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The Application of Committee Machine Model in Power Load Forecasting for the Western Region of Saudi Arabia

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Abstract. Load forecasting has become in recent years one of the major areas of research in electrical engineering. Most traditional forecasting models and artificial intelligence techniques have been tried out in this task. Artificial neural networks (ANN) have lately received much attention, and many papers have reported successful experiments and practical tests. This paper presents the development of an ANN-based committee machine load forecasting model with improved accuracy for the Regional Power Control Centre of Saudi Electricity Company. The proposed system has been further optimized using Particle Swarm Optimization (PSO) and Bacterial Foraging (BG) optimization algorithms. Results were compared for standard ANN, weight optimized ANN, and ANN committee machine models. The networks were trained with weather-related, time based and special events indexes for electric load data from the calendar years 2005 to 2007.

Keywords. Artificial neural networks, Short-term load forecasting, back propagation, Committee machine, Particle swarm optimization, Bacterial foraging.

List of Symbols

POS : Particle Swarm Optimisation
ANN : Artificial Neural Networks
GB : Bacterial Foraging
STFL: Short Term Load Forecasting
RBF : Radial Basis Functions
MLP:Multi-layer Perceptron

1. Introduction

Load forecasting has become in recent years one of the major areas of research in electrical engineering. Load forecasting is however a difficult task. First, because the load series is complex and exhibits several levels of seasonality. Second, the load at a given hour is dependent not only on the load at the previous day, but also on the load at the same hour on the previous day and previous week, and because there are many important exogenous variables that must be considered[1]. Load forecasting plays an important role in power system planning and operation. Basic operating functions such as unit commitment, economic dispatch, fuel scheduling and unit maintenance, can be performed efficiently with an accurate forecast[2, 3-4].

Various statistical forecasting techniques have been applied to Short Term Load Forecasting (STLF). Examples of such methods including, time series[5, 6], similar-day approach[7], regression methods[5, 8] and expert systems[7, 9-10]. 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 Networks (ANN) has been proved as powerful alternative for STLF that does not rely on human experience. It has been formally demonstrated that ANN's 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. Also, ANN is data-driven method, in the sense that it is not necessary for the developer to postulate tentative models and then estimate their parameters. Given a sample of input and output vectors, ANN is able to automatically map the relationship[1, 11, 12].

This paper presents a study on the use of ANN model to STLF, particular attention has been given to the network's topology. Different techniques were used in the modelling stage, a simple ANN, a weight optimized ANN, and a committee machine network. Optimization methods were used to further tune the network for achieving higher prediction accuracy. The models were developed based on electrical load data for a typical 24-hours load for the western area of Saudi Arabia. Time, weather, special season events, and load related inputs are considered in this model. Three years of historical dependent data were used. The forecasting system design was customised to features of Saudi Arabia electrical load.

2. Electric Load Features

Western operational area of Saudi Electricity Company is covering very important cities with special features. It includes the two holy mosques in Makkah and Al-Madina, beside, the most economical and tourism city like Jeddah and other small cities such as Taif and Yanbu. There are many factors affecting the load of this area, which makes the forecasting unique and challenging.

The weather changes greatly affecting the load demand due to a huge air conditioning load in the system. Figure 1 shows a linearity relationship between system daily peak load and related temperature for the years 2005-2007. Another important factor is the time of the day, as social life and activities of the consumers depend on the time of the day such as working and schools hours and prayer times, as well as the seasonal load behaviour factor, which reflects how load draws a changeable profile, due to the impact of seasonality. The effect of working days and weekends on the load trend is essential. One more important factor is special events factor mainly religious events such as the month of Ramadan and Hajj, and other events such as public holidays, school and exams. These events, based on the lunar calendar will cause un-similarity in load conditions every year, so that it has to be considered. Figure 2 shows the electric load data set which is spread over 3 years.

Examples of a daily load consumption profile of a typical weekday/weekend during summer and winter are shown in Fig. 3. The difference between winter and summer profiles is clear; the effect of hot weather is reflected on the great amount of load consumption at afternoon in the summer day. At Friday a sudden increase in the load demand afternoon is due to Friday's prayer, and at weekend the load is stable in the morning.

2.1. *Input Vector Indices*

The independent variables of the system can be specified as the date, time, weather conditions, special events data, and associated historical load data for the day to be forecasted, in hourly bases.

Typically, it is configured as seven indexes that represent the time during the day, date (day, month, year), day type (weekday or weekend), temperature, relative humidity, wind speed and direction.

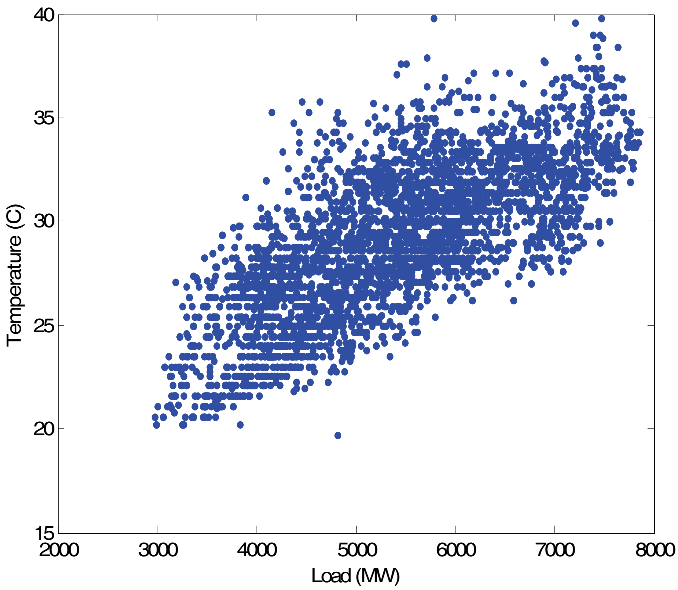


Fig. 1. Relationship between temperature and the systems daily peak load of 2005.

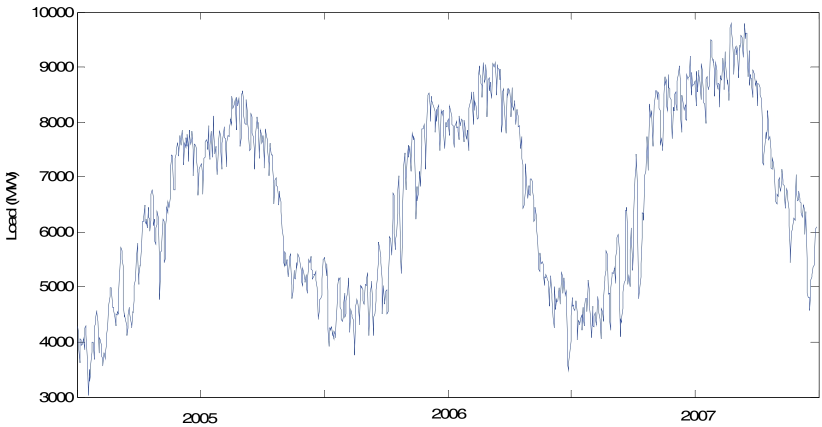


Fig. 2. Load profile for 3 years.

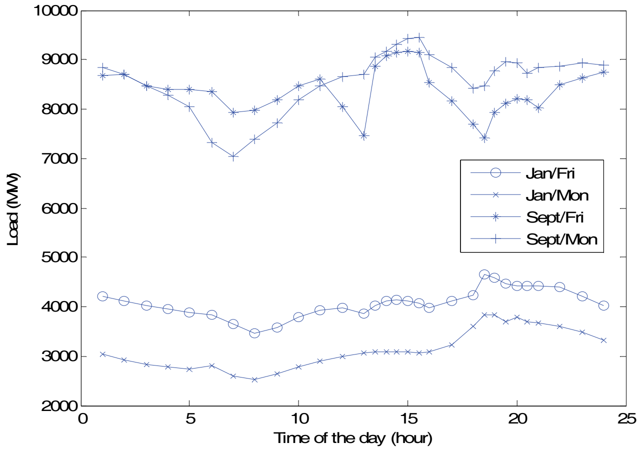


Fig. 3. Examples of daily load consumption profile of a typical weekday/weekend, winter and summer days.

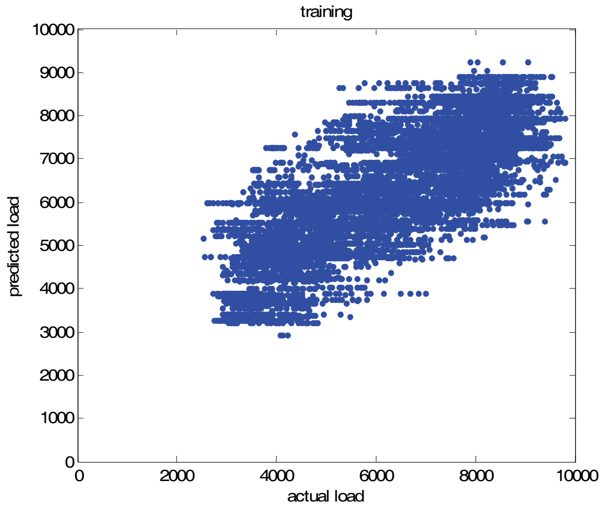
Numerical indexes were given to represent the inputs for the forecasted hour. Indexes of [1:12] were given to represent the month, [1:24] to represent the hour and [1:7] to represent the day type starting from Saturday to Friday (the weekend is Thursday and Friday). Moreover, half-hourly load data is considered for the high load variation periods of the day, typically 13:30, 14:30, 15:30, 18:30, 19:30 and 20:30 which were represented by the fractions (13.5, 14.5, 15.5, 18.5, 19.5 and 20.5) respectively.

3. Neural Networks Modelling

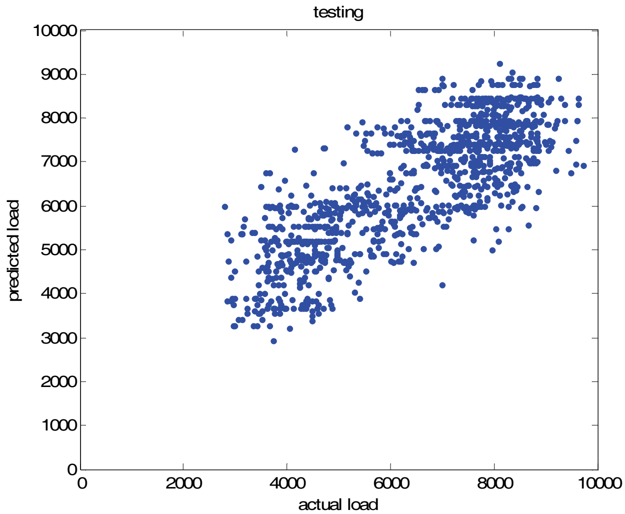
3.1. *Neural Network Training*

The ANN models developments were performed using the Matlab Neural Networks Toolbox. The initial ANN models were trained for the data using 9 input variables: day, month, year, day type, time of the day, temperature, humidity, wind speed and wind direction, while the output is the load. In previous studies [19, 23], different ANN topologies were trained using back propagation training algorithm and tested in order to find the best network structure that gives the best modelling accuracy. The ANN topologies were selected as: Linear, Multi-Layer Perceptron (MLP) and Radial Basis Functions (RBF). A maximum two hidden layers were selected [14, 16, 17]. The MLP was found to be the best type of topology that provides accurate predictions. The data were selected as

90% for training (Jan 2005 to September 2007), and 10% for testing (October – December 2007). Training and testing results are shown in Fig. 4. Table 1 shows the training results for MLP topology for the training and testing error. The results are compared to predictions using logistic regression technique which can show 20.8% improvements in the testing data prediction accuracy.



(a) Training



(b) Testing

Fig. 4. Simple ANN training and Testing (single layer, 18 hidden neurons, 100 epochs).

Table 1. ANN training and testing RMS results.

	Training	Testing	Testing Improvements (%)
Logistic Regression	25.4507	25.0036	-
Standard ANN	19.3296	19.8466	20.8

3.2. *ANN Weights Optimization*

For the MLP topology of 1 hidden layer with 18 hidden neurons, 9 inputs and a single output, there are 166 parameters in the network that are adjusted and optimized during the learning phase. However, due to the learning algorithm shortcoming, sometime the back propagation learning algorithm falls short of finding the exact parameters for the optimum solution. Therefore, an optimization algorithm can improve the prediction accuracy by fine tuning the ANN parameters within a constrained range. In this stage, two optimization algorithms were utilized, namely Particle Swarm Optimization and Bacterial Foraging, in order to fine tune the weights in the network with a margin of 10% change for each parameter.

3.2.1. *Particle Swarm Optimization Algorithm (PSO)*

Particle Swarm Optimization is a global minimization technique [24, 25] for dealing with problems in which a best solution can be represented as a point or and a velocity. Each particle assigns a value to the position they have, based on certain metrics. They remember the best position they have seen, and communicate this position to the other members of the swarm. The particles will adjust their own positions and velocity based on this information. The communication can be common to the whole swarm, or be divided into local neighbourhoods of particles.

With the PSO algorithm constant weights factors 9c1 and c2) were set to c1 = 1.49618; c2 = 1.49618; while the inertia weight (w) was set to w = 0.7298. The algorithm was set to start with a random weights tuning which has recorded an increment in the training data RMS. The PSO algorithm was iterated for 100 epochs which has achieved a smaller RMS. Figure 5 shows the training RMS error against the iteration number. The tuned network was tested using the testing data and the recorded RMS has also shown an improvement compared to the standard ANN. Figure 6 shows the optimized ANN prediction against the actual loads for the testing data.

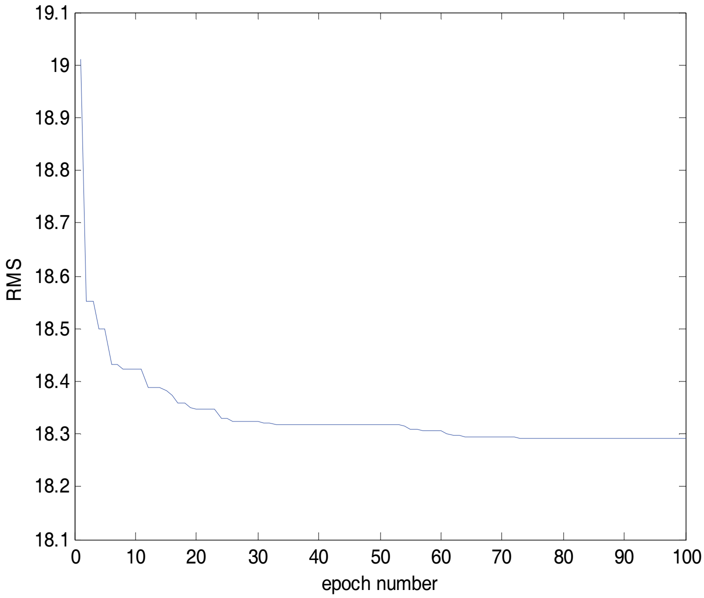


Fig. 5. ANN weights optimisation using PSO.

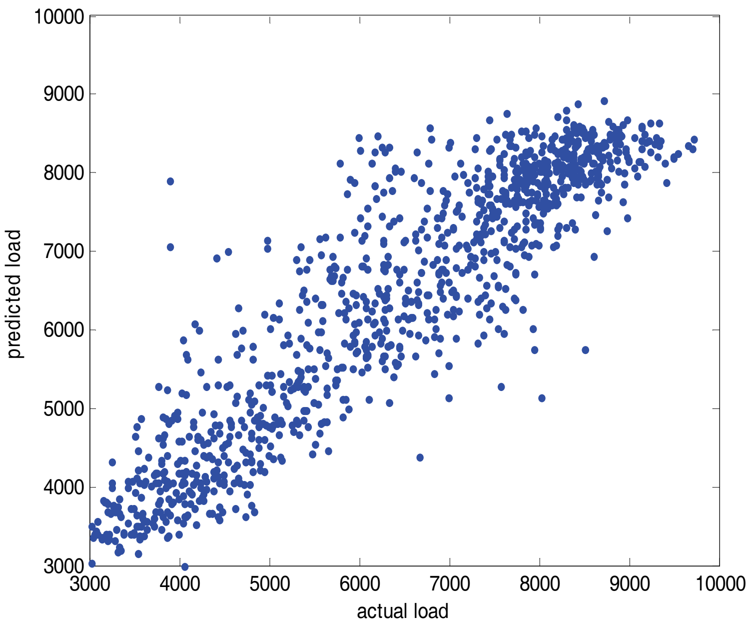


Fig. 6. Predicted against actual testing data for weights optimised ANN using PSO.

3.2.2. *Bacterial Foraging Optimization Algorithm (BG)*

Recently, search and optimal foraging of bacteria have been used for solving optimization problems [21, 26]. To perform social foraging, an animal needs communication capabilities and over a period of time it gains advantages that can exploit the sensing capabilities of the group. This helps the group to predate on a larger prey, or alternatively, individuals could obtain better protection from predators while in a group.

Its behaviour and movement comes from a set of six rigid spinning (100–200 r.p.s) flagella, each driven as a biological motor. An E. coli bacterium alternates through running and tumbling. Running speed is 10–20 lm/s, but they cannot swim straight. The chemotactic actions of the bacteria are modelled as follows:

- In a neutral medium, if the bacterium alternatively tumbles and runs, its action could be similar to search.

- If swimming up a nutrient gradient (or out of noxious substances) or if the bacterium swims longer (climb up nutrient gradient or down noxious gradient), its behaviour seeks increasingly favourable environments.

- If swimming down a nutrient gradient (or up noxious substance gradient), then search action is like avoiding unfavourable environments.

Therefore, it follows that the bacterium can climb up nutrient hills and at the same time avoids noxious substances. The sensors it needs for optimal resolution are receptor proteins which are very sensitive and possess high gain. That is, a small change in the concentration of nutrients can cause a significant change in behaviour. This is probably the best-understood sensory and decision-making system in biology [21].

At this stage, the BG optimization algorithm was utilized to fine tune the NN weights in a similar fashion to the PSO algorithm. Figure 7 shows the training RMS for the same number of iterations. Figure 8 shows the optimized ANN prediction against the actual loads for the testing data.

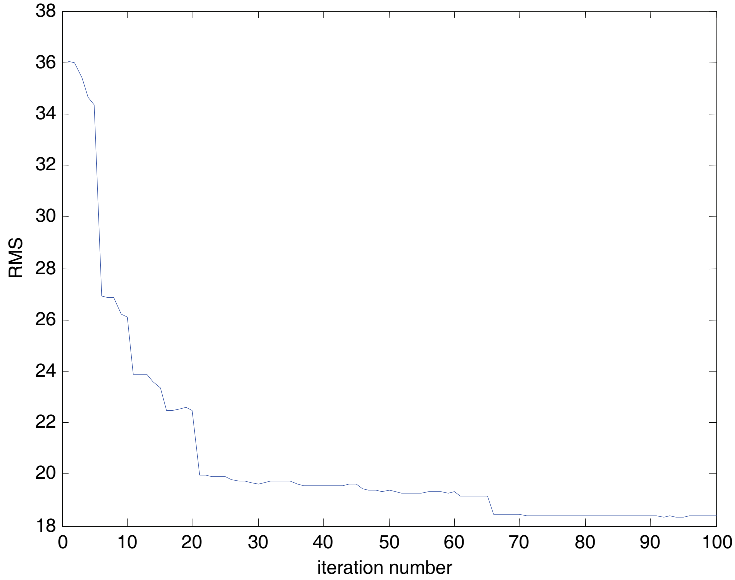


Fig. 7. ANN weights optimization using BG.

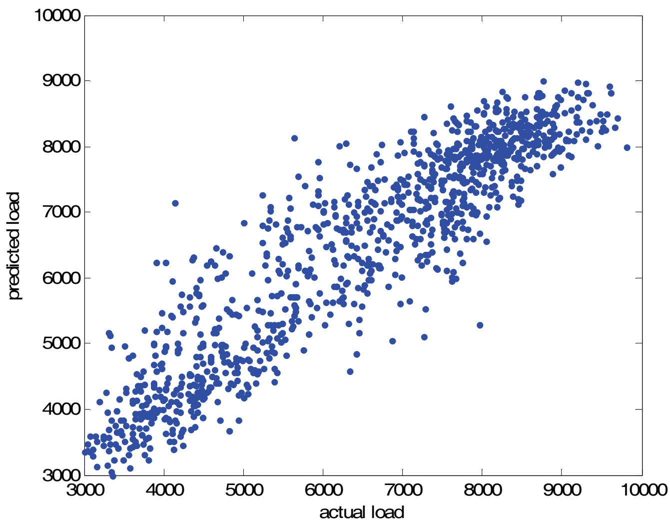


Fig. 8. Predicted against actual testing data for weights optimized ANN using BG.

Table 2 shows a comparison between the two optimization algorithms for the training and testing errors. Both algorithms show improvements in the testing data prediction accuracy. However the PSO has achieved 26.8% improved prediction compared to the BG algorithm which has achieved 25.6%. There is a 5% improvement in the performance compared to standard ANN.

Table 2. ANN training and testing RMS using PSO and BG weights optimization.

	Training	Testing	Testing Improvements (%)
PSO	18.2908	18.3856	26.8
BG	18.5544	18.6378	25.6

3.3. *Committee Machine*

Ensembles are a well established method for obtaining highly accurate classifiers by combining different algorithms. A number of researchers have applied ensemble methods to improve the performance of neural networks [22, 27]. The basic idea of a committee machine is to combine a mixture of experts and to effectively make use of the results produced by each expert within the ensemble. Figure 9 provides the architecture of the committee machine system with 10 copies of the same algorithm. By combining the result of each classifier, the final result can be realized with improved performance. Each classifier gives its result *R* and the confidence *Cf* for the result to the combiner. The confidence is utilised as a weighted vote for the combiner to avoid affecting the final decision by the result of individual expert featuring low confidence.

The committee machine modelling approach used in this paper consists of two stages: generating of individual candidate neural networks while the second stage is combining the individual neural networks into an ensemble model. In the first stage, it is necessary to determine what variations, such as the initial weights, training algorithms and training options, training data *etc*., are to be introduced to generate the individual models. Standard training procedure can then be used to generate the models. Some discretion needs to be applied during the training of the individual models, since in some cases training might end up with a poor model and it is not wise to include such a poor model into the ensemble candidates. The aim of the first stage is to produce an ensembled neural network models with acceptable prediction performance, and confidence bands.

The ensemble model has many advantages over its single (best) neural network model; among these are the improvement of prediction accuracy, the strong robustness, and better generalization ability.

Moreover, it can give an error bound on its prediction as a by-product, since all the individual models in the ensemble set are different and the difference in their predictions can be used as an indication of the reliability of the ensemble model on the given input. Based on this concept, the error bound can be calculated from the standard deviation of the individual predictions. For a given prediction $\hat{y}(k)$, its error is given by:

$$EB(k) = 2\sigma(k) = 2\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i(k) - \hat{y}(k))^2}\,; \quad \hat{y}(k) = \frac{1}{N}\sum_{i=1}^{N} y_i(k) \tag{1}$$

where $\hat{y}(k)$ is the output of the ensemble model for input $x(k)$, $y_i(k)$ is the corresponding output of the *i th* neural network, $EB(k)$ is the error bounds for the $\hat{y}(k)$ with 95% confidence, N is the number of neural networks in the ensemble set, and $\sigma(k)$ is the standard deviation among the output predictions $y_i(k)$. Apparently, the error bounds will be affected by the characteristics of input regions where prediction is to be made. Generally speaking, the error bound tends to be small in regions covered by dense training data, and vice versa.

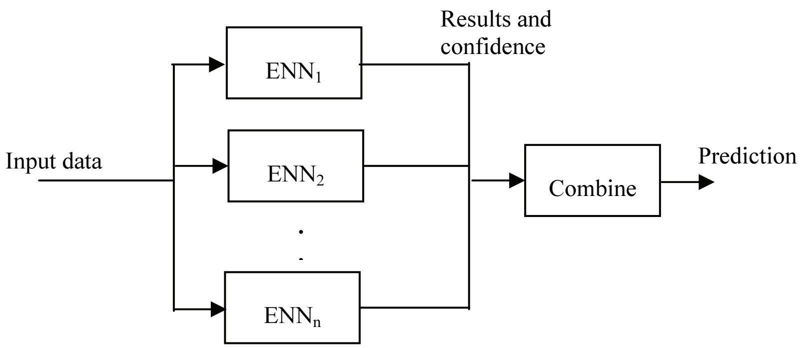


Fig. 9. Ensembled NN embedded in the committee machine architecture.

In the second stage the individual ensemble neural networks are combined into the committee machine. Using the confidence band as a weight coefficient for each classifier will therefore give very little weighting coefficient to the best classifier over the worst one. In this work, an optimization method is proposed to tune the weighting factor of each member on the machine. The weighting function defined by:

$$Wi = P_i\, Pw\, Pop \tag{2}$$

where *Wi* is the weight of a given predictor *i* with a given prediction *Pi*. *Pi* is defined as the average prediction performance of each individual ensembled NN models in the committee machine. *Pop* is the optimiser weighing which can be adjusted during the optimization process. *Pw* is the predictor confidence based on its prediction performance within the ensemble.

The committee machine has been optimized using two techniques, PSO and BG. For the same setting used in section 3.2, both algorithms were utilized to optimize the weights of the committee machine. Figure 10 shows the optimisation RMS using PSO, while Fig. 11 shows the optimized network prediction against the actual load for the testing data.

Figures 12 and 13 show the optimization RMS and the testing data predictions when the BG algorithm is utilized. Despite the complexity of the committee machine algorithm, the PSO algorithm did not improve on the prediction error. However, the BG has achieved marginal improvements on the prediction accuracy. Table 3 shows the error for both optimization algorithms for the training and testing errors. The optimized committee machine weights are shown in Table 4 for both algorithms.

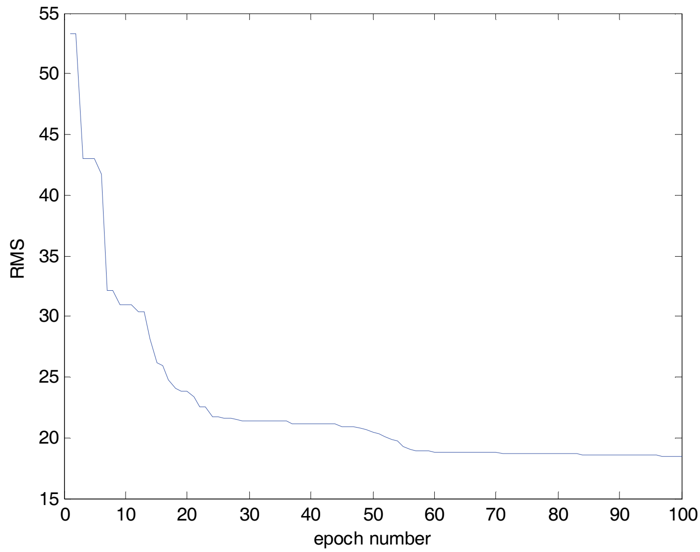


Fig. 10. Committee machine learning error using PSO.

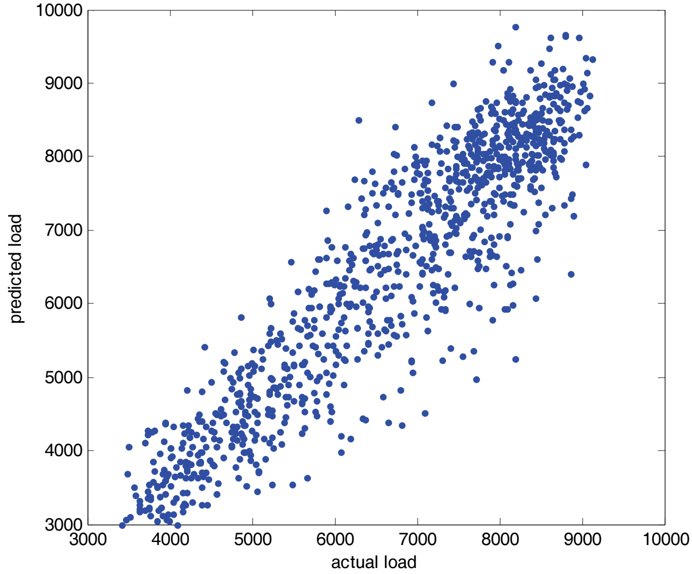


Fig. 11. NN committee machine predicted against actual load for testing data.

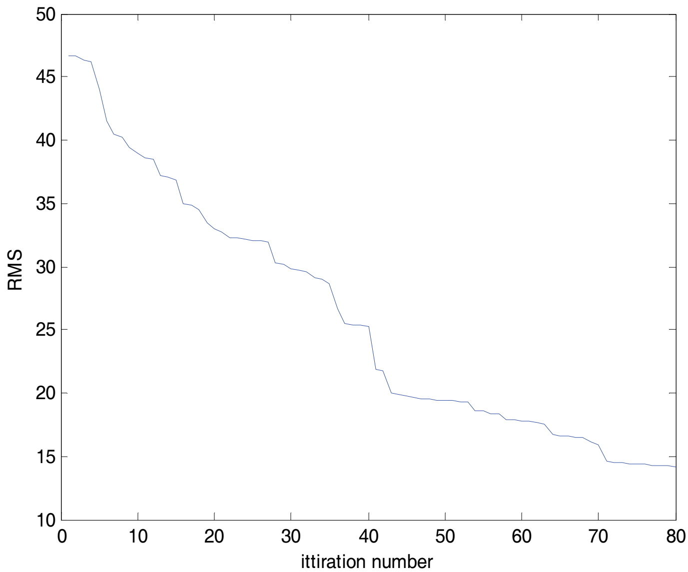


Fig. 12. Committee machine learning error using BG.

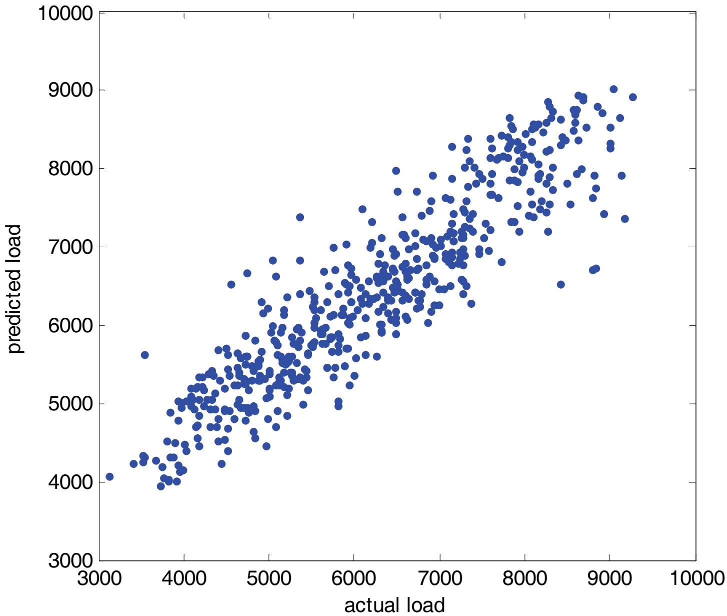


Fig. 13. BG committee machine testing data predictions.

Table 3. NN training and testing RMS using PSO and BG.

	Training	**Testing**	**Testing Improvements (%)**
PSO	18.4800	18.4792	26
BG	14.5750	14.6788	41.6

Table 4. Ensembled weights optimization using PSO and BG.

	NN_1	**NN_2**	**NN_3**	**NN_4**	**NN_5**	**NN_6**	**NN_7**	**NN_8**	**NN_9**	**NN_{10}**
PSO	0.5721	1.0005	0.6946	1.2257	1.0390	1.0483	0.9602	1.0162	0.8896	1.0788
BG	1.0031	1.0524	0.9478	0.9605	0.9517	0.9034	1.0440	0.9906	1.0861	0.9162

Despite the fact that both PSO and BG have shown equivalent improvements when used to optimize the ANN, the use of BG with the committee machine algorithm proves the BG can perform better results for a complex system. The improvements have been raised to 40% which proves that PSO can handle simple system only due to its algorithm simplicity, whereas BG is more complicated and can achieve better results.

4. Conclusion

This paper presents an ANN system for predicting the electrical loads on the Western grid in the Kingdom of Saudi Arabia. This network has a load pattern with special features. These features are to cope with the special religious activities. Moreover, the load pattern is much affected by the time schedule, the temperature, humidity, wind speed and direction. The load patterns have varying features especially in the holy cities of Makkah and Madinah which host millions of people in different seasons during the year to perform religious activities. In fact, the religious tourism influences the system load profile [19]. Different modelling techniques were used, a standard MLP ANN was utilised to develop a standard model, and consequently optimized further using PSO and BG. The advantages of the ANN is that it can cope with large number of data and high input dimension, this is a positive feature with load data, as it has high dimension and vast amount of data point. However, due to the noise in the data and the variation of the load, the ANN training algorithm does not guarantee a optimum network which is a disadvantage of the algorithm. An assistant tool need to be introduced to the system so that the network can learn the least error. This can be achieved by the introduction of an optimization algorithm or an ensemble. A more sophisticated algorithm was also investigated which is based on committee machine. Committee machine has the advantage of combining many ANN together so that the network which has some misfit in a specific area of the model can be compensated by the other networks. However, the committee machine algorithm will require further tuning in order to find the weights of each network. The algorithm was further optimized using PSO and GB. Improved results have been achieved using the committee machine modelling technique. The two optimization algorithms are simple and fast in finding the optimal setting of the algorithm, PSO in particular has a simple structure but it can only do search locally, on the other hand, BG is better searching algorithm but it is more sophisticated which consequently takes longer calculation time.

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Appendix

Correlation Analysis

The correlation is one of the most common and useful statistical analysis tools that can be used in data modelling and analysis. A correlation is a number that describes the degree of relationship between two variables. The correlation is defined as the covariance between Xi and Xj divided by the product of their standard deviations. Matlab provides a function for calculating the correlation matrix of a set data with multiple variables. A correlation study has been conducted to test the relationship between the input variables and the load. The aim of this test is to see how much each variable is related to the load forecasting, so the variable can either be considered as important or redundant that can be dropped from the data set for the purpose of simplifying the developed models. Table A1 shows the correlation matrix. An extra input variable has been added to the data set as the day number in the week (Sat:1 – Fri:7). The correlation matrix shows that the month, year, time and day type variables have considerable correlation to the output, while the temperature, wind direction and humidity have significant correlation with the load. Otherwise, the other variables, day and day type have low correlation.

Table A1. Correlation table of the load with respect to the individual input variables.

Input variables		**Load**	**Rank**
Date	Day	-0.0007	9
	Month	0.3334	2
	Year	0.1731	4
Event	Day type	-0.0287	8
Time	Hours	0.0795	7
Atmosphere	Temperature	0.5775	1
	Humidity	0.1020	5
	Wind speed	-0.0964	6
	Wind direction	0.2856	3

نموذج المكائن المتعددة لشبكة العصبية الاصطناعية للتنبؤ بالأحمال الكهربائية للمنطقة الغربية – المملكة العربية السعودية

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المستخلص. أصبحت دراسة الأحمال في السنوات الأخيرة أحدى مجالات البحث والدراسة في الهندسة الكهربائية، درست غالبية طرق التنبؤ التقليدية والاصطناعية لأجل هذا الغرض. الشبكة الاصطناعية حازت على اهتمام الباحثين ونشرت أبحاث تدل على نجاح الشبكة الاصطناعية وتطبيقاتها في مجال التنبؤ في الأحمال الكهربائية قصيرة المدى. تتضمن هذه الورقة تطوير نموذج مجموعة المكائن المتعددة للشبكة الاصطناعية للحصول على نتائج أفضل لدراسة التنبؤ بالأحمال في مركز التحكم في المنطقة الغربية بالشركة السعودية للكهرباء. النموذج المقترح تم دمجه مع نظام الحشد الأمثل للجزيئات والانتشار البكتيري للحصول على نتائج جيدة، ثم مقارنة ما تم التوصل إليه من نتائج خلال النموذج المقترح مع الشبكة العصبية الاصطناعية والأوزان المثلى للشبكة.

شبكة الأحمال بالمنطقة الغربية تم تدريبها مع متغيرات الطقس والزمان والمناسبات (الحج – رمضان – العمرة) إضافة إلى قيم الأحمال ما بين الفترة من ٢٠٠٥–٢٠٠٧م .