2,\ldots n. \qquad (8)$$

The price penalty factor for a particular load demand P_D (*MW*) is computing as follows:

1) Find the ratio between maximum fuel cost and maximum emission of each generator.

2) Arrange the values of price penalty factor in ascending order.

3) Add the maximum capacity of each unit ($P_{i,max}$) one at a time, starting from the smallest h_i unit until $\sum P_{i,max} \geq P_D$.

4) At this stage, h_i associated with the last unit in the process is the price penalty factor for the given load.

2.5 Procedure to Find Modified Price Penalty Factor

The procedure just shown gives the approximate value of price penalty factor computation for the corresponding load demand. Hence, a modified price penalty factor h_m is used in this project to give the exact value for the particular load demand. The first two steps of computation remain same for the calculation of modified price penalty factor. The remaining steps are modified as follows:

3) Form an array, m by adding $P_{i,max}$ one by one from the lowest h_i value unit.

4) Add the elements of m_i one at a time, starting from the smallest h_i unit until $\Sigma m > P_D$

5) The modified price penalty factor h_m is computed by interpolating the values of h_i for last two units by satisfying the corresponding load demand.

III. RADIAL BASIS FUNCTION NETWORKS

To construct radial basis function (RBF) network previous data of CEED for different power demands with various weights are set by lambda iteration method.

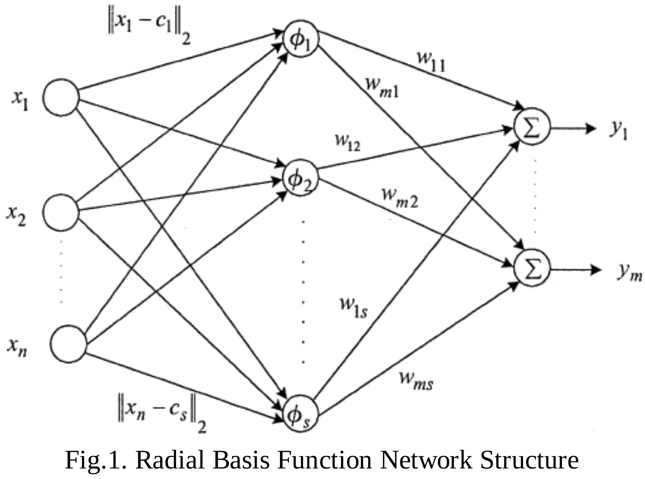


Fig.1. Radial Basis Function Network Structure

$$y_i = \sum_{k=1}^{s} \varphi_k \left\| x_n - c_s \right\| . w_{ik} \qquad \text{for } i=1,2\ldots..m \quad (9)$$

where $x = [x_1, x_2 \ldots\ldots\ldots x_n]$ is an input vector, n is number of input vectors c_k is the is the kth center node in the hidden layer , k= 1,2……………s ,in which s is the number of hidden layers , $\left\| x_n - c_s \right\|$ denotes Euclidean distance between c_k and x vector here hidden layer contains nonlinear transfer function of the kth center w_{ik} is the weight value between the kth center and the ith output layer. and m is the number of output layers

h() is a strictly positive radially symmetric function with a unique maximum at its center μ_j, and which drops off rapidly to zero away from the center. In other words, φ_k has an appreciable value only when the "distance" $\left\|\mathbf{x}_n - c_s\right\|$ is smaller than the width **.** and $\square_k$ is output of hidden layer

and $\boldsymbol{\mu_j}$ **,** $\mathbf{w_j}$ are center and width

Gaussian Function

$$\varphi_k(x) = \exp\left(\frac{-(x-\mu_j)^2}{w_j^2}\right)$$

3.1 Method for Selection of Centers:

Using K-Means Cluster Centers [7]*:* The objective is to locate a "set *k* of RBF centers that represent a local minimum of the SSE (sum of squared errors) between the training set vectors **x** and the nearest of the *k* receptive field centers μ_j."

- In other words, the *k* RBF's are initially assigned centers μ_j, *j=1, 2, ...,k*, which are set equal to *k* randomly selected training vectors. The remaining vectors are assigned to class *j* of the closest center μ_j. Next, the centers are recomputed as the average of the training vectors in their class.

3.2 Method for Selection of Widths:

Distance Averaging [7]: A "Reasonable" estimate for the global width parameter is the Average $w_j = \rangle\|\mu_i - \mu_j\|\langle$, which represents a global average over all Euclidean distances between the center of each unit *i* and that of its nearest neighbor j

3.3 Plan Of Training Data Created By Lambda Iteration Method

Inputs: power demand (Pd), operators preference (w1 and w2): all possible combinations of w1, and w2, both varying in steps of 0.05 in the range of 0 to 1

Output: Active power output of each generator

3.4 Parameter Setting

Input Nodes: 3 (Pd, w1, w2)

Hidden Nodes: 65(Selected by Clustering Technique)

Output Nodes: No. of Generators

Learning rate(η): 0.0002

Acceleration Factor (α):0.995

Epsilon: 0.001

No of iterations: 1200

See Fig.2

3.5 Centers

Firstly no of centers required is chosen randomly about 1/5th to 1/7th of total number of patterns Those centers are chosen randomly among given patterns Such choosing must ensure that no two centers are very close to each other, or even next to each other but fairly far apart from each other covering the whole of input space.

Randomly chosen centers are finalized or adjusted according to clustering technique see fig.4, then weights b/w hidden layer and output layer are initialized randomly between 0 and 1. Then RBFNN is trained for iterations (some fraction of maximum iterations) or until convergence which is more than actually required (say 0.005/ 0.004 if actual is 0.001).Repeat above process for a few trials (say 5 to10 times) until satisfied results are obtained. After each complete trial/process store the finalized centers and weights onto a file and the most favorable set of centers and weights. After choosing, the most favorable centers and weights, they are taken as initial values for problem for the next time, instead of taking randomly the centers and weights see fig 3and fig.4. Above step can be repeated for faster convergence or quick weight stabilization processing

IV. TEST RESULTS

The method, Combined Economic and Emission dispatch using RBF Network and lambda method was implemented on WSSC 9-Bus 3-Generator System, IEEE 30-Bus system that has 6-Generators [8] , Indian utility Practical System of Uttar Pradesh State Electricity Board (UPSEB) that is of 75-Bus 15-Generators [8].

Average Percentage Absolute Error (APAE)
Considered has

$$\text{APAE}(\%) = \frac{1}{m}\sum_{i=1}^{m}\frac{|\text{Actual Output }(P_{Gi}) - \text{Estimated Output }(\hat{P}_{\text{Gi}})}{\text{Actual Output }(P_{Gi})} \times 100\%$$

Where m is No of generators

Test results:
The comparison of test results of RBF method and Lambda iteration method
1. Table I Table II shows active power output of different unit in both methods for 6-Generator system ,same has Table III Table IV for 15-Generator system.
2. Case 1:In 3-Generator System
Table V shows active power output , APAE and cost of both methods with different demand and different weights
Case 2: IEE 30-Bus 6- Generator System
Comparison of Total cost and APAE
In Table I (Pd=217, W1=0.3 , W2=0.7) the total cost of the lambda iteration method \$/hr. 478 and RBF method \$/hr. 479 APAE=0.084%.
In Table II (Pd=347, W1=0.5,W2=0.5) the total cost of the lambda method \$/hr.997 and RBF method \$/hr.989 APAE=0.633%.
Case 3:75-Bus 15-Generator System
Comparison of Total cost and APAE
In Table III (Pd=3450, W1=0.7 , W2=0.3) the total cost of the lambda iteration method \$/hr.5212 and RBF method \$/hr.5227 , APAE=0.673% .
In Table IV (Pd=2750, W1=0.35,W2=0.65) the total cost of the lambda method \$/hr.3861 and RBF method \$/hr.3850 APAE=0.846%

Comparison of generations for 6-Generator system

Table I

S.No	Lambda iter $P_{generator}$ (MW)	RBF $P_{generator}$ (MW)
1	***94.2716***	***94.6084***
2	***37.5017***	***37.4304***
3	***22.4668***	***22.2899***
4	***21.6014***	***21.2436***
5	***19.9972***	***20.0274***
6	***21.1612***	***21.5034***

Table II

S.No	Lambda Iter $P_{generator}$ (MW)	RBF $P_{generator}$ (MW)
1	***148.8221***	***148.2532***
2	***63.3716***	***63.2481***
3	***33.3157***	***32.6584***
4	***35.0000***	***34.5196***
5	***30.0000***	***30.0827***
6	***36.4018***	***36.3468***

Table III Comparison of Generations for 15-Generator system

S.No	Lambda Iter $P_{generator\ (MW)}$	RBF $P_{generator\ (MW)}$
1	***331.1324***	***331.1961***
2	***297.7298***	***290.7176***
3	***200.0000***	***201.1689***
4	***170.0000***	***171.0384***
5	***240.0000***	***241.4921***
6	***120.0000***	***121.5157***
7	***100.0000***	***100.2106***
8	***100.0000***	***99.8010***
9	***297.4392***	***297.4031***
10	***250.0000***	***252.1001***
11	***200.0000***	***198.9616***
12	***381.5344***	***381.9169***
13	***331.1302***	***331.1220***
14	***150.0000***	***152.2316***
15	***277.4469***	***277.3163***

Table IV Comparison of Generations for15-Generator system

SNO	Lambda Iter $P_{generator\ (MW)}$	RBF $P_{generator\ (MW)}$
1	***215.5636***	***216.5688***
2	***193.8220***	***194.7960***
3	***193.8272***	***192.6157***
4	***170.0000***	***165.0843***
5	***215.5534***	***216.8286***
6	***120.0000***	***118.2841***
7	***100.0000***	***100.0000***
8	***100.0000***	***100.0000***
9	***193.6295***	***195.3947***
10	***237.3199***	***235.6972***
11	***200.0000***	***199.8326***
12	***248.3612***	***248.2313***
13	***215.5572***	***216.5679***
14	***150.0000***	***145.8771***
15	***180.6130***	***182.8414***

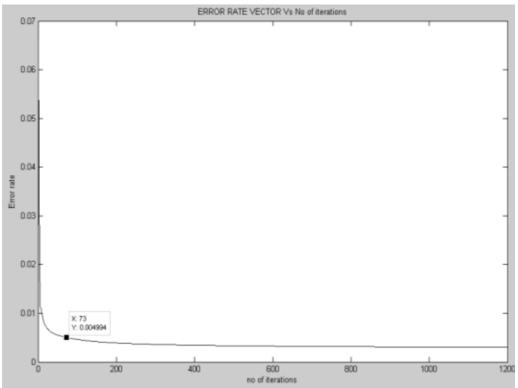
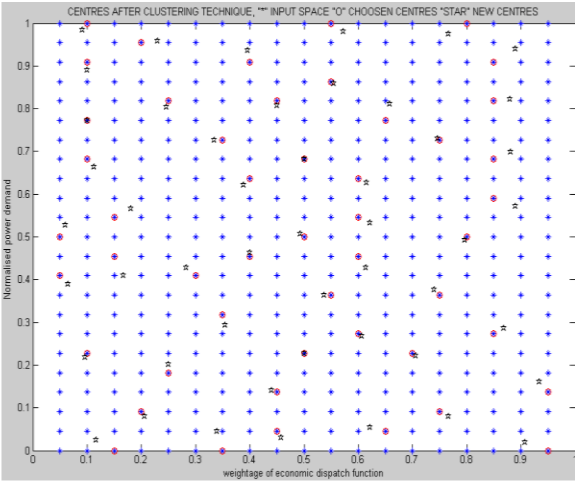


Fig.2. Error rate Vs Iter for RBF showing no of iterations (1200) for 0.005 Accuracy



0: Initial RBF centers, *: Retained RBF centers
Fig.3. Distribution of Initial (437) and Retained (65) RBF centers

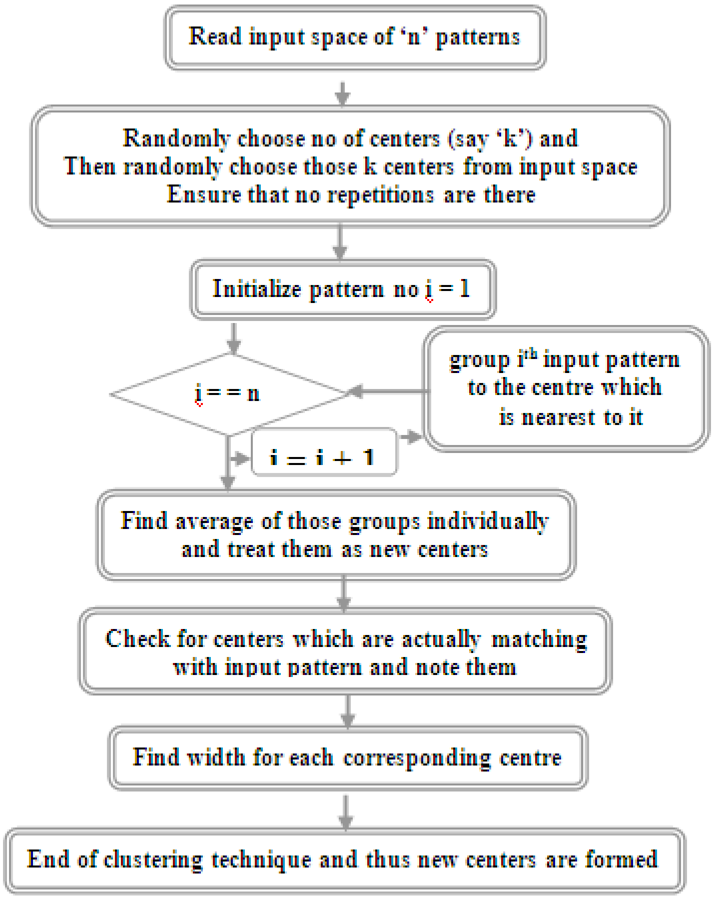


Fig.4. Flow chart of clustering technique

Table V Comparison of test results for 3-Generator system

Power Demand (MW) W1 w2	Method	P1 (MW)	P2 (MW)	P3 (MW)	Total Fuel Cost (Rs/hr)	Total Emission Release (Kg/hr)	Total cost Rs/hr	APAE %
610 0.80 0.20	**Lambda iter.**	***145.2789***	***234.0502***	***230.6709***	***30016.1922***	***451.0365***	***28188.33***	
	RBF	***145.6566***	***233.7527***	***230.3347***	***30005.1615***	***450.549279***	***28174.99***	***0.0043***
570 0.20 0.80	**Lambda Iter.**	***144.8022***	***212.7760***	***212.4217***	***28175.6457***	***389.4735***	***19992.28***	
	RBF	***145.4145***	***212.3038***	***211.2764***	***28131.4432***	***388.018104***	***19929.79***	***0.2128***
630 0.75 0.25	**Lambda Iter.**	***152.1468***	***240.1697***	***237.6834***	***30962.7347***	***483.04240***	***28824.17***	
	RBF	***153.5925***	***239.8800***	***237.4552***	***31009.6389***	***484.3965***	***28875.06***	***0.1445***

V. DISCUSSIONS

The results obtained from the three test cases the following observations are

1. As shown in Fig.3. the clustering technique can effectively reduce the size of the RBF network that provides some contributions in decreasing the computation time
2. Tables I III reveals that the present method has better estimating accuracy but total cost is little bit higher than actual value ,Tables II IV reveals that the present method has poor estimating accuracy but total cost is lesser than actual value
3. The performance of the present method is related to the estimating accuracy of the active power of each generation .since the estimating value of the each generator maybe higher or lower than the actual value. the solution with lower APAE seems not to ensure that it's objective value including fuel cost, emission are closer to the actual objective value than other once with higher APAE value

VI. CONCLUSION

An algorithm has been developed for the determination of the global or near-global optimal solution for the Combined Economic and Emission Dispatch (CEED). The formulated algorithm of RBFNN has been tested for three test systems with three, six generating units and fifteen generating units. The results obtained from RBFNN method are compared with conventional lambda iteration method considering Average Percentage Absolute Error. The results obtained for three test systems are found to be in good agreement with conventional generation values from lambda technique. The RBFNN approaches provide a global optimal solution than the other methods

REFERENCES

[1] Allen J. Wood, Bruce F. Wollenberg, "Power Generation, Operation, And Control", John Wiley & Sona, Inc., New York, 2004

[2] I. J. Nagrath, D.P. Kothari, "Modern Power System Analysis", Tata McGraw-Hill Publishing Company Ltd., New Delhi, India, 1989.

[3] C. L. Wadhwa, "Electrical Power Systems", New Age International (P) Ltd. Publishers, New Delhi, India, 2001.

[4] M R Gent, J W Lamont, "Minimum Emission Dispatch", IEEE Trans. Power Apparat. Syst., Vol. 90, pp. 2650-2660, June 1971.

[5] Palanichamy.C, Srikrishna K. Economic thermal power dispatch with emission constraint, Journal of Institution of Engineers (India),Vol.72, pp.11-18, April 1991.

[6] P. Venkatesh, R. Gnanadass, and Narayana Prasad Padhy,"Comparison and application of evolutionary Programming techniques to combined economic Emission dispatch with line flow constraints", IEEE Trans. Power Syst.,Vol.18, No. 2, pp 688-697, May 2003.

[7] Christian J. Darken and John Moody by "Fast learning in networks of locally-tuned processing units, Nueral computation"Vol.1,No.2,pp 281-294,Summer1989.

[8] I. Jacob Raglend and Narayana Prasad Padhy "Solutions to Practical Unit Commitment Problems with Operational, Power Flow and Environmental Constraints" 2006 IEEE.

[9] E. H. Chowdhury, Saifur Rahrnan, "A Review of Recent Advances in Economic Dispatch", IEEE Trans. on Power Syst., Vol. 5, No. 4, pp 1248- 1259, November 1990.

[10] A. A. El-Keib, H. Ma, J. L. Hart, "Economic Dispatch in View of The Clean Air Act of 1990", IEEE Trans. Power Syst., Vol.9, No.2, pp. 972-978, May 1994.

[11] M. A. Abido, "Environmental/Economic Power Dispatch Using Multiobjective Evolutionary Algorithms", IEEE Trans. Power Syst., Vol.18, No. 4, pp 1529-1537, Nov. 2003.

[12] J. H. Talaq, F. El-Hawary, and M. E. El-Hawary, "A Summary of Environmental/Economic Dispatch algorithms," IEEE Trans. Power Syst., vol. 9, No.3 , pp. 1508–1516, Aug. 1994.

[13] Chao-Ming Huang and Fu-Lu Wang "An RBF Network With OLS and EPSO Algorithms for Real-Time Power Dispatch", IEEE Transactions On Power Systems, Vol. 22, No. 1, FEB 2007

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