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A Modified Ant Colony Optimization Algorithm for Power Scheduling

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Abstract*: The purpose of this work is to solve the problems related to the power system in an efficient manner by assigning the optimal values. To meet the demand loads with good quality and quantity is a challenging problem in the field of the power system. Artificial Neural Network is realized in the field of energy management and load scheduling. The Backpropagation algorithm is used for the training purpose. It has the aspects of the quick meeting on the local bests but it gets stuck in local minima. To overcome this drawback an Ant Colony Optimization algorithm is presented to allocate optimal output values for the power system. This has the capacity for searching the global optimal solution. Present work modifies the ant colony optimization algorithm with backpropagation. This hybrid algorithm accelerates the network and improves its accuracy. The ant colony optimization algorithms provide an accurate optimal combination of weights and then use backpropagation technique to obtain the accurate optimal solution rapidly. The result shows that the present system is more efficient and effective. These algorithms significantly reduce the peak load and minimize the energy consumption cost.

Keywords: Load scheduling, Artificial Neural Network, Ant Colony Optimization, Backpropagation

I. INTRODUCTION

The efficient load management of parallel power systems is concerned with scheduling the power based on the operating cost, availability and load demand. To meet the power necessities the hydropower sources are inadequate. Hence the proper scheduling of different power sources is important. The total conception in the power system must be balanced with the generated power. To maintain the stability of power between consumption and generation, it needs to control the input parameters [1]. There is no efficient way to store this large quantity of energy. The economical scheduling problems are unit commitment and online dispatch. For least cost of scheduling, a specific quantity of power will supply through the network over a required period of time. Online dispatching in the system means the parallel distribution of power. To fulfill the essential power, it is considering all existing sources of power. Efficient scheduling has become an important tool in the field of energy management for proper energy-saving and meets the power demand [2]. When the different sources are considered, thermal power is unreasonable. In a practical scheduling approach, a low priority is assigned to the expensive power sources. At the time when hydropower is necessarily available, utmost power is traced from the same and rest of power is drawn from further sources. The generation of electric power may be planned and the future power needs can be predicted by using Artificial Neural Network (ANN) [3] method. Exact scheduling reduces the cost and provides efficient operation. Economic, time, weather and random disturbance are some important categories of factors that affect the system load. The economic trends have a significant impact on the system load demand. The seasonal effect, weekly-daily cycles and holidays are influencing the load structure. Temperature and humidity are the major weather factors that affect the system load. Neural Networks are capable to handle the non-linearity between the load and the factors affecting the load [4]. It is trained and tested using Backpropagation Neural Network (BPNN) algorithm. This is the most powerful error reducing algorithm. It has the characteristics of fast approach on the local optima and at the same time, it gets stuck in local minima. Sometimes BPNN fails to find the global optimum. Therefore global optimization algorithm Ant Colony Optimization (ACO) [5] is used to predict the better path.

To handle the qualitative and quantitative knowledge, BPNN uses parallel distributed processing approach. It has fault tolerance and adaptability, strong robustness, and can completely estimate every complex nonlinear association. Because of this dominance, BPNN is more suitable for processing the electric energy signals which are unbalanced, disorderly and nonlinear. For the scheduling process, the feed-forward neural network practiced by Backpropagation algorithm (BP) is used. This is a controlled learning method; means the neural network create a model from the examples of information with a predicted output value. The mean square error (MSE) is used as the cost function. The structure of this paper is as follows. A summary of ANN and BP algorithms is presented in part II. In part III, the intended ACO-BP algorithm is described. Section IV and V provides the load performance and assessment respectively. Section VI concludes the work.

II. METHODOLOGY

A. Artificial Neural Network

It is a technology that contributing a substitute way to resolve complex and incorrect difficulties. It is a machine learning prediction process, modeling of a real biological network and that mimics the learning process of the human brain. ANNs are used to assess functions that can depend on a large number of inputs and are generally unknown. It introduced as the systems of interrelated neurons that communicate with each other.

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The connections have numeric weights that can be adjusted based on knowledge, assembly neural nets, adaptive to contributions, and proficiency of learning. It is considered as a nonlinear statistical data modeling tool. Neural networks consist of the input-output layers and hidden layer. It consists of a number of processing nodes which are connected in a network [6]. This node is similar in working in a real neuron. Interconnected artificial neurons are used to make the structure of ANN, which are trained to recreate the biological neuron properties. When handling with several kinds of data, the neural networks are self-directed and continuously alter their structures in order to familiarize the different circumstances [7].

B. Backpropagation Neural Network

At present, this is the superlative neural network learning algorithm and the majority of neural network presentations are grounded on this algorithm [8]. In a BP network, the transfer function for neurons is frequently a differentiable function with the sigmoid. This can acquire any non-linear representation between the contribution and response. The ANN supervised learning algorithm is named as [BPNN] is used to optimize the neural networks by forwarding the neural network training process. Fig.1 exhibits the structure of the presented ANN. The inputs are the independent variables [$x_1, x_2, \ldots x_n$] and the responses are [$y_1, y_2, \ldots y_n$]. The BPNN is a learning method based on the error-correction rule. This method gradually minimizes the error function by adjusting the connection weights [9]. The alteration between the actual response and the preferred response is considered as the error function.

$$e_i = (t_i - o_i) \tag{1}$$

$$E = \frac{1}{2}\sum_{i=0}^{j}(t_i - o_i)^2 \tag{2}$$

where i denotes the layer index, t_i is the preferred output, and o_i is the actual response of the network.

To define the weights in the system, they can be trained via the learning process. They exhibit high self-adaptability to the situation and a self-learning capability [10]. BPNNs are fault-tolerant and highly robust. The algorithm can be summarized in the following stages: (a) feed-forward stage computation, the (b) error is backpropagated to the hidden and output layers, (c) connection weights updating. The weight modifying process can be expressed as follows

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \ , \ w'_{ji} = w_{ji} + \Delta w_{ji} \tag{3}$$

where Δw_{ji} is the weight vector updates for the network connections between the layers indexed by i and j, η is a constant mentioned to as the learning rate, and w'_{ji} are the current and updated connection weights respectively for the connections between layers i and j.

Table I. Parameters in Artificial Neural Network

Parameter	*Value*
Weight range	[-1,1]
Threshold range	[-1,1]
Activation function	Sigmoid
Learning coefficient	0.2
Momentum	0.8
Stopping rule (epoch)	1000

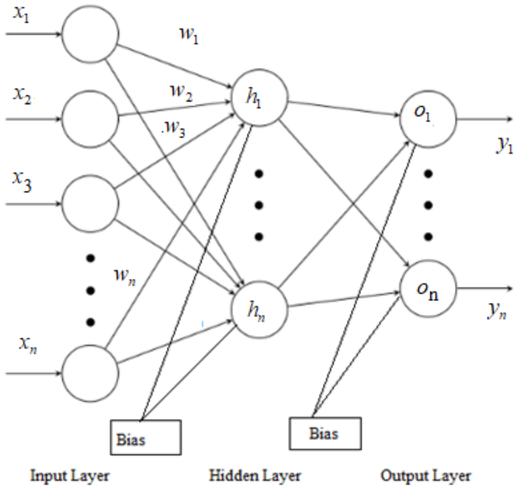

Figure 1. ANN structure

The algorithm terminated its training process when generalization stops refining. It improves the BP network by using the Levinburg- Marquardt(LM) BP algorithm [11] because the BP has low adeptness, slow merging speed, and restricted precision. The LM training algorithm is used in the BPNN for getting more stability. For the multi-layer perceptron, BP is considered as the best algorithm. With the constraints shown in Table 1, using the BP algorithm the feed-forward ANN model is trained.

III. ANT COLONY OPTIMISATION

The nature-inspired metaheuristic algorithm ACO was introduced in 1992 by Dorigo [12] based on the external performance of the ant colony when foraging. The ACO is a conventional swarm intelligent technique for interpreting combinatorial optimization problems. The foremost motivation behind the ACO algorithm is the thought of 'stigmergy' in nature. Stigmergy is a method of self-organization and it refers to the modification of the situation by genetic organisms to interconnect with each other [13]. In fact, indirect communication takes place when an individual configures the environment and at a later time, others respond to that modified environment.

This algorithm gives a better solution for complex problems of combinatorial optimization in the field of industry, engineering, commerce, many others. It's a fast-growing field with many applications. It is inspired by the searching behavior of ant, which enables an ant colony to find the shortest path between its nest and source [14] [15]. When ant starts to find the food source it place quantities of a volatile chemical substance, pheromone on the ground. Other ants have a tendency to follow the previous ants by attracting these pheromone trails.

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In case searching ants realize many paths between source and nest, a short path naturally gets advanced with pheromone faster than a longer path. The majority of ants choose the shortest path, where the more pheromone is deposited until all the ants elect the shortest track. The probability of following a track increases with the number of ants selecting the path at earlier times and with the strength of the pheromone concentration placed. When looking for food, ants initially explore the surrounding area, placing pheromones on the path that is to be followed by the other ants. When an ant treasures food, it calculates the amount and superiority of it and transfers some of them back to the nest. At that time it places pheromones proportional to the quality and quantity of the searched food [16]. Demonstration of this pheromone updating is illustrated in Fig.2. To create artificial ants a predetermined set of accessible solutions are used. All Ant takes values from this finite set. In its, each iteration an ant can select the entire unvisited node available from the current position [17]. An ant 'k' at node 'r' will choose the destination node 's' at a later stage with a probability,

$$P_{k(r,s)} = \frac{\tau_{r,s}^{\alpha}\eta_{r,s}^{\beta}}{\sum \tau_{r,s}^{\alpha}\eta_{r,s}^{\beta}} \tag{4}$$

where $\tau_{r,s}$ shows the quantity of pheromone of r, s edge; α, distinct the pheromone influence, $\eta_{r,s}$ shows the desirability of r,s edge, and β, describes the influence of the desirability.

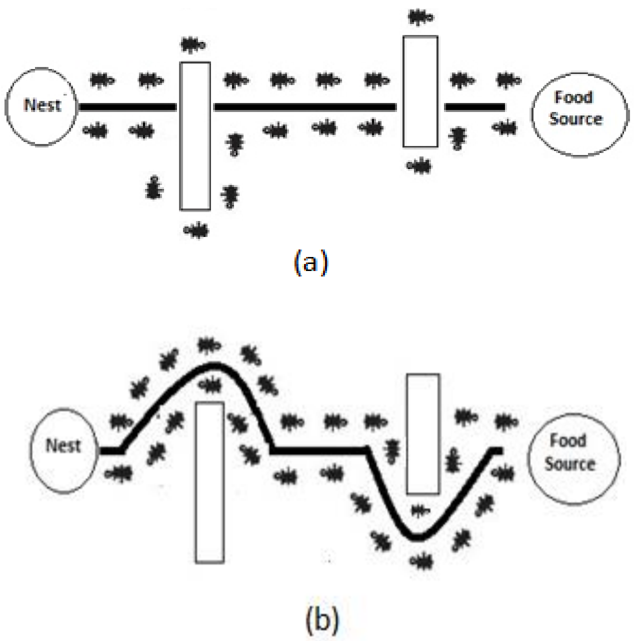

Figure 2. Adapting the behavior of a real ant colony: (a) when an obstacle occurs with equal probability, check whether to shortest or longest path; (b) the shortest path is chosen by the majority of ants.

If the distance should be minimized, $\eta_{r,s}$ can be defined as,

$$\eta_{r,s} = \frac{1}{d_{r,s}} \quad \text{Where } d_{r,s} \text{ is the length of the edge r, s} \tag{5}$$

For the communication between the artificial ants, the pheromone phase is used and it helps to make decisions. In this phase pheromone evaporation and deposit are the major components. The amount of pheromone on r, s edge is:

$$\tau_{r,s} = (1-\rho)\tau_{r,s} + \Delta\tau_{r,s} \tag{6}$$

Where ρ defines the pheromone vaporization proportion and $\Delta\tau_{r,s}$ is the total amount of pheromone deposited on r, s edge which is defined as,

$$\Delta\tau_{r,s} = \begin{cases} \dfrac{1}{L_k} & ;\ k^{th} \text{ ant travels on edge r, s} \\ 0 & ;\ \text{otherwise} \end{cases} \tag{7}$$

Where L_k indicates the length (cost value) of the track that k^{th} ant travels.

In this algorithm, virtual pheromones generated by the artificial ants are used for updating the path. The density and the amount of pheromone are the major factors that affect their path updating [19]. It depends on the comparison of the quality of the pheromone with the former artificial ant of the same iteration. Algorithm 1 explains the training process for ACO-BPNN hybrid network.

Algorithm 1:

1) Initialize the constraints like pheromone value, heuristic information and stopping function.
2) Generate and calculate a solution for each ant. Recurrence the process until exit benchmarks met. If the criterion is not met then update the pheromone value using the modified ACO (MACO).
3) On the occurrence that the exit criterion is fulfilled; update the initial weights of BP.
4) Train the BP network and obtain MSE. Again the process checks for the exit criterion.
5) If the condition fails repeat step 4. Otherwise, save the results for MSE and Regression.

IV. LOAD SCHEDULING FORMULATION

The requirement is to find the optimal combination of sources based on demand to reduce the cost. For any unit, the cost curve is supposed by quadratic function segments of the active response of the sources. For a power system, the optimization of cost is defined by the equation [20],

$$F_{tot} = \sum_{i=1}^{n} F(P_i) = \sum_{i=1}^{n} (a_i P_i^2 + b_i P_i + c_i) \tag{8}$$

Where, F_{tot} is the aggregate rate of generation, a_i, b_i and c_i are the cost coefficients and P_i, is the generated power by the i^{th} unit and n is the number of sources.

The optimization of rate is subjected to the discrimination constraints of the system.

$$P_{i,\min} \le P_i \le P_{i,\max} \quad \text{For i=1, 2, 3……n} \tag{9}$$

Where, $P_{i,\min}$ *and* $P_{i,\max}$ are the least and extreme power productions.

The total power demand, $P_D = \sum_{i=1}^{n} P_i - P_L$ (10)

where P_L is the total transmission loss

V. RESULTS AND DISCUSSION

For load scheduling three-layer feed-forward neural networks are used. For the load optimization, metaheuristic scheduling algorithm MACO is presented. It reduces the operation cost, diminishes the energy conception during peak time, and make the availability of the power to the prior demanded areas. The demand for electricity is not reduced, but it tries to shift the demand from peak to off-peak period by considering all parameters. By using this scheduling process completely avoid the traditional load shedding process. It consists of a cascaded of power stations, whose total scheduling period is 24 hours with an hour interval. Fig. 3 shows the total output and demanded power. In the present work, scheduled the power stations based on availability and cost. After the scheduling, the system always met the demanded load.

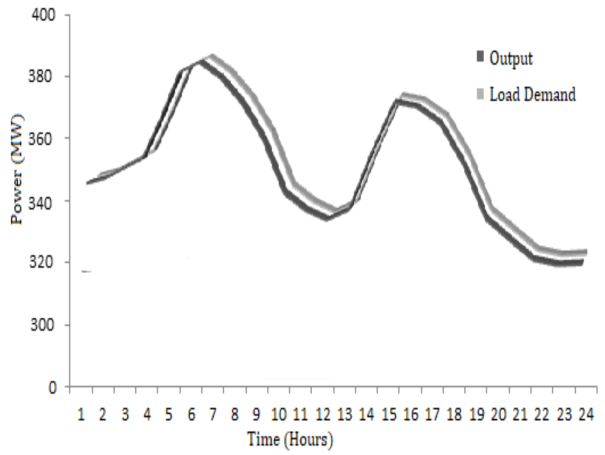

Figure 3. Demanded and Output Power

Fig. 4 shows the losses of power after scheduling. This work helps to meet the rapidly growing requirement for energy, in extension to the enhanced generation, better efficiency, durability, and energy preservation. In this present work, self-determining and supervision of energy are presented.

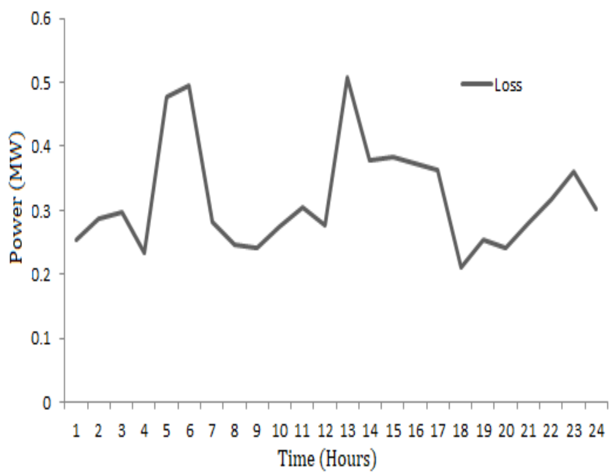

Figure 4. Power Loss after scheduling

Table II shows the ACO parameters used for training. Best cost vs the number of iterations is shown in Fig 5. The system tries to minimize the cost when iteration started by updating the pheromones. The system optimized to the minimum cost within the iteration limit.

Table II- ACO Parameters

Parameter	***Value***
Maximum number of Iteration	150
Number of Ants (Population size)	20
Initial Pheromone	1
Pheromone Exponential Weight	1
Heuristic Exponential Weight	1
Evaporation Rate	0.05

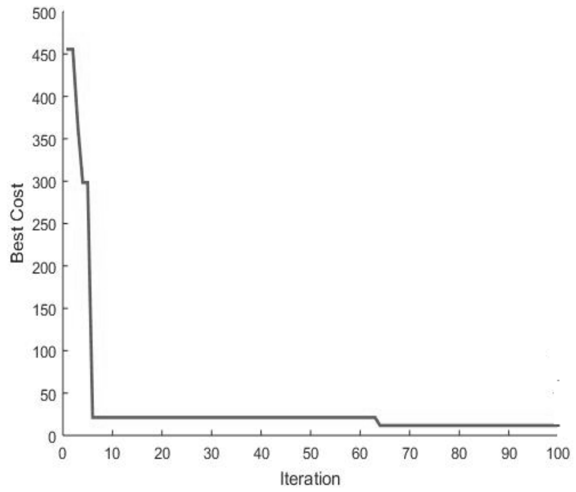

Figure 5. Best cost vs the number of iterations

The simulations have been conducted with different requirements of the system. The presented scheduling algorithm runs many times and the average makespan value is computed. In all the training, the solutions are finished before reaching the maximum iteration. The result is compared with the BPNN.

Fig. 6 shows the network architecture of the presented ANN system. Fig. 7 shows the best training performance of the modified algorithm. The performance of the network is analyzed in provisions of MSE and Epochs. The graph shows the trends of training, validation and test data in terms of MSE and Epochs. From the graph, it is clear that the MSE shrinks with an increase in the figure of epochs for all trained, validation and test data. The accuracy of the system is 97.01% on the basis of performance parameters. Table III shows the comparison of the proposed system with BPNN.

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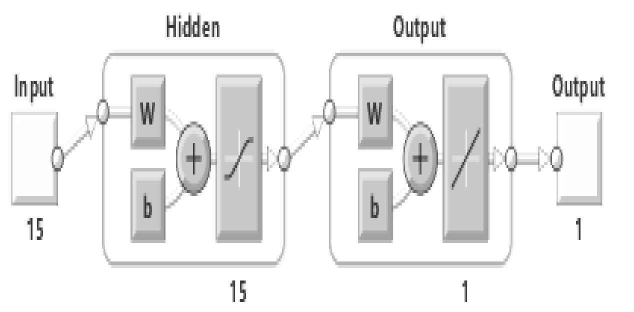

Figure 6. Network Architecture of the presented system

Table III. Time, MSE and Epochs for ANN architecture

Algorithm	*BPNN*	*MACO_BP*
CPU Time	98.14	126.42
Epochs	100	35
MSE	6.45440e-3	2.67870e-3
Accuracy (%)	82.12	97.01

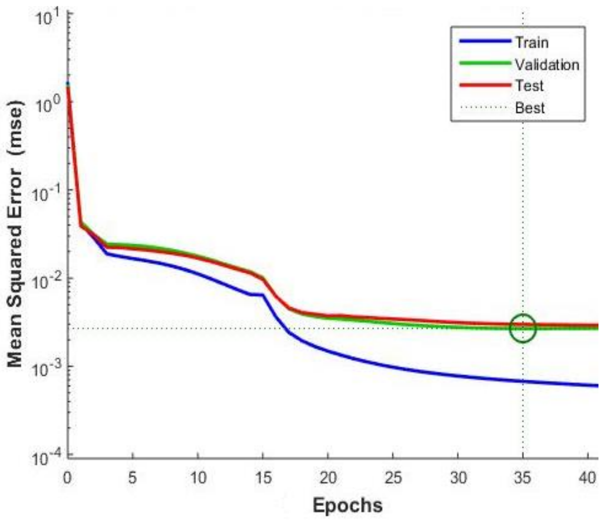

Figure 7. Training performance of the present system

VI. CONCLUSION

In ANN, BP algorithm has been used to adjust the connection weights. Basic BP algorithm is unstable and there is a possibility to get stuck in local optima. Here the Levenberg-Marquardt algorithm is used in BP. In this work, a global optimization algorithm(ACO) is hybridized with the BP algorithm. There is a chance for convergence of initially connected weights selected for BP to a local optimum. The present work leads to get good initial connection weights through ACO and then pass the result to BP network for training. From the response of the system, it is clear that the presented hybrid training performance is better than the basic BP algorithm.

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