

Application and Comparison of Evolutionary Techniques for Forecasting the Hellenic Grid Electricity Load

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Abstract. Electric load forecasting is a process that has to be both fast and reliable. An accurate method of load forecasting plays the most crucial role in achieving the aforementioned properties and also is a valuable tool in overcoming a variety of economic and operational problems connected to electrical energy production and distribution. In this study real data is used and the performance of three different techniques for adaptive electric load forecasting is evaluated. The first method is a combination of the well-established multimodel partitioning filter (MMPF) implementing extended Kalman filters (EKF) with Support Vector Machines (SVM), the second is the adaptive MMPF Kalman filters (KF) model and the third one is an artificial three layer feed-forward neural network (ANN). The results indicate that all three methods are reliable, however the combination of MMPF and SVM provides a more accurate load forecasting and at the same time identifies successfully both normal periodic behavior and any unusual activity of the electric grid.

Keywords: Adaptive multimodel partitioning filter (MMPF), Support vector machines (SVM), artificial neural networks (ANN), forecasting, Kalman filters (KF), electricity demand load.

1 Introduction

Electrical energy is considered as one of the most important factors that are closely related to both economic and social development. Accurate and fast load forecasting is related to a number of operational functions, such as system safety, power system real-time control, economic planning, grid's maintenance and also fuel planning.

The problem of load forecasting has been studied extensively during recent decades. Some of the proposed techniques make use of time series analysis using ARMA [1-5] or ARIMA models [6-10]. Other algorithms achieve load forecasting by adopting evolutionary techniques such as ANN's [11-12], SVM's [13-14] either alone or combined with other methods for the same purpose [15-17].

The purpose of this study is not to introduce one more load forecasting criterion, but it focuses on applying three different methods to real electric load data and evaluating their performance.

The first method is based on a hybrid model that combines the adaptive MMPF [18-20], known for its stability, with SVM. The idea of using this method for electric load forecasting came from the fact that it was applied for wind speed prediction with very good results [21]. The data used now is not subjected to any prior – offline manipulation in order to remove weekly and annual seasonality as was done in previous cases [5]. That's why in this case the MMPF implements a bank of extended Kalman filters (EKF) with ARMA models instead of simple Kalman filters (KF) with ARMA models in order to handle data's non-linearities. MMPF with EKF combined with genetic algorithms (GA) were successfully applied in prediction of epilepsy and in the evolution of stock values using biomedical and financial data respectively [22].

The second method, presented analytically in [5], implements MMPF with ARMA models and from the real data applied annual and weekly seasonality have been removed.

The third method incorporates a three layer feedforward ANN, with input variables ambient temperature T, relative humidity RH, day of the week WD, month of the year MY, contribution factor CF and output variable Electricity Demand Load ED_L .

2 Method Presentation

2.1 The Hybrid model (MMPF with SVM)

This hybrid method is analytically presented in [21]. A schematic diagram of its operation is shown in Figure 1 below:

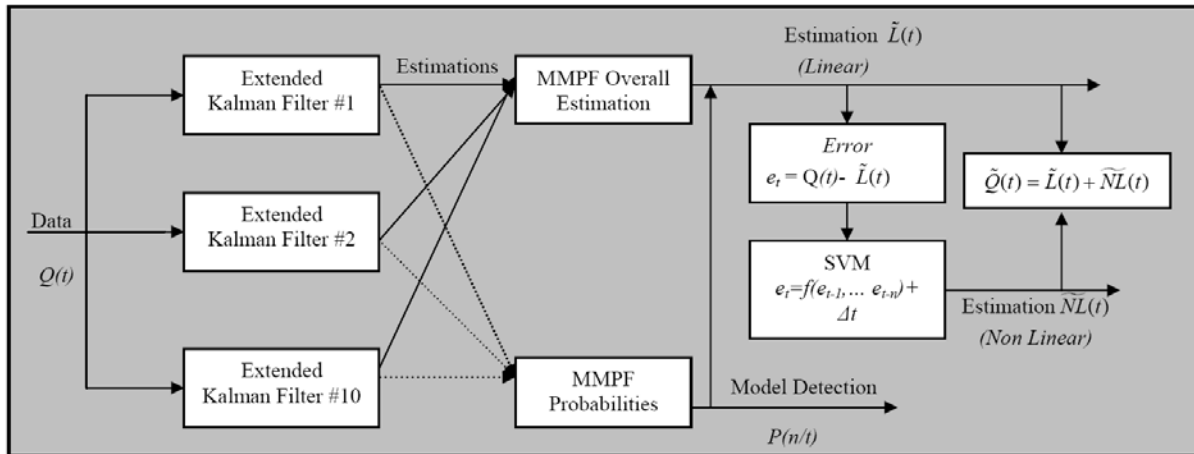


Figure 1. Schematic representation of the hybrid model.

The hybrid model proposed is based on a linear pattern, $L(t)$ produced by the MMPA and a non-linear one, $NL(t)$ produced by the SVM. It can be represented as:

$$Q(t) = L(t) + NL(t) \tag{1}$$

Both parts are directly calculated from the electric load time series.

If $e(t)$ is the MMPA estimation error at any time instant t , then:

$$e(t) = Z(t) - \tilde{L}(t) \tag{2}$$

It is now the SVM that models these residuals as:

$$e(t) = f(e_{(t-1)}, e_{(t-2)}, \dots, e_{(t-n)}) + \Delta t \tag{3}$$

where f is non linear and Δt is random error.

Consequently the forecast of the hybrid model is:

$$\tilde{Q}(t) = \tilde{L}(t) + \tilde{NL}(t) \tag{4}$$

2.2 MMPF with KF

This method is analytically presented and tested in [5]. A schematic diagram is shown in Figure 2. For both MMPF models 10 EKF or 10 KF were implemented. An important feature of the MMPF is that all the EKFs or KFs needed to be implemented can be independently realized. This enables to implement them in parallel, saving an enormous computational time [23].

2.3 ANN

A typical three layer feed-forward (FF) ANN is presented in Figure 3. This architecture has four inputs, 3 outputs and each node is represented by a single neuron. All layers between input and output ones are called hidden layers. In this case study one hidden layer is implemented.

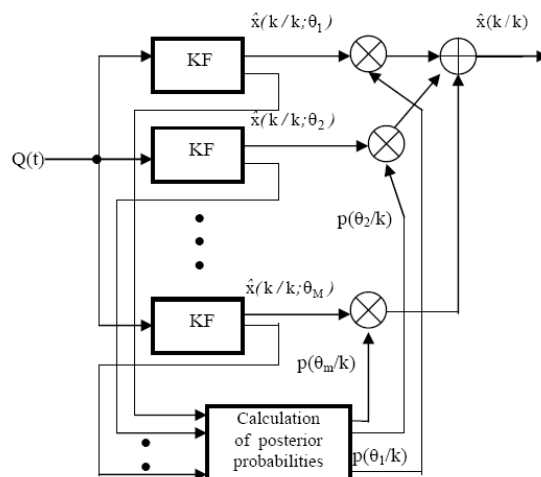


Figure 2. MPPF with ARMA block diagram. Each KF implements an ARMA model.

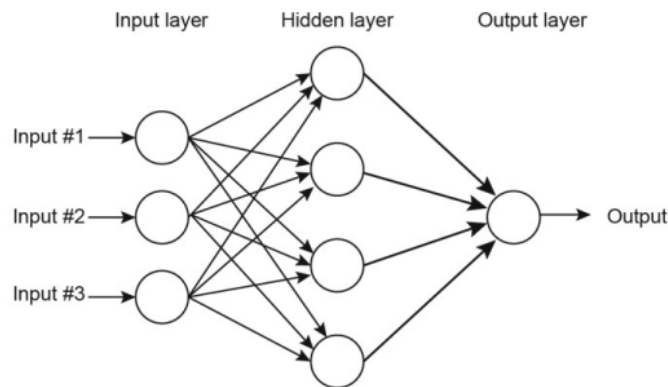


Figure 3. Structure of a three layer feedforward ANN.

Every neuron can be modelled as shown in Figure 4. Each input $x_1 \dots x_n$ is associated to an adjustable weight $w_1 \dots w_n$ respectively. These two values are multiplied together. Additionally a bias input b maybe added as well. The combined inputs are summed and fed into an activation function which is actually the output of each neuron.

$$y = k\left(\sum_{j=1}^n w_j x_j + b\right) \tag{5}$$

where k is a logarithmic sigmoid function, or a hyperbolic tangent sigmoid function, or a hard limit function [24, 25].

Table 1. ANN architecture.

Input Variables	Output Variables
Ambient Temperature T	Electricity Demand Load ED_L
Relative Humidity RH	
Day of the week WD	
Month of the year MY	
Contribution factor CF	

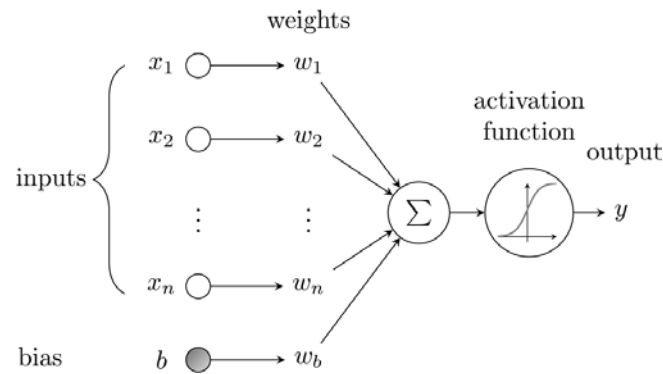


Figure 4. Structure of a three layer feedforward ANN.

The contribution factor CF is estimated based on real data provided by the Hellenic Ministry of Economic and Finance and includes economic and social factors such as gross national product, gross domestic product and population [26].

The design and training of the ANN is shown in Table 2.

Table 2. ANN design.

Structure	Learning Algorithm	Transfer Function
1 – 3 hidden layers	Gradient Descent	Hyperbolic Tangent Sigmoid
2 – 30 neurons in each hidden layer	Levenberg-Marquardt	Logarithmic Sigmoid
		Hard - Limit

The training of the ANN was done using the Matlab® neural network toolbox, and was accomplished using real data for all inputs and outputs covering the period from January 1st 2011 up to December 31st 2015. For every training iteration 20% random data was rejected and the process was repeated until the root mean square error between the actual and the desired output was not more than 1%, or until a maximum number of epochs were performed (in our case it was set to 10,000 which constitutes a standard training procedure) [24, 25].

3 Results

Figure 5 indicates the Hellenic power market daily system-wide load from January 1st 2014 to December 21st 2016. Annual and weekly seasonalities are apparent. Another obvious fact is that the consumption is progressively decreasing. This possibly reflects the low level of economic output and consumer confidence of the country [27].

3.1 Day-Ahead Load Prediction Using a Time Interval of Two Months

This application covers three different time periods. Period 1 covers from January 1st 2016 – February 29th 2016, period 2 covers from April 1st 2016 – May 31st 2016 and finally period 3 covers from August 1st 2016 – September 30th 2016. It must be noticed that the hybrid MMPF-SVM and ANN use the data presented in Figure 5, while the second method uses deseasonalized data as presented in [5]. Finally all three methods were trained using data up to December 31st 2015 and their performance was tested against new data covering the period of January 1st 2016 – December 31st 2016.

From Figures 7, 9 and 11 it is obvious that all three methods perform successfully since the corresponding relative percentage error has a largest value of three. However a closer look indicates that the hybrid method of MMF-SVM outperforms the other two techniques.

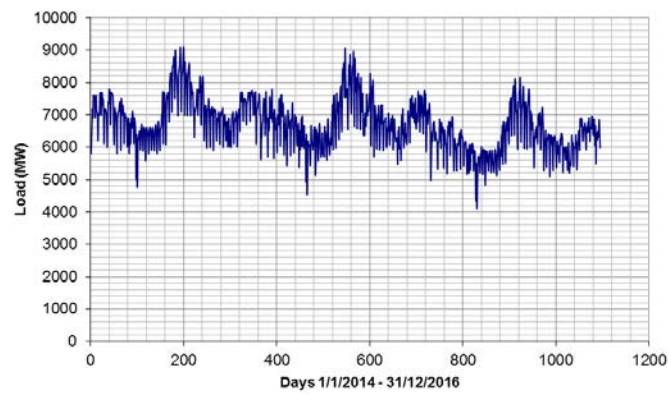


Figure 5. Hellenic market daily system-wide load from January 1st 2014 – December 31st 2016.

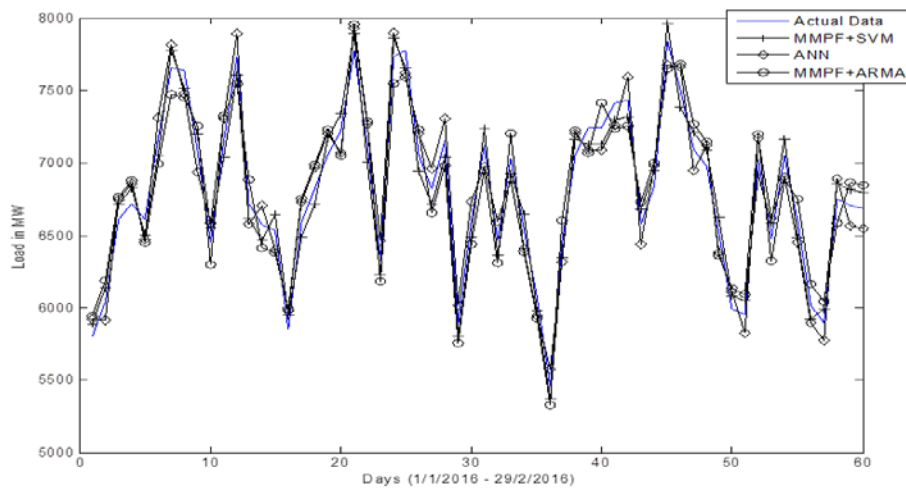


Figure 6. Hellenic market daily system-wide load from January 1st 2016 – February 29th 2016, compared with the three methods, day-ahead forecasts.

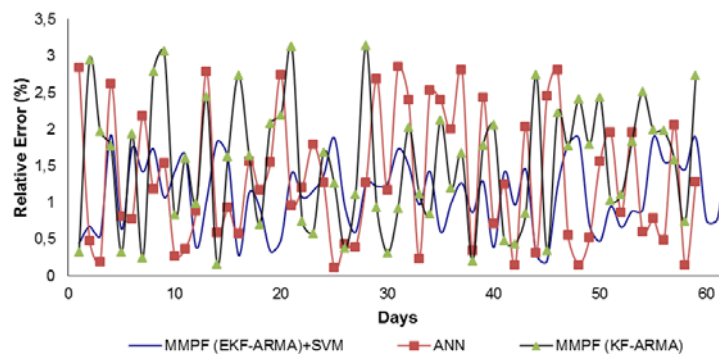


Figure 7. Propagation of relative percentage error for day ahead forecasts (January 1st 2016 – February 29th 2016).

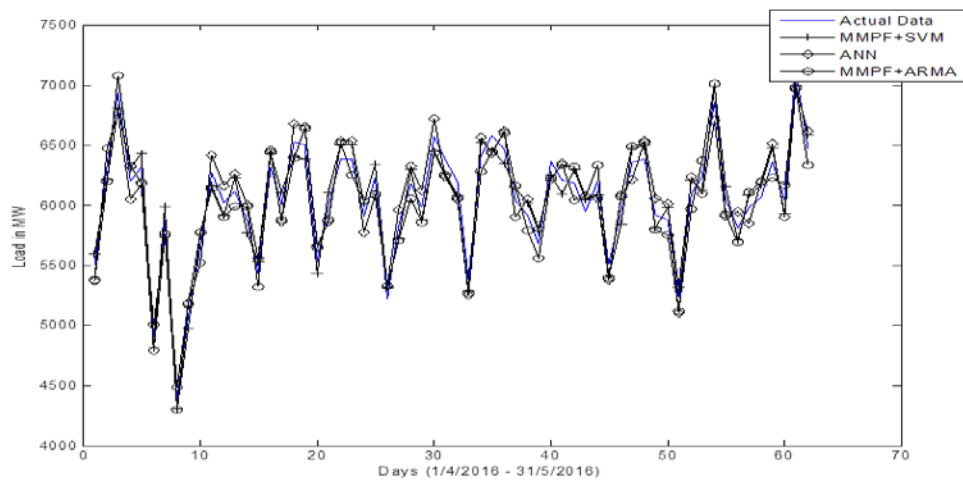


Figure 8. Hellenic market daily system-wide load from April 1st 2016 – May 31st 2016, compared with the three methods, day-ahead forecasts.

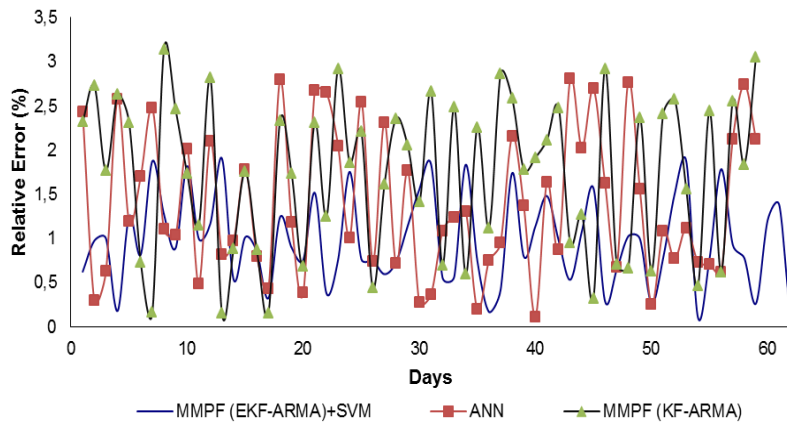


Figure 9. Propagation of relative percentage error for day ahead forecasts (April 1st 2016 – May 31st 2016).

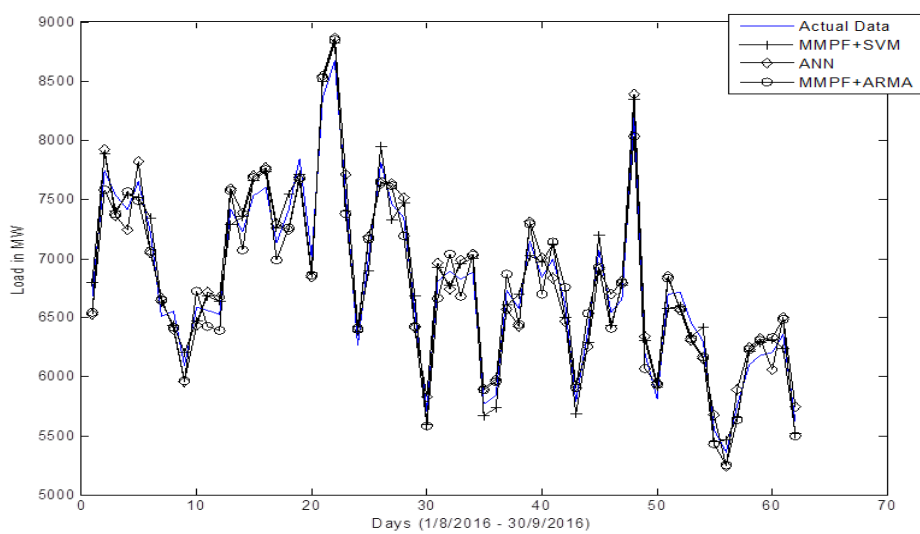


Figure 10. Hellenic market daily system-wide load from August 1st 2016 – September 30th 2016, compared with the three methods, day-ahead forecasts.

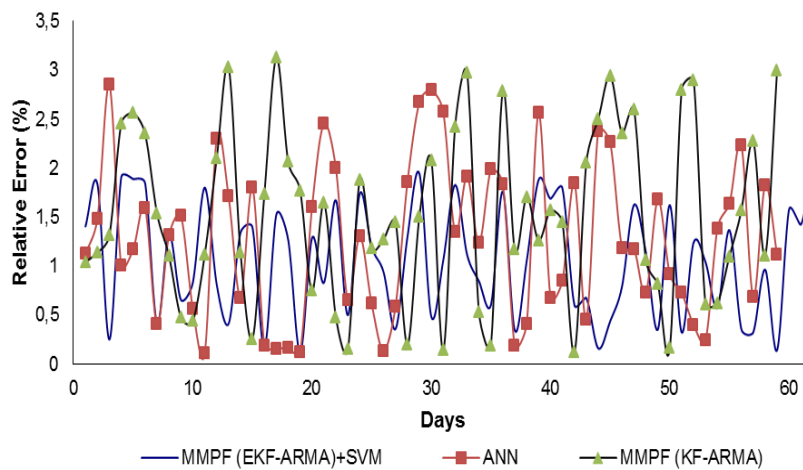


Figure 11. Hellenic market daily system-wide load from August 1st 2016 – September 30th 2016, compared with the three methods, day-ahead forecasts.

The relative percentage error in all cases was calculated as:

$$\left(\frac{|\text{Real Value} - \text{Predicted Value}|}{\text{Real Value}} \times 100\% \right) \tag{6}$$

3.2 Day-Ahead Load Prediction Using a Time Interval of One Week

This is a test case in order to evaluate whether or not the techniques are able in forecasting the day-ahead load accurately in a time interval of one week (short term forecasting). The data set under investigation is the electric load consumption from Monday July 4th 2016 up to Sunday July 10th 2016. Only MMPF (EKF-ARMA) and the ANN will be considered, since the MMPF (KF-ARMA) cannot be applied successfully in periodic data. A variation of the latter method using MMPF with KF and ARIMA models is suitable for such cases (with periodic data) and is analytically presented in [4].

This test is more challenging since both techniques should adopt the seasonalities contained in the data set much faster than in the two months period. Figures 12-15 depict that both methods perform satisfactorily in day-ahead forecasting over a time period of one week. The hybrid method MMPF (EKF-ARMA)-SVM, is however more accurate since its propagation of percentage error is always lower than the ANN's.

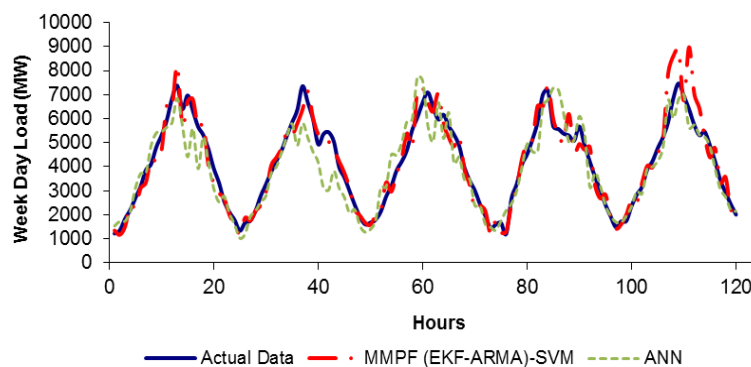


Figure 12. Hellenic market daily system-wide load from Monday July 4th 2016 up to Friday 8th 2016, compared with the MMPF (EKF-ARMA)-SVM and the ANN.

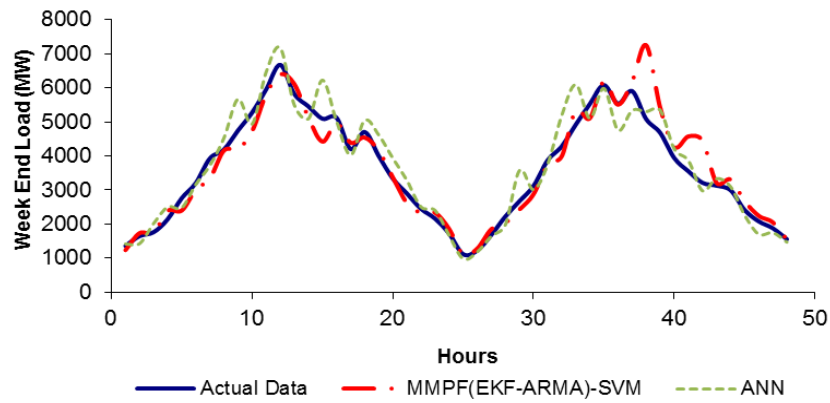


Figure 13. Hellenic market daily system-wide load from Saturday July 9th 2016 up to Sunday Friday 10th 2016, compared with the MMPF (EKF-ARMA)-SVM and the ANN.

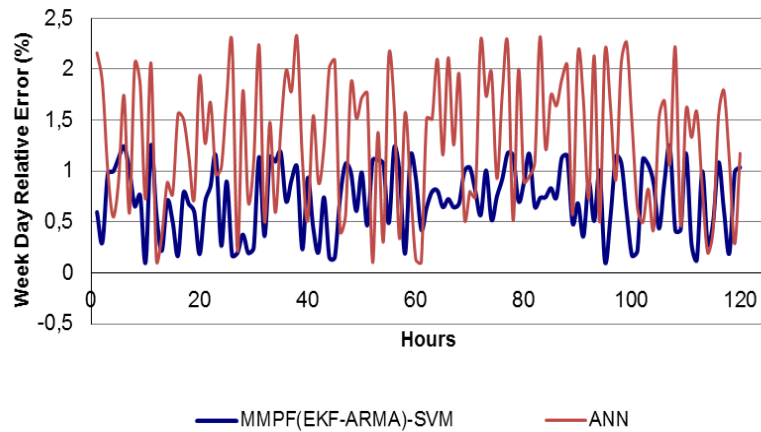


Figure 14. Propagation of relative percentage error for day ahead forecasts, using MMPF (EKF-ARMA)-SVM and the ANN (Monday July 4th 2016 up to Friday July 8th 2016).

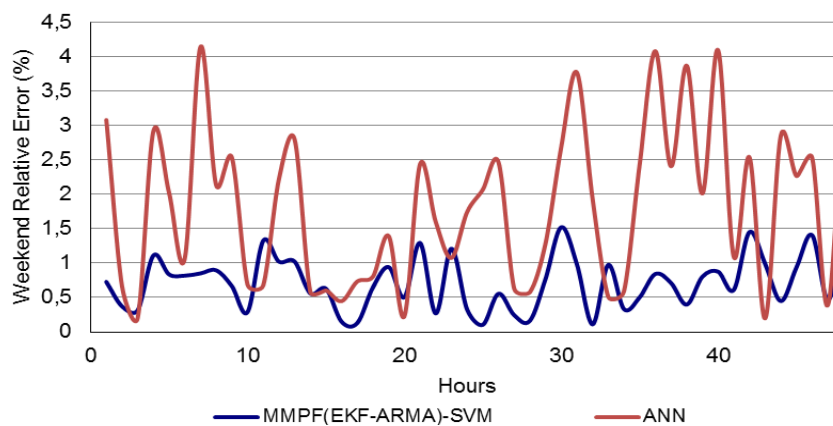


Figure 15. Propagation of relative percentage error for day ahead forecasts, using MMPF(EKF-ARMA)-SVM and the ANN (Saturday July 9th 2016 up to Sunday July 10th 2016).

3.3 Fault Detection

In order to test the efficiency of the two methods, namely MMPF (EKF-ARMA)-SVM and ANN, a test dataset is created from real cases as shown in Figure 16. The dataset represents 10 working days and two weekends. In this dataset were deliberately introduced two failures (blackouts) and two peaks (high load demands). A similar work with good results has been done in [5], where the MMPF was loaded with four SARIMA models, (each one modelling one of weekdays, weekends, failure and peak). The disadvantage of this method is that the models were determined off-line, while in our case the two techniques are adjusted to the data provided without any prior data manipulation.

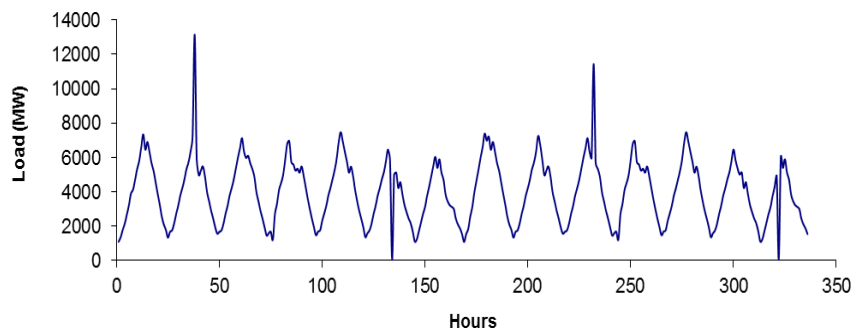


Figure 16. Test data set containing faults.

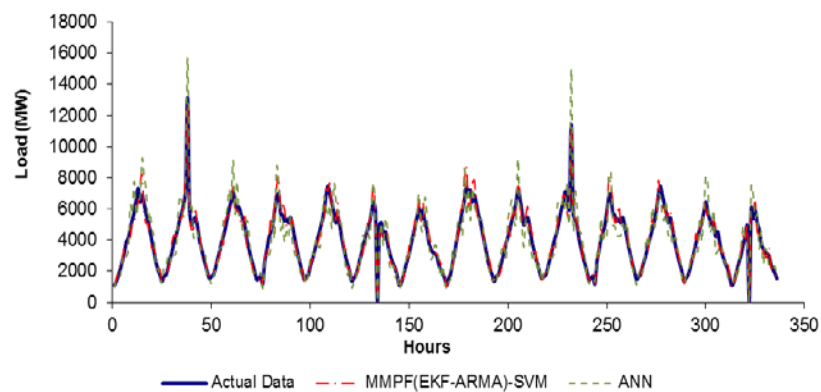


Figure 17. Test data set containing faults, compared with MMPF (EKF-ARMA)-SVM and the ANN.

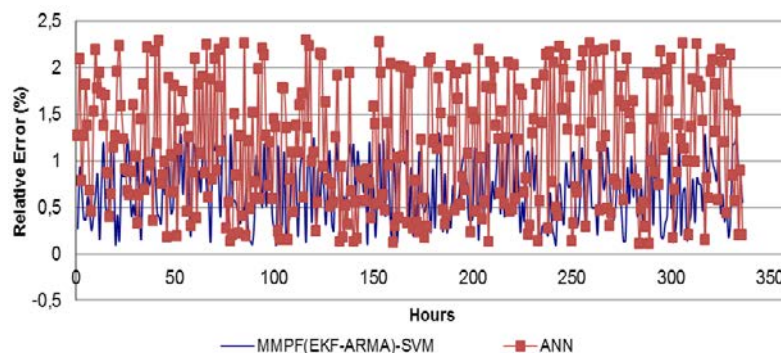


Figure 18. Propagation of relative percentage error using MMPF (EKF-ARMA)-SVM and the ANN.

Figure 17 indicates that the two methods under consideration detect successfully not only the changes from weekends to working days but also the faults (peak - high load demands and failures - blackouts) introduced equally well. Once more the hybrid method has constantly smaller percentage error than the ANN, as shown in Figure 18.

4 Discussion

Figures 6,8,10, concern the case of a midrange load forecasting and indicate that all three methods perform well and their predictions are very close to the real values since their percentage error is not greater than 3%. The same argument also holds for the day-ahead prediction using a time interval of a week as Figures 12 and 13 indicate.

A closer look at Figures 7, 9, 11, 14, and 15 indicates that the hybrid model of MMPF (EKF-ARMA)+SVM performs much better than the rest since it has the lowest percentage error. The actual reason is because although the MMPF is indeed adaptive has a main disadvantage which is that in its initial structure is not able to handle non-linearities and seasonalities. Its implementation with the EKF tackles the successfully non-linearity problem but not the second one. A solution to this comes with its combination with the SVM. The problem of complexity and computational burden is overcome since the separate EKF's can be parallel implemented, thus saving enormous computational time. A decision of how many EKF's have to be implemented needs to be taken. The more filters considered the greater the precision but also the greater the complexity, a fact that creates problems, especially if on-line prediction is required. Literature shows [2, 3, 22] that a maximum number of 10 parallel EKF's are adequate in producing a reliable and fast prediction.

For the sake of completeness of this research a fault detection scenario is designed. It contains two faults and two peaks in a time interval of 15 working days (Figure 16). Only the hybrid MMPF (EKF-ARMA)+SVM and the ANN were considered in this case. Both methods perform satisfactorily (Figure 17) but the hybrid one outperforms the ANN in terms of relative percentage error, since its maximum value is not greater than 1.5% (Figure 18).

5 Conclusions

The purpose of this work is to apply and compare the performance of adaptive methods into electric load demand forecasting. Real data supplied by the Hellenic Public Power Corporation S.A. [28] was used. All three methods performed satisfactorily but the hybrid method MMPF (EKF-ARMA)-SVM seem to outperform the rest two methods in terms of its percentage relative error. Additionally the hybrid MMPF (EKF-ARMA)-SVM and the ANN method doesn't need deseasonalizing, or prior manipulations of the dataset as was the case in [3-5] and can handle with accuracy any anomalies detected. The last feature is what makes both MMPF (EKF-ARMA)-SVM and ANN useful tools for system administrators, in the sense of uninterrupted energy supply.

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