FACTA UNIVERSITATIS
Series: **Electronics and Energetics** Vol. 31, N^o 4, December 2018, pp. 571-583
https://doi.org/10.2298/FUEE1804571F

A SELF ORGANIZING MAP (SOM) BASED ELECTRIC LOAD CLASSIFICATION

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Abstract. *It is of vital importance to use proper training data to perform accurate short-term load forecasting (STLF) based on artificial neural networks. The pattern of the loads which are used for the training of Kohonen Self Organizing Map (SOM) neural network in STLF models should be of the highest similarity with the pattern of the electric load of the forecasting day. In this paper, an electric load classifier model is proposed which relies on the pattern recognition capability of SOM. The performance of the proposed electric load classifier method is evaluated by Iran electric grid data. The proposed method requires a very few number of training samples for training the Kohonen neural network of the STLF model and can accurately predict electric load in the network.*

Key words: *Short-term load forecasting, similar sampling process, Kohonen self-organizing map, pattern recognition, electric load classification, load classifier*

1. INTRODUCTION

Electric load forecasting is of high importance for efficient generation and distribution of electric energy in power grids. Therefore, load forecasting is usually performed in different time horizons such as very short-term, short term, medium term, and long term. Short-term load forecasting (STLF) refers to the prediction of electric load during one day to one week and is performed in different situations such as for unit commitment, evaluation of net interchange scheduling functions, system security analysis, and control and scheduling of power systems [1, 2].

The STLF models require neural network training using appropriate training data to achieve optimal forecasting. The behavior of load data used in the training process of neural network in the STLF models should be of the highest degree of similarity with the behavior of the data load in the forecasting days. High similarities between the behaviors of training sample days used in the training phase of Neural Networks and the behavior of forecasting day largely guarantee the accuracy of forecasting. So, finding appropriate training samples is of great importance in the process of STLF.

Received August 1, 2017; received in revised form August 23, 2018
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To design STLF models, some load classification studies are needed to identify the exact patterns consumption of electricity in the network. By accurate recognition of daily power consumption curve behavior in earlier times, the ability to forecast power requirements is provided in short-term period. In fact, daily load classifier provides the capacity to identify the pattern of consumption power and the required knowledge to design and propose efficient models of STLF provides for designers and operators of power grid.

Clustering techniques are widely used for grouping customers and consumption loads in the network. Different classification methodologies based on discriminate analysis, linear regression, and artificial intelligence (fuzzy logic and neural networks) techniques have been proposed in literature [3]. Among different neural network classifiers, Kohonen Self Organizing Map (SOM) is one of the most effective methods. Kohonen SOM has two valuable features, namely, pattern recognition and pattern complementarity. These two Kohonen SOM properties are exploited for short-term load classification and for forecasting, respectively.

In recent years, classification algorithms have been subject of extensive research activities and these algorithms have been widely used for different applications in the area of electrical engineering.

For instance, in [4] a theoretical framework is formulated for customer classification using annual load profiles. It is also demonstrated how to extract characteristic attributes in frequency domain (CAFD) to represent signatures for customer classes and subclasses. The CAFDs are obtained by using a data mining method called CART which is composed of classification and regression tree. These CAFDs are then used for systematic customer load classification.

A method with low computational cost, but yet with sufficient accuracy is proposed in [5] to extract signatures for load classification. This method, instead of utilizing digital signal processing and frequency-domain analysis, quantifies the similarity of voltage–current (V–I) trajectories for different loads and maps V–I trajectories to a grid of cells with binary values. Next, graphical signatures can be extracted and be used for several applications. This technique significantly reduces the computational cost compared with the existing frequency-domain signature extraction methods.

In [6] an algorithm, which is called ISODATA, is developed for customer classification and load profiling. This method takes into account the impact of temperature on the loads for classification and filters the impact of outlier samples.

A novel iterative active learning technique based on self-organizing map (SOM) neural network and support vector machine (SVM) classifier is proposed in [7]. The technique exploits the properties of SVM classifier and that of SOM neural network to identify uncertain and diverse samples to be included in the training set. It selects uncertain samples from low-density regions of the feature space by exploiting the topological properties of SOM.

In addition to the extensive use of classification methods for different applications in electrical engineering, classification methods particularly have been used for load management and load forecasting. For instance, a novel load profile management software framework is presented in [8] for boosting the efficiency of power systems operation. The proposed framework performs real-time encoding and classifies load profiles. The classifier engine is based on an implementation of a locality sensitive hashing algorithm.

In [9], the identification of operating electrical appliances inside residential buildings has been addressed. A method is proposed that can identify each appliance from the aggregate power readings of the electrical measurement panel. The possibility of applying a temporal multi-label classification approach in the domain of non-intrusive load monitoring (nonevent-based method) is also investigated. In [10], a non-intrusive appliance load classification and monitoring strategy is proposed for energy management in smart buildings.

The use of ISODATA algorithm for customer classification proposed in [11]. Temperature dependency correction and outlier filtering are considered in the proposed customer classification and load profiling method. O.E. Dragomir et al in paper [12] have proposed an object-oriented software application using MATLAB Toolbox to classify customers and the results have been assessed for three urban areas in Romania in the form of several different scenarios.

In this paper, to make a software system to analyze daily electricity usage of network across the country an efficient and flexible load classifier model has been proposed. We implemented the proposed Kohonen SOM model in MATLAB programming environment. The flexible program of the developed load classifier has the capacity to adjust the classifier accuracy by changing the dimensions of a two-layer Kohonen network for different time periods. We propose efficient rules of Similar Sampling Process to train Kohonen neural network in the load forecasting models. According to these rules, each of the 'normal week days', 'official holidays', 'before official holidays', 'after official holidays' and 'Ramadan days' have their own specific behaviors [13].

It is noteworthy that previous author's papers [13], [17] forecast the short-term (the next day) load, while the present paper focuses only on the method of classifying daily electric load and the classification of loads with the same behavior for the time period selected (e.g. one week, one month, or one year, or any desired time interval from one day to several years). Although all three papers are based on the Kohonen neural network function, two reference articles [13], [17] use the Pattern-Complement Property of Kohonen neural network in the process of daily electric forecasting, while the present paper use Pattern Recognition Property of kohonen neural network in order to classification of daily electric load. In fact, the classification technique used in this paper is a prerequisite for finding suitable training patterns for training Kohonen's neural network used in the process of electric load forecasting in reference papers [13], [17].

Section 2 addresses the structure, specifications, and the algorithm of SOM network classifier. In section 3, the classifier system which is implemented and designed in MATLAB programming environment is presented and related input and output parameters are explained. In section 4, the proposed classifier program is evaluated, and its performance is verified by sampling the classifier in monthly time intervals of network data of Iran. In section 5, the advantages of the proposed model and the implemented classifier program of SOM and the sampling process are discussed. An effective method called Similar Sampling Method is introduced to specify the pattern of an appropriate training sample to train Kohonen neural network in the STLF Models. In Section 6, the method for correcting the predicted load based on the fuzzy expert system is briefly described, and finally, the paper is concluded in section.

2. KOHONEN SELF-ORGANIZING-MAP NEURAL NETWORK

Kohonen is a specific type of SOM which is capable of classifying complex sets of patterns in an unsupervised way [14]. This classifier extracts some classification criteria from the data and uses it in an implicit manner. To perform the classification, it spans input space over output space of a lower dimension, while still preserving the topological features of the patterns in the input space. A set of elements so called neurons, which are illustrated over a plane or a line in a rectangular or hexagonal shape, represent the output space. Fig. 1 shows a neighborhood function which is defined in the output space.

The internal connections and links of the self-organized network must incorporate the important properties, patterns, categories, regularities, and correlations which are extracted from the input data. The neurons self-organize themselves based on the inputs as external stimuli [15].

SOM architecture consists of a two-layered neural network. There are *N* neurons in the input layer, each of which is associated to one input variable. The output layer consists of neurons, which are spatially distributed along a 2D grid.

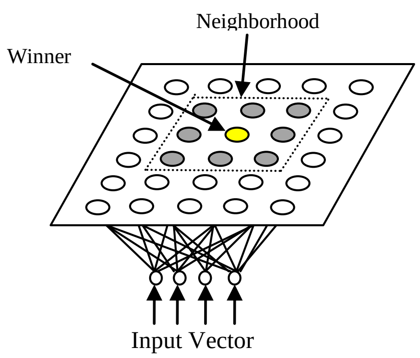

Fig. 1 Kohonen Neural Network

The *i*th input neuron and the *j*th output neuron are connected together by a weight *Wij*. The *j*th output neuron represents the average prototype vector of the category, and the reference weight vector *Wj* called codebook [15]. The steps of SOM algorithm are as follows [16]:

Step 1: Initialize neuron weights
Step 2: Select input vector
Step 3: Calculate a distance between any neurons and the input vector
Step 4: Select the nearest output neuron
Step 5: Adjust the output neuron and its neighbors
Step 6: Repeat the process from Step 2

3. SOM ELECTRIC LOAD CLASSIFIER

In order to implement an electric load classifier, we created a self-organizing layer of Kohonen with adjustable dimensions of $m \times n$ and implemented the training algorithm of SOM in MATLAB programming environment. In the implemented classifier program, input and output parameters of classifier algorithm is defined. After finishing the classifier process, the similar days are assigned to one neuron or close neurons of the two-layered self-organizing Kohonen.

3.1 MATLAB Software

MATLAB provides a powerful environment for numerical computations [16], data analysis, simulations, algorithm implementation, programming development, and rather easier model implementation compared to other programming languages. In this paper, the classifier has developed using MATLAB programming language based on the Kohonen classification algorithm, instead of using the neural network library of MATLAB. In addition, a MATLAB GUI has developed which provides an interface to receive inputs and illustrate outputs of the proposed classifier. Our implemented software provides a flexible and powerful environment.

3.2. Classifier's Structure

As mentioned earlier, the structure of the proposed classifier is formed by an autonomous Kohonen network with adjustable and flexible set of $m \times n$ neurons according to Fig. 1. The accuracy of the classifier is adjusted by changing the dimensions of the Kohonen network and the number of neurons which are located in the network. The classifier module which we implemented in MATLAB is shown in Fig. 2.

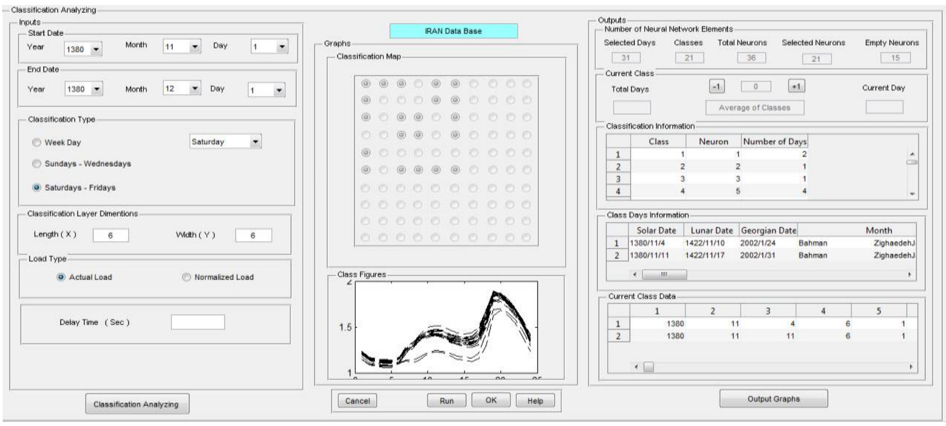

Fig. 2 Classifier module

Input and output parameters of the classifier program are listed in the following:

3.2.1. Inputs

As shown in Table 2, in addition to the dimensions of the inputs of the Kohonen network such as *m* and *n* parameters, other inputs of the classifier include calendar inputs of the program are the *first date*, the *last date* and the *number of days*. Other input quantities of the classifier algorithm include the *number of load values* (which is fixed value equal to 24), *learning cycle*, *start value of the learning rate*, the *end value of the learning rate*, the *start value of the neighborhood radius*, and the *end value of the neighborhood radius*.

3.2.2. Outputs

As shown in Table 2, the outputs of the classifier program include the *number of classes*, *selected neurons* which is equal to the *number of classes*, and *empty neurons*.

3.3. Model's Structure

According to Fig. 3 the inputs of the SOM network are two vectors of normalized active power consumption during 24 hours in Iranian power grid network.

As shown in Fig. 3 the classifier model receives two vectors of length 24, *Load-Normal (d–1)* and *Load-Normal (d)*, where the vectors represents normalized electric load in consequent days *d-1* and *d* (d = 2,…,365), respectively. These values of vectors for a period of one year would be used for the classification of the daily electric load vectors [13, 17].

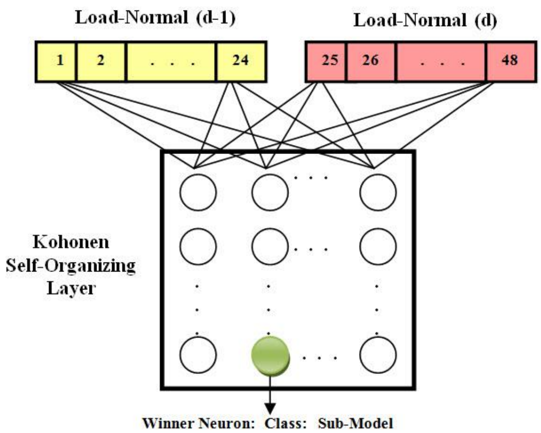

Fig. 3 The load SOM model in the Classification Process

These normalized inputs were calculated as follows:

$$Load - Normal(d-1) = L(d-1) / Average(L(d-1)) \quad (1)$$

$$Load - Normal(d) = L(d) / Average(L(d-1)) \quad (2)$$

Where L (*d*–1) and *L* (*d*) represent the loads for the pre-forecasting and forecasting days, respectively, as the following:

$$L(d-1) = [L_1(d-1)L_2(d-1)L_3(d-1)\cdots L_{24}(d-1)] \quad (3)$$

$$L(d) = [L_1(d)L_2(d)L_3(d)\cdots L_{24}(d)] \quad (4)$$

The normalized loads of the previous and present days could be obtained by dividing 24 hourly loads of the previous and 24 hourly loads of the present days by the average applied load of the previous day. Therefore, training of all the samples of different years could be performed concurrently by the **omission of the load growth**.

4. Validation of the Classifier Model

The proposed classifier has flexible classifier capability in all electric networks that follow Persian official calendar. In order to validate the classifier operation of the implemented model, the data of electric load of Iran network is used which follow the Persian official calendar according to Table 1. According to the Persian official calendar, Saturday to Wednesday are Working Days, Thursday is half-holiday Working Day, and Friday is the official weekend holiday. It is noteworthy that Official Holidays are days according to the Persian official calendar in various occasions such as national celebrations, religious celebrations, national mourning, religious mourning, etc. and are divided in two groups of official solar holidays and official lunar holidays. Official solar holidays include national celebrations and mourning that happens in specific times of the solar Persian year. Lunar official holidays also include religious mourning and celebration which happens with 11day difference of days between lunar and solar calendar in variant times of a Persian solar year.

Table 1 The months of a year based on Persian official calendar.

Year	First Half of a Year						Second Half of a Year					
Season	Spring			Summer			Autumn			Winter		
No	1	2	3	4	5	6	7	8	9	10	11	12
Month	Farvardin	Ordibehesht	Khordad	Tir	Mordad	Shahrivar	Mehr	Aban	Azar	Dey	Bahman	Esfand

In this paper, the classifier is evaluated in a time interval of 10 years from 1370 to 1380 (Thursday, March 21, 1991 to Wednesday, March 21, 2001). The classifier used hourly active power consumption (in Mega Watts) in the Iranian electric grid for the classification, training and forecasting purposes. The electric load consumption in the Iranian nationwide grid follows a considerably nonlinear pattern and composed of base loads and peak loads.

Kohonen SOM in general has scalability problem, however, the volume of the data which is required for the training of the model to be used for the specific application which is addressed in this paper is not big (maximum 365×24 data points). Therefore, there is not any scalability problem in this case study and no technique is needed to manage the increasing size of the input data.

In this study, due to the high volume of output tables and curves, samples of the results for monthly experiments are provided for the classifier of days in Bahman of 1380 from 1/11/1380 to 1/12/1380 (From Monday, January 21, 2002 to Wednesday, February 20, 2002). In this experiment, the curves of daily load of the network are classified in a two-dimensional array with dimensions of 6×6. The input parameters of the classifier are adjusted completely according to Table 2.

Table 2 Input parameters of the classifier based on Kohonen self-organizing network

Classification Input Parameters			
First Date	1380/11/1	Learning Cycle	7
Last Date	1380/12/1	Start Value of Learning Rate	0.9
Number of Days	31	End Value of Learning Rate	0.1
Number of Load Value	24	Start Value of Neighborhood Radius	10
m	6	End Value of Neighborhood Radius	1
n	6		

By running the classifier module which we implemented in MATLAB (the interface is shown in Fig. 2), the output numerical results are inserted according to the classifier curves based on the number of established classes. As shown in Fig. 4 , the SOM network assigns 21 of the established classes into four distinctive groups such as After Official Holidays, Official Holidays, Before Official Holidays and Normal Working Days (from Sunday to Wednesday). The neurons related to each of these classes are illustrated, respectively, by yellow, red, blue and green color.

The dates of the days in each class of the SOM network of Fig. 4 are shown in Table 3. Also, the curves of daily average load related to four sample classes of the 21 established classes are shown by the colors related to each class in Fig. 4. The displayed classes such as 1, 16, 21 and 4 include After Official Holidays, Official Holidays, Before Official Holidays and Normal Days. According to the classifier results in this example, 31 sample days are assigned to 21 classes. Among the established classes, a few classes had the highest share of a specific type of days. For example, out of 21 established classes, four classes such as 1, 2, 5 and 8 included After Official Holidays, two classes such as 16 and 17 included Official Holidays, three classes such as 19, 20 and 21 included Before Official Holidays and eleven classes included the remained days of Normal Days. It is noteworthy to mention that the association of classes to neurons is such that the adjacent neurons represent days which have relatively similar electric load patterns. In particular, the class associated to Saturday is beside the class of After Official Holiday; the classerepresenting Tuersday is beside that of Before Official Holidays; and the classcoresponding Friday is near that of Official Holiday. In addistion, normal working days in the middle of the week including Sunday, Monday, Tuesday and Wednesday are located in their own specific classes.

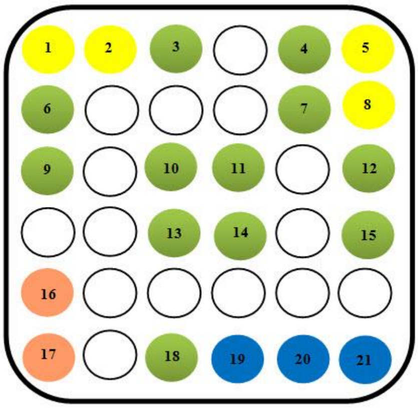

Fig. 4 Two-dimensional neural network SOM classifier with dimensions of 6×6 for the month of the Bahman of 1380.

By increasing the number of classifer days, the dimension of Kohonen network is increased. Increasing the dimensions of a Kohonen network, i.e. increasing the number of neurons in the network, leads to higher accurancy of the classifier. By distributing the input sample days between more neurons, more classes with lower sample patterns would be created. Therefore, the neurons in each class would have higher similarity compared to the case with a network with lower dimension.

Table 3 Dates of SOM network classifier with dimensions of 6×6 for Bahman of 1

Class 1 **After Holiday** Sat 80/11/20 Sat 80/11/27	**Class 2** **After Holiday** Tues 80/11/23	**Class 3** **Normal Day** Tues 80/11/30		**Class 4** **Normal Day** Mon 80/11/1 Tues 80/11/2 Wed 80/11/3 Mon 80/11/8	**Class 5** **After Holiday** Sat 80/11/13
Class 6 **Normal Day** Mon 80/11/29				**Class 7** **Normal Day** Tues 80/11/9 Wed 80/11/24	**Class 8** **After Holiday** Sat 80/11/6
Class 9 **Normal Day** Wed 80/12/1		**Class 10** **Normal Day** Wed 80/11/10 Sat 80/11/27	**Class 11** **Normal Day** Sun 80/11/14		**Class 12** **Normal Day** Sun 80/11/7 Tues 80/11/16
		Class 13 **Normal Day** Mon 80/11/15	**Class 14** **Normal Day** Wed 80/11/17		**Class 15** **Normal Day** Sun 80/11/28
Class 16 **Holiday** Fri 80/11/5 Fri 80/11/12 Fri 80/11/19 Mon 80/11/22					
Class 17 **Holiday** Fri 80/11/26		**Class 18** **Normal Day** Sun 80/11/21	**Class 19** **Before Holiday** Thurs 80/11/25	**Class 20** **Before Holiday** Thurs 80/11/18	**Class 21** **Before Holiday** Thurs 80/11/4 Thurs 80/11/14

The curves of daily average electric loads related to four sample classes are shown in Fig. 5.

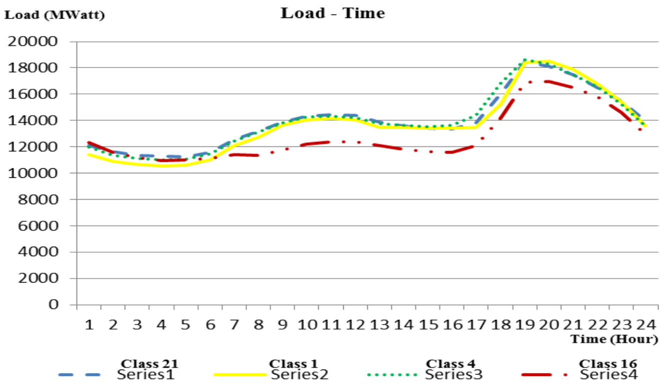

Fig 5 The curves of daily average electric load related to four sample classes:
(a) Class 1: After Holidays (b) Class 4: Normal Days
(c) Class16: Holidays (d) Class21: Before Holidays

5. Similar Sampling Method for STLF

Although none of the outputs of the SOM classifier is directly used for the prediction purpose, the results of the SOM network classification process can be used as an effective way for sampling the appropriate training patterns for training and forecasting 24-hour active power consumption of the nationwide electricity. This can be used in a separate SOM network. The details of the training and forecasting processes of this SOM network are presented by the same authors in [13]. According to the outcomes of the classifier, every Normal day of a week has its specific load consumption curve and holidays have distinguished ones.

In the similar sampling method, the maximum of a sample is used to train Kohonen SOM neural networks. Maximum 17 training samples have been selected in the time interval of two weeks before forecasting day and two weeks after that in three past years according to similar calendar features of the forecasting day; so that the date of the forecasting day is in the center of these four weeks [13].

Given the possibility of changing the behavior of load curves over many years, using the samples of many years away may degrades the results of load forecasting; therefore, the samples of three years ago are used to train neural networks. For example, to forecast Tuesday in date 5/04/1380 (26/06/2001), the samples of Monday and Tuesday are used in the time interval of 22/03/1380 (12/06/2001) to 4/04/1380 (25/06/2001), 22/03/1379 (11/06/2000) to 22/04/1379 (12/07/2000), 22/03/1378 (12/06/1999) to 22/04/1378 (13/07/1999) and 22/03/1377 (12/06/1998) to 22/04/1377 (13/07/1998) in order to train Kohonen Neural Networks.

The average annual mean of the *MAPE* (*Mean Absolute Percentage Error*) index to predict the load of the normal days of the years 1380 (from 21/03/2001 to 20/03/2002), 1381(from 21/03/2002 to 21/03/2003) and 1382 (from 21/03/2003 to 19/03/2004) are

1.83%, 1.77%, and 1.29%, respectively [17]. The details of load forecasting model incorporating temperature degree are discussed by the authors in [13].

6. FUZZY EXPERT SYSTEM FOR STLF

A fuzzy-expert system adjusts the primary predicted load for special days by taking into account the modifications in the load which happened in same day's load behavior. The relative difference between the actual and forecasted hourly loads of the same day is defined as *Relative Gap* regardless of the possible influence of a holiday [15, 16] and calculated via the following formula:

$$\mathrm{Re}\,lative\ \ Gap(i) = \frac{Load_{real}(i) - Load_{forecast}(i)}{Load_{forecast}(i)} \times 100(\%) \tag{5}$$

Where $Load_{real}(i)$ and $Load_{forecast}(i)$ represent the actual and forecasted loads for hour i, respectively. It's worth noting $Load_{forecast}(i)$ in the formula (5) is the same forecasted load which resulted from kohonen neural network.

The input variables of a fuzzy system are the day type (*Day*) and day-night hours (*Hour*) (which specifies the time of a particular event) and its output variable is the *Relative Gap* which is represented by adding to or subtracting from the primary predicted load for the purpose of a more precise forecasting.

Finally the ultimate load to be forecasted is acquired by the following formula:

$$Final\ \ Load\ \ (i) = Load_{forecast}(i) + \frac{\mathrm{Re}\,lative\ \ Gap\ \ (i) \times Load_{forecast}(i)}{100} \tag{6}$$

A complete description of the predicted load correction process based on the fuzzy system is available in the reference [17].

MAPE of the initial forecasted load by Kohonen neural network and the final forecasted load by the fuzzy-expert system for official holidays in the year 1380 are respectively 3.19% and 1.78% [17]. The complete numerical results of this studies are presented by the author in references [13,17].

7. CONCLUSION

We implemented a SOM classifier using MATLAB coding environment and performed numerical tests for the validation of the classifier. The flexibility, efficiency, and usefulness of the proposed classifier program would make it a suitable solution to be used in the power industry. The flexibility of the proposed classifier program due to the capability of changing the dimensions of the Kohonen network provides the possibility to adjust and increase the accuracy of electric load classifier by increasing the dimensions and the number of neurons of the neural network in an optimal form.

According to the outcomes of the classifier program, each working normal day (Saturday to Friday) has its own specific load curve. Also, the curves of power consumption in working day in the mid-week from Sunday to Wednesday have high similarity. The curves of load consumption in official holiday and official working days of a week have completely different patterns. The official holidays' behavior is relatively similar to its nearest Friday. Also, the curve of load consumption in the days before working days and the ones after official days are completely different. The electric consumption pattern of working days before official holidays is considerably similar to that of the nearest Thursday, and the electric consumption pattern of the working day after official holiday is similar to that of the nearest Saturday before it. In addition, in the curve of morning consumption during the month of Ramadan in which people pray early in the morning and late night, a relative peak of power consumption is observed. In the different seasons of a year, the curve of load consumption is changed according to different factors in each season such as the length of daytime. Over the time, the average load consumption is increased by increasing the population and the economic growth which results in load growth in each year. All these factors should be considered in the modeling of load consumption.

In summary, there are ten classes for electric load consumption in Iranian power grid including normal working days a week (Saturday to Friday) and specific days (official holiday, before official holiday and after official holiday). In order to design models to forecast electric load based on Kohonen neural networks, ten sub-models related to all type of days are created, and the load patterns for each class according to Similar Sampling Process are used to train and forecast the neural networks. The Similar Sampling process with maximum 17 training samples and high accuracy and low computation time is able to supply the training data which is required for the process of electric load forecasting and benefits the variant models of Kohonen self-organizing neural networks.

In addition to the valuable capability of the proposed classifier program to perform load forecasting in an industrial scale, the insightful outcomes of the proposed program are other valuable advantages of the implemented code to identify the behavior of power consumption curve in a power network desired which need to be studied by designers and the users of the power network.

Acknowledgement: *The paper is a part of the research work within the project supported by Industrial Parks Company of Khorasan e Jonoobi Province, Birjand, Iran. The author would like to thank the manager and the experts of the mentioned company.*

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