# Short Term Load Forecasting Using Neural Networks and Particle Swarm Optimization

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**Abstract**: - *Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. A precise electric power system short term load forecasting will lead to economic cost saving and right decisions on generating electric power. In this paper, a short-term load forecasting (STLF) method based on back propagation (BP) neural networks which is optimized by particle swarm optimization (PSO) algorithm is presented. The PSO is used to optimize the initial parameters of the BP neural networks, and then based on the optimized results; the BP neural networks are used for short-term load forecasting. The results obtained show that the proposed technique has improved the accuracy and velocity of convergence of the BP neural networks method. Also it is shown that the proposed method can provide more accurate results than the back propagation (BP) neural networks techniques. The mean percent relative error of the BP neural network optimized by PSO model is less than 2 %.*

**Keywords**: *short term load forecasting, BP neural networks, particle swarm optimization.*

## 1. Introduction

The ability to accurately forecast load is vitally important for electric power systems. Load forecasting helps energy management system to make important decisions on purchasing and generating electric power, load switching, and infrastructure development. Short- term load forecasting helps to estimate load flows and to make decisions which can avoid overloading. This will result in improvement of network reliability [1]. Many methods have been developed for solving the problem of short-term load forecasting over the past few decades. The traditional load forecasting algorithms such as linear time series models, regression analysis, stochastic time series, and integrated autoregressive - moving, multiplicative autoregressive models had been widely used before [2-5]. Nowadays, neural networks, fuzzy logic, genetic algorithms and expert systems have already been applied to this field [6-10]. Among those algorithms, artificial neural networks have gained more attention. BP neural networks are one of the widest application networks for STLF. It has the powerful capability to generalize the nonlinear relationships between the inputs and the desired outputs, without considering real problem domain. Considering the conventional BP algorithm problems of slow convergence speed and easily getting into local minimum value, a new approach using BP neural networks which optimized by PSO algorithm is proposed in this paper. The PSO is used to optimize the initial parameters of the BP neural networks, and then based on the optimized result; the BP neural network is used for STLF. PSO has rapid speed of convergence and strong capability of global search to improve the prediction accuracy and convergence speed of the model [11-13].
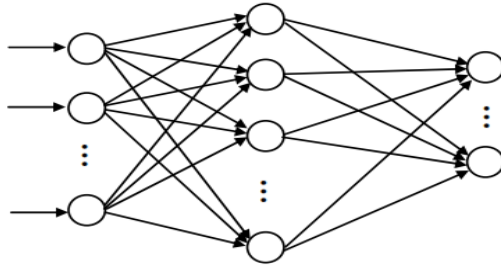
## 2. BP Neural Network Algorithm

The BP training algorithm is an iterative gradient descent algorithm designed to minimize the mean square error (E) between the actual output of a multilayer feed forward neural network and the desired output and updates the weights by moving them along

the gradient-descendent direction [14]. This process is made up of two passes through the network layers, one forward and one backward. In the forward pass, the input is applied to the sensory nodes, and its effect propagates through the network layers, the response then appears at the output nodes. This output is compared against a desired value, to produce an error signal which then propagates backward through the network. In the forward pass, the synaptic weights of the network are fixed, but during the backward pass they are adjusted so that the network output moves closer towards the desired response. This can be summarized by the following expression [15]:

$$\Delta w = - \eta \nabla E \qquad (1)$$

Where $\Delta w$ is the change in weights of neural network, E is the root mean square error and $\eta$ is the learning rate which has the value in the range of $(0 < \eta < 1)$ this parameter controls the learning speed. Fig.1 shows the structure of the BP network.



Input layer    hidden layer    output layer

Fig.1 BP neural network

## 3. Particle Swarm Optimization Algorithm

Particle swarm optimization algorithm (PSO) is a randomly optimal algorithm based on swarm intelligence [16]. The PSO algorithm works on the social behavior of particles in the swarm.    Therefore, it finds the global best solution by simply adjusting the trajectory of each individual towards its own best position and towards the best particles of the entire swarm at each time step. The PSO method is becoming very popular due to its simplicity of implementation and ability to converge    to

a reasonably good solution quickly. Each particle in PSO flies in the dimensional problem space with a velocity, which is dynamically adjusted according to the flying experiences of its own and its colleagues. The position of the ith particle is represented as:

$$X_i = (x_{i1}, \dots, x_{id}, \dots, x_{iD}),$$

Where $x_{id} \in [1d, ud]$, $d \in [1, D]$, 1d, ud are the lower and upper bounds for the dth dimension, respectively. The best previous position of the ith particle is recorded as:

$P_i = (p_{i1}, \dots, p_{id}, \dots, p_{iD})$, which is also called pbest. The index of the best particle among all the particles in the population is represented by the symbol g. The position p is also called gbest. The velocity for the ith particle is g represented as:

$V_i = (v_{i1}, \dots, v_{id}, \dots, v_{iD})$, is clamped to a maximum velocity

$V_m = (v_{m1}, \dots, v_{md}, \dots, v_{mD})$, which is specified by the user. The particle swarm optimization concept consists of, at each time step, changing the velocity and location of each particle toward its pbest and gbest locations according to equations (2) and (3), respectively [15]:

$$v_{id}^{(k+1)} = w^{(k)}v_{id}^{(k)} + c_1 r_1 (P_{id}^{(k)} - x_{id}^{(k)}) + c_2 r_2 (P_{gd}^{(k)} - x_{gd}^{(k)}) \qquad (2)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k)} \qquad (3)$$

$$\begin{cases} v_{id} = -v_{md}, & v_{id} < -v_{md} \\ v_{id} = v_{md}, & v_{id} > v_{md} \end{cases} \qquad (4)$$

Where w is inertia weight, $c_1$ and $c_2$ are acceleration constants [17]. $r_1$ and $r_2$ are random functions in the range [0, 1]. Initially, a population of particles is generated with random positions, and then random velocities are assigned to each particle. The fitness of each particle is then evaluated according to user defined objective function. At each generation, the velocity of each particle is calculated according to (2) and the position for the next function evaluation is updated according to (3). Each time if a particle finds a better position than the previously found best position; its

location is stored in memory. The PSO algorithm works on the social behavior of particle in the swarm. Therefore, it finds the global best solution by simply adjusting the trajectory of each individual towards its own best location and towards the best particle of the entire swarm at each time step. The PSO is becoming very popular due to its simplicity of implantation and ability to quickly converge to a reasonable good solution.

## 4. Load Forecasting Models

The two models that are used to solve the problem of short term load forecasting are:

1. Forecasting model using BP neural networks.
2. Forecasting model using BP neural network optimized by PSO.

In the first model the back propagation neural networks is used to train the node weights nodes of the networks, while the second model uses the PSO with BP model to optimize the weights of neural networks.

### 4.1 Forecasting Model Using BP Neural Networks

Artificial neural networks are powerful tools for prediction of nonlinearities. These neural networks models consist of three layers (input layer & hidden layer & output layer). The BP has a strong non –linear mapping ability and a flexible structure. It trains the nodes weights by error–back propagation algorithm. The neurons activation function is the tan–sigmoid. The non linear transformation function is:

$$\partial = \sum_{i=i}^{n} w_i y_i \tag{5}$$

Where $w_i$ the conjunctions weights between hidden layer and output are layer; $y_i$ is the output of hidden layer; n is the number of hidden layer. Networks weight coefficients updated as the following [15]:

$$w_{ij}^m = w_{ij}^m(k-1) + \Delta w_{ij}^m \tag{6}$$

Where, m is the number of input layer. However, pure BP network has the defect of easily getting into the local extreme, which results in the difficulty of accurate prediction.

### 4.2 Forecasting model Using BP Neural Networks Optimized By PSO

The process of BP neural networks optimized by PSO model can be summarized as follows [18]:

***Step 1***: Normalization of the sample data groups according to equation (7), and then definition of the structure of the BP network according to the input and output sample as shown in Fig. (1) [18].

$$y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{7}$$

Where $x_i$ is defined as the initial group of data among the collected data groups. $x_{max}$ and $x_{min}$ express the maximum and minimum data group among the collected data groups, respectively.

***Step 2***: Initialization of variables, $x_{mn}^0$ and $v_{mn}^0$ that express the initial position and initial speed respectively; in addition, they are all random numbers in the range [0, 1]. Define m as the number of particles. $\varepsilon$ is the threshold value of the fitness E. $T_{max}$ is the maximum iteration time while $c_1, c_2$ are acceleration factors respectively. $w_s$, $w_e$ are the inertial factor and constraint factor respectively.

***Step 3***: calculation of the RMS error and individual extreme of relevant particle from the following equations [18]:

$$E_i = \sum_{K=1}^{n} (y_k - \hat{y}_k)^2 \tag{8}$$

$$\xi_i = \frac{1}{\exp(E_i)} \tag{9}$$

Where $E_i$ is the RMS error and $\xi_i$ is the individual extreme of relevant particle, n is the number of training sample; $\hat{y}_k$ is output value of the kth nodes, while $y_k$ is the expected output. As known the global extreme originates from individual extremes. The position of current optimal particles denoted by pbest, the optimal particle values is defined as gbest.

**Step 4**: According to equation (10), define the fitness of each particle, if this position is better than pbest, then , pbest will be replaced by this position ;otherwise, pbest remains; the position of current optimal particles best updated as well [18]:

$$Fitness = \frac{1}{1+0.5 \sum_{K=1}^{n}(y_k - \hat{y}_k)^2} \quad (10)$$

**Step 5**: According to equations 2 and 3 update the position and speed of each particle.

**Step 6**: Judge the stopping criteria, if the maximum iterative time are met, stop the iteration, and the positions of the particles represented by gbest are the optimal best solution. Otherwise, the processes are repeated from step 4.

**Step 7**: Take the weights and threshold value which optimized by PSO as the initial parameters, the BP network makes autonomous learning and forecasting.

**Step 8**: Obtain the output of the forecast results. In this forecast model, the BP network calculates the input and the output values of the hidden layer according to the optimized weights. The output value is the forecast value which is needed.

### 5. Data Set

The actual power load is taken from the Egyptian Electricity of Canal Zone, Sharkia Network - Egypt. This data is used to perform the study. The data given represents the hourly MW load for the summer season for two months (July and August 2011) for Zagazig city. Also, the weather data is taken for Zagazig city for the same period. The weather data represents the hourly temperature, relative humidity and wind speed.

Fig. 2 shows an example of hourly power consumption for a period of two weeks. This represents a typical cycle for the electric load in Zagazig city in summer season (July

2011). The load changes during this weekly cycle are attributed to factors as:

1. The day of the week: the load characteristics on Friday and Saturday are different from the usual weekdays. This is because of the fact that most businesses and public works are closed over the weekend, thus giving rise to an overall lower load demand.
2. The time of the day: power consumption during the night time is much lower than that of the day time. Furthermore, power consumption during the day time varies with the time of the day. It starts with a minimum value early in the mornings and reaches a maximum loads at evening.
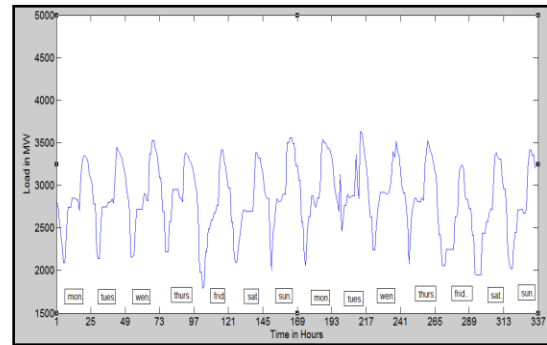3. Weather factors: such as temperature, humidity and wind speed.



Fig. (2) Example of electric load over two weeks period in summer season for Zagazig city.

### 6. Weather Important Factors Affecting the Electric Load

The impact of weather on electricity demand is complex, highly non- linear, and primarily influences the energy needed for space cooling and space heating. Weather conditions influence the load. The principal weather variables which influence short term loads are temperature, humidity and wind speed. Figs. (3–5) show the relationship between the real data of loads for Zagazig city for three weeks in summer season and the weather factors that affect the load in the city.
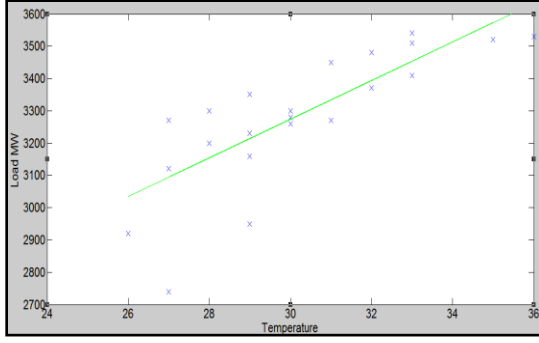
Fig. (3) A sample of temperature (°c) vs. load (MW) for summer season.
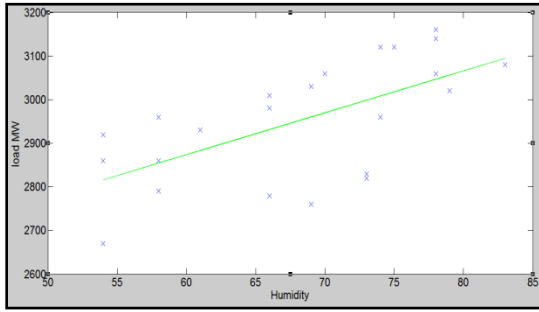


Fig.(4) A sample of humidity (%) vs. load for summer season.
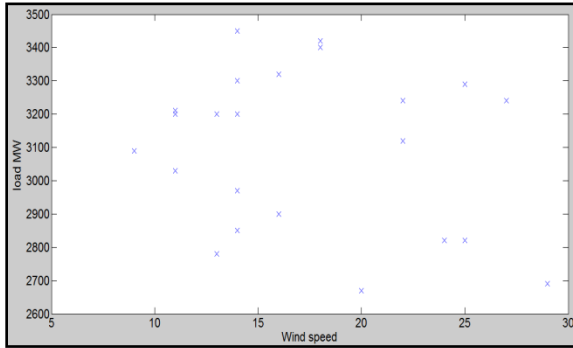


Fig. (5) A sample of wind speed (km / hr) vs. load for summer season.

The above figures showed that during the summer time, as the temperature and humidity increase, the demand for electricity increase. But for wind speed, it does not affect the electric consumption in the Zagazig city. So, it will not be taken into account during solving the problem of short term load forecasting.

The SPSS (statistic package of social science) program is used to obtain the correlation between the load and the weather factors. The results of correlation analysis are shown in Table (1).

Table 1 The correlation between load and weather factors.

| Correlation between | Correlation factor |
|---|---|
| Load and temperature | 0.781 |
| Load and humidity | 0.654 |
| Load and wind speed | -0.231 |

From Table 1 the correlation coefficient between the load and the temperature is ($\partial = 0.781$) which is very high correlation. Also, the correlation coefficient between the load and the humidity is ($\partial = 0.654$) which is high correlation. The correlation coefficient between the load and the wind speed is ($\partial = -0.23$) which is very low correlation.

From this analysis and correlations that are performed on actual load of Zagazig city and the weather factors that affecting the short term load forecasting, it is concluded that the factors affecting the short term load forecasting are: hourly temperature and relative humidity, so, the two factors are used in the proposed model as inputs which makes the model more accurate and reliable.

**7. Simulation Results**
**7.1 Parameters of the BP Neural Networks Model and BP Neural Networks Optimized By PSO Model**

For PSO, all swarm particles start at a random position (i.e., weights) in the range [0, 1] for each dimension. The velocity of each particle is randomized to a small value to provide initial random impetus to the swarm. The swarm size (m) was limited to 100 particles. The selections of some parameters to carry out the procedures of the work successfully has great effect on the model, these parameters are maximum

velocity and inertia weight. The maximum speed parameter limits the maximum jump that a particle can make in one step, thus a too large value for this parameter will result in oscillation [19-20]. A small value, on the other hand, can cause the particle to become trapped in local minima. The inertia weight (IW) is gradually changed according to the following [18]:

$$IW = w_s - \frac{T(w_s - w_e)}{T_{max}} \qquad (11)$$

Where $w_s$ is the starting inertia, $w_e$ the final inertia, $T_{max}$ the maximum number of iterations, and T is the current iteration. The most suitable values of maximum speed is set to be 0.1, $w_s$ and $w_e$ are 1.0 and 0.4, respectively. The parameters of the BP model and BP model trained by PSO are shown in Tables 2.

Table 2 Parameters of the BP neural networks and BP neural networks optimized by PSO algorithms

| parameter | BP neural networks | BP neural networks optimized by PSO |
|---|---|---|
| acceleration factor | − | $c_1 = c_2 = 2$ |
| learning rate | $\eta = 0.15$ | $\eta = 0.15$ |
| neuron function | tan sigmoid | tan sigmoid |
| max iteration | 10000 | 10000 |
| Convergence error | 0.01 | 0.01 |
| Hidden layer | One (containing 10 processing elements.) | One (containing 10 processing elements.) |
| starting inertia ($w_s$) | − | 1.0 |
| final inertia ($w_e$) | − | 0.4 |
| Swarm size(m) | − | 100 |
| Maximum speed | − | 0.1 |

## 7.2 Results

The historical load and weather data for period (1 July 2011 – 10 August 2011) used for training. Data for period (11 August 2011 – 17 August 2011) used for testing. These data used to develop the proposed models, and the model was then used to forecast the testing load data.

The hourly load forecasting results of the proposed method are shown in Figs. (6) – (13). The mean absolute percentage error (MAPE) are calculated as shown in Eq.12 [18]

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left[ \left| \frac{(actual - forecasted)}{actual} \right| \right] *100 \qquad (12)$$

Fig. (14) shows the MAPE of the proposed method.

In week end days (Friday and Saturday), the BP neural networks optimized by PSO model (BP + PSO) are more accurate than the BP neural networks model (BP) in all hours of the day, the percentage error of the BP neural networks optimized by PSO model are less than the BP neural networks model.

The maximum error of (BP + PSO) model is 2%, while for the (BP) model is 4.5%.

In week days (Sunday and Thursday), the (BP + PSO) model are more accurate than the (BP) model in all hours of the day, the percentage error of the (BP + PSO) model are less than the (BP) model.

The maximum error of (BP + PSO) model is 1.9 %, while for the (BP) model is 4.6%.

The results shown that the (BP + PSO) model are more accurate and practical than BP neural model.
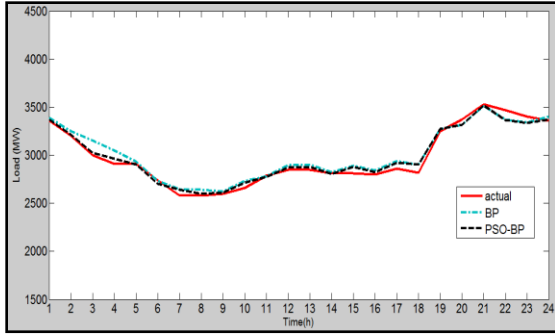
Fig. (6) Actual load, forecasted load by BP neural networks and forecasted load by BP neural networks optimized by PSO (Thursday 11 August 2011) (Week day).
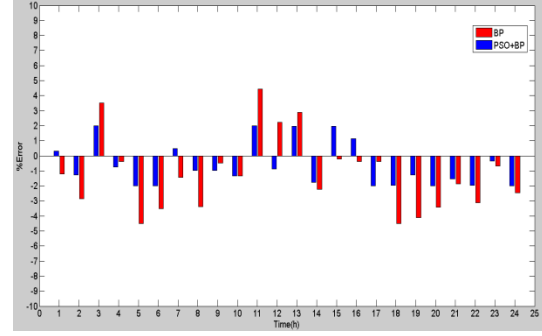


Fig. 9 The percentage error of BP neural networks and BP neural networks optimized by PSO. (Friday 12 August 2011) (Week end).
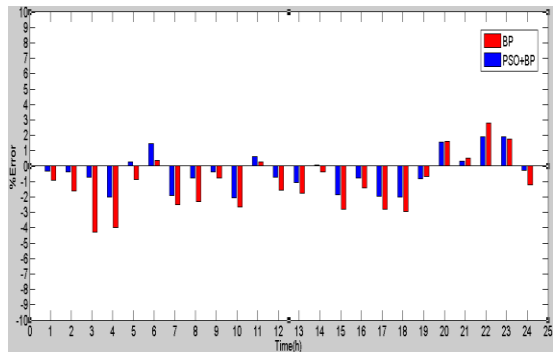


Fig. 7 The percentage error of BP neural networks and BP neural networks optimized by PSO. (Thursday 11 August 2011) (Week day).
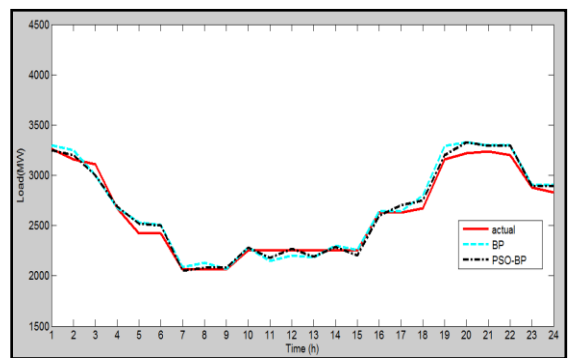


Fig. 10 Actual load, forecasted load by BP neural networks and forecasted load by BP neural networks optimized by PSO (Saturday 13 August 2011) (Week end).
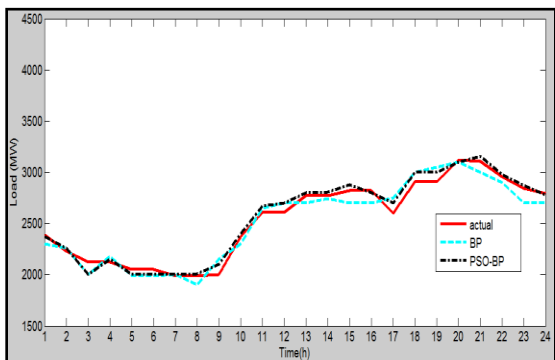


Fig. 8 Actual load, forecasted load by BP neural networks and forecasted load by BP neural networks optimized by PSO (Friday 12 August 2011) (Week end).
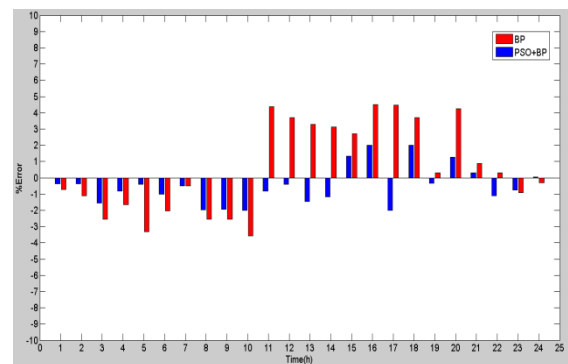


Fig. 11 The percentage error of BP neural networks and BP neural networks optimized by PSO. (Saturday 13 August 2011) (Week end).
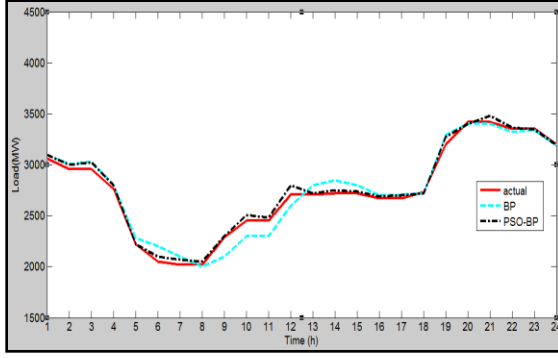
Fig. 12 Actual load, forecasted load by BP neural networks and forecasted load by BP neural networks optimized by PSO (Sunday 14 August 2011) (Week day).
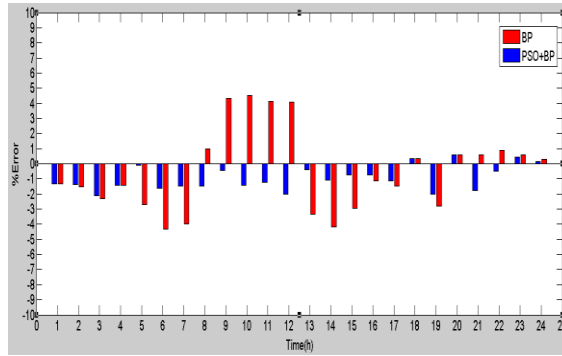


Fig. 13 The percentage error of BP neural networks and the percentage error of BP neural networks optimized by PSO (Sunday 14 August 2011) (Week day).
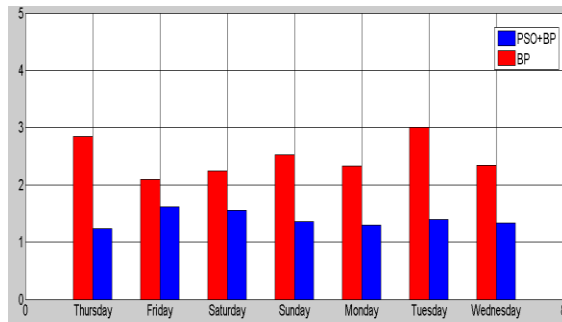


Fig. (14) MAPE of the BP neural networks and forecasted load by BP neural networks optimized by PSO test summer week.

## 8. Conclusions

The capability to accurately forecast load is vitally important for electric power systems. The objective of this research is to design a compact and accurate model. The weather factors play an important role in short term load forecasting, so temperature and humidity are used as input to train the back propagation neural algorithm, 960 points of hourly load are used as training input and one week in summer is used to test the proposed model.

A new load forecasting system based on BP neural networks and particle swarm algorithm was applied to optimize the parameters of the neural networks was proposed in this paper. The forecasting model presented in this paper shows that BP neural networks optimized by PSO is better than BP neural networks algorithm. The accuracy of the BP neural networks optimized by PSO model is high.

In week end days, the BP neural networks optimized by PSO model are more accurate than the BP neural networks model in all hours of the day. The percentage errors of the BP neural networks optimized by PSO model are less than the BP neural networks model. The maximum error of (BP + PSO) model is 2%, while for the (BP) model is 4.5%.

Also, in week days, the (BP + PSO) model are more accurate than the (BP) model in all hours of the day. The percentage errors of the (BP + PSO) model are less than the (BP) model. The maximum error of (BP + PSO) model is 1.9 %, while for the (BP) model is 4.6%.

The results shown that the (BP + PSO) model are more accurate and practical than (BP) neural model.

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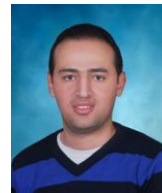
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