Backpropagation neural network based adaptive load scheduling method in an isolated power system

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ABSTRACT

This work introduces an efficient load scheduling method for handling the day-to-day power supply needs. At peak load times, due to its instabilitythe power generation system fails and as a measure, the load shedding process is followed. The presented method overcomes this problem by scheduling the load based on necessity. For this load scheduling is handled with an artificial neural network (ANN). For the training purpose the backpropagation (BP) algorithm is used. The whole load essential is the input of the neural network (NN). The power generation of all resources and power losses at the instant of transmission is the NN output. The optimum scheduling of different power sources is important when considering all the available sources. Load scheduling shares the feasibility of entire load and losses. It is well-known as optimal scheduling if the constraints such as availability of power, load requirement, cost and power losses are considered. Training the system using a large number of parameters would be a difficult task. So, finest number of communally independent inputs is selected. The presented method aims to lower the power generation expenditure and formulate the power available on demand without alteration. The network is designed using MATLAB.

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1. INTRODUCTION

Nowadays, there is an increase in insistence for power. The economically scheduling efforts are unit commitment and online dispatch. In unit commitment, low-cost scheduling through a given period requires a preset quantity of power supplies over the network. Online dispatching is the distributing of power parallel with the system [1]. The finest scheduling of dissimilar power sources is significant, considering all the available sources to meet the power demand. Economic power sources like hydropower are insufficient to meet power demand; at that instant, some expensive sources such as thermal units are used. When considering solar energy is readily available, but the amount of power generated from it is insufficient to meet the load demand [2]. Based on these aspects, the power system requires an optimum load scheduling technique to save energy and meet load demand. In these, power from thermal source is costly. Thus, in optimally scheduling procedure, little priority is given to thermal units. If the hydropower is sufficiently available, maximum power is obtained from the hydropower station, and the remaining power is received from other sources [3], [4].

In the power system functioning most significant concept is the stability of frequency and voltage. The unsteadiness of such specifications generates serious intimidation to system protection. The faults such as short circuits, load growth, and generation shortage may disturb the voltage and frequency [5]–[7]. Such unsteadiness drives to the total failure of the system. Power generation instability is one of power plants' significant drawbacks. The proposed technique surmounts this negative aspect by scheduling the load based on the necessity. The overall load is the sum of the utmost load requisite by the whole region and the power loss. The system analysis the regions' highest load if any region needs further power to meet the load condition. This evaluation helps to learn the minimum load needed units and schedule this load to the appropriate region. The system not ever interrupts the power source [8].

In this work, artificial neural network (ANN) is instructed with various 'load demands.' Once it has been trained with the different load parameters, the system acquires capability to provide load forecast patterns to every value for the load demand. In present system, the maximum load to each region and the further load required for any region is the inputs, and the generated power and its losses are the outputs. The backpropagation neural network (BPNN) algorithm is suggested for this scheduling. The present neural network (NN) comprises three inputs, four middle, and one output neuron [9]–[11]. The inputs for the NNs are the power insists for each section, the additional power required for each region due to extra load, and the power loss. The output is the total power required for the entire section [12]. Network architecture is known as the organization of neurons into the layer and the interconnection configurations within and between the layers. Figure 1 shows the multilayer perceptron with n input nodes [13]. The different layers in network are input, hidden, and output as shown in Figure 1.

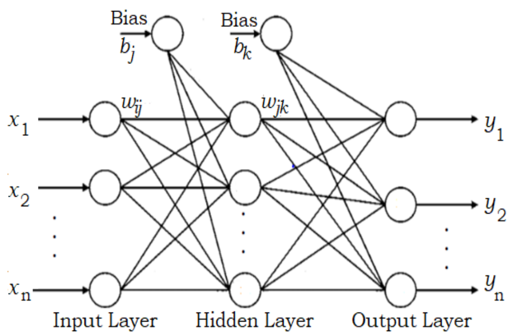

Figure 1. The multilayer perceptron with 'n' input nodes

The *net* input of the hidden unit *j* is shown in (1) and the outputs of neurons in the hidden is shown in (2) and output layers are as in (3):

$$net_j = \sum_{i=1}^{n} w_{ji} x_i + b_j \tag{1}$$

$$y_j^h = f(\sum_{i=1}^{n} w_{ji} x_i + b_j) \tag{2}$$

$$y_k^o = f(\sum_{i=1}^{n} w_{kj} y_j^h + b_k) \tag{3}$$

2. THE PROPOSED SYSTEM MODEL

2.1. Optimal schedulingofpowerplants

Load scheduling shares the accessibility of entire load and losses in power generators. Overall load is scheduled consistently then it is acknowledged as uniform scheduling. If parameters such as load requirement, availability of power, power losses, and cost are considered, then it is known as optimal scheduling [14]. In the present work, an optimal load scheduling algorithm is implemented. Various power generating plants are connected to a standard grid to deliver power to the load centers [15].

The expenditure of power production is different for all plants. So, it requires optimal scheduling to meet the essential load. The total load is the sum of networks load insist and losses at some stage in transmission. Most systems have a non-linear cost function [16]. The electrical energy insistence in any country depends on several parameters, mainly temperature, load, time and population. Training an ANN using a large number of constraints would be a complex task. So, an optimum number of mutually independent inputs are selected [17]. Figure 2 shows the proposed system model for scheduling using the backpropagation (BP) algorithm.

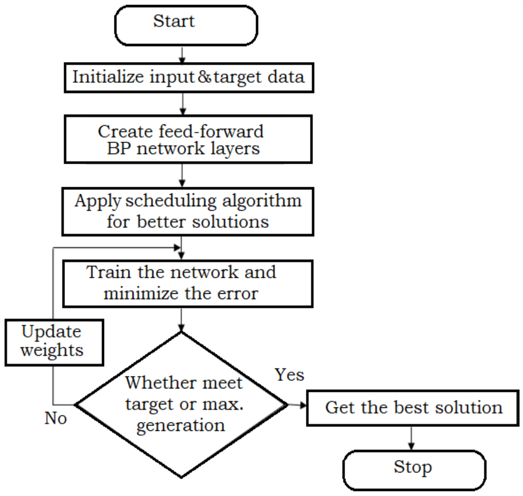

Figure 2. Proposed system model

3. METHOD

3.1. Model for scheduling using backpropagation algorithm

The intention of this miniature is to schedule electric energy on-demand for future years with marginal input data. ANNs find wide acceptance in many areas for modeling complex real-world problems. Each layer in ANN has a set of neurons designed to perform a particular task [9]. The learning ability of the system depends on the hidden layer. Selecting the number of neurons in the hidden layer is challenging, whereas designing a network is a challenge. So, trial and error methods are performed to select hidden layers. If the numbers of hidden neurons increase, the design complexity also increases [18]–[20].

Figure 3(a) shows the ANN structure at the source end. It shows the ANN-based scheduling of power sources based on accessible and cost. It consists of two input, three central, and three output neurons. In the network, the total power required is the sum of power demands by load and power loss during the transmission time, and these two parameters are considered the inputs [21], [22]. The three different power generators are the outputs. In the figure, w_{ij} is the weights between input and hidden neurons, w_{jk} is the weights between hidden and output neurons, w_o is bias weight, and P is power.

Figure 3(b) shows the ANN structure at the user end. To resolve the response of the present system an activation function sigmoid is used. The error is determined by analyze the expected value with the actual response, and the error is backpropagated. The weights adjust until the actual output, and target values are equal. If both values become equal, the system is said to be trained. The weight updation at hidden and output layer is shown in (4) and (5) respectively:

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij} \tag{4}$$

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \tag{5}$$

The error is calculated at the output unit (Δk) by comparing the response (O_k) with target (t_k), as in (6):

$$\Delta k = (t_k - o_k)net_k \tag{6}$$

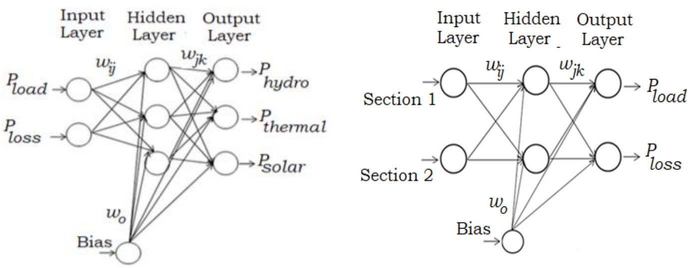

Figure 3. ANN structure (a) at the source end and (b) at the user end

3.2. Backpropagation neural network algorithm for load scheduling

The BP algorithm is more efficient in training the ANN and is a systematic training method. This algorithm provides better efficiency in updating neurons' weights using different activation function units [23]. The system is equiped with supervised learning algorithm. In this method, NN is trained to achieve a better capability to lend an excellent response to input pattern. All the weights are adjusted during the training process to minimize the error [24]. The detailed BPNN algorithm is described in Algorithm 1.

Algorithm 1:
```
1. Initialize input-target standards, learning rate coefficient, nodes of input and
   output, and weight initialization with small arbitrary values;
2. All hidden units receive the input signal and transmit to all units in the layers;
3. The weighted input signals are then processed by hidden neurons;
4. The output from hidden layer is then processed by the non-linear activation function
   to generate the response from hidden layers;
5. Error is calculated at the output unit;
6. Each unit is updated with its weights and bias;
7. Calculate the final output;
8. Check the condition for termination;
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4. RESULTS AND DISCUSSION

Figure 4 gives block diagram of BPNN scheduling structure, showing the input-output variables and how these are connected with the ANN-based approach. The distinction between actual response and target response gives error. The errors are back-propagated, and the weights are modified until the actual response and target become identical. Using the BPNN algorithm, power sources are scheduled based on cost and availability. Figure 5 illustrates the ANN performance characteristics. A more number of iterations gives better performance for the system. The errors are gradually decreased with the number of iterations increases.

The network is trained with different patterns, and after training, the system's execution time decreases compared to other methods. The sigmoid activation function is used to determine the response of each neuron. For the training purpose, the BP algorithm is used. The inputs are given to the present system after the training process, and it takes 103.11 seconds to complete the process.

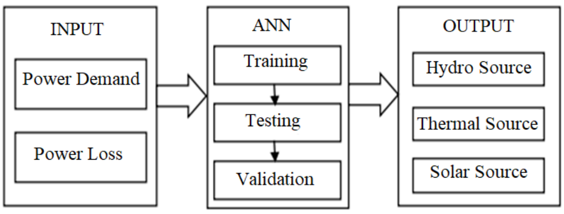


Figure 4. Block diagram of BPNN scheduling system

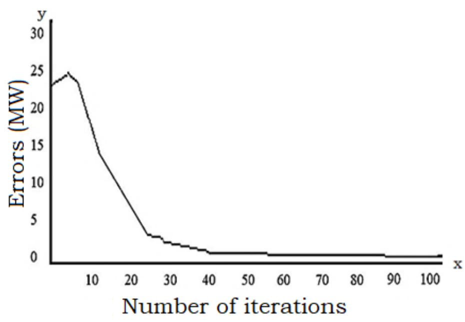
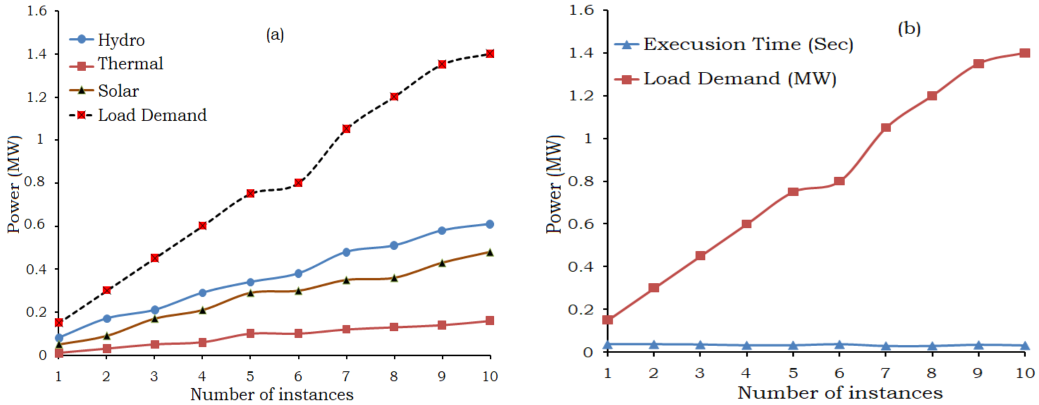


Figure 5. ANN performance characteristics

Scheduling using different power stations, viz. hydro, thermal, and solar, is discussed to meet the load demand. During the daytime, the highest priority is given to solar power plants, which are less expensive to meet the power demand. If it fails to meet the requirements, the following economical source considered is the hydropower system. The thermal power system is assigned the lowest priority as it is costly. The total load demand is fulfilled using three different power sources and delegated execution time as shown in Figure 6. Figure 6(a) gives the graphical representation of power distribution during the daytime.

The load demand is fulfilled at any instant by scheduling these three power sources based on availability and cost. Every power source is used in all instances because it helps improve the system's overall performance. In the first instant, the total load demand is 0.15 MW, which can be achieved by sharing the total load with all the active sources. Here 0.084 MW is from a hydro source, 0.053 MW from solar, and 0.01 MW from a thermal source. A graphical representation of execution time during the daytime is shown in Figure 6(b). The execution time is significantly less for performing the system scheduling process. Here the time for execution is between 36.6 and 29.8 milliseconds.

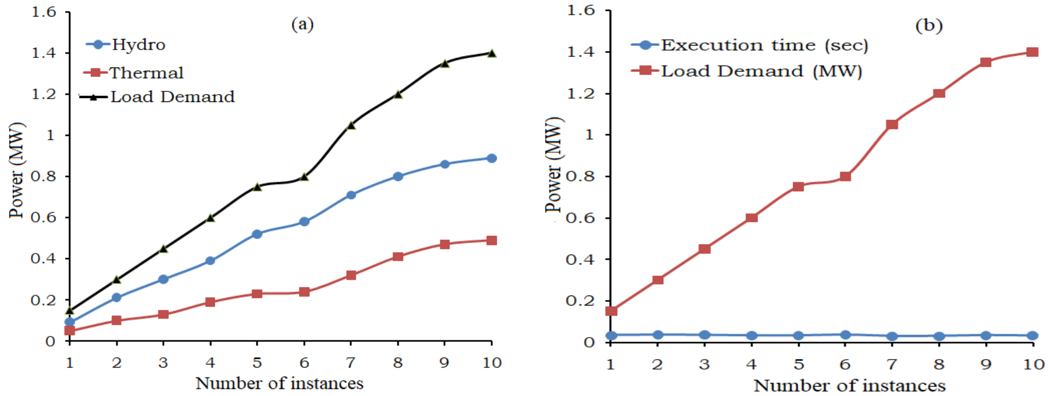


(a) (b)

Figure 6. Graphical representation of (a) power distribution and (b) execution time during daytime

During the nighttime, the power demand is fulfilled by using hydro and thermal power sources. In these two power sources, the highest priority is given to the hydropower source and the lowest to the thermal source. Its graphical representation of power distribution and execution time is depicted in Figures 7(a) and 7(b), respectively. During first instant, the load demand is 0.15 MW and is drawn from two sources, such as 0.096 MW from the hydro source and 0.052 MW from the thermal source. In all instants, a significant portion of the load demand is fulfilled by a hydropower source, and the remaining use a thermal power source. The execution time for this is in between 32.4 and 22.4 milliseconds.

When comparing Figures 6(b) and 7(b), it can be concluded that carrying out time varies with respect to the statistic of power sources. Energy from the solar power station is cheap, but it becomes costlier if the storage facility is considered. Here distinct load demands and load losses are considered as input. Performed the scheduling operation with present method based on cost, availability and demand. Reducing the number of generators reduces the run time.



(a) (b)

Figure 7. Graphical representation of (a) power distribution and (b) execution time during nighttime

After the training, the inputs–load demand and loss–are given to the trained system for validation and testing. The present system gives a scheduled response in the least time. The scheduling structure of tested data is shown in Table 1. It indicates the consumption of different power sources. The present system has effective scheduling for the different load demands. Figure 8 shows the graphical representation of the system's power distribution after the learning procedure.

Table 1. Schedulingstructure

Total load	Execution time (sec)	Hydro (MW)	Thermal (MW)	Solar (MW)
1.05	0.0314	0.368	0.158	0.523
1.7	0.0316	0.595	0.253	0.841
2.05	0.0318	0.718	0.308	1.025
2.4	0.0322	0.840	0.360	1.200
3.05	0.0325	1.068	0.458	1.525
3.4	0.0315	0.280	0.510	1.700
4.05	0.0331	1.418	0.608	2.025
4.6	0.0321	1.610	0.690	2.300
5.05	0.0304	1.768	0.758	2.525
5.2	0.0319	1.820	0.780	2.600

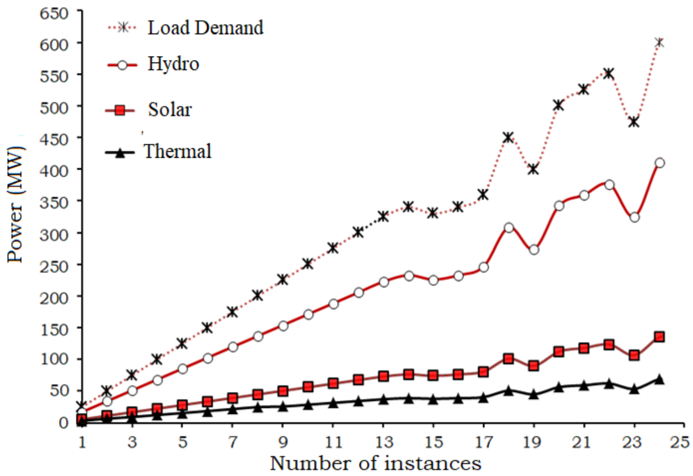


Figure 8. Graphical representation of power distribution

The graph shows how load demand is scheduled from different sources and observes the system's effectiveness with different loads. The result is compared to the work done by Naresh and Sharma [25], Mahajan and Dev [6], Rongrong *et al.* [26], and it shows that the present system has better performance. Table 2 shows the statistical analysis of the data using the 'confusion matrix' [27]. The bounds such as precision, accuracy, specificity and racall are determined from the matrix. True positives (TP) are the system predicts 'YES' for actual data. True negatives (TN) mean that the system predicts 'NO' and does not have actual data. The system predicts 'YES,' but does not have actual data in the false positives (FP) cases. The false negatives (FN) condition is the system predicts 'NO,' but it has actual data.

Table 2. Confusion matrix elements-BP algorithm

Predicted load	Actual load	
	YES	NO
YES	TP=43	FP=3
NO	FN=2	TN=24

Note: Specificity-0.89; Accuracy-0.93; Recall-0.96; Precision-0.93

5. CONCLUSION

This work focused on the advancement of an ANN-based method for on-demand and economically scheduling of electric energy. In the present system, power fluctuation heads to significant problem. A considerable variation of load decreases the efficiency of the system. The solution is to freeze the voltage and frequency constraints and modify the load-on-demand. An instructed ANN is practiced to determine the scheduling grounded on cost and demand. The presented algorithm minimize the run time. It also gives quick response and accurate results compared with other existing methods.

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