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Next 24-Hours Load Forecasting for the Western Area of Saudi Arabia Using Artificial Neural Network and Particle Swarm Optimization

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ABSTRACT. This paper presents an effective load forecasting model for the western area of Saudi Arabia (WESA). Weather, load demand, wind speed, wind direction, heat, sunlight and so on are quite different in a desert land than other places. Thus this model is different from typical forecasting model considering inputs and outputs. Two models are implemented: firstly, a load forecasting model for prediction, however, is not sufficient for accurate forecasting, and, secondly, an optimization process to improve the results to be at least better than existing results.

This paper includes an artificial neural network (ANN) and a particle swarm optimization (PSO) models for 24-hours ahead load forecasting. The ANN is a complex mathematical tool for mapping complex relations; it is also well proved for the successful use of forecasting, categorization, classification, and so forth. The 24 calculation steps are preformed ahead in the ANN model and the obtained results are moderate. On the other hand, PSO is the most promising optimization tool. PSO is chosen as the optimization model of the weight matrix of the ANN. By analyzing the model of standard ANN for the load-forecasting problem with hundreds of thousands of data and changing-uncertain load demand in deregulated market, the PSO is applied for the ANN weight adjustment and to optimize the uncertain load demand, as the ANN is not an optimization method. Results show the effectiveness of the method. Sensitivity of ANN structure is also checked. Scalability of the method is alsotested.

Keywords: Load forecasting, Neural network, Particle swarm optimization, Western area of Saudi Arabia, Power system operation.

1. Introduction

Load forecasting is very important in power system operations and planning. It increases power systems reliability, and decreases cost and emission. Power is used everywhere and load demand is increasing day by day. In recent years load forecasting became one of the major areas of research in electrical engineering because it is practically used for unit commitment, real-time dispatch, maintenance, optimization of power systems and so on. Load forecasting and its optimization are challenging tasks depending on previous real data. Unit commitment uses this forecast load demand as input and generates proper schedule for available units with minimum cost. This research has been proposed for the Western Area of Saudi Arabia, as there are no computer aided systems in this area and thus planning and scheduling of this area are done manually. Approximate load demand is 10,000 MW and there are about 110 thermal generating units. Manual operation of this large system obviously involves higher operating cost than near optimum.

Many researchers have addressed load forecasting. Load forecasting is a difficult task of many input attributes and huge practical data complex mapping. Firstly, the load series is complex and exhibits several levels of seasonality. Secondly the load at a given hour is dependent not only on the load at the previous hour, but also on the load at the same hour on the previous day and because there are many important exogenous variables that must be considered, specially the weather-related variables [1]. Load forecasting plays an important role in power system planning, operation, dispatch, maintenance and so on. Basic operating functions such as unit commitment, economic dispatch, fuel scheduling and unit maintenance and so on can be performed efficiently with an accurate load forecast [2–3]. Various statistical forecasting techniques have been applied to short-term load forecasting (STLF). Examples of such methods include time series [4–5], similar-day approach [6], regression methods [7] and expert systems [8–9]. In general, these methods are basically linear models and the load pattern is usually a nonlinear function of the exogenous variables [1]. On the other hand, artificial neural network (ANN) has been proved as powerful alternative for STLF as it does not rely on human experience. It has been formally demonstrated that ANNs are able to approximate numerically any continuous function to the desired accuracy and it should be expected to model complex nonlinear relationships much better than the traditional linear models that still form the core of the forecaster's methodology. Besides, the ANN is a data-driven method, in the sense that it is not necessary for the researcher to postulate tentative models and then estimate their parameters. Samples of input and output vectors for the ANNs approach are given in [10–15]. In these works it is agreed that the ANN is not an optimization method. Therefore, in order to improve the performance of the ANNs approach for short-term load forecasting, it is decided here to include the PSO technique to optimize the weight matrix of the ANN.

A bibliographical survey on the load forecasting reveals that various numerical optimization techniques have been employed to solve the UC problem. Load forecasting [16–21] is essential for reliable and economical operation of power systems. Depending on the time horizon, load forecasting is generally classified as a short-term, midterm, or a long-term process. Short-term load forecasting [21–22], ranging from one hour to a week, is important for unit commitment, economic emission dispatch, energy transfer scheduling and real-time control. Mid/long-term load forecasting, covering time periods ranging from few weeks to several years, is used for maintenance, purchasing fuel, and future planning of generation and distribution. Many operational decisions such as generation scheduling, load management and system security assessment are based on such forecasts. Accurate load forecasting has a significant impact on the electricity utility's operation and production costs. Therefore, a wide variety of forecasting methods have been proposed. Most of these methods can be generally classified into two broad categories: statistical methods and artificial intelligence (AI)-based methods. Most of statistical models are based on linear analysis and have deficiencies in solving the load forecasting problem, because the load series is usually nonlinear. Some short-term load forecasting models have been proposed for regional load data processing by utilities in some countries such as: Greek [23], Taiwan [24], Brazil [25], Britian [26], and Japan [27].

In recent years, AI-based techniques [28], such as neural networks, have been used to obtain promising results. Neural networks have the capability to approximate any continuous nonlinear function, and can adapt to a changing forecasting environment through self-learning. However, selection of pre-training parameters and network architecture significantly affects the performance and requires users to have in-depth knowledge of neural network methods. Furthermore, due to the tedious and trial-and-error tuning process of the ANN, it is often difficult to decide whether the obtained neural network is the best and the forecasting results are less satisfactory [1].

The conventional back propagation algorithm trains neural network parameters (weights and biases) using gradient descent or conjugate gradient decent methods by calculating the partial derivative of the performance with respect to the weights and biases values. However, using this technique adds some constraints to a neural network where the transfer function of each neuron must be differentiable. Moreover, it has been proven that gradient techniques are slow to train and are sensitive to the initial guess which could possibly be trapped in a local minimum [29]. A back propagation (BP) algorithm is employed to update the weight and membership function parameters.

The advantage of using PSO algorithm [30-32] over other techniques is that it can be computationally inexpensive, easily implementable, and does not require gradient information of an objective function, but only its values. Therefore, the particle swarm optimization algorithm is applied in this paper to the neural network in the training phase, to obtain a set of weights that minimize the error function in competitive time. Weights are progressively updated until the convergence criterion is satisfied. The objective function to be minimized by the PSO algorithm is the predicted error function. Besides, fuzzy methods are described in [33-35].

2. Components of the Proposed Model

2.1 ANN and Sensitivity of ANN

A flowchart for the proposed short-term load forecasting technique in which the ANN is supported with the PSO is shown in Fig. (3). The number of inputs is 25 (24 inputs for previous day load data and one input for day type) and number of outputs is 24 (load forecast for the next 24-hours). Number of neurons in the hidden later is determined by using sensitivity analysis of the ANN structure. The ANN is fully connected and has 25, 22, and 24 neurons in the input-, hidden-, and output layers, respectively. Weather data are not included as inputs in this ANN model because of the lack of physical computer memory in our system.

2.2 Particle Swarm Optimization for Weight Optimization

The weight matrix of the ANN is adjusted by particle swarm optimization. The PSO is similar to other evolutionary algorithms in that the system is initialized with a population of random solutions. Each potential solution flies in the multi-dimensional problem space with a velocity that is dynamically adjusted according to the flying experiences of its own and its colleagues (see Fig. 2). The best previous position of the i^{th} particle is recorded and called *pbest*$_i$. The index of the best *pbest* among all the particles is represented by the symbol g. The location *pbest*$_g$ is also called *gbest*. The modified velocity and position of each particle are calculated using the current velocity and the distance from *pbest* to *gbest*. In PSO, the first part indicates the current velocity of the particle (inertia), the second part presents the cognitive part of the PSO where the particle changes its velocity based on its own thinking or memory, and the third part is the social part of the PSO where the particle changes its velocity based on the social-psychological adaptation of knowledge. All the terms need to be multiplied by appropriate parameters. For the ANN and load forecasting, dimension of a particle depends on the number of neurons. A generalized modified PSO is proposed to handle the weights matrix in the ANN used for load forecasting. This proposal is based on Fig. (1) and equations (1) – (6) given below.

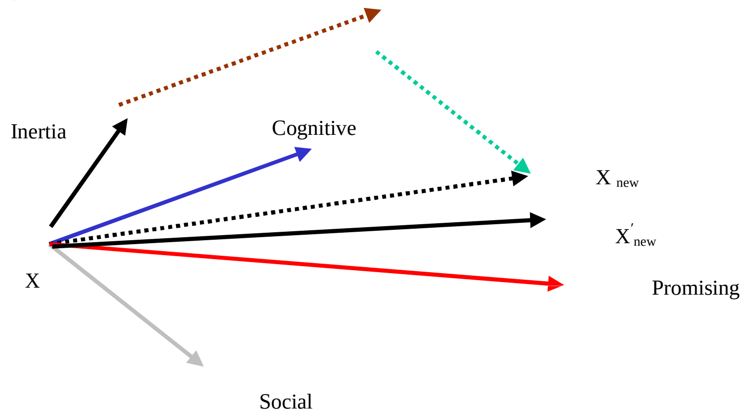

Fig. (1). Modified PSO.

$$v_{ij} = w * v_{ij} + \sum_{r=1}^{k} c_r rand() * (Prm_{ij}^{(r)} - p_{ij}) \tag{1}$$

$$Prm_{ij}^{(1)} = pbest_{ij} \tag{2}$$

$$\bar{u} = \frac{v_{ij}}{V_i} = \frac{v_{ij}}{\sqrt{\sum_{j=1}^{N} v_{ij}^2}} \tag{3}$$

$$x_{ij} = x_{ij} + f(Error)\bar{u}_{ij} \tag{4}$$

$$Prm_{ij}^{(3)} = \text{Promising value depends on problem complexity} \tag{5}$$

$$Prm_{ij}^{(2)} = gbest_{j} \tag{6}$$

In standard PSO, the parameters k, $Prm_{ij}^{(1)}$ and $Prm_{ij}^{(2)}$ are set, respectively, equal to 2, $pbest_{ij}$ and $gbest_{ij}$.

However, more than two promising vectors are proposed in this work for the calculation of the velocity vector (see Fig. 1), *i.e.*, $k \geq 3$ as we need to make use of huge practical data of Western Area of Saudi Arabia for training the ANN to be used for load forecasting.

Everything is imprecise if one looks closely enough, but more than that, most things are imprecise even on careful inspection. Practically, actual load differs from forecasted load. Analysis of short-term load forecasting results obtained in the past few years shows that predicted percentage load demand deviates from actual loads by ±1% to ±7% and the errors are not equal in both positive and negative sides. For uncertain or imprecise load data, the fuzzy approach is the right optimization method for load forecasting. ***Investigated Algorithms***

A block diagram of the proposed method is shown in Fig. (2). The first sub-block is implemented by an ANN, the second sub-block is implemented by PSO and third sub-block is used for output. However, a fuzzy method is used in the third sub-block to deal with the vulnerable nature of load in KSA where output has a Gaussian error with determined mean and standard deviation. A flowchart for the proposed approach is shown in Fig.(3). Step by step operations are given below for describing the method in detail.

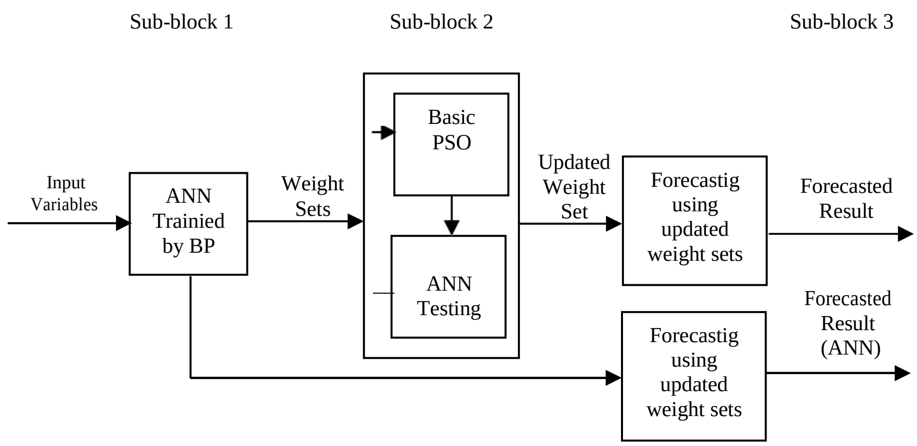

Fig. (2). Block diagram of the proposed method (BP = Back propagation).

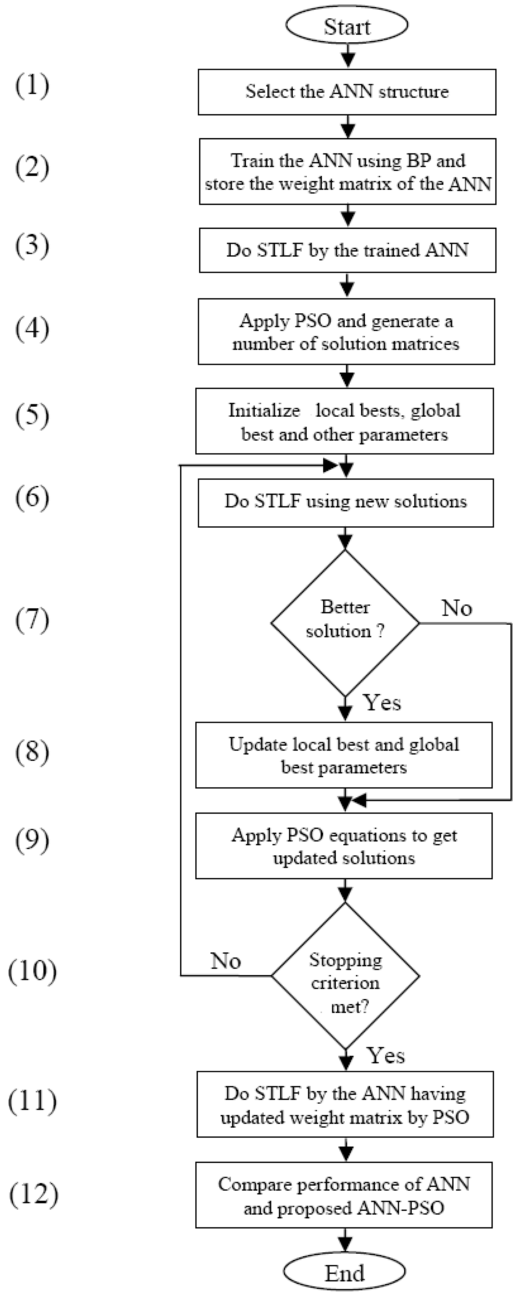

Fig. (3). Flowchart of the Proposed Algorithm .

Step 1: To select the ANN structure initially a fully connected three layered feed forward ANN is taken. The numbers of input and output neurons are determined by the input factors and the number of targeted outputs. To determine the number of hidden neurons we performed various experiments of STLF with different numbers of hidden neurons and finally selected the number that gave the best result.

Step 2: Train, validate and test the ANN by using the given dataset. The dataset is divided into training, validation and testing datasets. The training dataset is used to train the ANN. The validation dataset is used for determining the stopping criteria of the ANN and the testing dataset is used for determining STLF performance. After training completion we store the weight matrix for further updates.

Step 3: STLF is done by using the present ANN found in Step 2

Step 4: We produce a number of matrix sets that means candidate particles generated from the stored weight matrices in Step 2. This step explores the opportunity of randomness and generates more search spaces.

Step 5: Initialize local best (pbest), global best (gbest), and other PSO parameters that is w, c1 and c2 following the conventional rules.

Step 6: STLF is done using the ANN having the new weight matrices.

Step 7: If the performance obtained in Step 6 is better than that obtained in the previous one, then go to Step 8; otherwise go to Step 9.

Step 8: Update *pbest* and *gbest* parameters based on the performances of current solutions.

Step 9: In this step the present solutions (particles) are updated based on equations (1) and (2). Thus, we get a new set of solutions and explore the new search spaces.

Step 10: Check whether the stopping criterion is met or not. If met, then the global best weight matrix set is taken as the solution attained by the proposed method, and go to next step, otherwise go to Step 6 for further exploration.

Step 11: The updated weighted matrix is put in the ANN structure. Thus, we get the new ANN applying the PSO. Therefore, we do the STLF by the modified ANN and the performance is treated as the performance of proposed method. In most of the cases the proposed method performs better with respect to only ANN approach.

Step 12: Compare the performance of Step 3 and Step 11.

The ANN delivers two weight matrices. The PSO is applied to tune these weight matrices to achieve more accuracy in forecasting. The performances of weight matrices are measured by putting them into the ANN to get a new forecast. Thus the evolution of the weight matrices happens and converges to find out the best set of weight matrices. In a summary, the PSO performs the following steps on the weight matrices:

i.) We produce n (30), used in our program, the number of matrix sets that means candidate particles generated from the main matrix set by multiplying each element by a random number ranging from 0 to 1.

ii.) Initialize the values of the PSO parameters that is w , c_1 and c_2 . In our experiment, w is decreasing in each iteration from 1.0 to 0.4 uniformly, $c_1 = 1.5$ and $c_2 = 0.5$.

iii.) m (500) used in our program, the maximum number of iterations that is performed in parallel for each weight matrix set.

iv.) This iteration continues until it reaches its upper limit (500 iterations). In each iteration, both weight matrix sets are updated according to the equation of the PSO, that is the velocity and position of a particle is updated based on local best and global best.

v.) Finally the global best set is taken as the best solution.

3. Simulation Results

A hybrid method for doing STLF is proposed in this work. Here we are able to forecast 24-hours load for any particular day. The proposed technique can be also used to forecast 24-fours load of a different day. We have worked on the dataset of the Western Area of Saudi Arabia. All calculations have been run on Intel(R) Core(TM) 2 Duo, 2.66GHz CPU, 2.96 GB RAM, Microsoft Windows XP OS and MATLAB compiler for coding.

The following four diagrams, Fig. (4 -7) are drawn based on the load forecasting results for Monday, December 1st , 2003.

In Figure. (4), blue, green and red curves represent the actual load, forecasted load by the ANN and the ANN-PSO, respectively, for the 24 hours of December 1st, 2003. It is clearly visible that the load forecast obtained by the ANN-PSO method is much closer to the actual load than that obtained by the ANN alone. The ANN depends on the BP training algorithm and it has been proven that gradient techniques are slow to train and are sensitive to the initial guess which could possibly be trapped in a local minimum [28], thus the performance of the ANN is lower. On the other hand, when we apply the PSO as a guided search mechanism a better solution is reached. As a result, the ANN-PSO performs much better to the extent that at some instances the load forecasted by the ANN-PSO is exactly same as the actual load.

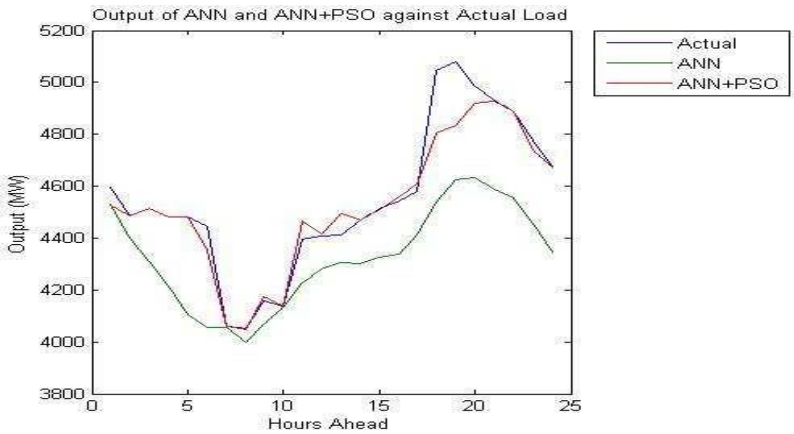

Fig. (4). Load comparison for the day December 1st, 2003 .

Initially the ANN and the ANN-PSO produce similar results which are close to the actual load. But during the period from the 2nd the 6th hour the performance of the ANN-PSO is much better than that of the ANN. At the 7th and 10th hours both perform the same and but between these interval ANN forecasts close to actual but still it is not as good as proposed ANN-PSO's performance. After 10^{th} hour, for the rest of the time again the output of ANN is far from the actual output, whereas the output of ANN-PSO is very close to the actual load. So it can be concluded that the overall performance of ANN-PSO method is significantly better with respect to ANN approach.

Figures (5) and (6) show the absolute errors, *i.e.* in MWs, and the relative error, expressed in % of the actual load, found in the forecast results demonstrated in Fig. (4). From the curves of Fig. (5 and 6), it is clear that the performance of ANN-PSO is much better than that of the ANN alone. The main reason for this superiority is that the PSO more search space has been generated and the guided search approach of the PSO becomes successful to converge into optimal solution.

Figure.(6) shows that the ANN alone produces an average error of 4.7146% with a maximum error of 10.026%, whereas the proposed ANN-PSO's results have an average error of 0.8734% and a maximum error of 4.8091%.

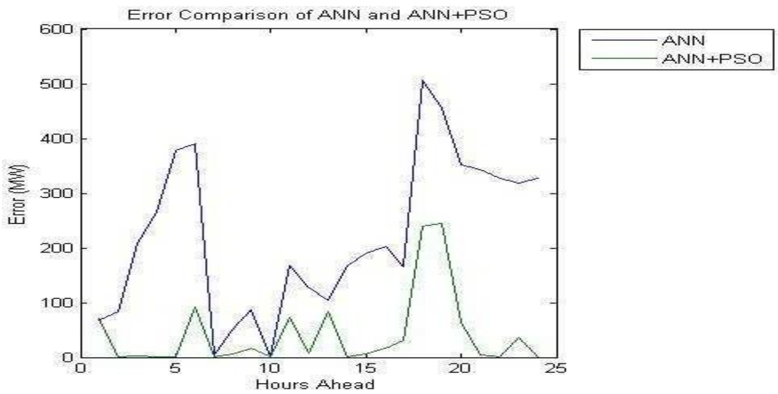

Fig. (5). Error comparison for the day December 1st, 2003 Absolute errors of the results shown in Fig. (4).

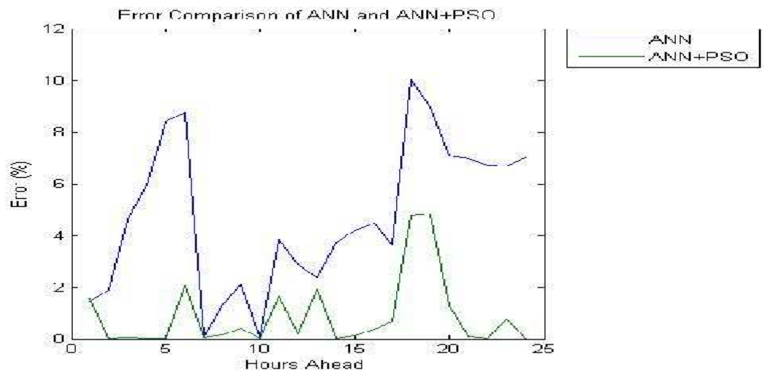

Fig. (6). Percent error comparison for the day December 1st, 2003 Percentage errors of the results shown in Fig. (4).

Figure.(7) shows the convergence of the ANN-PSO method. It is observed that the major performance improvement starts somewhat after 200 iterations and needs 300 iterations to get to its best values. It spends the first 200 iterations to make balance between local and global search abilities.

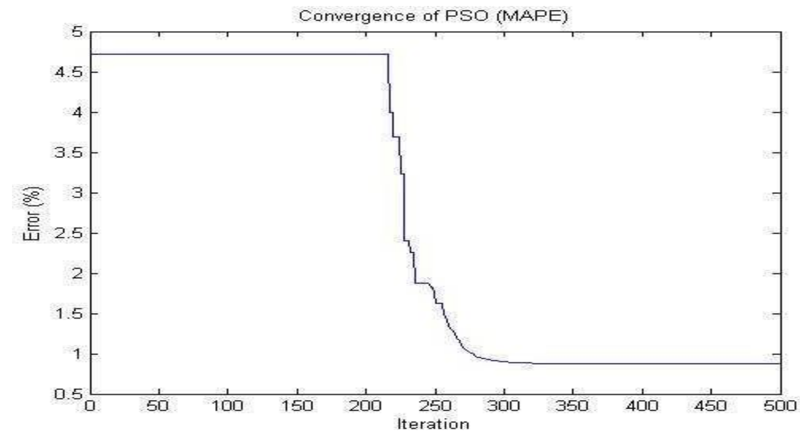

Fig. (7). Convergence of MAPE for the day December 1st, 2003 .

Figures (8-11) shows the load forecasting results obtained for the next day, *i.e.* December 2nd, 2003.

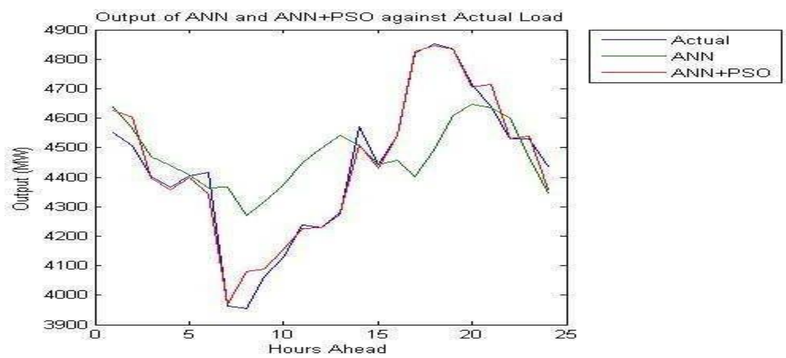

Fig. (8). Actual and forecasted loads for the day December 2nd, 2003 .

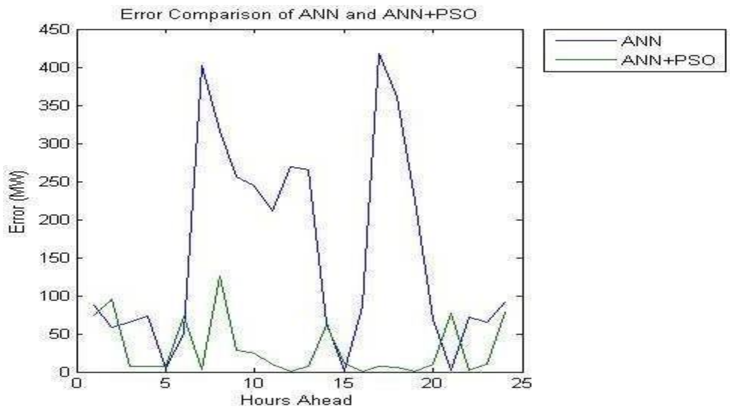

Fig. (9). Error comparison for the day December 2nd, 2003 Absolute errors of the results shown in Fig. (8).

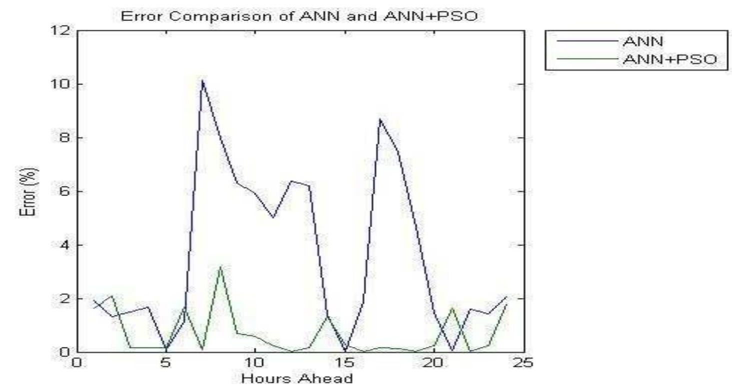

Fig. (10). Error rate comparison for the day December 2nd, 2003 Percentage errors of the results shown in Fig. (8).

It is clearly visible in the results obtained here agree to a great extent with those obtained for the day December 1st, 2003.

Figure.(10) shows that the results obtained by the ANN method have an average error of 3.5916% and a maximum error of 10.124%, whereas those obtained by the proposed ANN-PSO method have an average error of 0.6909% and a maximum error of 3.1721%.

Figure.(11) shows how the MAPE varies with the number of iterations performed during the ANN-PSO exploration. This figure is almost the same as that shown in Fig. (7).

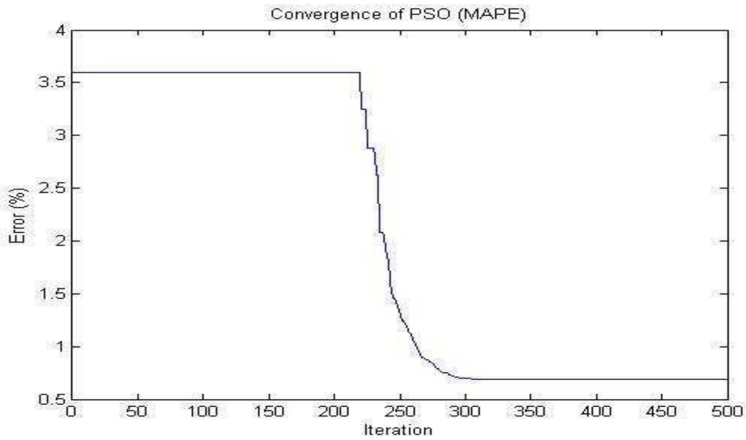

Fig. (11). Convergence of MAPE for the day December 2nd, 2003.

Figures (12-15) show load forecasting results obtained for the day December 6th, 2003.

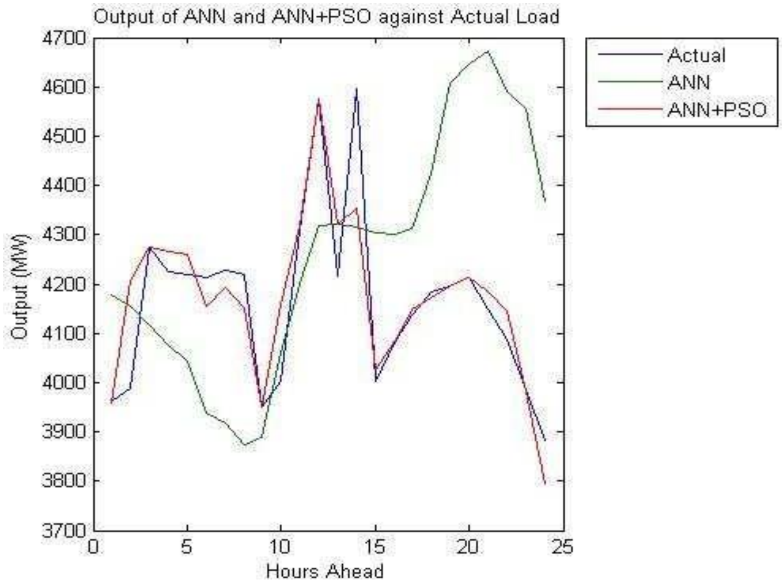

Fig. (12). Actual and forecasted loads for the day December 6th, 2003 (Model 1).

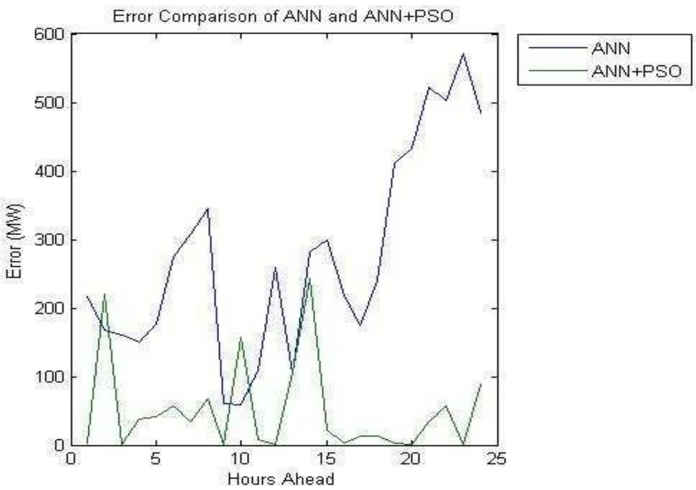

Fig. (13). Absolute errors of the results shown in Fig. (12).

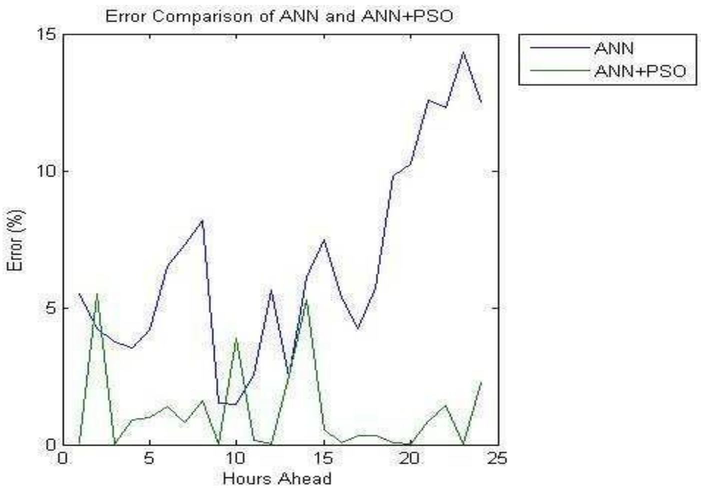

Fig. (14). Percentage errors of the results shown in Fig. (12).

Figure (15) shows how the MAPE varies with the number of iterations performed during the ANN-PSO exploration of the load forecast for the day December 6th, 2003. This figure is almost incomplete agreement with those obtained for the days December 1st and 2nd, 2003 and shown in Fig.(7 and 11), respectively. Figures (7, 11 and 15) assure that the number of iterations necessary for minimizing the error in load forecasting results is 300.

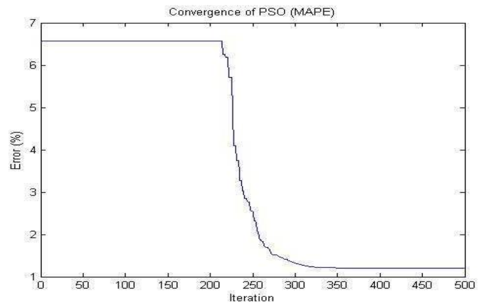

Fig. (15). Convergence of MAPE for the day December 6th, 2003 .

4. Robustness of the ANN-PSO Method

To establish the robustness scalability of the proposed method, it has been applied to forecast the load for much longer time periods extending to a complete week. Fig. (16–19) and Table (1) shown below demonstrate the load forecasting results obtained for the week December 1st to 7th, 2003.

According to Table (1), the performance of the ANN alone is not satisfactory. The average MAPE using the ANN alone is 14.329%. However, it is significantly improved when the ANN is supported by the PSO. For most of the days, the MAPE is reduced to less than 1% when the ANN+PSO technique is applied. The average MAPE is reduced to 1.4367%, which is acceptable for real applications.

Table (1). Performance of ANN and ANN-PSO and achieved improvements .

TYPE		1-12-03 (Mon) Test_01	2-12-03 (Tue) Test_02	3-12-03 (Wed) Test_03	4-12-03 (Thur) Test_04	5-12-03 (Fri) Test_05	6-12-03 (Sat) Test_06	7-12-03 (Sun) Test_07	Average
MAPE	ANN	4.7146	3.5916	10.135	25.137	26.369	6.5639	23.794	14.329
	ANN-PSO	0.8734	0.6909	0.7885	2.0071	1.9541	1.2095	2.5331	1.4367
	Improvement	3.8412	2.9007	9.3466	23.13	24.414	5.3544	21.261	12.893
MIN	ANN	0.0735	0.0318	0.6648	9.6287	10.636	1.4797	16.301	5.5451
	ANN-PSO	0.0001	0	0	0.0081	0.0002	0.0016	0.0036	0.0019
	Improvement	0.0734	0.0318	0.6648	9.6206	10.635	1.4781	16.298	5.5431
MAX	ANN	10.026	10.124	16.743	35.452	46.249	14.339	32.452	23.626
	ANN-PSO	4.8091	3.1721	4.2106	12.593	6.9431	5.5193	13.518	7.2521
	Improvement	5.2166	6.9523	12.533	22.859	39.306	8.8196	18.935	16.374
STD	ANN	2.9014	3.0654	6.1712	7.7198	8.5006	3.6996	4.9746	5.2904
	ANN-PSO	1.3746	0.8651	1.1475	3.5502	1.9718	1.6166	3.4929	2.0027
	Improvement	1.5268	2.2003	5.0237	4.1696	6.5288	2.083	1.4817	3.2877

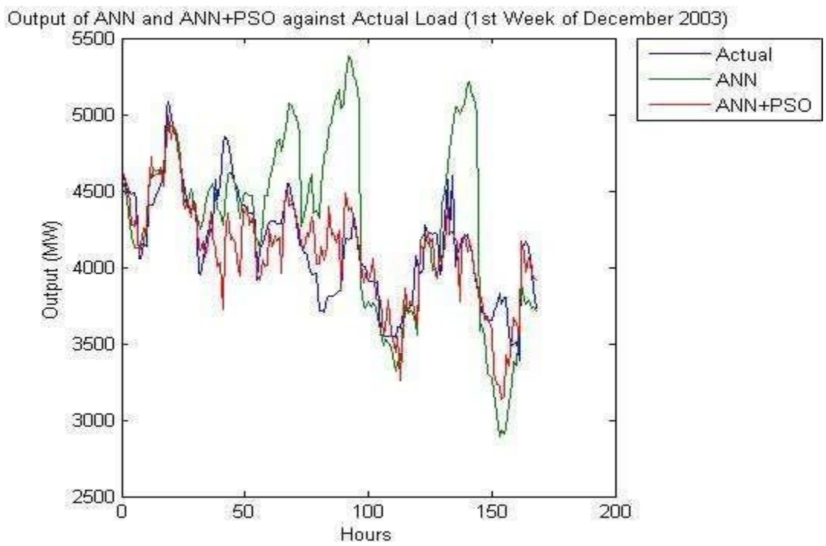

Fig. (16). Load comparison for the week December 1st -7th, 2003 .

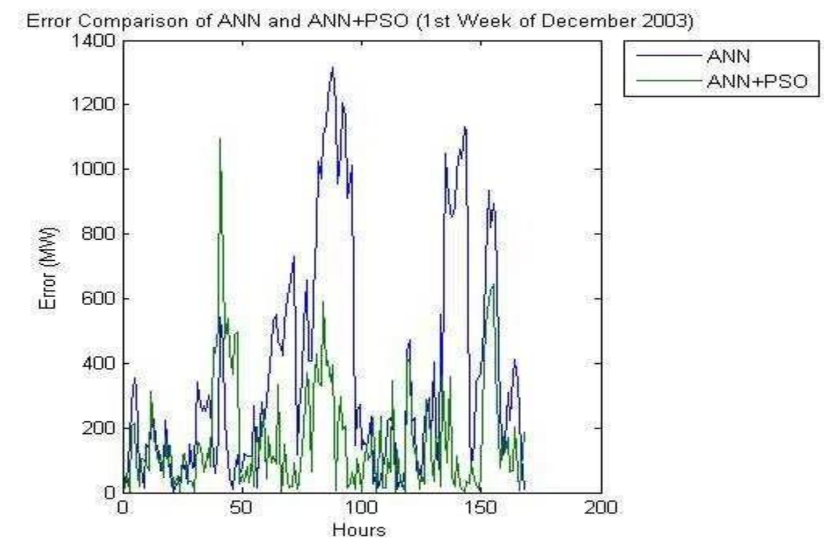

Fig. (17). Absolute errors of the results shown in Fig. (16).

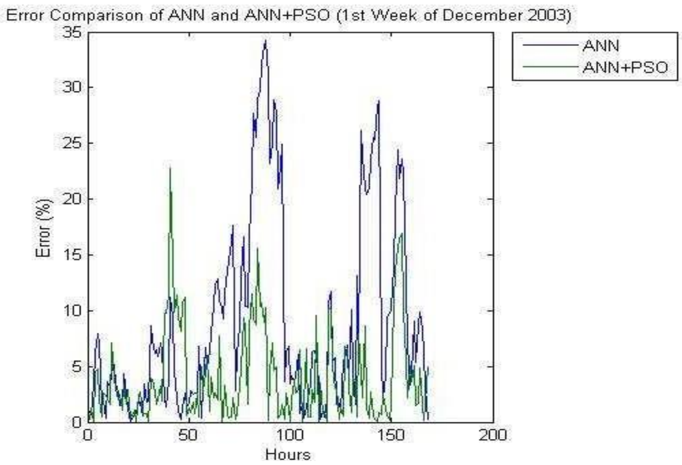

Fig. (18). Percentage errors of the results shown in Fig. (12).

Figure(18) shows that the load forecasting results obtained by the ANN alone for a complete week have an average error of 9.1479% and a maximum error of 34.281%. These errors drop, respectively, to 4.0218% and 22.742% when the ANN-PSO technique is applied.

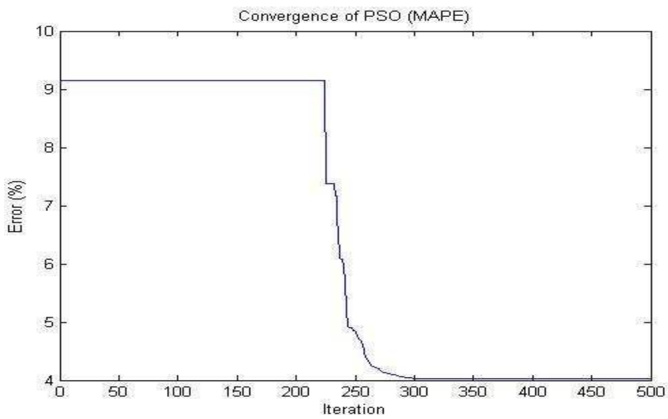

Fig. (19). Convergence of the MAPE for the week December 1st -7th, 2003.

Figure (19) shows the convergence of ANN-PSO. It is observed that the major performance improvement occurs during 200 – 300 iterations. Around 200 iterations are spent to make a balance between local and global search abilities.

5. Conclusions

This paper presents a short-term load forecasting for the Western Area of Saudi Arabia using an ANN and PSO. ANNs are in common use in the load forecasting arena. ANNs are used to map the complex mathematical relationship of load and its causes. However, the ANN is not an optimization tool. On the other hand, PSO is used to optimize the input and output weight matrices of the ANN. The short-term load forecasting model proposed in this paper makes use of a hybrid approach combining the ANN and the PSO. A fully connected feed-forward ANN trained by back propagation algorithm is taken to do the STLF and the PSO is applied to enhance the accuracy of this ANN through updating its weight matrices. A significant improvement has been achieved in the load forecasting results by applying the ANN-PSO approach. This hybrid approach has been applied to forecast the load of the load of the Western Area of Saudi Arabia based on a data set obtained from its past records and the obtained results are quite satisfactory.

6. References

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