Real Time Economic and Emission Dispatch using RBF Network with OLS and MPSO Algorithms

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ABSTRACT

This paper proposes a new approach to real time economic and emission dispatch by using orthogonal least-squares (OLS) and modified particle swarm optimization (MPSO) algorithms to construct the radial basis function (RBF) network. The objectives considered are fuel cost and NOx/CO2 emissions. The RBF network is composed of input, hidden, and output layers. The OLS algorithm provides a simple and efficient means for fitting radial basis function networks. The MPSO algorithm is implemented to tune the parameters in the network, including the dilation and translation of RBF centers and the weights between the hidden and output layer. The proposed approach has been tested on the IEEE 30-bus six-generator system. Testing results indicate that the proposed approach can make a quick response and yield accurate Real time economic and emission solutions.

Keywords

Modified particle swarm optimization, orthogonal least-squares, radial basis function, Real time economic and emission dispatch.

1. INTRODUCTION

As growing technology lot of techniques has been inventing to solve the real time economic and emission dispatch problem. Depending on convention, electrical power plants are operated based on minimizing operational cost while satisfying the system constraints[1][2]. As public concern the dispatch strategies, considering both economic factors and emission reduction [3]-[5]. Although economic and emission dispatch problems have been effectively solved by quite a lot of excellent techniques, the related dispatch programs need to be rerun when the system load changes and thus is unsatisfactory for the Real time dispatch.

Artificial neural networks (ANN) [7], [8] are mathematical tools originally inspired by the way human brain processes information and applied to solve the real-time dispatch problem. These methods can accurately and efficiently capture complex input-output relations. However, ANN still has some unsolved problems, including the local and slow convergence during training and the fact that the network structure and parameters are problem dependent.

The radial basis function networks [9]–[11] similar to ANN. However, in difference to ANN, the RBF network has a more compact topology and less training time for learning. a common learning algorithm for an RBF network is based on first choosing randomly some data points as radial basis centers and then the weights between hidden and output layer can then be estimated by using the stochastic gradient approach. However, it is clearly unsatisfactory to use such a mechanism to build RBF networks.

This paper make use of orthogonal least-squares learning algorithm [12] to select a suitable set of centers from the input data.The MPSO approach is used to tune the parameters in the network, including the position of RBF centers, the width of RBFs, and the weighting values between hidden and output layer.

The PSO was first introduced by Kennedy and Eberhart in 1995 [13] and it is based on the behavior of individuals of a swarm. All individuals in a swarm approaches to the optimum through its present velocity, previous experience, and the experience of its neighbors. It has successfully been applied to solve the power dispatch problems [14]–[19].

2. PROBLEM FORMULATION

As consideration of competitive and deregulated environment, the quick response of the Real time power dispatch (RTPD) problem will be more and more important for the power utilities than the vantage points of operating cost and environmental protection.

2.1 Fuel Cost

The fuel cost function of the system can be represented as a quadratic function of generator active power output as follows:

$$F(P_G) = \sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad \left(\frac{rupees}{h}\right) \qquad (1)$$

Where F(PG)is the total fuel cost of the system; PGi is the power output of the ith unit; N indicates the number of generators; and ai,bi and ci are the cost coefficients.

2.2 Emission

The emission function of the system can be expressed as the polynomial function of generator active power output as follows:

$$E(P_G) = \sum_{i=1}^{N} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \ldots + \varphi_i P_{Gi}^n \left(\frac{ton}{h}\right) \quad (2)$$

Where, α_i, β_i, γ_i and φ_i and are emission coefficients.

2.3 Economic and Emission Power Dispatch

The economic and emission objective functions are having conflicting nature and cannot be minimized simultaneously. So the two conflicting functions can be converted into a single objective function by giving relative weights.

$$Min\ C_T(P_G) = w_1 F_t(P_G) + w_2 E(P_G) \qquad (3)$$

Where W_1 is the weight of the total cost, W_2 is the weight of emissions, $W_1 + W_2 = 1$.The optimization of (3) must be subjected to power balance constraints, generation capacity constraints.

$$\sum_{i=1}^{N} P_{Gi} = P_D + P_{loss} \qquad (4)$$

$$P_{Gi,min} \leq P_{Gi} \leq P_{Gi,max} \qquad (5)$$

Where P_D the total load demand; P_{loss} is the transmission loss of the system; $P_{Gi,\ min}$ and $P_{Gi,\ max}$ are the lower and upper limits of the ith power generation.

2.4 Real-Time Power Dispatch

Traditionally, various existing methods have been solving power dispatch problems by using the successive adjustment of weighting value as given in (3). However, these methods are needed to rerun when the system load changes so these methods are not suitable for the RTPD problem.

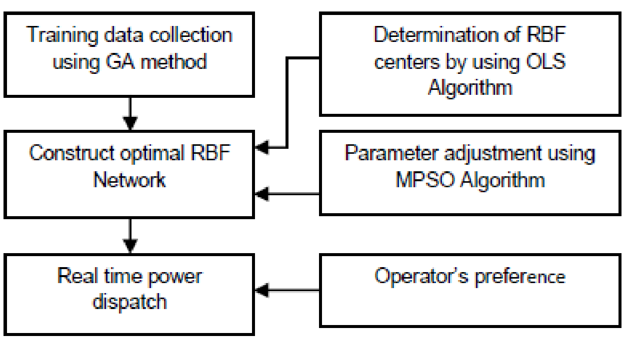

Fig. 1. Schematic diagram of the proposed method.

To overcome the limitations of existing EEPD methods, this paper proposes a combination of OLS and MPSO algorithms to construct the best RBF network. Once this network is constructed, scheduling the demand to available generators quickly and efficiently.

3. PROPOSED APPROACH

Before constructing the RBF network, have to need historical records of EEPD training data for different power demands with various weights are set up by the GA method.

3.1 RBF Network

A schematic of the RBF network with n inputs and a scalar output is depicted in Fig. 2. The network is comprised of three layers: input layer, hidden layer, and output layer. By implementing a learning algorithm, the error between the actual and desired response is minimized relative to some optimization criterion.

$$y_i = \sum_{K=1}^{S} \varphi_k(\| x - c_k \|).w_{ik}\ i = 1,2, \dots, m \qquad (6)$$

Where $x = [x_1, x_2, \dots, x_n]^T$ is an input vector; n is the number of input node; C_k is the th center node in the hidden layer, k=1,2,..,5 in which S is the number of hidden nodes; $\| x - c_k \|$ denotes Euclidean distance [12] between c_k and x vector; $\phi_k(.)$ is a nonlinear transfer function of the *k*th center; is the weighting value between the *k*th center and the *i*th output node; and m is the number of output nodes. Generally, the hidden unit function is Gaussian function $\phi_k(.)$ is chosen as follows:

$$\varphi(x) = \exp(-\frac{(x-\gamma)^2}{\psi^2}) \qquad (7)$$

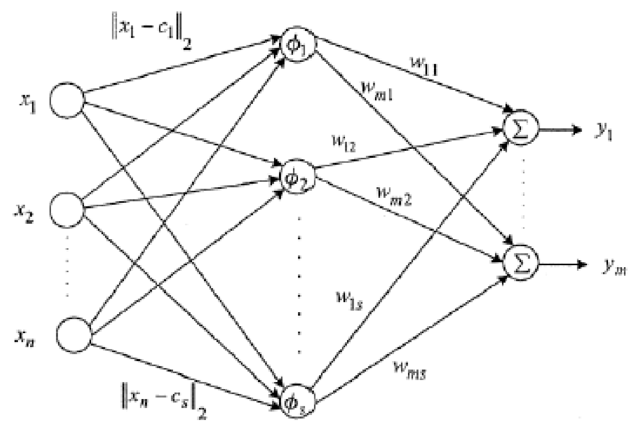

Fig. 2. Schematic diagram of RBF network.

Where ψ and γ are the parameters that control the "width" and "position" of the RBF centers, respectively

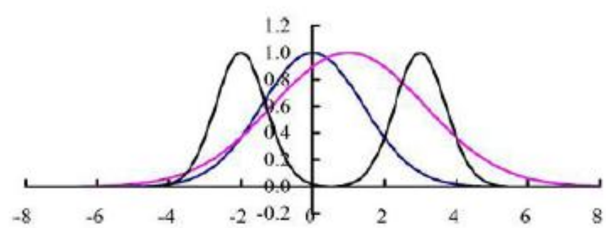

Fig. 3. RBF centers with different width and position.

It follows from (6) and (7) that there are four sets of parameters governing the mapping properties of the network: the number of centers in the hidden layer, the position of RBF centers, the width of RBFs, and the weights W_{ik}. In general, a sufficient number of centers are randomly chosen as a subset of the input space according to the probability density function of the training data. Then the stochastic gradient approach is used to tune the parameters however it is very difficult to define number of centers.

To overcome this limitation, this paper employs the OLS algorithm to determine the number of centers.

3.2 OLS Algorithm

The OLS algorithm can be implemented by introducing an error term e_i in (6) as follows:

$$y_i = \sum_{K=1}^{S} \varphi_k(\| x - c_k \|).w_{ik} + e_i \quad (8)$$

Using matrix form, (8) can be expressed as

$$Y = \Phi W + E \quad (9)$$

By using the Gram–Schmidt orthogonalization [14], the regression matrix φ can be decomposed into a set of orthogonal basis vectors as follows

$$\Phi = \mathrm{DA} = [\mathrm{d}_1\ \mathrm{d}_2 \dots \mathrm{d}_n] \begin{bmatrix} 1 & a_{12} & \cdots & a_{1S} \\ 0 & 1 & \cdots & a_{2S} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \quad (10)$$

Where A ε $R^{s\times s}$ is an upper triangular matrix, and D ε $R^{m\times s}$ is a matrix with mutually orthogonal vector di . Aggregating (9) and (10), the desired network outputs can be rewritten as:

$$Y = DAW + E = DG + E \quad (11)$$

Where G = AW. Since the Gram–Schmidt orthogonalization ensures the orthogonality between *E* and DG in (11). Therefore, the error reduction ratio (ERR) due to the inclusion of the *k*th center can be defined as

$$Y^TY = G^TD^TDG + E^TE = \sum_{k=1}^{S} h_k g_k^2 + E^TE \quad (12)$$

$$EER_k = \frac{h_k g_k^2}{Y^TY} \quad (13)$$

The above equation selects the RBF centers in a forward regression manner. The regression is terminated at the S_1th step when

$$1 - \sum_{k=1}^{S_1} EER_k < \Theta \quad (14)$$

Where$0 < \theta < 1$ is a tolerance value selected by the operators.

3.3 MPSO Algorithm

The PSO simulates the behavior of a swarm as a simplified social system. The particle tries to modify its position using the current velocity and the distance from Pbest and Gbest The current velocity and position are calculated as follows:

$$v_i^d(t+1) = C[wv_i^d(t) + \alpha_1 rand_1[Pbest_i^d - R_i^d(t)] + \alpha_2 rand_2[Gbest_i^d - R_i^d(t)]] \quad (15)$$

Where $v_i^d(t)$ is the current velocity of the ith particle, i=1,..,p, in which p is the population size; d is the dimension of population; $Pbest_i^d$ is the best previous position of the ith particle; $Gbest_i^d$best previous position among all the particles in the swarm; $R_i^d(t)$ is the current position of the ith particle; α is an accelarated factor; represents the uniform random number between 0 and 1; C is constriction factor; ω represent the inertia weight. This is set according to the following equation [15]:

$$w = (w_{max} - w_{min}) \times \frac{(iter_{max} - iter)}{iter_{max}} + w_{min} \quad (16)$$

Where $iter_{max}$the maximum number of iterations and iter is is the current number of iterations. Equation (16) restricts the value ω to $\omega_{max} - \omega_{min}$ the range. The next position of the th particle can be modified by

$$R_i^d(t+1) = R_i^d(t) + v_i^d(t+1) \quad (17)$$

To improve the convergence of PSO algorithm, the constriction factor is as follows:

$$C = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 + 4\varphi}|} \quad (18)$$

Where $4.1 \le \varphi \le 4.2$; As φ increases, the factor C decreases and convergence becomes slower.

3.4 Parameters adjustment using EPSO

1) Initialization: Generate the initial trial vectors randomly$R_i^d(i) = 1,2,..p,$, where p is the population size. $R_i^d(i) = [R_i^0 + R_i^1 + R_i^2]$, where R_i^0, R_i^1 and R_i^2 represent the desired values of the position of RBF centers, the width of RBFs, and the weighting vector, respectively. The element in vector R_i^d is randomly generated as follows:

$$R_i^d \sim U[x_{min}^d, x_{min}^d] \quad (1 = 1, \dots.. p, d = 0 \sim 2) \quad (19)$$

Where $U[x_{min}^d, x_{max}^d]$designates te outcome of a uniformly distributed random variable ranging over the given lower- and upper-bounded values x_{min}^d and x_{max}^d of the weighting factors or the parameters of translation and dilation.

2) Determination of Fitness Function: For each trial vector R_i^d, a fitness value should be assigned and evaluated. The criterion of least-squared fitting error (LSFE) function defined below is adopted to stand for the fitness value of the RBF network

$$LSFE = \frac{1}{m} \sum_{i=1}^{m} [y_i - \hat{y}_i]^2 \quad (20)$$

Where $\hat{y}_i$ is the ith computed output of the RBF network by using (6). y_i is the corresponding actual output, and m is the number of network output nodes.

3) Selection and Memorization: Each particle R_i^d memorizes its own fitness value and chooses the minimum one that has been better so far as $Pbest_i^d$. On the other hand, each particle also memorizes another particle's fitness values to known their experiences.

4) Modification of Velocity and Position: Modify the velocity of each particle according to (15). Modify the position of particle according to (17).

5) Mutation: The particles with poor individuals are selected for mutation. In this step, the population size remains unchanged.

6) Stopping Rule: Repeat Steps 2) to 5) until the best fitness value

4. NUMERICAL RESULTS

The proposed approach has been verified on the system under various power demands. For comparison, the conventional RBF network method and basic PSO method implemented by the commercial MATLAB package.

4.1 IEEE 30-Bus Six-Generator System

For the IEEE 30-bus six-generator system, the objectives of fuel cost and NO emission are converted into a single objective optimization problem as given in (3). Table I shows the coefficients of fuel cost and NO emission functions.

Table 1. Coefficients of Fuel cost and Emission Functions

Unit	Fuel Cost Function ($/h)			NO_x Emission Function (ton/h)		
	a	b	c	$\propto$	β	γ
P_{G1}	10	200	100	0.04091	-0.05554	0.06490
P_{G2}	10	150	120	0.02543	-0.06047	0.05638
P_{G3}	20	180	40	0.04257	-0.05094	0.04586
P_{G4}	10	100	60	0.05326	-0.03550	0.03380
P_{G5}	20	180	40	0.04257	-0.05094	0.04586
P_{G6}	10	150	100	0.06131	-0.05555	0.05151

Note: The lower and upper limits of each generating unit are 0.05 and 1.5(p.u), respectively

Table II shows the parameter settings for diverse methods. Note that the conventional RBF network has 315 centers distributed over the defined input space, while the proposed method employs an OLS algorithm to perform the reduction of the network size. Furthermore, the same numbers of input and output nodes are given to the existing and proposed methods, while the number of intermediate layers remains to be determined independently.

Table II. Parameter Settings for Different Methods

Methods	parameters	values
Conventional RBF network	Input nodes	3
	No. of RBF centers	315
	Output nodes	6
	Position of RBF centers	0.0
	Width of RBF centers	0.1
	No of iterations	15,000
	LSFE	10^{-6}
Proposed Method	Input nodes	3
	No. of RBF centers	65(selected by OLS)
	Output nodes	6
	Accelerated factor$\propto_1$ $(=\propto_2)$	0.50
	(w_{max}, w_{min})	(0.80,0.30)
	position of RBF centers [-6 6]	0.10(tuned by MPSO)
	Width of RBF centers [-6 6]	0.25(tuned by MPSO)
	Population size	200
	No. of iterations	1200
	LFSE	10^{-6}

Table III. Plan of training data created by GA Method

Inputs	Power demand: ranges from 2.251 to 2.834 pu, Separated by 0.04
	Operator's preferences (w_1 and w_2): all possible combinations of w_1 and w_2, both varying in steps of 0.05 in the range of 0 to 1.
Outputs	Active power output of each generator

Table IV. The results for different load levels in test system

Methods	Inputs		Active power outputs						Calculated values		
	P_D	W_1	P_{G1} (mw)	P_{G2} (mw)	P_{G3} (mw)	P_{G4} (mw)	P_{G5} (mw)	P_{G6} (mw)	APAE (%)	Fuel cost ($/h)	NO_x emission (ton/h)
Conv. RBF	217	0.5	96.482	33.740	22.999	22.760	21.000	21.909	0.231	339.632	0.192
Proposed			94.271	37.501	22.466	21.601	19.997	21.161	0.199	335.780	0.186
Conv. RBF	237	0.75	136.569	46.120	18.479	12.532	11.999	12.530	0.401	425.239	0.228
Proposed			133.964	44.391	19.591	15.136	11.407	12.000	0.395	423.620	0.210
Conv. RBF	277	0.5	105.639	45.290	35.926	31.990	28.519	30.505	0.218	536.999	0.263
Proposed			107.533	46.929	31.321	30.191	29.519	31.505	0.206	536.611	0.244
Conv. RBF	337	0.25	155.250	61.399	25.107	34.667	30.359	29.982	0.263	547.127	0.254
Proposed			153.049	60.329	28.818	35.000	29.149	30.243	0.261	546.381	0.249

Table III reveals the plan of training data created by the GA method. These load levels are defined in such a way that they cover the whole range of system load within the normal condition. As shown in table, a lot of 315 training samples are created.

Fig 4 exhibits the typical relationship between number of iterations and error rate. While increasing the number of iterations the error rate gets reduce and stands as constant at certain iteration value.

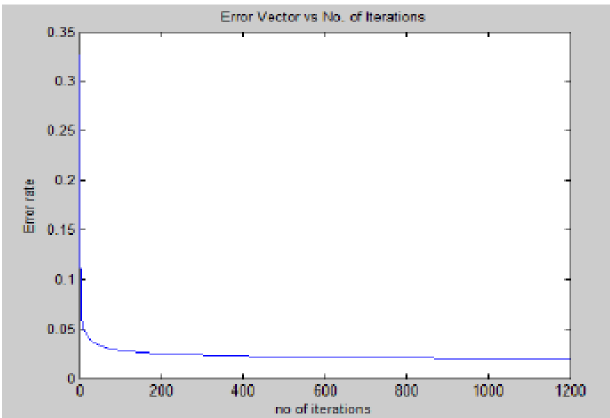

Fig 4 Error rate Vs Number of Iterations

The input space and centers comprises of power demand Pd, weights w1 and w2. Below figure is a plot between Power demand (PD) and one of the weights say w1. It clearly signifies that as generated each and every pattern is equidistant from each other. There are 315 patterns generated for training RBF NN for 6-Generator case.

The below fig 5 clearly describes that the number of patterns available to RBF network for choosing centers in hidden layer. The RBF network chooses the number of centers from input vector pattern randomly initially.

Fig 6 depicts the selection of centers from available centers through orthogonal least square algorithm (OLS) by adding error value to RBF network output. The ERR in(13) provides an effective criterion for selecting the RBF centers in forward regression, an adequate RBF center is selected so that the value of ERR is the maximum. The regression is terminated at given in (14).

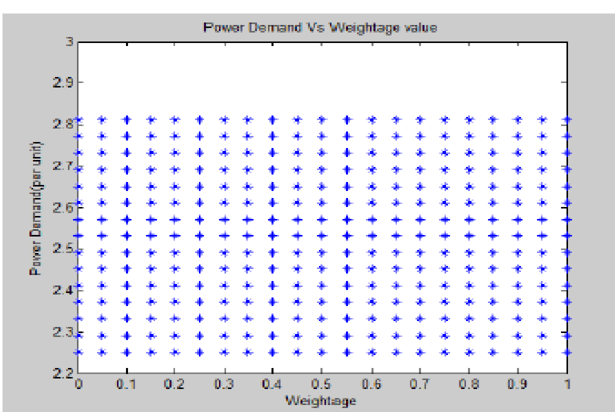

Fig 5 Distribution of input space and centers for RBF network

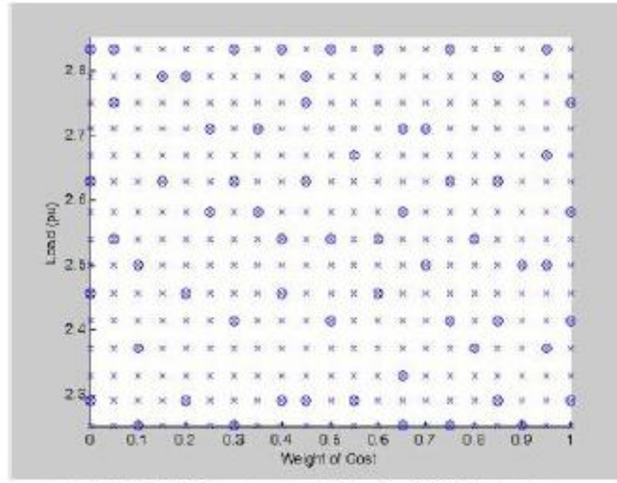

Fig. 6. Distribution of initial (315) and retained (65) RBF centers.

Table IV summarizes the comparisons of test results for various load levels. Notably, the cases of PD=237 and 277(mw) are in the range of trained historical data (interpolation cases), while the cases of PD = 217 and 337(mw) are beyond the trained range (extrapolation cases). Results of this table indicate that the proposed method is more accurate than the existing methods for both interpolation and extrapolation cases. The associated values of fuel cost and NOx emission are also listed for reference. Note that the values of fuel cost and NOx emission are obtained from table I. To compare the accuracy of different methods, the criterion of average percentage absolute error (APAE) is adopted in this paper, where m is the number of generators.

5. CONCLUSION

A new technique that combines OLS and MPSO algorithms to construct the optimal RBF network has been presented to solve the RTPD problem in this paper. Compared to the existing techniques, the superiority of the proposed method is summarized as follows.

1) Compared with the conventional RBF network method, the proposed approach provides an effective method to simplify the network structure.

2) Based on the same network structure, the proposed MPSO algorithm provides a more efficient search scheme to determine the related parameters of the RBF network than the PSO method.

3) Testing on IEEE 30 bus six generator system has shown that the proposed approach is superior to the existing methods in constructing the network and estimating the outputs of the generating units.

4) After the network is constructed, the proposed approach can make a quick response and yield accurate RTPD solutions as soon as the inputs of system load with the weight of cost are given.

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