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Original Article

Optimal Model for Effective Power Scheduling using Levenberg-Marquardt Optimization Algorithm

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Abstract *- A well-organized scheduling method is needed to meet the time-varying power necessities. The distribution of power in forthcoming days must be scheduled. The system's accuracy extensively impinges on economic function and reliability. At peak load time, the load detaching procedure is necessary for decreasing the demand load. This complexity is conquered by the present system by forecasting the load centered on the constraints which affect the load. Predicting and scheduling load based on prior data is an exigent process. It isn't easy to manage the load when an unpredicted alteration occurs. It is feasible to precede the accessible demand for the load with the advances in artificial intelligence tools. The Levenberg-Marquardt Optimization-based backpropagation technique is employed in artificial neural networks for optimal learning purposes and to diminish error. The outcomes are then contrasted with correlation exploration.*

Keywords *- Artificial neural network, Backpropagation, Load demand, Optimization, Power scheduling.*

1. Introduction

Artificial Neural Network (ANN) is utilized to develop a consistent load scheduling system. To face the demand load, this network provides a smart technique for balanced power and provides units as an alternative to fluctuation. There is a possibility to fail the power production system owing to its uncertainty. Usually, it is accomplished through the load-detaching or shedding method. In this procedure, isolation is provided for the additional loads. The proposed system helps to defeat this situation. Consider weather factors, time, weekdays, temperature, extra loads, and unpredicted events, such as emergencies, special programs, and holidays for effective scheduling purposes. The additional loads enhance the power utilization of the system. For efficiently handling these constraints, an optimal design structure is needed. To get an intelligent performance, train the neural network with the expected value for several circumstances [1-4].

Nowadays, ANN-based technology is universally established due to its non-linearity property. An intelligent network is used to carry out an isolated mission by updating the weights and bias function values between neuron layers. The system is up to date according to the modification of system feedback and target till the response of the network is comparable to the target. Until the input accrues the exact goal, the learning process is carried out in the network. Many input-target pairs are employed to learn the network in a supervised learning algorithm. Manage the production based on accessibility and cost using the network to get system stability. The proposed system experienced different load requirements [5]. It can give load scheduling configuration for any assessment on-demand after the learning process. ANN and human brain performance are strongly related and have parallel data processing with a specific configuration [6-8].

ANNs encompass a significant non-linear detaining facility. Input, output, and hidden layers are the three different layers in the system. Neurons' behavior is consumed by these layers and recognized to comprehend a particular task. The network has mostly existed structures similar to neurons, which are in touch with each other. The systems have adaptable numerical weights, layers of neural nets, training capabilities, and flexibilities [9-11]. The NN layers consist of many processing nodes connected to a system. The neuron tries to imitate biological neuron functions and behavior. ANN-level utilization is required to indicate the structural design and training algorithm. In engineering applications, Backpropagation (BP) network is treated as a well-known system [1, 3].

2. Design Methodology

2.1. Backpropagation Neural Network

Nowadays, the most remarkable techniques used in engineering applications are BPNN. It is a multi-layered network that contains "feed-forward" relations connecting the input layer to the next layer, known as hidden layers. It formerly expanded to the final stage of the system [12, 13]. The input layer of the system receives the information from external sources, and for processing this collected data, it is given to the network. The hidden layer manages the response from the input layer. The output layer directly receives the organized information from the middle layer to a peripheral accepter [5, 14].

BPNN is centered on non-linear association through the load, and their significant correlative constraint is organized by an uninterrupted learning method. The BPNN is a commonly used learning method, and for optimization, Levenberg-Marquardt Optimization (LMO) method is used [15-18]. It stopped its refining process when there was no further improvement in generalization. Formulate an evaluation among target and actual value and then backpropagate the error. The error-correction method is used in the BPNN learning algorithm. Altering the weight connections and bias functions system minimizes the error [19]. The bias function is added with the weighted inputs and thus generates a net response, as shown in Equation 1.

$$net = \sum_{i=1}^{n} w_i x_i + b \tag{1}$$

Where x_i is the network's different dependent or independent input variables, before applying to the summing point, each signal is multiplied with associated weights w_i, and b is the bias function [16].

For expressing the performance index, the BP algorithm uses mean square error (MSE), which is to be reduced by modifying the neural network parameters. The expression for calculating the error function is shown in Equation 2.

$$e = \frac{1}{N} \sum_{i=1}^{n} (t_i - o_i)^2 \tag{2}$$

where t_i is the target, and output is o_i at an instant i.

For the approximate MSE, the gradient descent algorithm is expressed in Equation 3, and the bias updates are shown in Equation 4.

$$w_{i,j}(n+1) = w_{1(i,j)}(n) - \alpha \frac{\partial e}{\partial w_{i,j}} \tag{3}$$

$$b_i(n+1) = b_{1i}(n) - \alpha \frac{\partial e}{\partial b_i} \tag{4}$$

where α is the learning rate.

If the value of the error function is not as much as the typical value, the algorithm halts its modernized practice. The LMO learning method is used in BPNN to get more constancy. For optimization using multilayer feed-forward NN, BP is measured by the finest algorithm. By using the standards in Table 1, learning the network with the help of the BP algorithm [8, 15].

Fig.1 shows the BPNN architecture used in this work. Several learning trials and learning rates, hidden unit count, initial stopping and overtraining conditions, regularization of inputs, activation function, and initial weights are the parameters that alter the functioning of BPNN. The activation function, such as sigmoid, produces an output with values from 0 to 1. The network is trained with 1000 iterations, and *trainlm* in MATLAB is used as the training function for this optimization. Using BP cryptogram considered the system weights [12, 20].

2.2. *Levenberg-Marquardt Optimization (LMO) algorithm*

LMO is one of the efficient optimization algorithms used in network modeling. This hybrid technique, such as the Gradient descents and Gauss-Newton method, converges for an optimum solution. Hybrid technology is the best practice for solving different optimization problems. In this hybridization, if the primary prediction is comparatively close to the optimum, the Gauss-Newton algorithm is faster than the LMO algorithm. The present system effectively solves non-linear equations and large feature sets. It is a typical method in non-linear least square problems, along with the iteration technique [7, 21]. The training structure is demonstrated in Fig. 2.

Table 1. ANN specifications

Specifications	Value
Activation function.	Sigmoid
Threshold value	[-1 1]
Weight range	[-1 1]
Momentum	0.8
Learning coefficient	0.2
Iterations	1000

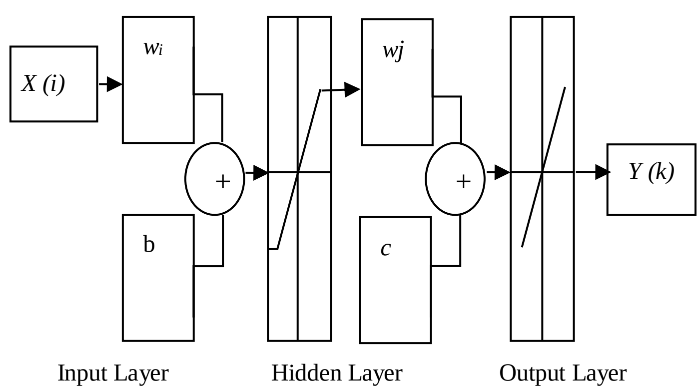

Fig. 1 BPNN architecture

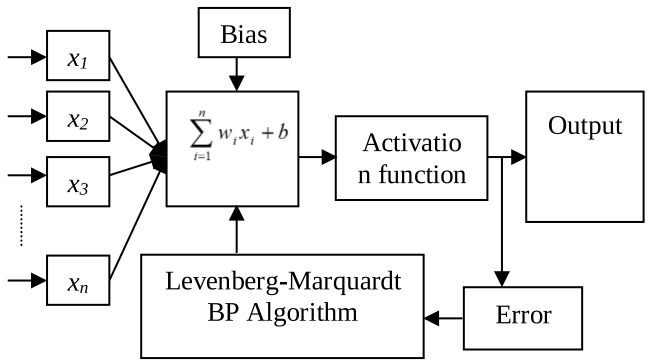

Fig. 2 LMO Algorithm training structure

The Gradient descent and Gauss-Newton methods use a series of calculations to find the solutions for non-linear problems. The MSE is minimized by moving toward the direction of the steepest descent [22, 23]. The LMO chooses Gradient descent and Gauss-Newton methods at each iteration and updates the solution. The BP algorithm is summarized as follows. Initially, the input propagated through the NN. Then from the last layer to the first layer, it propagates the error values backward through the network. Finally, biases and weights are revised with the Gradient descent method [24, 25]. For the performance index of the training process, the BP algorithm uses MSE, which is reduced by modifying the neural network parameters, as illustrated in Equation 5 [30, 31].

$$E_{(x,w)} = \frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^{2} \tag{5}$$

Where *P* and *p* are several patterns and index of patterns, respectively, *M* and *m* are the numbers of outputs and index of output, and also *x* is the input vector, $e_{p,m}$ is training error, and *w* is the weight vector.

2.3. The LMO-Based Training Algorithm

- Start;
- Learn the whole thing, like input, learning rate, and destination values. Forecast the input-output nodes, the absolute number of input layers, the all-out value of the input, and the determined value of the objective and constant;
- Every hidden element takes in the input signal and addresses the signal to entire units in the layers. Also, each hidden element improves with all biased input signals. Progress the output of the hidden layer over a non-linear behaviour.
- Calculate the error using randomly created initial weights;
- Update every unit based on the modified LMO algorithm to adjust its weights and biases;
- Estimate the net error using these new weights;
- After the update, calculate the error function. The system returns to the initial weight value if the existing total error increases. Move to step 5 after improving the combination coefficient factors;
- After the update, the system keeps the new weights if the existing total error is reduced and which decreases the combination coefficient;
- Check the termination status;
- Move to step 4 with the new weights until the existing total error is less than the prescribed value;
- Stop.

3. Results and Discussion

The realization of the present system is analyzed with real hourly load data. The important ANN learning parameters are shown in Table 2.

The training structure using the NN tool of the present system is illustrated in Figure 3. It consists of fourteen input, fifty hidden, and one output neuron (14:50:1). The present system is learned with diverse hidden neurons. The result shows that the prediction is more accurate with increased hidden neurons.

MSE and RMSE for various numbers of neurons present in the hidden layer are shown in Table 3. The constraints affecting to load are the inputs, and the expected load is the response. By using the LMO-BP algorithm, train the collected data. When generalization stops improving, the algorithm terminates its training procedure.

Table 2. ANN training parameters

Number of inputs	Number of outputs	Number of hidden layers	Number of hidden neurons	No. of Iteration
14	1	1	50	1000
Training functio	Perform function	Activation function	Training method	Network type
LM	MSE	Sigmoid	BP	Feed Forward

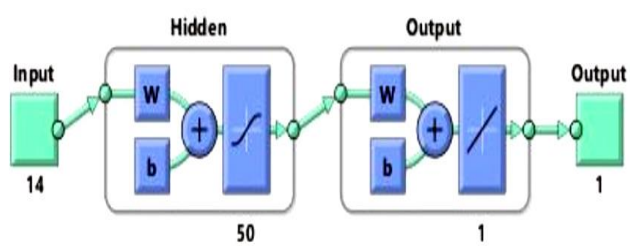

Fig. 3 Training structure of the present system

The functioning of the current ANN system is illustrated in Figure 4. The lowest value of MSE is exceptional; close to zero means flawless. 2.678x10-3 at epoch 35 is the best validation performance in this presented method.

The regression model of the proposed system is shown in Figure 5. This study is an arithmetical method for conforming the connection between the variables. The standard regression scale is the association between goals and system response. The significance of the regression is that '1' means an adjacent association, and '0' means the random relationship between the parameters. Here, 70% of data is adopted for the training of the system, 15% is employed for validation, and the surviving 15 % is treated for testing.

Table 3. MSE and RMSE for different hidden neurons

Hidden neurons	10	20	30	40	50
MSE	0.0277	0.0176	0.0159	0.0086	0.0003
RMSE	0.1663	0.1328	0.1259	0.0925	0.0173

A regression study is used to analyze the neural networks' certainty during the system performance, such as training, testing, and validation. The certainty of the network is 97% means that there is no statistical relevance for the remaining 3% of the estimated data.

Based on the error, the network has been self-adjusted during the training time. The system's generalization efficiency and independent performance are analyzed through the validation and testing process, respectively. Table 4 illustrate the training response of the present system.

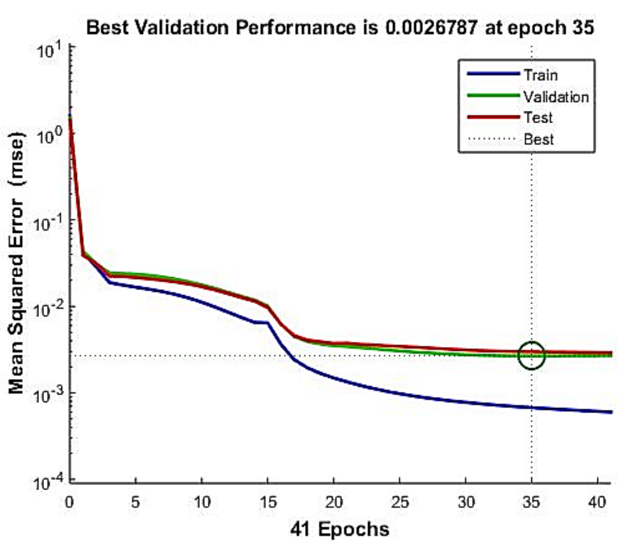

Fig. 4 Performance of the present neural network

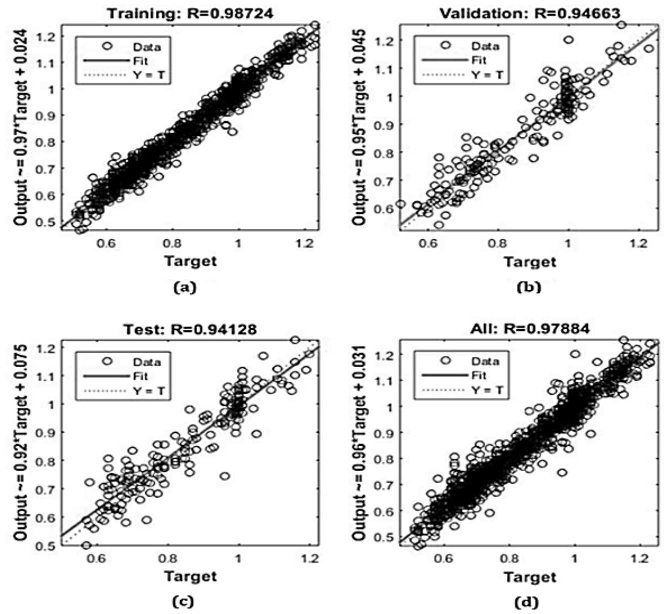

Fig. 5 Regression Study: (a)Training (b)Validation (c)Test (d) Overall functioning of the Presented System.

Table 4. Training response of the present system

	MSE	R
Training	$3.048x10^{-4}$	$9.872x10^{-1}$
Validation	$2.923x10^{-3}$	$9.466x10^{-1}$
Testing	$3.530x10^{-3}$	$9.413x10^{-1}$
Overall	$2.252x10^{-3}$	$9.788x10^{-1}$

The system's accuracy is evaluated using the MAPE method as in Equation 6.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Actual\ Power_i - Scheduled\ Power_i}{Actual\ Power_i}\right)*100 \tag{6}$$

The LMO-BP-based load scheduling results for two different cases performed on two different days and variant parameters are shown in Figure 6 and Figure 7. The figures show that this algorithm improves the system's performance and meets the demand. In many power systems, inefficient power distribution results from high energy loss. The applications of these types of scheduling methods not only make a considerable reduction in energy loss but also reduce cost.

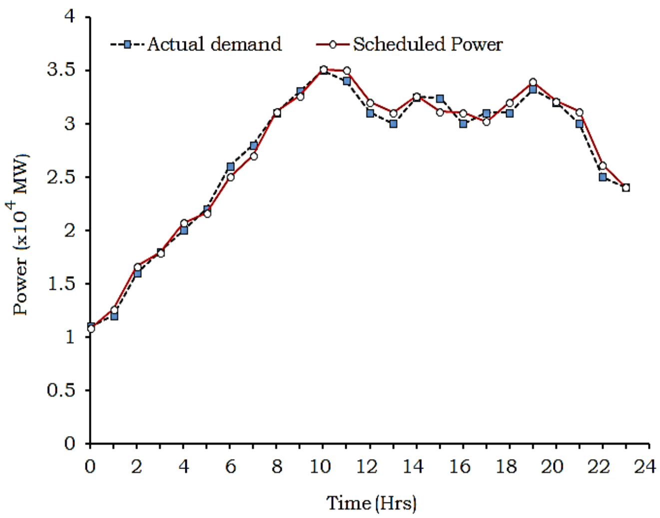

Fig. 6 Scheduling and demands to result of the system for 24Hrs – Day 1

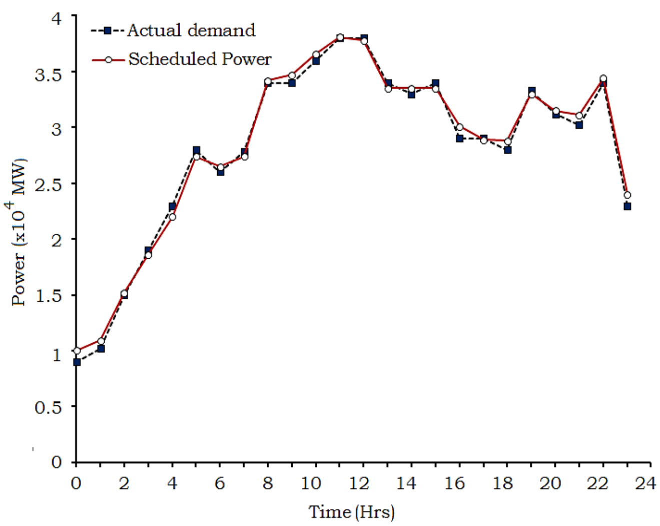

Fig. 7 Scheduling and demands to result of the system for 24Hrs – Day 2

Three different studies are considered to figure out the presented system performance. The regression study demonstrates the relationship between exact load demand and scheduled load. A comparative study with BPNN and LM NN shows that the present system has less MAPE. In this method, the MAPE for Day 1 and Day 2 are 2.56 MW and 2.52 MW, respectively.

The regression analysis comparison of BPNN [24], LM NN [24], and the present model is given in Table 5. The comparative study indicates that the behaviour of the present system is more exceptional than other learning capabilities and generalization techniques. The overall functioning of the present system is 97.88%. Training data is used to fit the network model and is now familiar with the model. The validation data is a pool of new data points used for the network evaluation when tuning hyperparameters and data preparation. Testing data is accustomed to analyzing the performance of the final tuned system model. Therefore, the training accuracy is usually more significant than the validation and testing accuracy.

Table 5. Regression analysis comparison of neural network

	BPNN	LMNN	LMO-BP Present Model
Training	0.9046	0.9562	0.9872
Validation	0.9022	0.9667	0.9466
Testing	0.9051	0.9538	0.9412
Overall	0.9043	0.9528	0.9788

4. Conclusion

The presented work intends to bring the advances of the ANN-centered method for load scheduling. For load scheduling, the LMO-BP method is used. This optimization method required more memory and less implementation time. The outcome of this algorithm reveals that the presented system is extremely effective when working out outsized sets of data. Calculate the RMSE and MSE. The system's response pursues the objective of training, testing and validation. The overall performance of the system is 97.88%. BP algorithm is very helpful for scheduling and error calculation. The experimental response of the system proves that the presented network model - LMO-BP - can perfectly approximate the scheduling, and its behavior is beneficial over alternative learning-based design.

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