Application of Neural Networks for Short Term Load Forecasting

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Abstract: *Short-term load forecasting (STLF) plays an important role for the economic and secure operation of power systems. This paper addresses an issue of the optimal design of a neural-network based short-term load forecaster. Currently, there is no systematic methodology for optimal design and training of an artificial neural network for load forecasting. This study describes the process of developing a multilayer, feed forward neural network for load forecasting, and then presents a heuristic search algorithm for performing an important task of this process, i.e. optimal network structure design. In addition, the input layer of the proposed ANN model receives all relevant information that contribute extensively to the prediction process. The proposed method is applied to STLF of the local utility. Data are clustered due to the differences in their characteristics. In this way, a solution is provided for all load types, including working days and weekends. A traditional ARIMA model is constructed for the same data as a benchmark. The proposed methodology gives lower percent errors all the time. Thus, it can be applied to automatically design an optimal load forecaster based on historical data.*

Keywords: ANN, STLF, Load forecasting, Power systems.

1.0 Introduction

The propose of power system load forecasting is to predict the expected power demands on the system. Load forecasting plays a key role in the operation and control of power systems. According to the forecasting period, it can be classified into the following categories [1].

- Very short forecasting of up to a few minutes ahead.
- Forecasting with a lead time of up to a few days ahead.
- Forecasting energy requirements over a six month or one year period.
- Long term forecasting of the power system peak load up to 10 years ahead.

Short-Term Load Forecast (STLF) is aimed at predicting loads for hours, days or weeks. It is essential for the economic and secure operation of the electric utility system. Basic functions such as unit commitment, economic dispatching, start up and shut down, hydro-thermal coordination, control of spinning reserve, interchange evaluation and unit maintenance can be performed efficiently with an accurate load forecasting. They are also required for power system security studies, including contingency analysis and load management [1]. Another application of short-time load forecasting is in optimizing the operational state of a power system in terms of load flow and reactive power management [2].

STLF is not an easy task. Load series are generally complex and the load at a certain hour depends on the loads from undetermined number of past hours. Moreover, weather variables such as temperature, daylight time, winds, humidity, etc. affect the consumption considerably [2]. Owing to the importance of STLF, a wide variety of methods have been proposed in the last two decades, such as the exponential smoothing model, ARMA model and multiple linear regression [3]. These methods are considered time consuming, have numerical instability and cannot be used for real time on-line load forecasting. Recently, intelligent methods, such as neural networks, fuzzy logic, expert systems, etc. have been started to be applied to STLF. Among the latest examples, [4-10] can be given. Metaxiotis et al. [4] provided an overview of artificial intelligence technologies applied to short-term load forecasting for the researcher.

In this paper, an ANN based approach is proposed as a solution of the STLF problem. ANN, whose operation is based on certain known properties of biological neurons, comprises various architectures of highly interconnected processing elements that offer an alternative to conventional computing approaches. ANNs are massively parallel, so that, in principle, they are able to respond with high speed. Furthermore, the redundancy of their interconnections ensures robustness and fault tolerance, and they can be designed to self-adapt and learn [11-12]. The main advantage of using neural networks lies in their abilities to learn the complicated nonlinear relationships between the load and explanatory variables directly from the historical data without necessity of selecting an appropriate model and explicit programming. It should be not that there are several nontrivial tasks associated with the design of a neural network based load forecaster. One such task is the network structure that would secure an acceptable forecast accuracy and network training time. For example, a network with too many hidden neurons will memorize the training data instead of learning general relationships and will perform poorly while applied to new data. Training data extraction and design of an efficient and reliable learning algorithm are also of great importance. At present, there is no systematic methodology for optimal design and training of an artificial neural network. One has often to resort to the trial and error approach. This paper briefly summarizes the design of a neural network based load forecaster and presents a heuristic search algorithm to design optimal neural networks structure based on R-squared fitness function, i.e.: statistical ratio that compares model forecasting accuracy with accuracy of the simplest model that just use mean of all target values as the forecast for all records. The effectiveness of the proposed method is demonstrated using practical data for STLF for the Ardebil city, Iran. The results show that the proposed ANN-based model not only is effective in reaching proper load forecast but also it can be applied to the automatic design of an optimal forecaster based on the available historical data. In addition, Comparison results with ARIMA model are shown to illustrate robust performance.

2.0 Load Data Analysis

The load data were collected in one of substation 63/20 Kv of the city of Ardebil, Iran, and considered one series of hourly actual loads supplied by a local utility in 2004 and 2005 for 15 months. In order to use these data in a meaningful and logical manner, first of all they should be closely analyzed and their dynamics should be clearly understood. Then they can be clustered into smaller sets according to some common characteristics and separate models can be built for each cluster. This is necessary because it has always been emphasized in the literature that it is impossible to reflect every different type of load behavior with a single model. Figure 1 shows hourly load curves for a sample week. It is seen that four working days (Sunday - Wednesday) have very similar patterns and Saturday (first working day of the week in Iranian calendar) a few different from the other workings days. Weekend days, i.e.: Thursday and Friday are different than the other days.

Based on the shape of the daily load curves and correlation analysis on the available data, an efficient clustering can be done. First of all, religious and national holidays should be excluded from the regular day data. Thus, four weekdays (Sunday– Wednesday) can be examined in the same group. It does not seem necessary to create a distinct group for each of these weekdays as they are highly correlated. Moreover, a separate group should be formed for the first working day (Saturday), because they come just after the weekend and do not resemble the other weekdays. For weekends, two groups should be formed as Thursdays and Fridays since they have unique characteristics.

3.0 ANN Based Model for STLF

The process of developing an artificial neural network based load forecaster can be divided into 4 steps:

1. Selection of input variables.
2. Extraction of training, test and Validation data.
3. Design of neural network structure and its training.
4. Trained ANN performance Analysis.

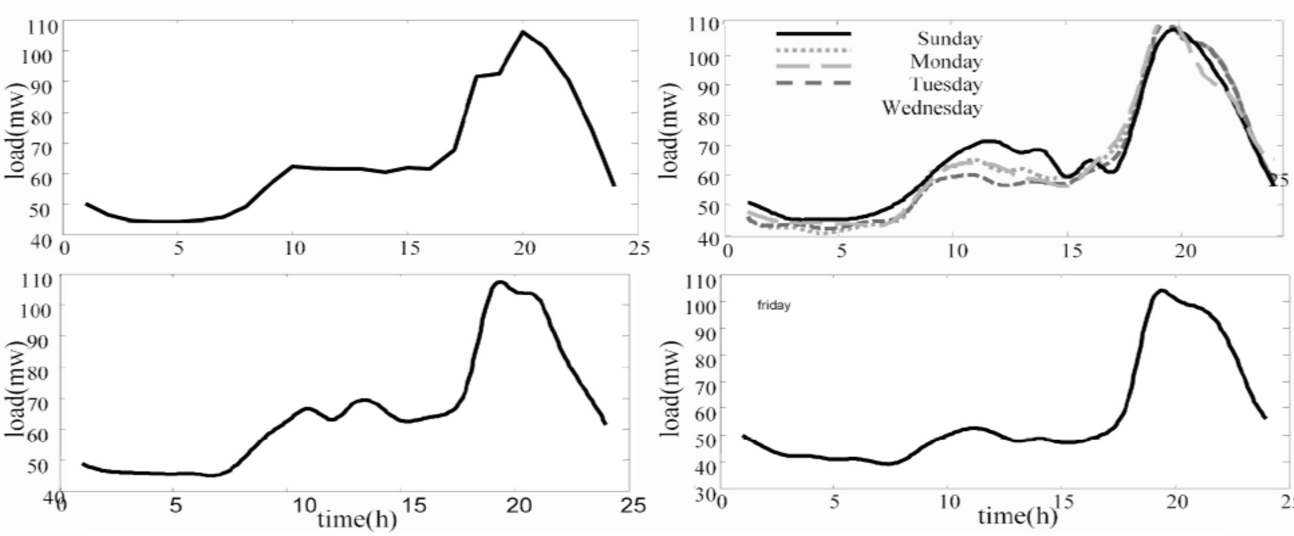

Fig. 1. Daily load curves for a typical week a) Saturday, b) Sunday to Wednesday c) Thursday d) Friday

This section briefly describes the three first steps. The last step is given in Sec. 5.

3. 1 Selection of input variables

The most important work in building an ANN load forecasting model is the selection of input variables from load affecting factors. Those factors may vary from one utility to another based on the load characteristics. There is no general rule that can be followed in this process. It depends on engineering judgment and experience and is carried out almost entirely by trial and error. However, some statistical analysis can be very helpful in determining which factors have significant influence on the system load. In general, three types of factors are used as inputs to the neural network: (a) hour and day indicators, (b) weather related factors like temperature, humidity and (c) historical loads.

As shown in Fig. 1, load changes during the day from one hour to another and from one day to another during the week. On the other hand, 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 on the load at the same hour on the day with the same denomination in the previous week [2]. As a result, combination of hourly and daily load indicator, $L(d,h)$ (where d and i are stand up for day and hour respectively) is helpful in STLF. Moreover, load forecasting is mainly affected by weather parameters. The results in Ref. [13] shows that temperature and humidity is the most importance weather factors that the daily load of Iran national power system is affected by them. Thus, the temperature and humidity is considered as other input variables in this application. Based on the above discussions, the ANN inputs are on information vector with the following elements:

$H(h)$	Hour indicator
$L(d,h-1)$	The load at hour-before in same day
$L(d-1,h)$	The load in day-before at same hour
$L(d-1,h-1)$	The load at hour-before in the day before
$L(d-7,h)$	The load in week-before at same hour
$L(d-7,h-1)$	The load in week-before at hour-before
T	Temperature
RH	Relative humidity percent

3. 2 Extraction of training, test and validation data

Collecting training data is very important to achieve the desired level of ANN performance to STLF problem. It should be noted that for network updating required a few patterns if the numbers of training data are much. Moreover, to assure a good network performance, the training data should be representative and it is normalized. A normalization step helps in preventing the simulated neurons from being driven too far into saturation. Also, since acceptable training errors do not always guaranty similar network performance for a different set of data, for example due to the lack of representativeness of the training set or the improperly selected network size, it is necessary to validate the network performance after it is trained. This is usually done by randomly selecting 10-20% of the total training data and setting it aside for testing. Based on the above discussions, test and validation data is randomly extracted by selecting 20% and 15% from the entire training data respectively and rest of entire data (about 65%) is used for networks training .

3. 3 Design of neural network structure and training

The design of neural network architecture involves making several decisions regarding the type, size and number of neural network used. The well-known Multi-Layered Percepteron (MLP) that it has proved its good performance is used in this application. According to discussions as mentioned in Sec. 2, A separate ANN model is designed for each of the four-day classes. Each network has eight neurons in input layer (see previous subsection for more detail) and its output layer consists of 24 neurons each represent the predicted hourly load covering 24 hours of day. To design a MLP network, one needs the number of hidden layers, type of connection between the layers, number of neurons in each layer and neuron's activation function. A fully connected network is a reasonable choice in practice. Good candidates for an activation function are sigmoid (S-shaped) functions. The exact shape of the sigmoid function has little effect on the network performance. It may have a significant impact on the training speed. Two commonly used activation functions are logistic and hyperbolic tangent. In this work, the output layer has not an activation function in order to eliminate additional errors for extreme forecasts due to the saturation of the activation.

The number of neurons in the hidden layer determines the network's learning capabilities. The selection of the number of hidden neurons is the key issue in optimal network design. A network with too few hidden neurons will not be capable of accurately modeling load. On the other hand, too many hidden neurons may force the network to memorize the training data. Thus, the network may perform poorly when applied to different data. In addition, the hidden-layer size affects the training time. The majority of the papers on neural network based load forecasters do not address this issue. The hidden layer size and its neurons number are selected either arbitrarily or based on the trial and error approach. In this research, a heuristic method is proposed for optimal design of neural network structure. This method is based on R-squared fitness function, i.e.: statistical ratio that compares model forecasting accuracy with accuracy of the simplest model that just use mean of all target values as the forecast for all records. The closer this ratio to 1 the better the model is. Small positive near zero indicate poor model. Negative values show models that are worse than the simple mean-based model. The proposed method need the search range parameters consist of hidden layers maximum size and the number of maximum neurons in each hidden layer, search step and the number of presentation cycles (epochs) . If search step equal to one, all network inside the range would be verified. In this study, the back propagation algorithm is being used for network training. Fig. 2 shows the value of R-squared fitness function in terms of some ANN structure in the given search parameters for design ANN model of Saturday cluster. The number of training patterns and epochs are 734 and 2000 respectively. It can be seen that the optimal ANN structure is 8-14-4-24, i.e.: a network with two hidden layers, 14 and 4 neurons in hidden layers 1 and 2 respectively.

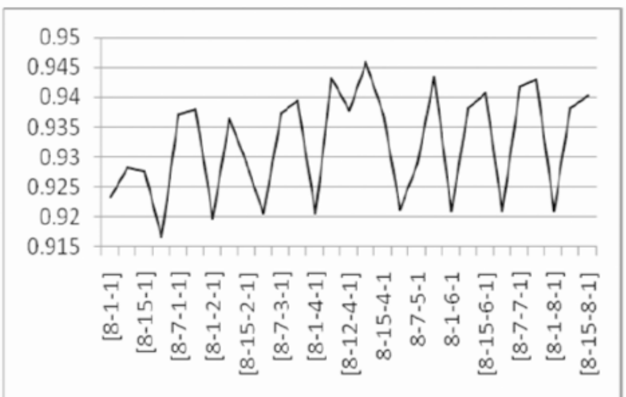

Fig. 2. Fitness function value in terms of ANN structure.

Using the same method, for other day clusters the optimal ANN structure is obtained which are listed in Table 1. The number of training patterns for three-day classes, remaining working days, Thursdays and Fridays is 500, 702 and 798 respectively.

Table 1. Optimal ANN structure

Day-classes	ANN structure
Saturdays	8-14-4-24
Remaining working days	8-14-4-24
Thursdays	8-14-4-24
Fridays	8-14-4-24

4.0 Stochastic Time Series ARIMA Model

Traditional STLF models, such as regression or stochastic time series are widely used in electric generation units as they have proven their validity especially for weekday forecasts. Any new method having a different approach than these conventional ones should give better results in order to be accepted. Thus, the proposed model in this work should also be compared with a classical model that does the same task. Stochastic time series model is a very popular method that has been used and is still being applied to STLF in the electric power industry [3]. There are many names encountered in the literature for this method, for example Auto Regressive-Moving Average (ARMA) models, Auto Regressive Integrated Moving Average (ARIMA) models, Box-Jenkins method, linear time series models, etc.

In the ARIMA model, the current value of the load series $Z(t)$ is expressed linearly in terms of its value at pervious periods and in terms of current and pervious values of a white noise, $\alpha(t)$. The basic ARIMA model can be written:

$$\begin{aligned} &\phi(B)\nabla^{d} Z(t) = \theta(B)\alpha(t) \quad , t = 1, \ldots , N \\ &\phi(B) = 1 - \phi_{1}B - \cdots - \phi_{p}B^{p} \\ &\theta(B) = 1 - \theta_{1}B - \cdots - \theta_{q}B^{q} \end{aligned} \tag{1}$$

Where, $\alpha(t)$ is a white noise sequence, $\Phi(B)$ and $\theta(B)$ are the AR and MA parameter polynomial respectively, B is the backward shift operator and is given by $B_nZ(t)=Z(t-n)$, θ_i and Φ_i are constants. ∇ is the differencing operator and d denotes the number of non-seasonal differences. For most practical applications, d is 1 or 2. But values of $d>2$ are rarely useful.

5.0 ANN Model Performance Evaluation

To demonstrate the effectiveness of the proposed ANN based model for STLF some simulation are carried out. A set of hourly load patterns for 11 days (264 patterns) is used to evaluate the performance of ANN load forecasting model. A maximum absolute percent error percentage of 23.67% and a Mean absolute Percent Errors (MAPEs) 4.97% was observed during the whole testing stage. Samples from the evaluation results are shown in Figs. 3 and 4 for four-day classes. From Fig. 4 the maximum absolute percent errors of 19%, 13%, 18% and 11% is found for the Saturday, remaining working days, Thursday and Friday, respectively. Also Table 2 summaries the MAPE and Root Mean Square Error (RMSE) for different day classes. Results show that ANN model has a good performance.

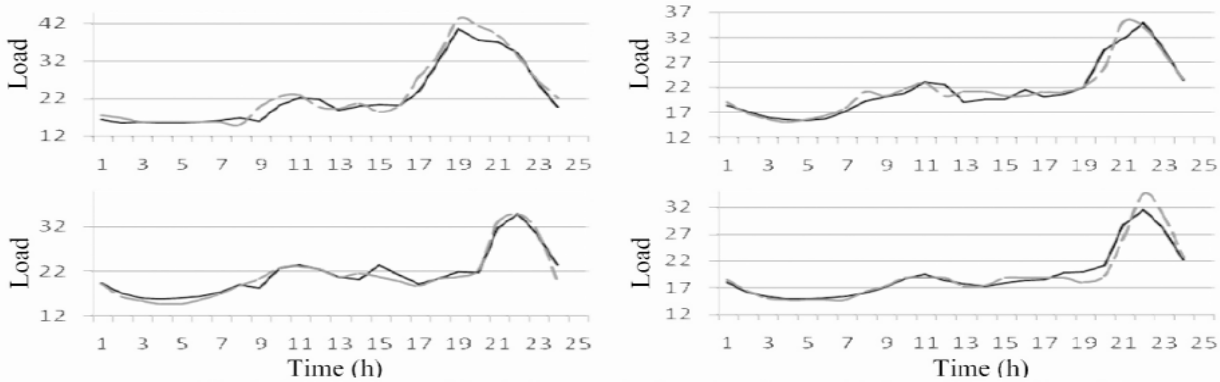

Fig. 3. ANN forecasted loads for sample four-day classes: (a) Saturday (b) Remaining working days (c) Thursday (d) Friday, (- Actual load), (-- Predicted load)

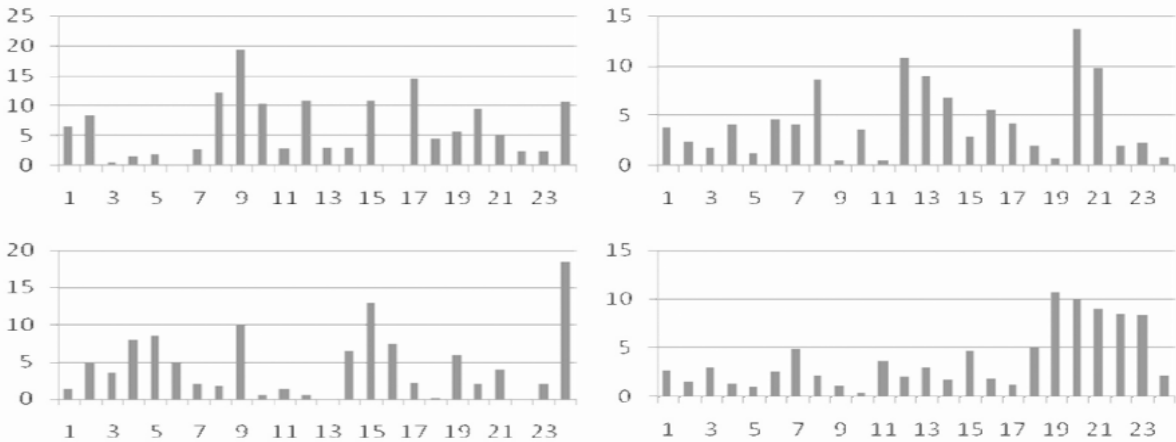

Fig. 4. Forecasted absolute errors for sample four-day classes: (a) Saturday (b) Remaining working days (c) Thursday (d) Friday

Table 2. MAPE and RMSE by the proposed model

Day-classes	MAPE	RMSE
Saturdays	3.94	1.51
Remaining working days	5.85	1.95
Thursdays	4.56	1.49
Fridays	5.53	1.59

In order to be compared with intelligent model based on ANN, a stochastic time series based model, ARIMA is constructed for solution of the STLF problem. Regular data are again clustered into four sets as before and tests are repeated for each of them. According to methodology mentioned in Sec. 4, from autocorrelation and partial autocorrelation functions analyzes, parameters p, d, q in Eq. (1) is chosen 1, 2 and 1 respectively and corresponding θ and Φ values are applied to hourly load data base for predication the 24-h ahead load. Figs. 5 and 6 show the forecasted loads using both of the ANN and ARIMA models for four-day classes. From Fig. 6 it is observed that, in the worst case, ANN model scores a maximum absolute error of 19% (at 9 Am) , while the ARIMA model scores a maximum absolute error of 37% (at 8 Pm) in the forecasting of Saturday daily load. Also, Table 3 summaries the MAPE and RMSE for different day classes. Examination of this table reveals that the forecasted load errors by ANN model is less than the ARIMA model.

Table 3. MAPE and RMSE by the proposed model

Day-classes	MAPE		RMSE	
	ANN	ARIMA	ANN	ARIMA
Saturdays	6.22	7.74	1.91	2.17
Remaining working days	4.41	9.08	1.37	3.18
Thursdays	4.54	11.88	1.25	2.70
Fridays	3.84	10.42	1.16	2.79

The above results show that the proposed ANN based model not only is effective for solution the STLF problem but also it provides a useful alternative to the traditional solution method for this problem.

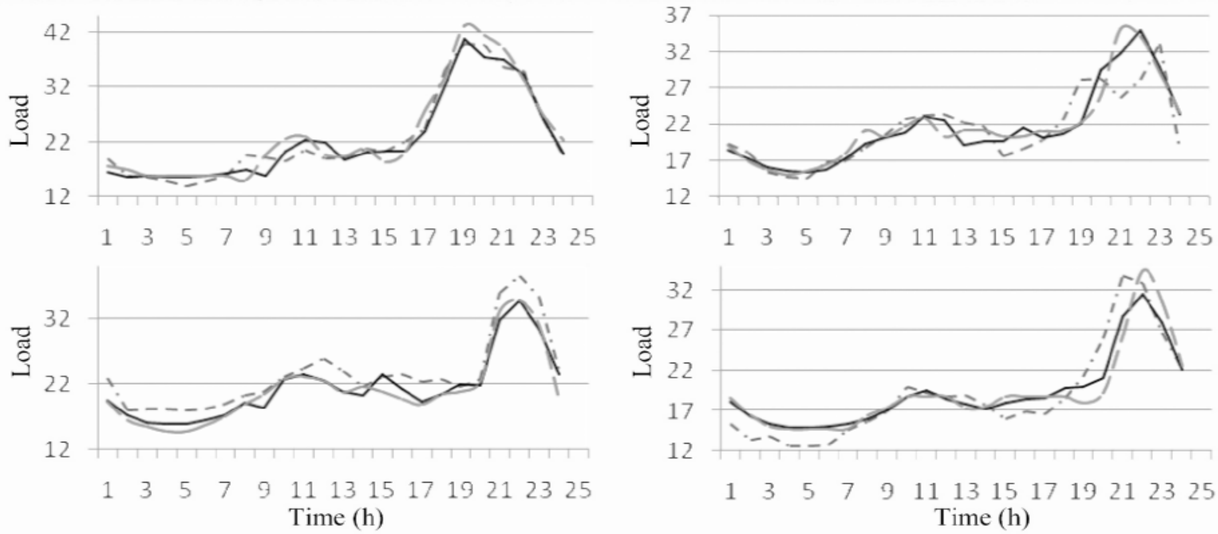

Fig. 5. ANN forecasted loads for sample four-day classes: (a) Saturday (b) Remaining working days (c) Thursday (d) Friday, (- Actual load), (-- Predicted load)

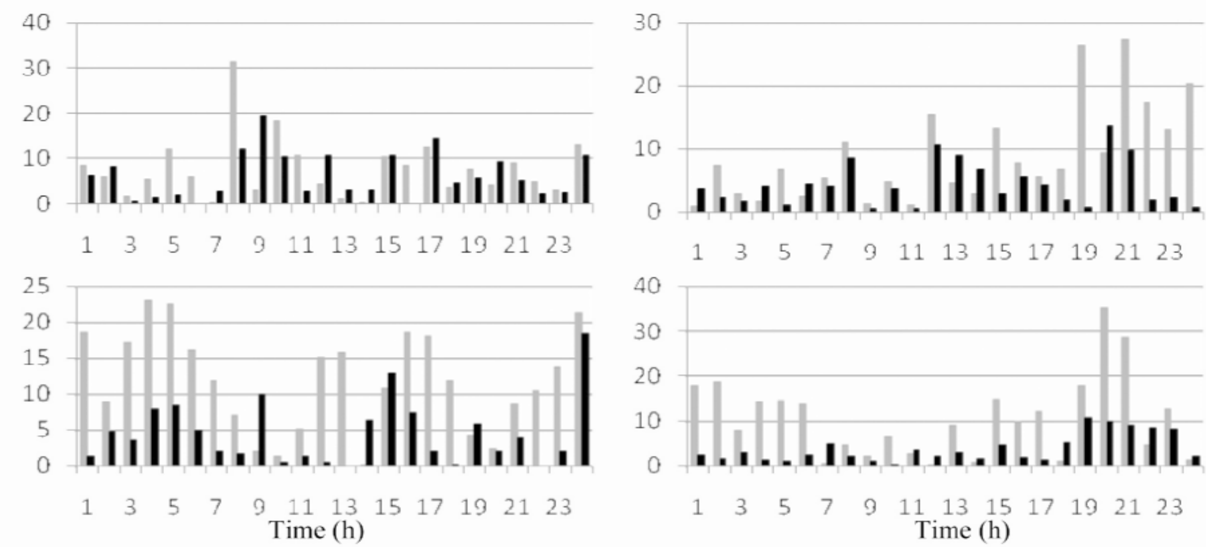

Fig. 6. Forecasted absolute errors for sample four-day classes: (a) Saturday (b) Remaining working days (c) Thursday (d) Friday

6.0 Conclusions

The system load forecasting model is a critically important decision support tool for operating the electric power system securely and economically. Because of their input-output mapping ability, artificial neural networks are well suited for this type of applications. However, at present there is no systematic methodology for optimal design and training of an artificial neural network for load forecasting. This paper addresses some of the issues involved in the forecaster design. Besides the general description of the process of developing a multilayer feed forward neural network for load forecasting, it presents a heuristic search method based on R-squared fitness function for performing optimal network structure design. The effectiveness of the proposed method is demonstrated using practical data for STLF the Ardebil city, Iran in comparison with a traditional ARMIA time series method and outperforms it in all day type results. The results show that the proposed ANN-based model not only is effective in reaching proper load forecast but also it can be applied to the automatic design of an optimal forecaster based on the available historical data. The model performance evaluation in terms of 'MAPE' and RMSE indices reveals that the proposed ANN based model produce lower prediction error and superior to the conventional method. Thus, it is recommended as a promising approach for solution the STLF problem.

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Biographies

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