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Short-term load forecasting based on the Kalman filter and the neural-fuzzy network (ANFIS)

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Abstract: In this article the possibilities of the KALMAN filter as well as the neural-fuzzy network ANFIS (adaptive neural-fuzzy inference system) for the short-term load forecasting are presented and compared. In any case, the load forecasting for one entire day as well as the load forecasting for one or more hours ahead are possible. The approach followed in this case is as follows: considering that the medium hourly load is divided in 24 distinguishable time series (each time-series concerns the load history for one concrete hour of the day in the duration of a year).One can take the corresponding 24 models (distinguishable between them) aiming at the forecast of the medium hourly electric load for each hour separately. The evaluation of the precision (quality) of the forecasts is realised via their comparison with the corresponding real values of the hourly load of the electric consumption of the Crete Island, which have not been used for the training of the forecast models.

Key-Words: Short-term load forecasting, Kalman filter, Adaptive neural fuzzy inference system (ANFIS).

1 Introduction

The continuous monitoring of the electric load, which is supplied by the electric energy system, is a basic requirement for its reliable operation. In an interval of seconds, where the load variations are relatively small and random, the *Automatic Control System of Production* ensures that the system production compensates the load demand. In intervals of a few minutes, where the load variations are more considerable, the *Economic Distribution of Load* is responsible for the distribution of the total system load to the already included network units, in the most economic way. In intervals of certain hours or even days, the load variations are even more considerable. In order to meet the load demands of such intervals, the commitment or standby of production units or the power exchange among the neighbouring electric systems is required. [1,2].

The motivation for precise forecasts is found in the nature of electricity as a commodity and a commercial form. The electricity cannot be stored, implying that for an electric use, the estimation of the future demand is essential for the production and marketing in an economic way. The short-term load forecasting (STLF) is a well-known subject in the literature of the electrical energy systems. The growth of computer technology has increased the possibilities for these and other methods that function in a real time environment. Another reason maybe the international trend of a competition growth in the deregulated markets of electric energy [3].

The forecasted load time-series is a non static stochastic process constituted by thousands of separate elements. Consequently, the range of possible forecasting approaches is wide. Usually, the only option is to take a macroscopic view of the problem and try to model the future load as a repetition of the previous behaviours. This leaves the field open to very different solutions. The most popular methods used extensively in practice are the *time_of_day* models [4], the models of dependent statistical variable divergence [5], the stochastic time-series models (ARMA models, ARIMA etc.) [6,7], the models of state spaces [8,9] the empirical systems (Fuzzy logic etc) [10-13] and the artificial neural networks [14,15].

In this article two methods of short-term forecasting of electric load are presented and compared, the Kalman filter and the neural fuzzy network ANFIS.

2 The Kalman Filter

The present article deals with the hourly load forecasting with regard to two specific hours of each day (maximum and minimum value), namely 02:00 and 14:00. The results refer to the years of 2000 and 2001. Our objective is to calculate the coefficients of recurrent equations of the form:

$$y(k)=a_o(k)+a_1(k)y(k-1)+...+a_n(k)y(k-n) \quad (1)$$

, where y (k) is the value of the electric load at the time moment k - where the Kalman filter is useful for the calculation of the coefficients of the recurrent equation $a_o(k),\ldots,a_n(k)$, in each step of the application [16]. The window of the load values that is used at the k time moment for the calculation of the equation (1) coefficients, via the filter Kalman, is shaped to include 5 values (Fig.1). One of them refers to the current load value, while the remaining 4 refer to the loads of the previous hour and week as well as the loads that precede 23 and 25 hours of the current value.

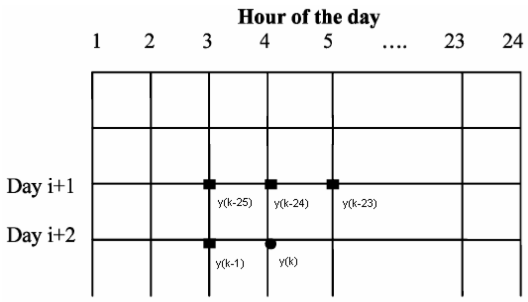

Fig. 1

The algorithm was applied separately for each one of the years 2000 and 2001 of the isolated system of Crete. In total, 120 values were calculated (hence 120 application steps of the algorithm) with regard to the load time series of 02:00 and 14:00 hours - from each day we only retain the forecasted values of 02:00 and 14:00 hours, resulting to 4 time-series (2 for each year) of 120 values, for each hour that we are interested in.

The training set for each step - for the determination of coefficients of the resulting recurrent equations - was selected after trials as the time interval of 90 days. As far as the calculation of forecasted values is concerned, two different approaches were followed which, obviously, result in different results. In the 1st case, for each step of the 120 steps of the process - having evaluated the coefficients of the recurrent equations - the forecasted load values of the corresponding day are calculated one by one, using as previous values the real values of the load. In the 2nd case, the forecasted values of the load are calculated for one day in total, using as previous values for each hour those that have been calculated in the previous step (namely the previous value of the hour). Apparently, the errors will be greater in the 2nd case, something that is also depicted in the following results.

Below, the graphic representations of the results for the year 2001 are given:

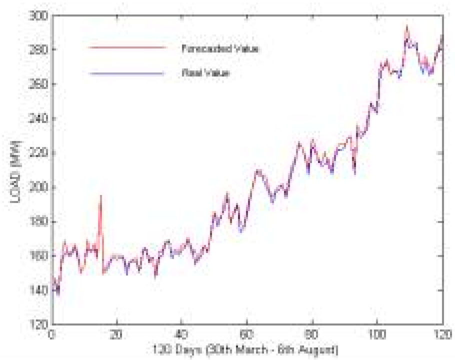

Fig 2. Load forecasting hour by hour (02:00h), year 2001

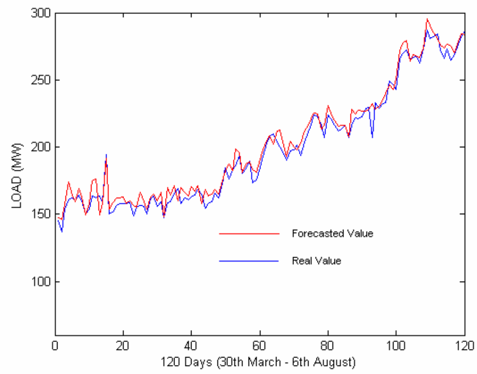

Fig 3. Load forecasting a day each time (02:00h), year 2001

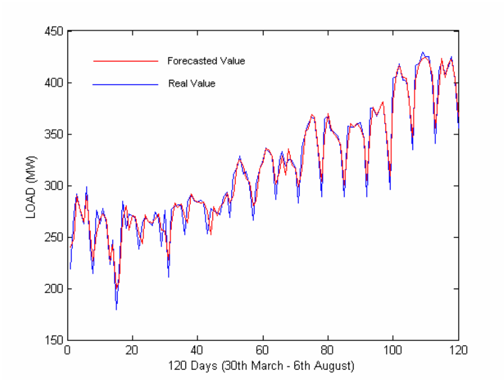

Fig 4. Load forecasting hour by hour (14:00h), year 2001

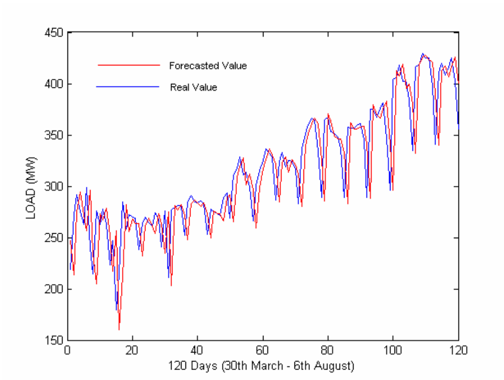

Fig 5. Load forecasting a day each time (14:00h), year 2001

3 The Neural-Fuzzy Anfis Network

Through a wide spectrum of trials of the ANFIS network, the final structure of the network is determined and settled: the number and the format of the inputs, the output format, the membership functions' format, etc [17]. For the application of the trials, the MATLAB 6.5 Toolbox was used. After continuous and extensive trials, we concluded to the following optimal structure for the ANFIS network:

- As a training set, the entire year 2000 is used, while the trials refer to the following year 2001.
- The network will have three inputs (3 fuzzy sets for each one) and one output. Totally there will be 27 rules, where the output for each one of them will take constant values, that is the conclusive functions for each rule will be of the form: $f_i = a_i$
- The membership functions were decided to have a triangular shape while the network training will be of a hybrid form (that is, back-propagation combined with least-squares' techniques) which is much faster than the typical back-propagation method.
- The activation rules outputs will take constant values.
- The training sets will be of the form:

$$x_{in} = \{Load_j(i)\ Load_j(i+6)\ Load_{j-1}(i+7)\},\ \ x_{out} = \{Load_j(i+7)\}$$

, that is for each output hour, the load values from the previous day, week and hour are taken as inputs.

- The herein presented results refer to the 02:00 and 14:00 hours (discrete ANFIS networks for each hour) for an interval of 120 days for each one.

The form of the ANFIS network, as it was used in the present article, will be the following:

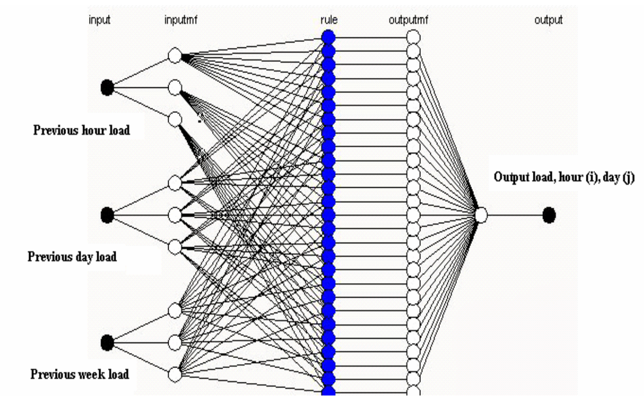

Fig.6 The neural fuzzy network ANFIS

Regarding to the year of 2001 and for an interval of 120 days, the following graphs were obtained:

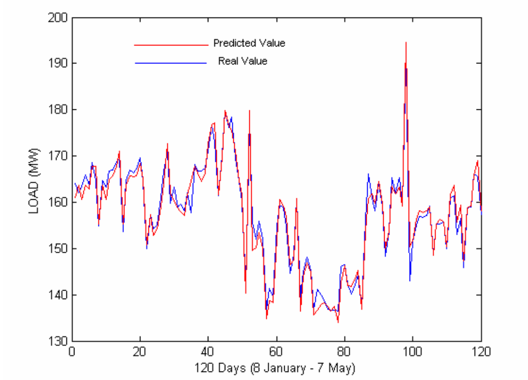

Fig.7 Load forecasting, 02:00h, year 2001

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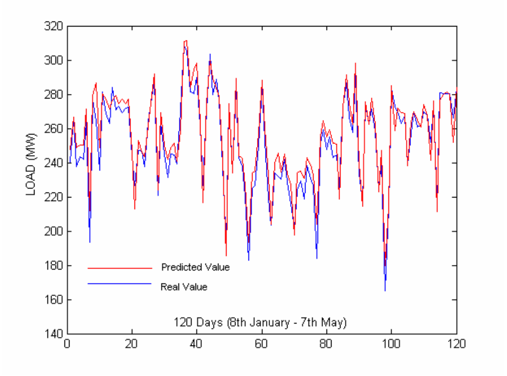

Fig.8 Load forecasting, 14:00h, year 2001

4 Numerical Results

As far as the error values are concerned, the following results were obtained:

Kalman Filter

Year 2000 (02:00h)

Prediction	Relative Error (%)	RMSE (%)	Standard Deviation Error
Hour by hour	1,55	2,53	4,6067
A day	3	4,76	9,095

Year 2000 (14:00h)

Prediction	Relative Error (%)	RMSE (%)	Standard Deviation Error
Hour by hour	2,48	3,77	9,8
A day	7,98	13,12	33,2

Year 2001 (02:00h)

Prediction	Relative Error (%)	RMSE (%)	Standard Deviation Error
Hour by hour	1,26	1,57	3,03
A day	2,64	3,47	6,367

Year 2001 (14:00h)

Prediction	Relative Error (%)	RMSE (%)	Standard Deviation Error
Hour by hour	2,67	3,82	10,6
A day	7,58	11,11	32,47

ANFIS network

Year 2001

Prediction	*Relative Error (%)*	*RMSE (%)*	*Standard Deviation Error*
02:00	*0,96*	*1,3*	*2,02*
14:00	*2,36*	*3,04*	*7,3007*

The following graph (Fig.9) shows the trial results from all the models referred in the literature [14] in relation to the ones in this paper:

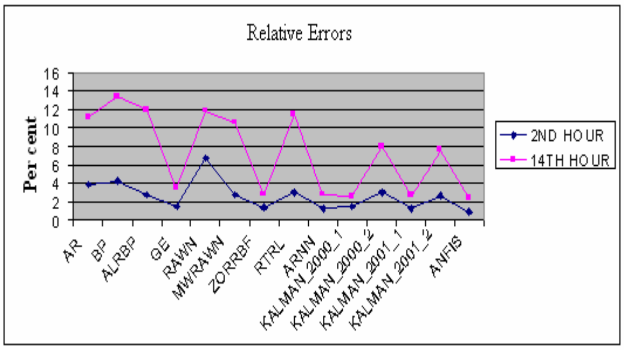

Fig 9.

- *KALMAN_2000_1: Kalman for the year 2000, predicting hour by hour, KALMAN_2000_2: Kalman for the year 2000, predicting a day each time, KALMAN_2001_1: Kalman for the year 2001, predicting hour by hour, KALMAN_2001_2: Kalman for the year 2001, predicting a day each time.*

5 Conclusions And Proposals

In the present article, the application of two relatively new methods was presented, with regard to their application in the short-term load forecasting; the Kalman filter and the neural-fuzzy ANFIS network. The average hourly values of the electric load of the isolated system of Crete from years 2000 and 2001 were used as data for the training and trial. The aim was to forecast the future load values with regard to two discrete time-series, which correspond to the 02:00 and 14:00 hours of each day, within a time frame of 120 days. The obtained results, as it is also shown by the error values in the previous section, range in quite satisfactory levels with regard to other load forecasting studies found in the literature [14], rendering thus the Kalman filter and the ANFIS network two alternative solutions of the typical neural networks and their variants that are widely used in the field of short-term load forecasting.

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