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Implementing soft computing techniques to solve economic dispatch problem in power systems

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Abstract

Soft computing is the state-of-the-art approach to artificial intelligence and it has showed an excellent performance in solving the combined optimization problems. In this paper, issues related to the implementation of the soft computing techniques are highlighted for a successful application to solve economic dispatch (ED) problem, which is a constrained optimization problem in power systems. First of all, a survey covering the basics of the techniques is presented and then implementation of the techniques in the ED problem is discussed. The soft computing techniques, namely tabu search (TS), genetic algorithm (GA), Hopfield neural network (HNN) and multi-layered perceptron (MLP) are applied to solve the ED problem. The techniques are tested on power systems consisting of 6 and 20 generating units and the results are compared to highlight the performance of the soft computing techniques. Future directions and open-ended problems in implementation of soft computing techniques for constrained optimization problems in power system are indicated. Suggestions are presented to improve soft computing techniques.

Keywords: Soft computing techniques; Constrained optimization; Economic dispatch; Tabu search; Genetic algorithm; Hopfield neural networks; MLP neural networks

1. Introduction

The economic dispatch (ED) is a constrained optimization problem and the nature of the problem is to find the most economical schedule of the generating units while satisfying load demand and operational constraints. The problem has been tackled by many researchers in the past. The economic dispatch problem using conventional methods are surveyed by Chowdhury and Rahman (1990) and Talaq et al. (1994). Due to the network connection of power systems and the further innovation in the electricity market, the power systems become large scale non-linear dynamic systems (Bai & Zhao, 2006). In consequence, conventional techniques become very complicated when dealing with such increasingly complex dynamic system to solve economic dispatch problems, and are further limited by their lack of robustness and efficiency in a number of practical applications. Thus developing a reliable, fast and efficient algorithm is still an active area in power systems. In the last decay, the success of artificial intelligence techniques in broad area of optimization problems and promising research direction in literature pave the way to employ artificial intelligence and soft computing techniques to solve long standing power system problems, such as economic dispatch (Hong & Li, 2002; Kulkarni, Kothari, & Kothari, 2000; Roa-Sepulveda & Herrera, 2000; Song & Chou, 1997; Yalcinoz & Altun, 2005; Yalcinoz & Altun, 2000; Yalcinoz & Short, 1997; Zhu & Tomsovic, 2007), environmental/economical dispatch (Chiang, 2007; Jayabarathi, 2003; Song, Wang, Wang, & Johns, 1997), unit commitment (Dieu & Ongsakul, 2006; Rajan, Christober, Mohan, & Manivannan, 2002; Rajan & Mohan, 2003).

In this paper, a brief survey covering recent implementation of soft computing techniques in ED problem is presented. Then performance evaluation of a number of soft computing techniques to solve the problem is elaborated.

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Some point to improve the performance of the soft computing techniques is explained. Genetic algorithm, Hopfield neural network, multi-layered perceptron neural network (MLP NN) and tabu search algorithm are employed to solve the economic dispatch problem for power plants consisting of 6 and 20 units.

The organization of the paper is as follows: Section 2 covers a review of the soft computing techniques employed. In Section 3, the economic dispatch problem is briefly defined. The implementation issues related to the soft computing techniques in ED problem are discussed in Section 4 and the simulation results are given in Section 5. Finally, we end the paper with the conclusions and discussion to point out further direction in the implementation of soft computing techniques in ED problem.

2. Soft computing techniques

Soft computing is the state-of-the-art approach to artificial intelligence and its role in effect is to model the human mind. In this respect, the soft computing techniques differ from the respective conventional computing techniques in that they are tolerant of imprecision, uncertainty, partial truth, and approximation. The soft computing techniques comprises of fuzzy logic, artificial neural networks, probabilistic reasoning and meta-heuristic techniques such as genetic algorithm, tabu search, etc.

In this section, soft computing techniques will be surveyed which follows the implementation issues of the soft computing techniques, such as Hopfield NN approach, MLP neural networks, genetic algorithm and tabu search, in the ED problem.

2.1. MLP neural network

The term multi-layered perceptron is used for the neural networks with a structure of input layer, one or more hidden layers and an output layer. Each of the layers consists of inter-connected assembly of simple processing elements called neurons. These processing elements are organized in a layered fashion. Each neuron in a layer is connected to the neuron in the subsequent layer and so on. The interconnections between layers are called weights. Despite of their simplified structure, neural networks have ability to mimic human characteristics of problem solving via learning and generalization. MLP can be used to model non-linear systems due to their ability to learn the system behavior under inspection from samples.

For a successful application of MLP neural networks, one should determine internal parameters, such as initial weights and network structure, to meet required performance criteria (Cigizoglu & Alp, 2006; Ghedira & Bernier, 2004). In engineering neural network models, this is one of the main problems, as an inadequate network would be unable to learn. The problem of finding a suitable architecture and the corresponding weights of the network, however, is a very complex task (García-Pedrajas, Ortiz-Boyer, & Hervás-Martínez, 2006; Saxén & Pettersson, 2006) and main difficulties arises from the fact that the theory does not provide instruments to choice optimal values for these parameters. This, in turn, results in the need to train an MLP NN multiple times, effectively using different initializations and architectures. Consequently, the practitioner is involved in a process that requires more development time as well as experience and intuition (Krimpenis & Vosniakos, 2005). Furthermore, this approach does not guarantee the optimality of the obtained parameters for a given problem (Esposito, Aversano, & Quek, 2001). The common practice in the literature is to determine the number of neurons in the hidden layers by experience and some rule of thumb. Therefore, there could be more than one topology for an MLP to model a process successfully. However, as it is indicated by Altun, Bilgil, and Fidan (2007), the performance criteria of a MLP NN could be achieved by modifying the training data distribution.

After a successful learning phase, a MLP neural network will have an ability to generalize for the unseen data. During the training phase the weights are optimized in order to minimize a predefined error function. MLP neural networks are trained using the backpropagation (BP) algorithm which is a gradient based supervised learning method proposed by Rumelhart, Hinton, and Williams (1986). According to the algorithm, a mean squared error between the predicted and target values for the given input parameters is propagated backward to adjust the interconnection between neurons in order to minimize the pre-defined error. In this structure each neuron in a layer is mapping the sum-of-weighted input into an activation level that is determined by an activation function. The most commonly used activation functions are the sigmoid, the tangent-hyperbolic, and the linear activation function. If a sigmoid function is used, the output of the kth neuron, O_k, in nth layer is determined by the following equation:

$$O_k = \frac{1}{1+\exp(-net_k)} \tag{1}$$

where $net_k = \sum_j W_{jk} O_j$ and O_j is the output of a neuron in the previous layer and W_{jk} is weight between neurons (jth neuron in a layer and kth neuron in subsequent layer).

In this structure the adjustable network parameters are optimized based on the BP algorithm as follows:

$$W_{jk}^{\text{new}} = W_{jk} + \Delta W_{jk} \tag{2}$$

where $\Delta \mathrm{W}_{jk}$ is weight update for the connection W_{jk}.

The weight update is calculated as follows:

$$\Delta W_{jk} = -\eta(\partial E/\partial W_{jk}) \tag{3}$$

where η is learning rate which is chosen between 0 and 1 and E is the error (the cost function) defined as

$$E = \frac{1}{2}\sum_k (t_k - O_k)^2 \tag{4}$$

where t_k is the target for the kth neuron in the output layer.

Notice that O_i and t_k pair constitutes the input and output parameters in the training data set. Implementation of MLP in ED problem request to supply the total load demand as the input parameter O_i and the power output of the units along with total cost as the output parameter t_k.

2.2. Hopfield neural network

The Hopfield model (Hopfield & Tank, 1985) is a single layer recursive neural network where the output of each neuron is connected to the input of every other neuron. The energy function of the Hopfield NN, which is a quadratic function, is associated with the objective function for minimizing a optimization problem. Therefore, it is crucially important to decide how to set weights and input biases for any minimization problem. This process is called "mapping". The sum of the constraints and an objective function are given as inputs to the energy function.

Aiyer, Niranjan, and Fallside (1990) developed a mapping technique which identified the valid constraints in the energy function using a single constraint term and successfully solved the traveling salesman problem. Gee, Aiyer, and Prager (1993) discussed a new methodology to improve the performance of Hopfield networks, by formalizing the mapping process and providing a computational method for obtaining the weights and biases. Gee and Prager (1994) improved their mapping to solve quadratic 0–1 programming problems with linear equality and inequality constraints. The mapping technique can be extended to include the inequality constraints which are converted to equality constraints by introducing slack variables (Yalcinoz & Short, 1997). The simple quadratic problem without inequality constraints is first considered. The feasible solution for equality constraints can be described as

$$x = T^{\mathrm{constr}}x + s \tag{5}$$

where

$$T^{\mathrm{constr}} = I - A^{\mathrm{eq}^{\mathrm{T}}}(A^{\mathrm{eq}}A^{\mathrm{eq}^{\mathrm{T}}})^{-1}A^{\mathrm{eq}} \tag{6}$$

and

$$s = A^{\mathrm{eq}^{\mathrm{T}}}(A^{\mathrm{eq}}A^{\mathrm{eq}^{\mathrm{T}}})^{-1}b^{\mathrm{eq}} \tag{7}$$

For this case, the energy function can be written as

$$E = E^{\mathrm{obj}} + \frac{1}{2}c_0\|x - (T^{\mathrm{constr}}x + s)\|^2 \tag{8}$$

The equality constraints have been combined into a single penalty term in the energy function. The network's weights T and input biases i^b are set as follows for satisfying the energy function (Eq. (8)):

$$T = T^{\mathrm{obj}} + c_0(T^{\mathrm{constr}} - I) \tag{9}$$

$$i^b = i^{\mathrm{obj}} + c_0 s \tag{10}$$

where

E^{obj}	optimization objective function
X	n dimension variable vector of objective function
T^{obj}	$n \times n$ symmetrical matrix of objective function coefficients
i^{obj}	n dimension vector of objective function
A^{eq}	equality constraint matrix
b^{eq}	meq dimension equality constraint vector
S	feasible subspace offset vector
T^{constr}	feasible subspace projection matrix
I	identity matrix

Weights T and input biases i^b for any minimization process must be defined. We can set the network's parameters as Eqs. (9) and (10). Hence the Hopfield NN is created with n neurons for variables and m^{in} neurons for slack variables.

To solve the ED problem using the Hopfield NN, one needs the total fuel cost function as the objective function of the ED problem. The objective function, equality and inequality constraints are embedded in the energy function of the Hopfield neural network. After the mapping of the problem, the Hopfield NN model is ready to be used for solving the ED problem. At this stage, we have to solve the dynamic equation of the Hopfield NN using the simulation algorithm described in Yalcinoz and Short (1997) and Yalcinoz et al. (2001).

2.3. Genetic algorithm

Genetic algorithm is a stochastic optimization technique which is based on the principle of natural selection and genetics (Park, Won, Park, & Lee, 1999). GA approaches are capable of successfully solving the ill-posed problems such as non-convex functions, non-differentiable functions, domains not connected, badly behaved functions, multiple local optima, and multiple objectives (Miranda, Srinivasan, & Proença, 1998). It is also able to search multiple solutions simultaneously in contrast to conventional optimal algorithms which increase the possibility of finding global optimal solution. The main advantages of GA is that it finds near optimal solution in relatively short time compared with other random searching methods, such as simulated annealing or dynamic programming (Won & Park, 2003).

Due to these attributes, GA has applied to solve successfully non-convex problems in power systems such as economic dispatch, unit commitment, reactive power control, hydrothermal scheduling and distribution system planning (Chiang, 2007; Kazarlis, Bakirtzis, & Petridis, 1996; Zhang, Lu, Li, & Xie, 2006). As convex minimization problem is guaranteed to have a unique local minimum, which is also the global minimum, these problems can be solved using conventional gradient, sub-gradient or Newton-based local search techniques, exploiting the fact that local solution is also global. On the other hand, non-convex optimization problems have in general many local minima and local search techniques cannot locate the global minimum since they may be trapped in local minimum (Damousis, Bakirtzis, & Dokopoulos, 2003).

The algorithm starts from a *population* which is a randomly selected initial solution set. The search for a global optimum is conducted by moving from the initial population of individuals to a new population using genetics-like operators such as selection, crossover and mutation, which are inspired from the mechanics of natural selection and genetics encountered in natural life. Each individual represents a candidate to the optimization solution and is modeled by a value called chromosome. Starting from a randomly selected population, the GA operators perform task on the chromosome, in the reproduction process, in order to produce new generations so that solution at the global optimum may be obtained. The operation is based on a selective nature, i.e. the best candidates in terms of fitness are chosen as parent so that the new generation holds best genetic heritage. For this purpose, a fitness function assigns a fitness value to each individual within the population. This fitness value is the measure for the quality of an individual. The basic optimization procedure involves nothing more than processing highly fit individuals in order to produce better individuals as the search progresses. A typical genetic algorithm cycle involves four major processes of fitness evaluation, selection, recombination and creation of a new population. Based on fitness criterion, poorer performing individuals are gradually taken out, and better individuals have a greater possibility of conveying genetic information to the next generation.

In order to formulate the algorithm for economic ED problem, let the chromosome of the kth individual C_k be defined as follows:

$$C_k = [P_{k1}, P_{k2}, \dots, P_{kn}] \tag{11}$$

where

$k = 1, 2, \dots,$ popsize,
$n = 1, 2, \dots,$ number_of_gene,
popsize means population size,
number_of_gene is the number of unit in our experiment,
P_{ki} is the generation power of the nth unit at kth chromosome.

Two chromosomes, selected randomly for crossover, C_i^{gen} and C_j^{gen} may produce two offspring, $C_i^{\text{gen}+1}$ and $C_j^{\text{gen}+1}$, which is a linear combination of their parents i.e.,

$$\begin{aligned} C_i^{\text{gen}+1} &= a \cdot C_i^{\text{gen}} + (1-a) \cdot C_j^{\text{gen}} \\ C_j^{\text{gen}+1} &= (1-a) \cdot C_i^{\text{gen}} + a \cdot C_j^{\text{gen}} \end{aligned} \tag{12}$$

where C^{gen} is an individual from the old generation, $C^{\text{gen}+1}$ is an individual from new generation and a is the weight which governs dominant individual in reproduction and it is between 0 and 1.

2.4. Tabu search

Heuristic search methodologies in general do not guarantee optimality as they may converge at a local optimum solution. This is the case, quite often, when using local searching procedures. In order to "escape" from local optimum and explore a larger portion of the feasible region, a tabu search (TS) heuristic methodology can be used.

Tabu search is a higher-level method or meta-heuristic algorithm for solving combinatorial optimization problems (Glover, 1989, 1990). As opposed to classical local search procedures, tabu search does not stop at the first local optimum when no improvement is possible. The best solution in the neighborhood is always selected, even if it is worse than the current solution. This allows to explore more solutions from the feasible region.

TS is an iterative procedure that starts from some initial feasible solution and attempts to determine a better solution, which minimizes an objective function. TS makes several neighborhood moves and selects the move producing the best solution among all candidate moves for current iteration.

In this paper, a modified tabu search algorithm proposed by Karaboga, Guney, Kaplan, and Akdagli (1998) is used for solving the economic dispatch. The modified tabu search algorithm uses a real-valued solution vector and adaptive mechanism for producing neighbors. However the classical TS algorithm uses a binary solution vector. The use of real-valued representation in the TS is to offer a number of advantages in numerical function optimization over binary representation. Efficiency of the TS is increased as there is no need to convert binary numbers to real numbers; less memory is required as efficient floating-point internal computer representations can be used directly and there is no loss in precision by discretization to binary or other values.

The design of the neighborhood is a key element in the formulation of the proposed tabu search method as it may considerably increase the computational and searching efficiency. Karaboga et al. (1998) created a new neighbor production mechanism for modified TS algorithm. Here, the neighbors are produced by adding an adjusted coefficient at each iteration. This neighbor production mechanism enables us to find the most promising region of the search space.

One of the parameters of the algorithm is the size of the tabu list. The list contains information that to some extent forbids the search from returning to previously visited solutions. Generally the tabu list size is kept small. The size can be determined by experimental runs, watching the occurrence of cycling when the size is too small, and the deterioration of solution quality when the size is too large (El-Amin, Duffuaa, & Abbas, 2000).

3. Economic dispatch problem

The economic dispatch problem aims to supply the required quantity of power at the lowest possible cost

(Wood & Wollenberg, 1996). The dispatch problem can be described mathematically as an objective function with two constraints.

The total fuel cost at thermal plants should be minimized as

$$C_T = \underset{P_i}{\mathrm{Min}} \sum_{i=1}^{n} F_i(P_i) \qquad (13)$$
$$F_i(P_i) = (a_i + b_i P_i + c_i P_i^2)$$

where F_i is cost function for unit i and a_i,b_i and c_i are cost coefficients of unit i. P_i is the power output of the ith generator and n is the number of generators committed to the operating system. The economic dispatch problem subjects to the following constraints:

$$\sum_{i=1}^{n} P_i - P_{\mathrm{D}} - P_{\mathrm{L}} = 0 \qquad (14)$$

where

$$P_{\mathrm{L}} = \sum_{i=1}^{n} B_i P_i^2 \qquad (15)$$

where P_{D} is total load demand and P_{L} is transmission loss. The inequality constraint of limits on the generator outputs is

$$P_{\min,i} \leqslant P_i \leqslant P_{\max,i} \qquad (16)$$

where $P_{\min,i}$ and $P_{\max,i}$ are minimum and maximum generation output of the ith generator.

4. Implementation of soft computing techniques in ED problem

For a successful application of soft computing techniques in ED problem, some issues related to the implementation of the soft computing techniques should be taken into account. As in the case of MLP neural network, the determination of the network structural parameters as well as the presentation of the training data are highly important for a successful application of the technique. It is also true for Hopfield neural network in that; network performance is highly relied on the success of mapping of the ED problem. Although GA and TS, as meta-heuristic algorithms, do not require the prior knowledge on the problem, the success of these techniques, however, is highly depended on the parameter settings of the algorithms. Hence, the implementation issues will be discussed in the following sections for a successful application of the soft computing techniques to ED problem.

4.1. Implementation of MLP neural network in ED problem

Although MLP neural network is suitable for function approximation, regression and pattern recognition problems, its employment in optimization problems such as ED is encountered in literature (Singh, Srivastava, Kalra, & Kumar, 1995). MLP neural network has been proposed for combined environmental and economical dispatch problem by Kulkarni et al. (2000) and has been applied to a test system consisting of 6 thermal units. Suitability of MLP neural network for the ED problem is investigated by Altun and Yalcinoz (2003) and comparisons are given between GA, Hopfield and MLP approaches.

To solve the constrained economic dispatch problem using the MLP Neural Network, a training set should be constructed by combining the input and target pattern as pairs, i.e. (O_i and t_k). Input patterns O_i's are consist of total power load $\sum_{i=1}^{n} P_i$ in Eq. (14) and the corresponding target patterns consist of the unit powers constraints P_i and the total cost $C_T = \sum_{i=1}^{n} F_i(P_i)$ in Eq. (13). An additional set of the target parameters is applicable as target patterns in the case of environmental economic dispatch problem, such as environmental constraints NO_x, and SO_x.

The number of neuron in the input layer of MLP NN in 6 units ED problem is determined by the total load. The number of the neuron in the output layer of MLP is set by the power generated by 6 units and the total operation cost. Therefore, a MLP NN with a structure of 1–10–17–7 is chosen to solve the 6 units ED problem and a MLP NN with a structure of 1–7–10–21 is chosen to solve the 20 unit ED problem.

The MLP NN algorithm is coded in MATLAB using Neural Network Toolbox with an adaptive gradient descent BP algorithm. The learning rate is chosen as 0.01 and %5 increment is allowed. The maximum allowed iteration is set to 1000. For 6 units ED problem, training and test data pairs are produced by using classical method (CM) which is based on sequential quadratic programming and implemented in MATLAB. Data range of total load demand is running from 660 MW to 2620 MW. Total load demand is chosen as input patterns and corresponding unit powers are target patterns. As for the 20 units ED problem, 357 data pairs are produced by using classical method and data range of total load demand is running from 2150 MW to 5710 MW.

As it is known that neural learning is sensitive to the initial weight settings, a fixed initial weight set should be used to fairly evaluate the performance of MLP neural network. If the initial weights are randomized at each training session, different final weights will be achieved and accordingly the obtained solution will be different. This makes the evaluation process incomparable. The other point is that the statistical characteristics of training data set affect neural learning in MLP neural networks. In literature, improved neural network training is proposed which exploits the statistical dependency of neural learning on training data statistics (Altun et al., 2007). Hence, two scaling procedure is employed to illustrate implementation of MLP in ED problem. In the first scaling procedure, the input data and the target data are linearly scaled between the range of $[-2, 2]$ and $[-3, 3]$, respectively. This scaling does not change the distribution characteristics and statistics of the training data set. In the second scaling procedure, a non-linear scaling is employed which results in more evenly distributed target data set in the range of $[-3, 3]$. As a result, two training data sets are produced. A MLP neural network with identical structure and initial weights is trained using the both training data set. The MLP NN trained using linearly scaled target data set is called as MLP-1, while the MLP NN trained using non-linearly scaled target data set is labeled as MLP-2, respectively.

4.2. Implementation of Hopfield neural network in ED problem

Over the past few years, a number of approaches using Hopfield neural networks have been proposed for solving economic dispatch problems after the encouraging results by Hopfield and Tank (1985) who presented the energy function approach for solving to several optimization problems. As it is an constrained optimization problem, Park et al. (1999) proposed to apply a Hopfield NN to the economic dispatch problem for a piecewise quadratic cost function. King, El-Hawary, and El-Hawary (1995) reported an improved Hopfield NN for the economic-environmental dispatch problem and illustrated 3-unit and 12-unit systems. Mohammadi and Varahram (2006) showed that Hopfield approach is more efficient and faster that classical methods for solving ED problem. Lee, Sode-Yome, and Park (1998) presented an adaptive learning approach in the Hopfield NN using the slope adjustment and the bias adjustment methods for application to the ED problem. To speed up the convergence of the Hopfield NN, Su and Chiou (1997) have proposed an analytic method for the economic dispatch problem. The method applied the linear model to describe the neuron's input–output characteristics. The generation outputs were directly calculated using explicit formulations; therefore no iteration was needed. The main disadvantage of the method is that if a unit hits its generation limit, this is not a feasible solution and the generation dispatch should be repeated. Therefore it is difficult to use this method for large systems. The analytic method has been applied to solve the unconstrained economic dispatch with transmission losses by Su and Lin (2000). Yalcinoz and Short (1997) have proposed a new approach for the Hopfield NN in order to solve the ED problem. Yalcinoz and Altun (2000) have improved the Hopfield NN structure for solving the ED problem. Recently, Silva, Nepomuceno, and Bastos (2004) presented a modified Hopfield approach designed to solve ED problems with transmission system representation.

In this study, we will present the Hopfield model described in Yalcinoz and Altun (2000) and discuss how weights and input biases should be determined. Weights and input biases are set for the economic dispatch problem using the mapping technique which was described in Section 3. The Hopfield NN is created with n neurons for generators and m^{in} neurons for inequality constraints.

The cost function of the economic dispatch problem (Eq. (13)) is considered as the energy function of the Hopfield NN (Eq. (8)). Therefore the cost function is mapped as

$$T^{\text{obj}} = -2 \times \begin{bmatrix} c_1 & 0 & \cdots & 0 & 0 \\ 0 & c_2 & & 0 & 0 \\ \cdots & \cdots & & \cdots & \cdots \\ 0 & 0 & \cdots & 0 & c_n \end{bmatrix} \tag{17}$$

$$i^{\text{obj}} = -[\,b_1 \quad b_2 \quad \cdots \quad \cdots \quad b_n\,] \tag{18}$$

We can convert inequality constraints to equality constraints and then A^{new} and b^{new} can be written as

$$A^{\text{new}} = \begin{bmatrix} A^{\text{eq}} \\ A^{\text{in}} \end{bmatrix} \quad \text{and} \quad b^{\text{new}} = \begin{bmatrix} b^{\text{eq}} \\ b^{\text{in}} \end{bmatrix} \tag{19}$$

where A^{eq} and b^{eq} are defined from Eq. (16) and A^{in} and b^{in} are defined from inequality constraint equations. For example, the lower limit of the ith generator may be converted to

$$P_i \geqslant P_{\min,i} \Rightarrow P_{\min,i}y_i - P_i = 0$$

where $y_i \geqslant 1$ and we can define A_i^{in} and b_i^{in} as follows:

$$A_i^{\text{in}} = [0 \quad 0 \quad \cdots \quad -1 \quad 0 \quad 0 \quad \cdots \quad P_{\min,i} \quad 0 \quad \cdots \quad 0]$$

and $b_i^{\text{in}} = 0$.

The other inequality constraints can be fixed as in the above example. After finding A^{new} and b^{new}, we can calculate T^{constr} and s using Eqs. (6) and (7). and the Hopfield NN models are ready to be used for solving the economic dispatch problems. In this study, transmission losses are calculated using Eq. (15), at the end of every period and then assumed to be constant over the next period.

4.3. Implementation of genetic algorithm in ED problem

Genetic algorithm (GA) has recently become to be an attractive tool to solve the power optimization problems. As a probabilistic heuristic algorithm, GA may find the several sub-optimum solutions within a realistic computation time, even if there is no guaranty that the GA may find the globally optimal solutions in a finite time. In the study of Sheble and Brittig (1995) GA solves the economic dispatch for an example with three units. Hong and Li (2002) have proposed a genetic algorithm solution to the economic dispatch problem for cogeneration units. Chen and Chang (1995) have presented a genetic algorithm for solving economic dispatch problem. The proposed method can take into account network losses, ramp rate limits and valve point zone. A fuzzy logic controlled genetic algorithm has been applied to environmental/economic dispatch by Song et al. (1997). Song and Chou (1997) have proposed a hybrid genetic algorithm that is combination strategy involving local search algorithms and genetic algorithm. The validity of a fuzzy logic controlled genetic algorithm (Song et al., 1997) and a hybrid genetic algorithm (Song & Chou, 1997) is illustrated on the economic dispatch problem with a 6-unit system. In the above papers, the binary representation was applied to economic dispatch problems. The genetic algorithm with arithmetic crossover was proposed for solving the economic dispatch by Yalcinoz, Altun, and Uzam (2001). Zhang et al. (2006) proposed a new hybrid real-coded GA with quasi-simplex techniques and applied 13-unit system. In a recent study, Chiang (2007) proposed an improved genetic algorithm equipped with an evolutionary direction operator and a migration operator.

The success of the genetic algorithm strongly depends on the problem mapping which involves the transformation of the problem solution to a chromosome representation and the design of the fitness function as assess the quality of a solution.

Each chromosome within the population represents a candidate solution. A chromosome must represent a generation scheduling in order to solve the economic dispatch problem by using a genetic algorithm approach. In the economic dispatch problem, the unit power output is used as the main decision variable, and each unit's loading range is represented by a real number. The representation takes care of the unit minimum and maximum loading limits since the real representation is made to cover only the values between the limits.

The main objective of the economic dispatch is to minimize fuel costs while satisfying constraints such as the power balance equation. The fittest individuals will have the lowest cost of the objective function of the economic dispatch problem. The fitness function is used to transform the cost function value into a measure of relative fitness. For the economic dispatch problem, the fitness function, $\mathrm{Fit}(P)$, may be expressed as

$$\mathrm{Fit}(P) = \sum_{i=1}^{n} g(a_i + b_i P_i + c_i P_i^2) \tag{20}$$

In order to produce two offspring, an arithmetic crossover operator is used. After crossover is completed, mutation is performed. In the mutation step, a random real value makes a random change in the mth element of the chromosome. After mutation, all constraints are checked whether violated or not. If the solution has at least one constraint violated, a new random real value is used for finding a new value of the mth element of the chromosome. Then, the best solution so far obtained in the search is retained and used in the following generation. The genetic algorithm process repeats until the specified maximum number of generations is reached.

4.4. Implementation of tabu search in ED problem

Tabu search has been applied for solving some power system problems, such as maintenance scheduling (El-Amin et al., 2000), network synthesis (Gallego, Romero, & Monticelli, 2000), the capacitor placement problem in a radial distribution system (Yang, Huang, & Huang, 1996), alarm processing (Wen & Chang, 1997), optimal power flow (Abido, 2002) and unit commitment (Mantawy, Abdel-Magid, & Selim, 1999). A hybrid algorithm, which integrates evolutionary programming, tabu search and quadratic programming methods, has been proposed for solving the non-convex economic dispatch problem Lin, Cheng, and Tsay (2001). Lin, Cheng, and Tsay (2002) proposed an improved tabu search for economic dispatch with non-continuous and non-smooth cost functions.

Here, the modified tabu search algorithm proposed by Karaboga et al. (1998) is used for solving the economic dispatch. The coefficient for the ith generator is defined as

$$\Delta_i = (-P_{\min,i}/2 + \mathrm{random}(P_{\min,i})) \tag{21}$$

where $P_{\min,i}$ is minimum generation output of the ith generator.

In the proposed methodologies, a tabu search module is used as part of an iterative process; where in each iteration a potential schedule is evaluated. The number of iteration (N) is arbitrarily set. It starts by selecting a feasible schedule of generators for economic dispatch to be the initial schedule and proceeds by selecting feasible schedules from the neighborhood of that initial selection. The schedule with the lowest total fuel cost (Eq. (13)) among the new set of candidate schedules is selected as the next schedule to move to. A solution is represented with a vector of generation outputs for the ED problem and an associated set of neighbors. A neighbor is reached directly from the present solution. A succession of moves is carried out to transform the arbitrary solution to an optimal one. The new solution is the highest evaluation move among the neighbors in terms of the performance value and tabu restrictions that exist to avoid new moves that were evaluated in earlier iterations.

The modified tabu search algorithm uses an adaptive mechanism for producing neighbors. The neighbors of a present solution for the economic dispatch are created by the following procedure. The solution vector S_k at the kth iteration can be defined as follows:

$$S_k = [P_{k1}, P_{k2}, \ldots, P_{kn}] \tag{22}$$

where P_{ki} is the generation power of the ith unit at kth iteration. The neighbor of the solution is produced by

$$S_k^{\mathrm{new}} = S_k + \Delta \tag{23}$$

where Δ is a coefficient vector with the same dimension as S_k at the kth iteration.

5. Simulation results

The results of the economic dispatch problem illustrated in this study are obtained by the techniques given in the literature i.e. an improved Hopfield NN approach (IHN) (Yalcinoz & Short, 1997), a fuzzy logic controlled genetic algorithm (FLCGA) (Song et al., 1997), an advance engineered-conditioning genetic approach (AECGA) (Song & Chou, 1997) and an advance Hopfield NN approach (AHNN) (Yalcinoz & Altun, 2000), genetic algorithm with arithmetic crossover (GAwAC) (Yalcinoz & Altun, 2005). Also results obtained by MLP neural networks and tabu search (TS) are employed to carry out comparison between the aforementioned approaches. We will demonstrate two case studies where the performance of these methods is compared to each others.

5.1. Case 1: Economic dispatch for a system with 6 units

In this experiment, the test system has 6 units and details of this test system are obtained from study of Song et al. (1997). The structure of MLP neural network is chosen as 1–10–15–7. The result obtained by MLP NN trained using linearly scaled target data set is given in Tables 1 and 2 as MLP-1, while the results from MLP NN trained using modified scaled target data set is labeled in the tables as MLP-2, respectively.

A great improvement in the performance of MLP neural network is experienced when modified training data set is used (see MLP-2 in the table) instead of linearly scaled training data (see MLP-1 in the table). The results produced by MLP-2 are at least comparable or in some case outperforms the results obtained by the rest of soft computing techniques. Furthermore, the MLP method has advantage of being faster, as a trained MLP will achieve the solution within first iteration, while the rest of methods require an iterative approach to find a solution.

Table 1 presents the results of IHN, AHNN, FLCGA, GAwAC, MLP-1, MLP-2, and TS when the load demands are 800 MW and 1200 MW. In the both cases, MLP-1 neural networks produced the highest operation cost among the others. The obtained operation costs by the GAwAC and TS are smaller compared to other soft computing techniques. For 800 MW of load demand, the best results are produced by GAwAC and TS. The operation cost of the AHNN is slightly higher than the operation costs of GAwAC and TS methods. Although MLP-2 gives the lowest cost for 800 MW demand, it is not a feasible solution. For 1200 MW of load demand, the best feasible results is obtained by MLP-2 neural network, followed by GAwAC, TS and AHNN.

Table 1
Results obtained by IHN, FLCGA, AHNN, GAwAC, MLP_1, MLP-2 and TS

Load (MW)	Methods	Cost ($/h)	Load (MW)	Methods	Cost ($/h)
800.0	IHN	8228.05	1200.0	IHN	11477.20
	FLCGA	8231.03		FLCGA	11480.03
	AHNN	8227.11		AHNN	11477.09
	GAwAC	8227.09		GAwAC	11477.09
	MLP-1	9486.42		MLP-1	11044.50
	MLP-2	8163.38		MLP-2	11476.86
	TS	8227.09		TS	11477.09

Table 2
Results obtained by IHN, AECGA, AHNN, GAwAC, MLP-1, MLP-2 and TS

Load (MW)	Methods	Cost ($/h)	Load (MW)	Methods	Cost ($/h)
1520.0	IHN	14169.54	2238.0	IHN	20465.44
	AECGA	14169.54		AECGA	20470.48
	AHNN	14169.54		AHNN	20465.24
	GAwAC	14169.54		GAwAC	20465.24
	MLP-1	13136.38		MLP-1	20623.45
	MLP-2	14169.69		MLP-2	20445.14
	TS	14169.54		TS	20465.24

Table 2 gives a comparison of the economic dispatch results of AECGA, AHNN, IHN, GAwAC, MLP-1, MLP-2 and TS for 1520 MW and 2238 MW of load demand. For the demand of 1520 MW, it seems that MLP-1 produces the lowest operation cost. However, it is not a feasible solution since the constraints on unit power in this solution is violated. It can be clearly seen that the GAwAC, TS, AHNN, IHN and AECGA achieved lower operation costs. MLP-2 produced slightly higher than the rest of the soft computing techniques. However, the best result for 2238 MW of load demand is produced by MLP-2. In contrast, the AECGA produced higher operation costs for this loading condition.

From the results, it is obvious that if training data set is not modified accordingly, the MLP neural networks are not performing well in the solution of the constrained optimization problem. This phenomenon is elaborated by Altun et al. (2007). All the soft computing techniques produced better solution than the MLP-1 methods for 6-units system. Furthermore, MLP-1 achieved some unrealistic, unfeasible solution, extremely violating the constraints on unit power range. For 6-unit system, genetic algorithm with arithmetic crossover (GAwAC), tabu search (TS) and MLP neural network (MLP-2) produce the best results for different load demands.

5.2. Case 2: Economic dispatch for a system with 20 units

In this case study, MLP neural networks with the structure of 1–7–10–21 are chosen for this task. A test system with 20 units is considered and the details of the system are given in Yalcinoz and Altun (2001). The input is the total load and output consists of the power generated by 20 units and the total operation cost. The maximum allowed iteration is set to 1500 and adaptive gradient descent BP algorithm is used. The learning rate is chosen as 0.01 and 5% increment is allowed. 357 data pairs are produced by using classical method and data range of total load demand is running from 2150 MW to 5710 MW for the 20 units test system. The MLP NN trained using linearly scaled target data set is called as MLP-1 and while the MLP NN trained using modified training data set is labeled as MLP-2, respectively.

Table 3 gives a comparison between IHN, AHNN, GAwAC, MLP-1, MLP-2 and TS. The MLP-1 produces the lowest operation cost of 38000.82$/h for 3150 MW load demand. However, this solution is not a feasible

Table 3
Simulation results for a 20-unit system

Load (MW)	Operation cost ($/h)					
	AHNN	IHN	TS	MLP-1	MLP-2	GAwAC
3150	46068.90	46460.84	46026.90	38000.82	46051.79	46027.35
3800	52981.76	53207.7	52852.36	60931.54	52845.31	52852.49
4600	63566.14	63791.72	63401.27	64498.73	63313.03	63401.84

solution since the constraints on unit power in this solution is violated. For 3800 and 4600 MW load demand, MLP-1 obtained the highest operation cost. These results show that MLP-1 is not suitable for such non-convex optimization problem. On the other hand, MLP-2 produces the best results for 3800 and 4600 MW load demand, followed by TS and GAwAC. The best result for 3150 MW load demand is obtained by TS. GAwAC produced slightly higher operation cost compared to that of TS. Among the rest, MLP-2 produced the best results of 46051.79.

6. Discussion and conclusion

In this paper, solution to the economic dispatch problem as a constrained optimization problem has been obtained using various soft computing techniques. The implementation of soft computing techniques such as tabu search, genetic algorithm, Hopfield NN and MLP NN for solving economic dispatch problem has been presented. Then, the performance of soft computing techniques for economic dispatch problem has been evaluated. The soft computing techniques were tested on power systems consisting of 6 and 20 generating units. Obtained results have shown that in average TS, GAwAC and MLP-2 methods can provide better solutions than an improved Hopfield NN (IHN) approach, a fuzzy logic controlled genetic algorithm (FLCGA), an advance engineered-conditioning genetic approach (AECGA), an advance Hopfield NN (AHNN) approach and MLP-1. In average, tabu search produces the lowest operation cost among the soft computing techniques for 6-unit and 20-unit systems.

Despite the fact that MLP neural network is more suitable for function approximation, regression and classification problems and it shows a poor performance in non-convex optimization problem, providing only good solutions for local optimization problems (Tao, Liu, & Xue, 2004), we have showed that the performance of MLP neural networks in optimization problems is improved with a proper data modification. Furthermore, the MLP method has advantage of being a quick method compared to the iterative optimization methods such as GA and Hopfield. Once a MLP neural network is trained, it provides solutions in a cycle.

As it is seen from the tables, stochastic global optimization approaches such as GA and TS exhibit in general very good performance in the ED problem. These methods do not require any prior knowledge or space limitations, such as smoothness or convexity of the function to be optimized, they exhibit very good performance on the majority of the problems applied and find near optimal solution in relatively short time compared with other random searching methods; such as simulated annealing or dynamic programming (Kazarlis et al., 1996; Park, Park, & Won, 2000; Won & Park, 2003). However, main disadvantages of these techniques over traditional methods are (a) their long execution time (b) the fact that they are not guaranteed to converge to the global optimal solution. GA can suffer from poor convergence qualities and TS can easily miss some promising areas of the search space and larger set of parallel solutions does not exchange information as in GA (Dansky & Pozivily, 2002). There are many situations in which the simple GA does not perform particularly well (Kazarlis et al., 1996). Thus, hybrid approaches may be considered to improve the efficiency of soft computing techniques for solving economic dispatch problem.

There is a direction of hybridization of soft computing techniques in literature to solve multi-constrained, multi-objective optimization problems. Global searching ability of GA is combined with the local ability of a neural network to solve non-convex quadratic programming problem with bound constraint is proposed in Tao et al. (2004). A hybrid TS algorithm with simulated annealing is proposed to solve the problem of packing circles into a larger containing circle. In this approach, TS enhances diversification and prevents cycling which simulated annealing suffers (Zhang & Deng, 2005). A fuzzy rule base along with neural networks and genetic algorithms is proposed to solve a multi-objective problem in market planning (Gholamian & Fatemi, 2004). Zheng, Ngo, Nguyen Binh, and Tjin (2004) proposes a hybrid optimization method which uses tabu search as a global optimization algorithm and a quasi-Newton local optimization algorithm. A computationally less expensive global neuro-genetic algorithm is proposed by Kumar, Kalra, and Dhande (2004). The algorithm uses neural network to provide a population initialization. Kumar and Palanisamy (2006) proposed a hybrid dynamic programming based Hopfield neural network approach to unit commitment problem. The computational results demonstrated that the saving in cost for the hybrid method is superior and takes less CPU time.

The direction of hybridization of soft computing techniques suggests that multi-hybrid soft computing techniques seem to be feasible powerful tools to provide robust and accurate solution for future works in power system problems such as economic dispatch, unit commitment and optimum power flow, etc.

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