One-Hour Ahead Electric Load Forecasting Using Neuro-fuzzy System in a Parallel Approach

Abderrezak Laouafi, Mourad Mordjaoui and Djalel Dib

Abstract Electric load forecasting is a real-life problem in industry. Electricity supplier's use forecasting models to predict the load demand of their customers to increase/decrease the power generated and to minimize the operating costs of producing electricity. This paper presents the development and the implementation of three new electricity demand-forecasting models using the adaptive neuro-fuzzy inference system (ANFIS) approach in parallel load series. The input-output data pairs used are the real-time quart-hourly metropolitan France electricity load obtained from the RTE website and forecasts are done for lead-time of a 1 h ahead. Results and forecasting performance obtained reveal the effectiveness of the third proposed approach and shows that 56 % of the forecasted loads have an APE (absolute percentage error) under 0.5, and an APE under one was achieved for about 80 % of cases. Which mean that it is possible to build a high accuracy model with less historical data using a combination of neural network and fuzzy logic.

1 Introduction

Forecasting electric load consumption is one of the most important areas in electrical engineering, due to its main role for the effectiveness and economical operation in power systems. It has become a major task for many researchers.

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The common approach is to analyse time series data of load consumption and temperature to modelling and to explain the series [30]. The intuition underlying time-series processes is that the future behavior of variables is related to its past values, both actual and predicted, with some adaptation/adjustment built-into take care of how past realizations deviated from those expected. The temporal forecasting can be broadly divided into 4 types:

- Very Short term (from few minutes to a 1 h).
- Short term (from 1 h to a week).
- Medium term (from a week to a year).
- Long term (from a year to several years).

Long term prediction is normally used for planning the growth of the generation capacity. This long term forecasting is used to decide whether to build new lines and sub-stations or to upgrade the existing systems. Medium-term load forecast is used to meet the load requirements at the height of the winter or the summer season and may require a load forecast to be made a few days to few weeks (or) few months in advance.

In STLF, the forecast calculates the estimated load for each hour of the day, the daily peak load and the daily/weekly energy generation. Many operations like real time generation control, security analysis, spinning reserve allocation, energy interchanges with other utilities, and energy transactions planning are done based on STLF.

Economic and reliable operation of an electric utility depends to a significant extent on the accuracy of the load forecast. The load dispatcher at main dispatch center must anticipate the load pattern well in advance so as to have sufficient generation to meet the customer requirements. Over estimation may cause the startup of too many generating units and lead to an unnecessary increase in the reserve and the operating costs. Underestimation of the load forecasts results in failure to provide the required spinning and standby reserve and stability to the system, which may lead into collapse of the power system network [1]. Load forecast errors can yield suboptimal unit commitment decisions. Hence, correct forecasting of the load is an essential element in power system.

In a deregulated, competitive power market, utilities tend to maintain their generation reserve close to the minimum required by an independent system operator. This creates a need for an accurate instantaneous-load forecast for the next several minutes. Accurate forecasts, referred to as very short-term load forecasts ease the problem of generation and load management to a great extent. These forecasts, integrated with the information about scheduled wheeling transactions, transmission availability, generation cost, spot market energy pricing, and spinning reserve requirements imposed by an independent system operator, are used to determine the best strategy for the utility resources. Very short-term load forecasting has become of much greater importance in today's deregulated power industry [5, 36].

A wide variety of techniques has been studied in the literature of short-term load forecasting [20]. For example, time series analysis (ARMA, ARIMA, ARMAX …etc.)

[4, 19], regression approach [34], exponential smoothing technique [44], artificial neural networks methods [35], hybrid approaches based on evolutionary algorithms [12] …etc.

The nature of electrical load forecasting problem is well suited to the technology of artificial neural networks (ANN) as they can model the complex non-linear relationships through a learning process involving historical data trends. Therefore, several studies in recent years have examined the application of ANN for short-term load forecasting [26].

Recently, hybrid neuro-fuzzy models have received a considerable attention from researchers in the field of short-term load forecasting [29, 30, 33]. Furthermore, the neuro-fuzzy approach attempts to exploit the merits of both neural-network and fuzzy-logic-based modeling techniques. For example, the fuzzy models are based on fuzzy IF-THEN rules and are, to a certain degree, transparent to interpretation and analysis, whereas the neural-networks based black-box model has a unique learning ability [32]. While building a FIS, the fuzzy sets, fuzzy operators, and the knowledge base are required to be specified. To implement an ANN for a specific application the architecture and learning algorithm are required. The drawbacks in these approaches appear complementary and consequently it is natural to consider implementing an integrated system combining the neuro-fuzzy concepts [41].

Nevertheless, very short-term load demand forecasting methods based on neuro-fuzzy approach are not so numerous [9, 10]. Therefore, this lack has motivated us to provide this paper to the development and the implementation of adaptive neuro-fuzzy inference system models devoted to VSTLF.

The paper is organized as follows. Section 2 is proposed to summarize very short-term load forecasting methods. Section 3 is devoted to the description of the ANFIS architecture. Section 4 describes the proposed estimation methods. Section 5 provides and explains forecasting results. Finally, Sect. 6 concludes the paper.

2 Overview of Very Short Term Load Forecasting Methods

Very short-term load forecasting (VSTLF) predicts the loads in electric power system 1 h into the future in steps of a few minutes in a moving window manner. Depending on the electric utilities, used data in VSTLF could be of, minute-by-minute basis [27, 43], 5-min intervals [11, 16, 17, 40], 15 min steps [6, 31], or a half-hourly intervals [24, 25].

Methods for very short-term load forecasting are limited. Existing methods include time series analysis, exponential smoothing, neural network (NN), fuzzy logic, adaptive Neuro-Fuzzy inference system, Kalman filtering, and Support Vector Regression. Usually, weather conditions in very short-term load forecasting are ignored because of the large time constant of load as a function of weather. The representative methods will be briefly reviewed in this Section.

2.1 Time Series Models

Time series models are based on the assumption that the data have an internal structure, such as autocorrelation, trend or seasonal variation. The forecasting methods detect and explore such a structure. A time series model includes:

- Autoregressive Model (AR)
- Moving Average Model (MA)
- Autoregressive Moving Average Model (ARMA)
- Autoregressive Integrated Moving Average model (ARIMA)
- Autoregressive Moving Average Model with exogenous inputs model (ARMAX)
- Autoregressive Integrated Moving Average with Explanatory Variable ARIMAX)

However, the most popular Time series models used in VSTLF are the autoregressive model [27], and the Autoregressive integrated moving average model [25].

2.2 Exponential Smoothing

The exponential smoothing approach is particularly convenient for short-time forecasting. Although it also employs weighting factors for past values, the weighting factors here decay exponentially with distance of the past values of the time series from the present time. This enables a compact formulation of the forecasting algorithm in which only a few most recent data are required and less calculation are needed. Principally, there are three exponential smoothing techniques, named simple, double and triple exponential smoothing technique. Simple exponential smoothing method is applied to short-term forecasting for time series without trend and seasonality. Double exponential smoothing is used in time series that contains a trend. For seasonal time series, the third technique, which known as Holt-winters method is useful because it can capture both trend and seasonality. For VSTLF, Holt winters technique is the mostly used [25, 31, 37, 43].

2.3 Neural Network

Neural networks (NN) assume a functional relationship between load and affecting factors, and estimate the functional coefficients by using historical data. There are many types of neural networks including the multilayer perceptron network (MLP), self-organizing network and Hopfield's recurrent network [27]. Based on learning strategies, neural network methods for load forecasting can be classified into two groups. The first one is a supervised neural network that adjusts its weights according to the error between pre-tested and desired output. The second are methods based on unsupervised learning algorithm. Generally, methods based on supervised learning algorithm like a feed forward multilayer perceptron are used.

Although MLP is a classical model, it is still the most favorite ANN architecture in forecasting applications. The structure of MLP consists of input layer, hidden layer, and output nodes connected in a feed-forward fashion via multiplicative weights. Inputs are multiplied by connection weights and passed on to the neurons in hidden layer nodes. The neurons in hidden and output layer nodes have a transfer function. The inputs to hidden layer are passed through a transfer function to produce output. ANN would learn from experience and is trained with back-propagation and supervised learning algorithm. The proper selection of training data improves the efficiency of ANN [8].

Most neural network methods for VSTLF use inputs e.g., time index, load of previous hour, load of the yesterday and previous week with same hour and weekday index to the target hour [5, 15, 39]. Chen and York [7] have presented a neural network based very short-term load prediction. Results indicated that under normal situations, forecasted minutely load values by NN-based VSTLP for the future 15 min are provided with good accuracy on the whole as well as for the worst cases.

2.4 Fuzzy Logic

Fuzzy logic is a generalization of Boolean logic; it can identify and approximate any unknown nonlinear dynamic systems on the compact set to arbitrary accuracy. However, model based on fuzzy logic are robust in forecasting because there are no need to mathematical formulation between system inputs and outputs. A defuzzification process is used to produce the desired output after processing logic inputs. A fuzzy logic system was implemented in the paper of Liu et al. [27] by drawing similarities in load trend (e.g., between weekdays and weekdays) from a huge of data. A pattern database generated via effective training was then used to predict the load change. The preliminary study shows that it is feasible to design a simple, satisfactory dynamic forecaster to predict the very short-term load trends on-line using fuzzy logic. The performances of FL-based forecaster are much superior to the one of AR-based forecaster.

2.5 Adaptive Neuro-fuzzy Inference System (ANFIS)

An adaptive Neuro-Fuzzy inference system is a combination of an artificial neural network and a fuzzy inference system. It is a fuzzy Takagi-Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [21].

An artificial neural network is designed to mimic the characteristics of the human brain and consists of a collection of artificial neurons. An adaptive network is a multi-layer feed-forward network in which each node (neuron) performs a particular function on incoming signals. The form of the node functions may vary from node to node. In an adaptive network, there are two types of nodes: adaptive and fixed. The function and the grouping of the neurons are dependent on the overall function of the network. However, the ANFIS network is composed of five layers. Each layer contains some nodes described by the node function. A few layers have the same number of nodes, and nodes in the same layer have similar functions.

de Andrade and da Silva [10] have presented the use of ANFIS for very short-term load demand forecasting, with the aim to regulate the demand and supply of electrical energy in order to minimize the fluctuations and to avoid undesirable disturbances in power systems operations. Used time series measured, in 5 min intervals, were collected from substations located in Cordeirópolis and Ubatuba, cities located in the countryside and seaside of São Paulo state, respectively. Authors denoted that a higher number of epochs didn't present better performance of ANFIS. The experimental results demonstrate that ANFIS is a good tool for forecasting one-step forward for very short-term load demand.

2.6 Kalman Filtering

The Kalman filtering (KF) algorithm is a robust tracking algorithm that has long been applied to many engineering fields such as radar tracking. In load forecasting, it is introduced to estimate the optimal load forecast parameters and overcome the unknown disturbance in the linear part of the systems during load prediction [48].

Very short-term load prediction in [45] was done using slow and fast Kalman estimators and an hourly forecaster. The Kalman model parameters are determined by matching the frequency response of the estimator to the load residuals. The methodology was applied to load data taken from the portion of the western North American power system operated by the BPA.

Guan et al. [18] have presented a method of wavelet neural networks trained by hybrid Kalman filters to produce very short-term forecasting with prediction interval estimates online. Testing results demonstrate the effectiveness of hybrid Kalman filters for capturing different features of load components, and the accuracy of the overall variance estimate derived based on a data set from ISO New England.

2.7 Support Vector Regression

Support vector machines (SVM) method, which was proposed by Vapnik [46], is used to solve the pattern recognition problems by determining a hyperplane that separates positive and negative examples, by optimization of the separation margin between them [32]. Later Vapnik promotes the SVM method to deal with the function fitting problems in 1998, which forms the support vector regression (SVR) method [47]. SVR produces a decision boundary that can be expressed in terms of a few support vectors and can be used with kernel functions to create complex nonlinear decision boundaries. Similarly to linear regression, SVR tries to find a function that best fits the training data.

Setiawan et al. [38] have presented a new approach for the very short-term electricity load demand forecasting using SVR. Support vector regression was applied to predict the load demand every 5 min based on historical data from the Australian electricity operator NEMMCO for 2006–2008. The results showed that SVR is a very promising prediction model, outperforming the back propagation neural networks (BPNN) prediction algorithms, which is widely used by both industry forecasters and researchers.

3 Adaptive Neuro-fuzzy Inference System

The hybrid neuro-fuzzy approach is a way to create a fuzzy model from data by some kind of learning method that is motivated by learning algorithms used in neural networks. This considerably reduces development time and cost while improving the accuracy of the resulting fuzzy model. Thus, neuro-fuzzy systems are basically adaptive fuzzy systems developed by exploiting the similarities between fuzzy systems and certain forms of neural networks, which fall in the class of generalized local methods. Therefore, the performance of a neuro-fuzzy system can also be represented by a set of humanly understandable rules or by a combination of localized basis functions associated with local models, making them an ideal framework to perform nonlinear predictive modeling. However, there are some ways to mix neural networks and fuzzy logic. Consequently, three main categories characterize these technologies: fuzzy neural networks, neural fuzzy systems and fuzzy-neural hybrid systems [2, 3]. In the last approach, both neural networks and fuzzy logic are used independently, becoming, in this sense, a hybrid system.

An adaptive Neuro-Fuzzy inference system is a cross between an artificial neural network and a fuzzy inference system. An artificial neural network is designed to mimic the characteristics of the human brain and consists of a collection of artificial neurons. Adaptive Neuro-Fuzzy Inference System (ANFIS) is one of the most successful schemes which combine the benefits of these two powerful paradigms into a single capsule [21]. An ANFIS works by applying neural learning rules to identify and tune the parameters and structure of a Fuzzy Inference System (FIS). There are several features of the ANFIS which enable it to achieve great success in a wide range of scientific applications. The attractive features of an ANFIS include: easy to implement, fast and accurate learning, strong generalization abilities, excellent explanation facilities through fuzzy rules, and easy to incorporate both linguistic and numeric knowledge for problem solving [22]. According to the neuro-fuzzy approach, a neural network is proposed to implement the fuzzy system, so that structure and parameter identification of the fuzzy rule base are accomplished by defining, adapting and optimizing the topology and the parameters of the corresponding neuro-fuzzy network, based only on the available data. The network can be regarded both as an adaptive fuzzy inference system with the capability of learning fuzzy rules from data, and as a connectionist architecture provided with linguistic meaning [2, 3].

3.1 Architecture of ANFIS

An adaptive Neuro-Fuzzy inference system implements a Takagi–Sugeno FIS, and uses a multilayer network that consists of five layers in which each node (neuron) performs a particular function on incoming signals. The form of the node functions may vary from node to node. In an adaptive network, there are two types of nodes: adaptive and fixed. The function and the grouping of the neurons are dependent on the overall function of the network.

A hybrid-learning algorithm proposed by Jang trains generally the ANFIS system [21]. This algorithm uses back-propagation learning to determine the parameters related to membership functions and least mean square estimation to determine the consequent parameters [41]. The role of training algorithm is tuning all the modifiable parameters to make the ANFIS output match the training data [30]. For representation, Fig. 1 shows an ANFIS with two inputs x_1 and x_2 and one output y, each variable has two fuzzy sets A_1, A_2, B_1 and B_2, circle indicates a fixed node, whereas a square indicates an adaptive node. Then a first order Takagi-Sugeno-type fuzzy *if-then* rule (Fig. 2) could be set up as

$$Rule\ 1 : if\ x_1\ is\ A_1\ and\ x_2\ and\ B_1, Then f_1 = f_1(x_1, x_2) = a_1x_1 + b_1x_2 + c_1 \quad (1)$$

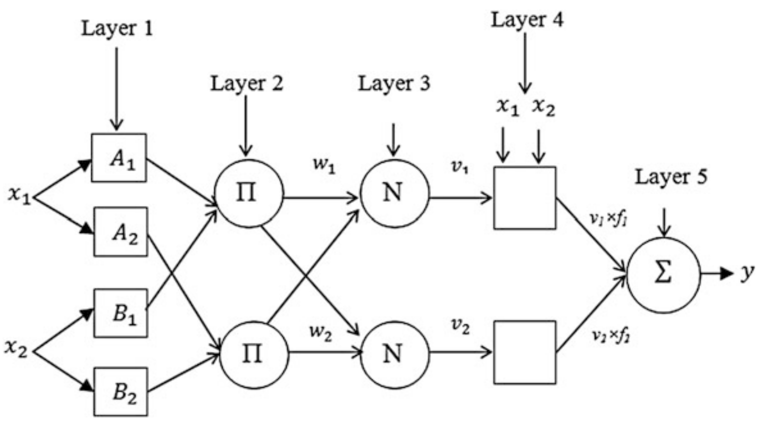


Fig. 1 ANFIS architecture

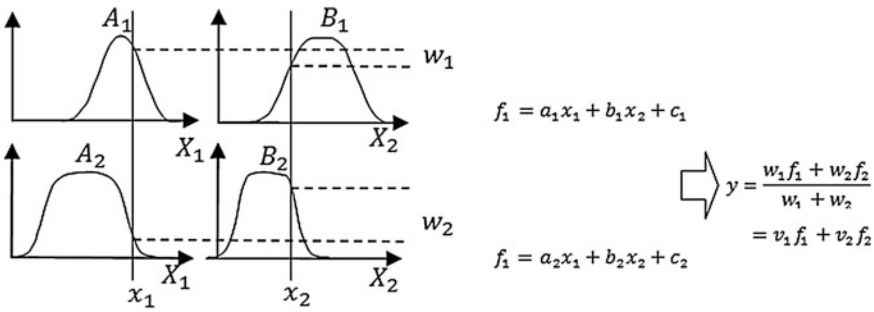


Fig. 2 A two input first order Sugeno fuzzy model with two rules

$$Rule\,2: if\; x_1\; is\, A_2\; and\; x_2\; is\; B_2,\; Then f_2 = f_2(x_1, x_2) = a_2x_1 + b_2x_2 + c_2 \tag{2}$$

f_i are the outputs within the fuzzy region specified by the Fuzzy rule, $\{a_i, b_i, c_i\}$ are the design parameters that are determined during the training process. Some layers of ANFIS have the same number of nodes, and nodes in the same layer have similar functions: ***Layer 1***: Every node i in this layer is an adaptive node. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O^1_{i,1} = \mu_{A_i}(x_1), i = 1, 2 \tag{3}$$

$$O^1_{i,2} = \mu_{B_i}(x_2), i = 1, 2 \tag{4}$$

It other words, $O^1_{i,1}$ is the membership function of A_i, and it specifies the degree to which the given input satisfies the quantifier A_i. $\mu_{A_i}(x_1)$ and $\mu_{B_i}(x_2)$ can adopt any fuzzy membership function. However, the most commonly used are Bell shaped and Gaussian membership functions. For example, if the bell shaped membership function is employed, $\mu_{A_i}(x_1)$ is given by:

$$\mu_{A_i}(x_1) = \frac{1}{1 + \left(\left(\frac{x_1 - c_i}{a_i}\right)^2\right)^{b_i}} \tag{5}$$

Where a_i, b_i and c_i are the parameters of the membership function, governing the bell shaped functions accordingly. ***Layer 2***: Every node in this layer is a circle node labeled Π, which multiplies the incoming signals and sends the product out. The Fuzzy operators are applied in this layer to compute the rule antecedent part [30]. The output of nodes in this layer can be presented as:

$$w_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2) \quad i = 1, 2 \tag{6}$$

Layer 3: The fuzzy rule base is normalized in the third hidden layer. Every node in this layer is a circle node labeled N. The *i*th node calculates the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths:

$$v_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{7}$$

Layer 4: Every node i in this layer is a square node with a node function:

$$O_i^4 = v_i \times f_i = v_i(a_i x_1 + b_i x_2 + c_i) \quad i = 1, 2 \tag{8}$$

Layer 5: Finally, layer five, consisting of circle node labeled with $\sum$ is the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} v_i \times f_i = \frac{\sum_{i=1}^{2} w_i \times f_i}{\sum_{i=1}^{2} w_i} \tag{9}$$

3.2 Learning Algorithm of ANFIS

The hybrid-learning algorithm of ANFIS proposed by Jang et al. [23] is a combination of Steepest Descent and Least Squares Estimate Learning algorithm. Let the total set of parameters be S and let S1 denote the premise parameters and S2 denote the consequent parameters. The premise parameters are known as nonlinear parameters and the consequent parameters are known as linear parameters. The ANFIS uses a two pass learning algorithm: forward pass and backward pass. In forward pass the premise parameters are not modified and the consequent parameters are computed using the Least Squares Estimate Learning algorithm [28].

In backward pass, the consequent parameters are not modified and the premise parameters are computed using the gradient descent algorithm. Based on these two learning algorithms, ANFIS adapts the parameters in the adaptive network. The task of training algorithm for this architecture is tuning all the modifiable parameters to make the ANFIS output match the training data. Note here that *ai*, *bi* and *ci* describe the sigma, slope and the center of the bell MF's, respectively. If these parameters are fixed, the output of the network becomes:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{10}$$

Substituting Eq. (7) into Eq. (10) yields:

$$f = v_1 \times f_1 + v_2 \times f_2 \tag{11}$$

Substituting the fuzzy if-then rules into Eq. (11), it becomes:

$$f = v_1(a_1x_1 + b_1x_2 + c_1) + v_2(a_2x_1 + b_2x_2 + c_2) \tag{12}$$

After rearrangement, the output can be expressed as:

$$f = (v_1x_1) \cdot a_1 + (v_1x_2) \cdot b_1 + (v_1) \cdot c_1 + (v_2x_1) \cdot a_2 + (v_2x_2) \cdot b_2 + (v_2) \cdot c_2 \tag{13}$$

This is a linear combination of the modifiable parameters. For this observation, we can divide the parameter set S into two sets:

$S = S_1 \oplus S_2$

S = set of total parameters,

S_1 = set of premise (nonlinear) parameters,

S_2 = set of consequent (linear) parameters

$\oplus$: Direct sum

For the forward path (see Fig. 2), we can apply least square method to identify the consequent parameters. Now for a given set of values of S_1, we can plug training data and obtain a matrix equation:

$$A\Theta = y \tag{14}$$

where Θ contains the unknown parameters in S_2. This is a linear square problem, and the solution for Θ, which is minimizes $\|A\Theta = y\|$, is the least square estimator:

$$\Theta^* = \left(A^TA\right)^{-1}A^Ty \tag{15}$$

we can use also recursive least square estimator in case of on-line training. For the backward path (see Fig. 2), the error signals propagate backward. The premise parameters are updated by descent method, through minimising the overall quadratic cost function:

$$J(\Theta) = \frac{1}{2}\sum_{N=1}^{N}\left[y(k) - \hat{y}(k, \Theta)\right]^2 \tag{16}$$

In a recursive manner with respect $\Theta_{(S2)}$. The update of the parameters in the ith node in layer L^{th} layer can be written as:

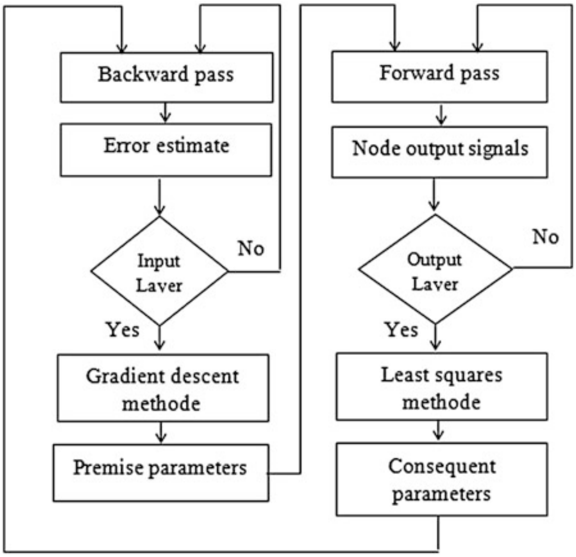


Fig. 3 ANFIS training algorithm for adjusting production rules parameters

$$\hat{\Theta}_i(k) = \hat{\Theta}_i^L(k-1) + \eta \frac{\partial^+ E(k)}{\partial \hat{\Theta}_i^L(k)} \tag{17}$$

where η is the learning rate and the gradient vector.

$$\frac{\partial^+ E}{\partial \hat{\Theta}_i^L} = \varepsilon_{L,i} \frac{\partial \hat{z}_{L,i}}{\partial \hat{\Theta}_i^L} \tag{18}$$

$\partial \hat{z}_{L,i}$ being the node's output and $\varepsilon_{L,i}$ is the backpropagated error signal.

Figure 3 presents the ANFIS activities in each pass. As discussed earlier, the consequent parameters thus identified are optimal under the condition that the premise parameters are fixed.

The flow chart of training methodology of ANFIS system is shown in Fig. 4. Usually, the modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and checking data sets. Training data constitutes a pairs of input and output vectors. In order to make data suitable for the training stage, this data are normalized and used as the input and the outputs to train the ANFIS. Once both training and checking data were presented to ANFIS, the FIS was selected to have parameters associated with the minimum checking data model error. The stopping criterion of ANFIS is the testing error when it became less than the tolerance limit defining at the beginning of the training stage or by putting constraint on the number of learning iterations.

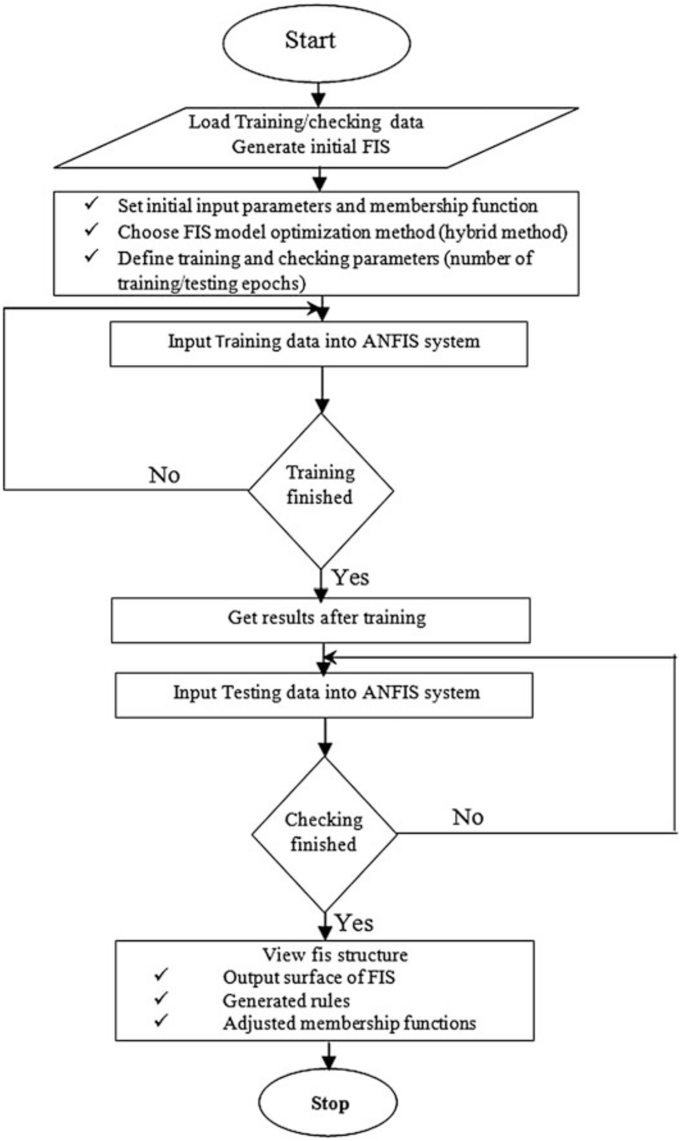


Fig. 4 Flow chart of training methodology of ANFIS system [2, 3]

4 Proposed Methods

4.1 Load Data Treatment

Variations in electrical load are, among other things, time of the day dependent, introducing a dilemma for the forecaster: whether to partition the data and use a separate model for each specified time of the day (the parallel approach), or use a single model (the sequential approach) [14].

In this work, the electrical load time series are separated in autonomous points. A set of independent points means that the load at each quarter-hour of the day is independent from the load at any other quarter-hour. These are called parallel series. We propose three suggestions. The first is to split the French quart-hourly load data into 96 parallel series, each series is composed by loads consumed at a specified time of a distinctive day (Saturday, Sunday …, etc.). In the second, the parallel series contain loads from all previous days consumed at a specified quarter-hour. In the third, parallel load series are classified in three categories: Saturdays, Sundays, workdays.

Data classification need some knowledge such as the identification of the first day in the historical load data (Saturday, Sunday,…), the number of days in each month, the number of days available in the historical load data. By effecting simple If-Then statements, the parallel load series for each class can be extracted.

4.2 ANFIS Architecture

The proposed ANFIS model can be represented by seven steps:

Step 1: We select the day and the hour in which we would like to predict the load. Hence, the four series of this hour, noted y(i), y(i + 1), y(i + 2) and y(i + 3), represents the output of the ANFIS.

Step 2: As inputs, we creates seven parallel load series noted y(i − 1), y(i − 2), y(i − 3), y(i − 4), y(i − 5), y(i − 6) and y(i − 7), and an input index x(i). Hence, the inputs load series records loads consumed at previous nearest quarter-hours.

Step 3: Then, we remove the last load value from inputs and outputs series, where the last value of y(i), y(i + 1), y(i + 2) and y(i + 3) represents the load to be forecasted. These new series are noted y(i)’, y(i + 1)’, y(i + 2)’, y(i + 3)’, y(i − 1)’, y(i − 2)’, y(i − 3)’, y(i − 4)’, y(i − 5)’, y(i − 6)’, y(i − 7)’ and x(i)’.

Step 4: We performs now an exhaustive search within the available inputs to select only one input vector that most influence in y(i)’. The exhaustive search builds an ANFIS model, trains it for twenty epochs, and reports the performance achieved. Selected model should provide the minimum RMSE in the outputs predicting.

Step 5: Selected input from the previous step is used then to generate and trains a Sugeno FIS of two fuzzy rules, two sigmoid membership and twenty epochs.

Step 6: At last, original input related to the selected input is used to predict the load in y(i).

Step 7: We repeat then the two last previous steps in order to predict the desired load in y(i + 1), y(i + 2) and y(i + 3).

However, we propose in the paper, three ANFIS models:

- ***Method 1***: the electrical loads series in this method are obtained by implementing the first classification.
- ***Method 2***: the electrical loads series in this method are obtained by implementing the second classification.
- ***Method 3***: the electrical loads series in this method are obtained by implementing the third classification.

5 Results and Discussion

All three methods are applied in the French real time load data. These data consists of quart-hourly recording ranging from Sunday 07 April 2013 until Friday 28 February 2014, where the last month is used in a one-hour ahead forecasting. Used data are represented by Fig. 5.

The graphical user interface developed for all three methods is represented by Fig. 6. The essential function of this tool is to ensure, at any quarter-hour selected

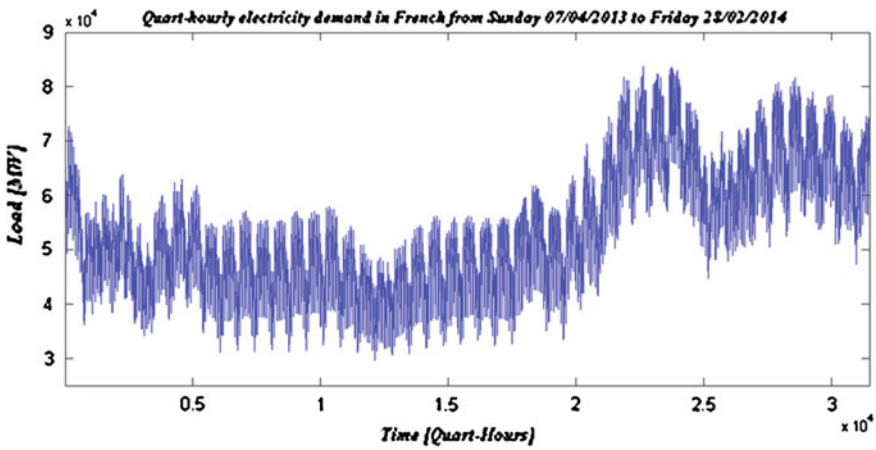


Fig. 5 Quart-hourly French electric load time series from Sunday 07 April 2013 to 28 February 2014

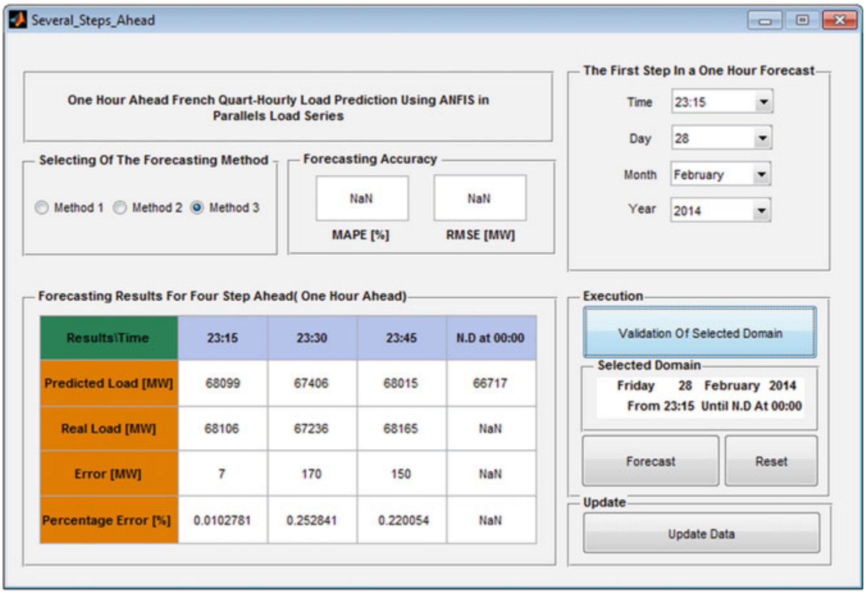


Fig. 6 Developed forecasting tool for a 1-h ahead electric load forecasting using ANFIS

from the user, a 1-h ahead demand prediction. In addition, when actual values of the load are available, the performance of forecasted loads could be verified using different error measurement criteria. Moreover, the tool has the advantage, by division the original data into 96 separated load series, to reduce the number of data should be taken into consideration before predicting the load at the specified hour and, and by the way reducing computational time.

To evaluate and compare the performance of the new proposed methods, forecasts are done along the month of February 2014. For each day in the selected Month, first steps in the 1-h ahead prediction are 00:15, 01:15, 02:15… until 23:15. Forecasts by Method 3 in the field “11:15 p.m. to 00:00” are based on the first classification.

Results of three methods are represented in Figs. 7, 8 and 9. As shown in these figures, the proposed ANFIS models have successfully predict the load over the month of February 2014, and there is almost no different between predicted and real load.

To evaluate the performance of developed models, we have used APE (Absolute Percentage error), MAPE (Mean absolute percentage error) and RMSE (Root mean square error) criteria. Evaluation results are summarized in Table 1.

$$APE = \frac{|\hat{y}_t - y_t|}{y_t} \times 100 \tag{19}$$

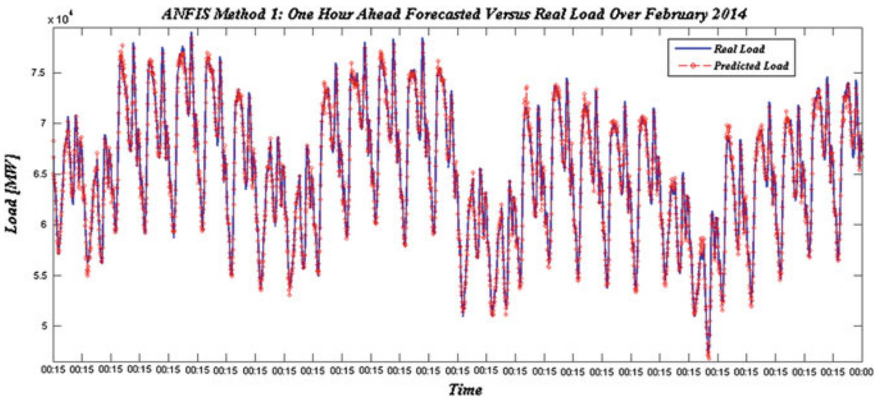


Fig. 7 One-hour ahead forecasted load versus real load for method 1

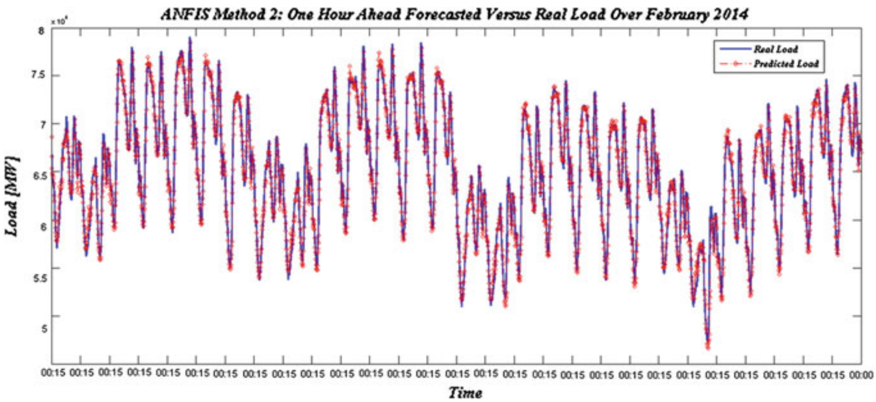


Fig. 8 One-hour ahead forecasted load versus real load for method 2

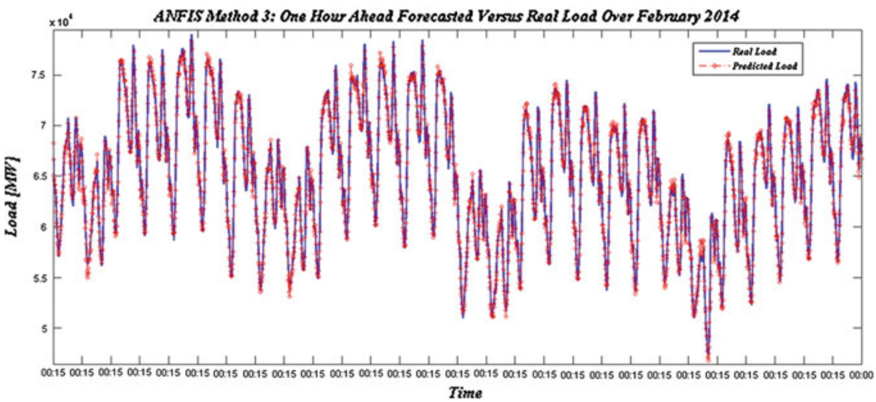


Fig. 9 One-hour ahead forecasted load versus real load for method 3

$$MAPE = \frac{1}{n}\sum_{m=1}^{n}\frac{|\hat{y}_t - y_t|}{y_t} \times 100 \tag{20}$$

$$RMSE = \frac{1}{n}\sqrt{\sum_{m=1}^{n}(\hat{y}_t - y_t)^2} \tag{21}$$

As shown in Table 1, all three methods achieve a high accuracy in the 1-h ahead load forecasting. We can perceive that's the accuracy of the second method decrease in free days compared to in working days, this can be justified by the fact that this model use loads from a specific quarter-hour in all previous days in the historical load data. Here, we should note that the load in Saturday and Sunday is very low compared to in working days. For example, if we would like to predict the load at a specified quarter-hour in a Saturday using the second method, than latest values of the parallel load series contains loads from previous nearest Monday until the previous day (a Friday). These values effects the prediction because they are height compared to the desired load in Saturday. This can be clearly observed in the first method, which is based on intraday classification and the parallel series contains load consumed at a specified quarter-hour in a typical day (Monday, Tuesday …), where the accuracy of prediction in Saturdays and Sundays is not different compared to in others days.

However, what is impressive; is that the number of data that should be taken into account in the second method is seven times higher than the used in the first method, while the obtained results clearly show that the first method is more accurate than the second method. This demonstrates that, in addition to the selection of an appropriate forecasting technique, classifying the historical data to extract useful knowledge and patterns from large database also, affect on the forecasting accuracy. Moreover, by classifying the data in the third method into three clusters: Saturdays, Sundays and working days, the accuracy is increased, and it is superior to that in the first and the second method.

Figure 10 represents the distribution of the maximum percentage error for three methods. We can perceive that the proposed ANFIS methods have failed to predict peaks consummation around 19:00 with a high accuracy, which make a real need in this field, to propose a separate model for predicting the peak consumption, or to train the ANFIS with more than one input. However, as shown if Fig. 11, for the third proposed method, 56 % of the forecasted loads have an APE under 0.5 and an APE under one was achieved for about 80 % of cases. Likewise, as demonstrate Figs. 12 and 13, the first and the second method provide also a good accuracy in most of time.

In addition to a robust model that assures a very high accuracy, time required in the forecasting procedure take an important role in real time electric load forecasting. Tables 2 show in detail, for all three methods, prediction results for four different hours. Results are obtained using Windows 7 64 bit and MATLAB R2013a in a

Table 1 One-hour ahead forecasting accuracy for a three proposed methods over the month of February 2014

	Method 1						Method 2					
	MAPE			RMSE			MAPE			RMSE		
Sat 01 Feb 2014	0.6117	0.7193	**0.7432**	614.3959	769.0680	**794.52**	1.0218	0.7877	**0.8404**	878.28	817.96	**862.22**
Sun 02 Feb 2014	0.9875			860.3865			1.2399			1102.7		
Mon 03 Feb 2014	0.7229			798.3312			0.6262			717.08		
Tue 04 Feb 2014	0.6374			761.9828			0.6081			681.86		
Wed 05 Feb 2014	0.7088			770.9580			0.6640			774.39		
Thu 06 Feb 2014	0.6188			704.2705			0.5958			699.53		
Fri 07 Feb 2014	0.7481			845.0963			0.7583			792.49		
Sat 08 Feb 2014	0.5808	0.6460		601.0464	733.7181		0.8091	0.7372		656.40	779.67	
Sun 09 Feb 2014	0.7268			783.3347			1.1295			1052.8		
Mon 10 Feb 2014	0.7171			779.3326			0.7075			769.91		
Tue 11 Feb 2014	0.7159			798.9643			0.6553			721.39		
Wed 12 Feb 2014	0.6148			687.2521			0.6556			720.37		
Thu 13 Feb 2014	0.6003			802.7999			0.6210			831.08		
Fri 14 Feb 2014	0.5661			656.5204			0.5823			627.08		
Sat 15 Feb 2014	0.6898	0.7493		715.4786	833.9910		0.9259	0.8790		783.74	891.84	
Sun 16 Feb 2014	0.7259			747.6218			1.4201			1291.7		
Mon 17 Feb 2014	0.9867			1076.7			0.9973			997.71		
Tue 18 Feb 2014	0.8307			977.6372			0.7036			795.45		
Wed 19 Feb 2014	0.6776			758.8888			0.6995			750.08		
Thu 20 Feb 2014	0.6761			748.8020			0.7456			765.08		
Fri 21 Feb 2014	0.6580			739.0911			0.6607			713.34		
Sat 22 Feb 2014	0.7332	0.8583		701.0428	836.5079		0.9180	0.9576		821.48	949.38	
Sun 23 Feb 2014	1.0665			949.4138			1.7065			1465.7		
Mon 24 Feb 2014	0.9972			991.8403			1.1547			1037.8		
Tue 25 Feb 2014	0.8315			787.2473			0.7563			710.35		
Wed 26 Feb 2014	0.7654			726.2326			0.7103			793.33		
Thu 27 Feb 2014	0.7744			790.2337			0.7671			819.81		
Fri 28 Feb 2014	0.8396			866.0148			0.6902			776.58		

(continued)

Table 1 (continued)

	Method 3					
	MAPE			RMSE		
Sat 01 Feb 2014	0.6117	0.6846	**0.6966**	614.39	733.23	**748.10**
Sun 02 Feb 2014	0.9875			860.38		
Mon 03 Feb 2014	0.5412			690.52		
Tue 04 Feb 2014	0.6077			695.24		
Wed 05 Feb 2014	0.7280			804.35		
Thu 06 Feb 2014	0.6035			694.97		
Fri 07 Feb 2014	0.7123			745.31		
Sat 08 Feb 2014	0.5808	0.6157		601.04	708.35	
Sun 09 Feb 2014	0.7268			783.33		
Mon 10 Feb 2014	0.6004			690.21		
Tue 11 Feb 2014	0.6115			721.01		
Wed 12 Feb 2014	0.6277			711.93		
Thu 13 Feb 2014	0.5954			811.52		
Fri 14 Feb 2014	0.5672			612.99		
Sat 15 Feb 2014	0.6898	0.6879		715.47	757.18	
Sun 16 Feb 2014	0.7259			747.62		
Mon 17 Feb 2014	0.8994			1010.3		
Tue 18 Feb 2014	0.6518			767.93		
Wed 19 Feb 2014	0.5989			685.11		
Thu 20 Feb 2014	0.6183			664.92		
Fri 21 Feb 2014	0.6313			648.38		
Sat 22 Feb 2014	0.7332	0.7982		701.04	791.16	
Sun 23 Feb 2014	1.0665			949.41		
Mon 24 Feb 2014	0.8746			872.60		
Tue 25 Feb 2014	0.6531			619.95		
Wed 26 Feb 2014	0.7518			758.67		
Thu 27 Feb 2014	0.7600			814.72		
Fri 28 Feb 2014	0.7484			776.89		

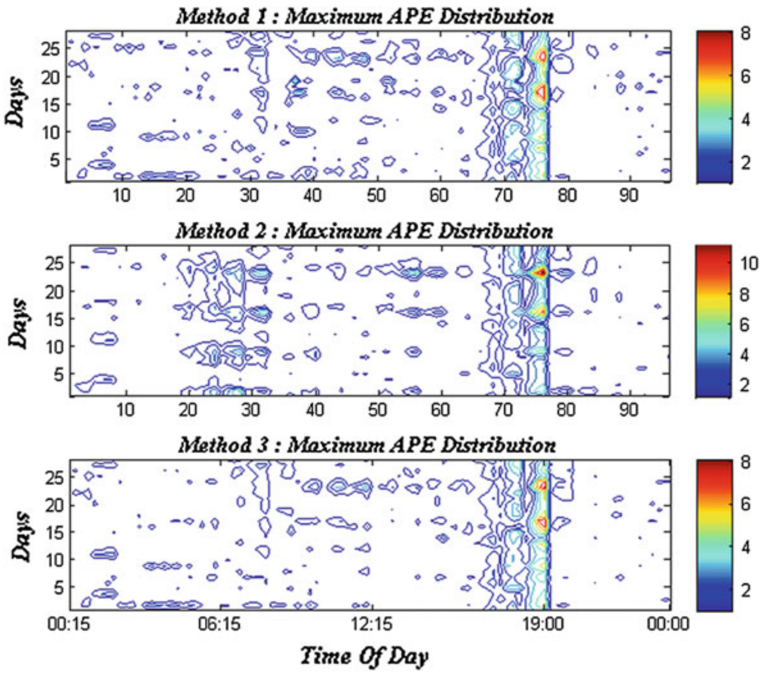
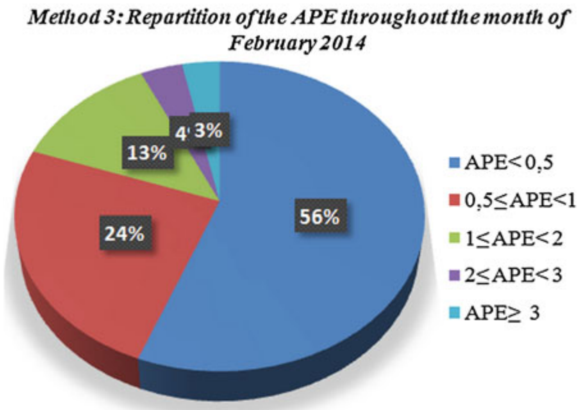


Fig. 10 Maximum APE distribution for all three methods

Fig. 11 Repartition of the APE throughout the month of February 2014 for the third method



laptop of 4 GB of RAM, Intel i3 380 M processor and 5,400-rpm hard drive. Results confirm the superior accuracy of the third proposed method. In addition, needed time in the forecasting procedure is less than two second. This time includes the exhaustive search affected to select the more appropriate input for training the ANFIS, and four ANFIS corresponding to each quarter-hour load series.

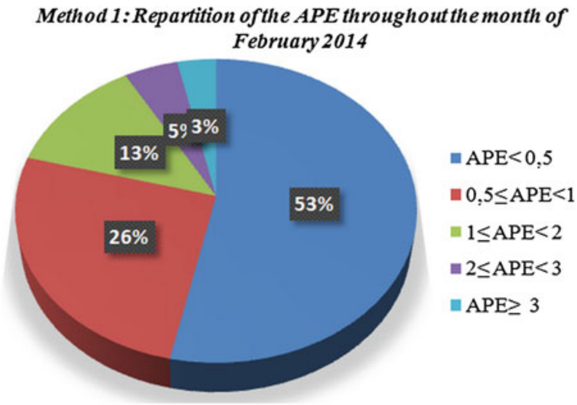


Fig. 12 Repartition of the APE throughout the month of February 2014 for the first Method

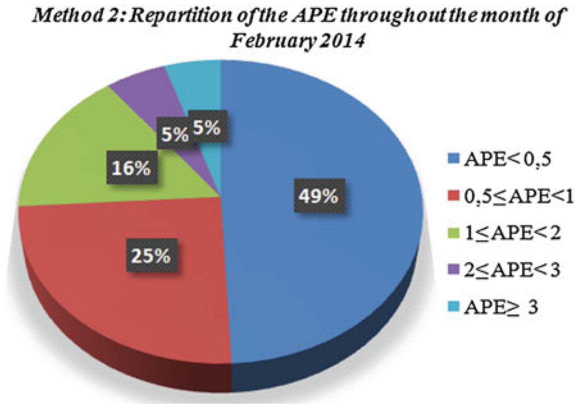


Fig. 13 Repartition of the APE throughout the month of February 2014 for the second method

Moreover, the accuracy decreases when the proposed methods are used to forecast the peak consummation at 19:00. For example, the MAPE pass from 0.23 % at the beginning hour of 1 February 2014 to 1.38 % at the field 18:15–19:00 of the last day of February 2014. These is more clearly perceived from Figs. 8, 9, 10 and 12 where maximums APE (between 3 and 8 % in first and third method, and between 3 and 10 % in the second method) are done around 18:15–19:00. This decrease can be justified by the non-consideration of weather condition in the proposed methods. As we know, changing weather conditions represent the major source of variation in peak load forecasting and the inclusion of temperature has a significant effect due to the fact that in winter heating systems are used specially in the evening around 19:00, whilst in summer air conditioning appliances are used particularly around 13:00. Other weather factors include relative humidity, wind speed and nebulosity. Therefore, numerous papers are devoted to electricity peak demand forecasting [13, 42]. However, since weather variables tend to change in a smooth fashion, Weather conditions are ignored in very short term load forecasting

Table 2 Forecasting results for four different hours in all three methods

		Method 1						Method 2				
Results / Time		Real load (MW)	Predicted load (MW)	APE (%)	MAPE (%)	RMSE (MW)	Elapsed time (s)	Predicted load (MW)	APE (%)	MAPE (%)	RMSE (MW)	Elapsed Time (s)
01 Feb	00:15	68,270	68,264	0.0087	0.2322	205.12	1.2480	68,597	0.4789	0.3141	262.74	1.4670
	00:30	66,626	66,653	0.0405				66,593	0.0495			
	00:45	65,407	65,074	0.5091				65,343	0.0978			
	00:00	64,252	64,490	0.3704				64,657	0.6303			
10 Feb	06:15	62,739	62,532	0.3299	0.7238	508.82	1.0920	62,062	1.0790	1.9104	1292.83	1.4510
	06:30	64,621	63,912	1.097				63,127	2.3119			
	06:45	65,548	65,953	0.6178				64,219	2.0275			
	07:00	67,153	67,724	0.8502				65,660	2.2232			
19 Feb	12:15	70,632	70,782	0.2123	1.5312	1435.65	1.1380	71,275	0.9103	1.0796	767.08	1.3730
	12:30	70,245	70,124	0.1722				70,964	1.0235			
	12:45	70,960	69,106	2.6127				71,706	1.0513			
	12:00	69,827	72,011	3.1277				70,758	1.3333			
28 Feb	18:15	68,734	68,795	0.0887	1.5536	1521.45	1.1390	68,720	0.0203	1.5818	1497.83	1.3420
	18:30	70,121	69,783	0.4820				69,656	0.6631			
	18:30	72,242	70,709	2.122				70,501	2.4099			
	19:00	74,000	71,394	3.5216				71,607	3.2337			

(continued)

Table 2 (continued)

		Method 3					
Results		Real load (MW)	Predicted load (MW)	APE (%)	MAPE (%)	RMSE (MW)	Elapsed time (s)
Time							
01 Feb	00:15	68,270	68,264	0.0087	0.2322	205.12	1.2480
	00:30	66,626	66,653	0.0405			
	00:45	65,407	65,074	0.5091			
	00:00	64,252	64,490	0.3704			
10 Feb	06:15	62,739	62,404	0.5339	0.57799	457.483	1.4660
	06:30	64,621	63,816	1.2457			
	06:45	65,548	65,285	0.4012			
	07:00	67,153	67,065	0.1310			
19 Feb	12:15	70,632	70,987	0.5026	0.6617	487.69	1.2950
	12:30	70,245	70,640	0.5623			
	12:45	70,960	71,354	0.5552			
	12:00	69,827	70,544	1.0268			
28 Feb	18:15	68,734	68,793	0.0858	1.3793	1366.3	1.2640
	18:30	70,121	69,872	0.3551			
	18:45	72,242	70,866	1.9047			
	19:00	74,000	71,653	3.1716			

and they could be captured in the demand series itself. By the way, it would be more appropriate for us to propose a separate model for predicting the peak consumption.

6 Conclusion

In this paper, three new models based on the use of adaptive neuro-fuzzy inference system technique in parallel data were developed to forecast the French real time quart-hourly load, in a 1-h ahead basis. The best ANFIS technique found was the third, which classify the parallel load series in three categories. We have perceive that the proposed ANFIS methods have some failed to predict peaks consummation around 19:00; which make a real need in this field, to propose a separate model for predicting the peak consumption, or to train the ANFIS with more than one input. However, for the third method, 56 % of the forecasted loads have an APE under 0.5, and an APE under one was achieved for about 80 % of cases. Therefore, at exception for peak consummation, the third proposed method can be successfully applied to build a 1-h ahead electric load prediction in real time.

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