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Adaptive load forecasting of the Hellenic electric grid

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Abstract: Designers are required to plan for future expansion and also to estimate the grid's future utilization. This means that an effective modeling and forecasting technique, which will use efficiently the information contained in the available data, is required, so that important data properties can be extracted and projected into the future. This study proposes an adaptive method based on the multi-model partitioning algorithm (MMPA), for short-term electricity load forecasting using real data. The grid's utilization is initially modeled using a multiplicative seasonal ARIMA (autoregressive integrated moving average) model. The proposed method uses past data to learn and model the normal periodic behavior of the electric grid. Either ARMA (autoregressive moving average) or state-space models can be used for the load pattern modeling. Load anomalies such as unexpected peaks that may appear during the summer or unexpected faults (blackouts) are also modeled. If the load pattern does not match the normal behavior of the load, an anomaly is detected and, furthermore, when the pattern matches a known case of anomaly, the type of anomaly is identified. Real data were used and real cases were tested based on the measurement loads of the Hellenic Public Power Cooperation S.A., Athens, Greece. The applied adaptive multi-model filtering algorithm identifies successfully both normal periodic behavior and any unusual activity of the electric grid. The performance of the proposed method is also compared to that produced by the ARIMA model.

Key words: Adaptive multi-model filtering, ARIMA, Load forecasting, Measurements, Kalman filter, Order selection, Seasonal variation, Parameter estimation

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INTRODUCTION

Accurate and fast forecasting of the electricity load is an important factor in various fields, ranging from power system real-time control, which ensures system safety, to reliable and economical operation. One day ahead load prediction and one week ahead load prediction, which are also referred to as short term predictions, are very useful in the preparation of the individual daily-schedule plan and weekly-schedule plan. This procedure includes the decision as to which units are going to contribute to the power generation, the coordination between hydroelectric power and electricity generated from any heat source, power interchange liaison, the economical distribution of load power, equipment inspection, etc. (Rajesh, 1997).

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 or ARIMA models (Nowicka-Zagrajek and Weron, 2002; Contreras *et al.*, 2003; Huang and Shih, 2003; Zhou *et al.*, 2004; Espinoza *et al.*, 2005; di Caprio *et al.*, 2006; Sisworahardjo *et al.*, 2006; Ediger and Akar, 2007). Other algorithms achieve load forecasting by adopting piecewise linear methods in order to relate the electricity load to weather variables (Haida and Muto, 1994; Charytoniuk *et al.*, 1999). Artificial neural networks (ANNs) have been extensively used either alone or combined with

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ARIMA models for the same purpose (AlFuhaid *et al.*, 1997; Darbellay and Slama, 2000; Lu *et al.*, 2004; Yap *et al.*, 2006; Pino *et al.*, 2008).

The aim of this paper is not to add yet another criterion for load forecasting to the rich literature in this area. Rather it focuses on applying the powerful adaptive multi-model partitioning algorithm (MMPA) (Lainiotis, 1971; 1976a; 1976b), known for its stability and well-established identification and modeling with respect to load forecasting, since it has never been tested before. The proposed method is not restricted to the Gaussian case; it is applicable to online/adaptive operation and is computationally efficient. Furthermore, as simulations will show, it is able to track any anomalies in the electric grid.

ARIMA AND STATE-SPACE ELECTRICITY LOAD MODELS

The electricity demand load demonstrates daily, weekly and even yearly periodicity. One method of modeling such behavior is to apply the seasonal ARIMA (SARIMA) time series model. The daily behavior is first classified into two categories: (1) the electricity load during normal working days and (2) the electricity load during weekends and holidays.

After several tests, a SARIMA model is derived that satisfies both categories. Provided that the past period data are from the same category as the forecasting period, the SARIMA $(1,1,1)\times(0,1,1)_{36}$ model predicts satisfactorily the future electricity load, as shown in Figs.1a and 1b.

Figs.2a and 2b show the relative error of the produced ARIMA model. Relative error (%)=|real value–predicted value|/real value×100. As shown, it ranges between acceptable values from 0.08% to 1.92% and always less than 2.5%, which is the recent standard. The average relative error for weekdays is 1.22% and for weekends is 1.80%. This difference is due to the fact that the load demand during weekends or holidays usually exhibits non-Gaussian characteristics (Fig.3) (Huang and Shih, 2003).

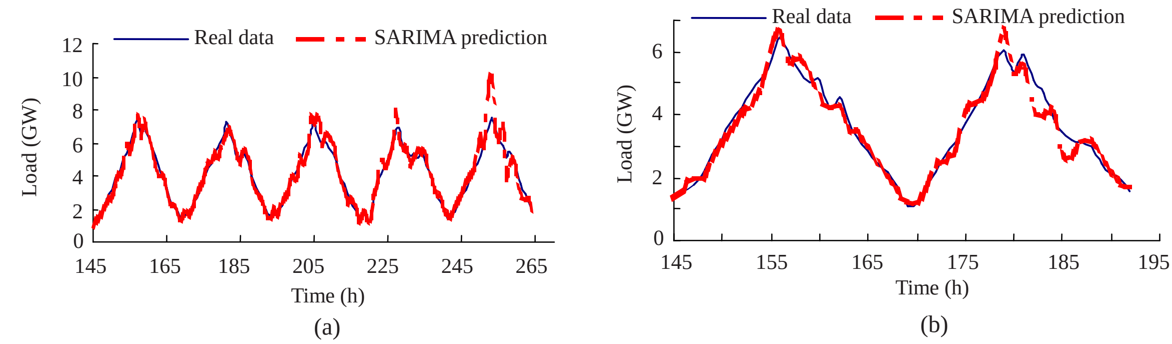

Fig.1 Weekday (a) and weekend (b) electricity load prediction using the SARIMA $(1,1,1)\times(0,1,1)_{36}$. Prediction starts at step 145. The previous period (109~145 h) is replaced by the average of all past periods (days) of the same type, i.e., (a) by weekdays and (b) by weekends. Real data (solid line) in (a) and (b) cover the periods between the 21st and 25th and between 26th and 27th, November 2005, respectively

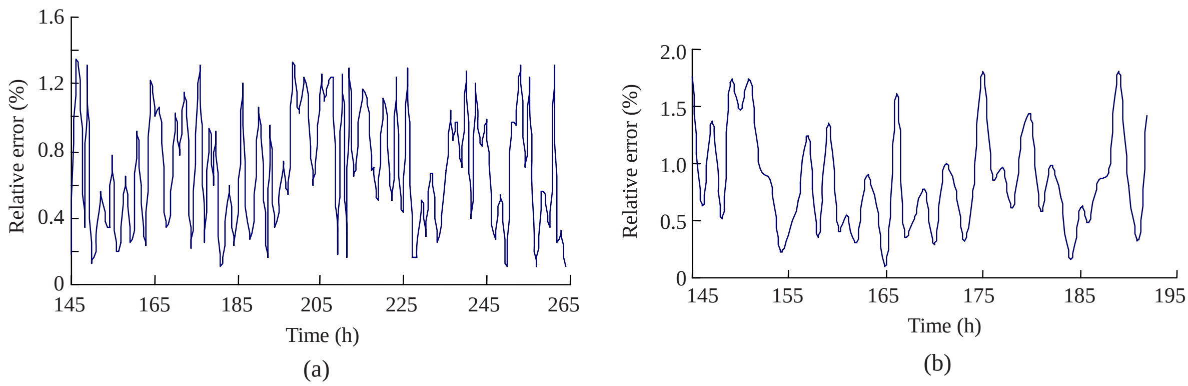

Fig.2 Relative error for weekday (a) and weekend (b) prediction

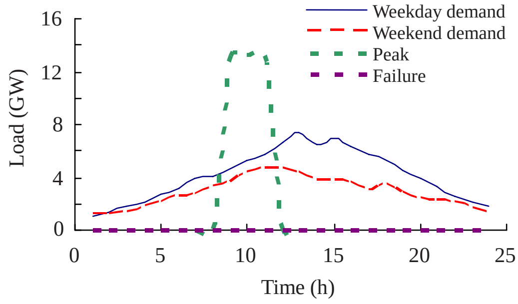

Fig.3 Sample electricity load sequence under different load demand conditions

Eq.(1) represents the above SARIMA model mathematically. The autoregressive (AR) and moving average (MA) parameters of the model are

$$\varphi_1=0.383\,027,\ \theta_1=0.895\,437,\ \Theta_1=0.929\,621,$$
$$\varphi(B)\nabla^1\nabla_{36}^1 X_k=\theta(B)\Theta(B^{36})u_k, \tag{1}$$

where $\varphi(B)=1-\varphi_1 B$, $\theta(B)=1-\theta_1 B$, $\Theta(B^{36})=1-\Theta_1 B^{36}$, and operators B and ∇ are defined as $B^s X_k=X_{k-s}$ and $\nabla_s{}^D=(1-B^s)^D$. Therefore the analytic expression for model Eq.(1) will be

$$\begin{aligned}&(1-\varphi_1 B)(1-B)(1-B^{36})X_k\\&\quad=(1-\theta_1 B)(1-\Theta_1 B^{36})u_k\\&\Rightarrow X_k-(1+\varphi_1)X_{k-1}+\varphi_1 X_{k-2}-X_{k-36}\\&\quad+(1+\varphi_1)X_{k-37}-\varphi_1 X_{k-38}\\&\quad=u_k-\theta_1 u_{k-1}-\Theta_1 u_{k-36}+\theta_1\Theta_1 u_{k-37}.\end{aligned} \tag{2}$$

In order to be compatible with the notation of the MMPA and Kalman algorithms (Anderson and Moore, 1979), model Eq.(2) can be rewritten in a state-space form. Based on the innovative representation of an ARMA process, an ARMA model of the type $z_k+a_1 z_{k-1}+\ldots+a_n z_{k-n}=b_0 u_k+b_1 u_{k-1}+\ldots+b_m u_{k-m}$ can be written in the following state-space form (Lainiotis and Papaparaskeva, 1998):

$$\boldsymbol{x}_{k+1}=\begin{bmatrix}-a_1 & \boldsymbol{I} & \cdots & \boldsymbol{0} & \boldsymbol{0}\\ -a_2 & \vdots & \ddots & \vdots & \vdots\\ \vdots & \vdots & \cdots & \boldsymbol{I} & \boldsymbol{0}\\ -a_{n-1} & \boldsymbol{0} & \cdots & \boldsymbol{0} & \boldsymbol{I}\\ -a_n & \boldsymbol{0} & \cdots & \boldsymbol{0} & \boldsymbol{0}\end{bmatrix}\boldsymbol{x}_k+\begin{bmatrix}b_1-a_1 b_0\\ b_2-a_2 b_0\\ \vdots\\ \vdots\\ \vdots\end{bmatrix}\boldsymbol{u}_k, \tag{3}$$
$$\boldsymbol{z}_k=\begin{bmatrix}\boldsymbol{I} & \boldsymbol{0} & \cdots & \boldsymbol{0} & \boldsymbol{0}\end{bmatrix}\boldsymbol{x}_k+b_0\boldsymbol{u}_k.$$

Apart from the normal periodic load, numerous other conditions also exist such as failures or unexpected load peaks. These events are not periodic and they occur at random instances and therefore the above seasonal models are not very helpful. Two such events are modeled in this study using state-space models, an unexpected rise (peak) in demand (not unusual in the summer) and a constant rate (i.e., failure). The corresponding state equations for these cases are

$$\boldsymbol{z}_k=\boldsymbol{x}_k+\boldsymbol{v}_k,\ \text{and}\ \boldsymbol{x}_{k+1}=1.8\boldsymbol{x}_k,\ \text{or}\ \boldsymbol{x}_{k+1}=\boldsymbol{x}_k\ \ (=\boldsymbol{0}). \tag{4}$$

MULTI-MODEL PARTITIONING ALGORITHM

It is clear that the correct model describing the electricity load at a certain period will be one of a family of models described by Eqs.(3) and (4). The problem is then to select the correct model n among various “candidate” models. By identifying the correct model, the type of electricity load, and consequently if it is normal behaviour or an electricity load anomaly, is identified.

The following approach has used a parallel bank of N Kalman filters, which operates concurrently on the same measurements (Fig.4). Each filter is based on one of the electricity load models of Eqs.(3) and (4). At time step k, each filter processes the measurement $\boldsymbol{z}_k$ and produces a state estimate $\boldsymbol{x}(k/k; n)$ of $\boldsymbol{x}_k$, conditioned on the hypothesis that the corresponding model is the correct one.

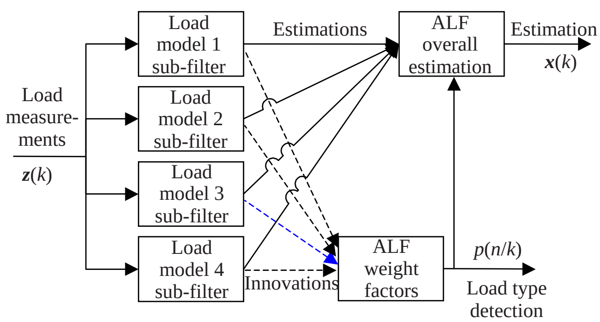

Fig.4 Structure of the multi-model partitioning algorithm for electric grid anomaly detection. ALF: adaptive Lainiotis filter

On a second level the MMPA uses the output of all filters to select the most likely model as being the one that maximizes *a posteriori* probability density $p(n/k)$. This density can be calculated recursively:

$$p(n/k)=\frac{L(k/k;n)}{\sum_{i=1}^{N}L(k/k;i)\cdot p(i/(k-1))}\cdot p(n/(k-1)), \quad (5)$$

where

$$L(k/k;n)=\left|P_{\tilde{z}}(k/(k-1);n)\right|^{-1/2} \cdot\exp\left[-\left\|\tilde{z}(k/(k-1);n)\right\|^{2}/2\cdot P_{\tilde{z}}^{-1}(k/(k-1);n)\right], \quad (6)$$

$\tilde{z}(k/(k-1);n)$ and $P_{\tilde{z}}(k/(k-1);n)$ are the conditional innovations and corresponding covariance matrices produced by the conditional Kalman filters.

At each iteration, the MMPA selects the model that corresponds to the maximum *a posteriori* probability as the correct one. This probability tends (asymptotically) to 1, while the remaining probabilities tend to 0. If the model changes, the algorithm senses the variation and increases the corresponding *a posteriori* probability, while decreasing the remaining ones. Thus the algorithm is adaptive in the sense of being able to track model changes in real time. This procedure incorporates the algorithm's intelligence.

The above MMPA was initially introduced by Lainiotis (1976a; 1976b). The algorithm possesses several interesting properties: (1) Its structure is a natural parallel distributed processing architecture and hence it is more suitable for current computer clusters; (2) By breaking a large and/or non-linear model to smaller sub-cases the algorithm has a much smaller dimensionality and hence much less architectural complexity; (3) Although computationally intensive, it works faster due to parallelism and hence it is much more appropriate for real-time applications; (4) It is more robust than any single filter as it is capable of isolating any diverging sub-filter [Numerous applications and simulations in the literature also show this (Lainiotis and Papaparaskeva, 1998; Nikitakos *et al.*, 1998; Katsikas *et al.*, 2001; Beligiannis *et al.*, 2004; Moussas *et al.*, 2005; Moussas and Pappas, 2005; Moussas and Katsikas, 2005; Pappas *et al.*, 2006)]; (5) The algorithm is well structured and modular, and it is easily implemented and can be modified to fit any standard programming environment (e.g., MATLAB).

DETECTION RESULTS USING REAL DATA

In order to test the efficiency of the MMPA method, real data based on actual measurements were supplied by the Hellenic Public Power Corporation S.A., Athens, Greece (PPC S.A., 2006). The test dataset is created from real cases, as shown in Fig.5. The dataset represents two weeks of load demand, i.e., 10 working days and two weekends. In this dataset two failures (blackouts) and two peaks (high load demands) are introduced.

The MMPA has four Kalman sub-filters that correspond to the four types of electricity load investigated. The *a posteriori* probability density $p(n/k)$ of each model is used to identify the type of the load demand. The model that maximizes this quantity is selected. If the selected model is also the correct daily pattern for that current day, then we have normal conditions; otherwise an anomaly is detected, as shown in Fig.6.

In Fig.7a the proposed method detects successfully both the changes from weekends to working days and vice versa. The method detects peaks (high load demands) and failures (i.e., blackouts) equally well. In addition to successful detection, the adaptive algorithm executes each iteration rapidly, thus permitting us to increase the sampling rate of the data collection. The default rate collects measurements over a one-hour period. The adjustment of the

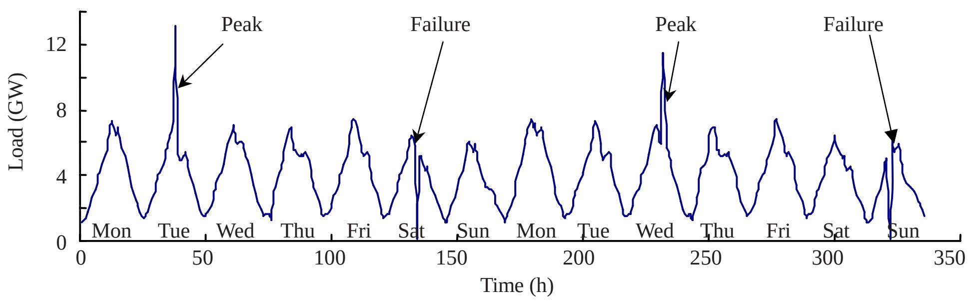

Fig.5 Test dataset for two weeks containing peaks and failures. Real data (i.e., the sample dataset without peaks or failures) cover the period between the 16th and 29th January 2006

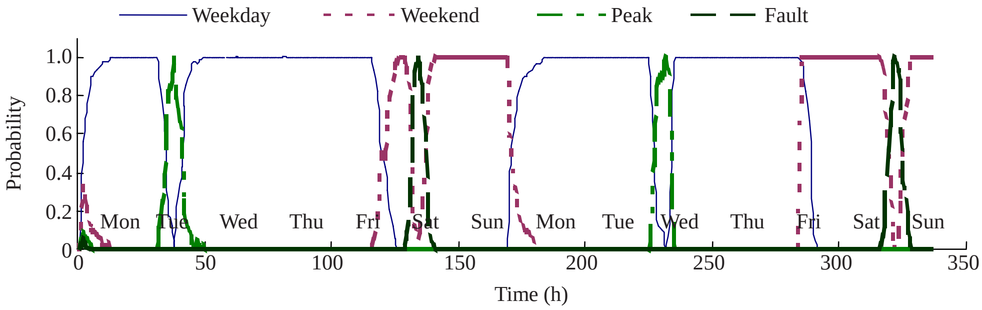

Fig.6 MMPA successful detection of the changes and anomalies in the test dataset

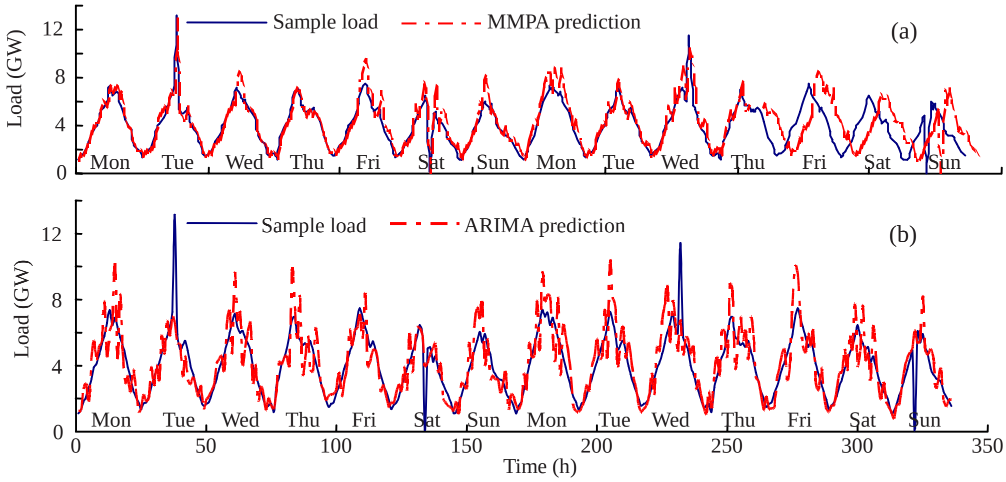

Fig.7 MMPA (a) and ARIMA (b) sample load prediction

sampling rate is essential for the online detection of electricity grid anomalies. The performance of the proposed method is evaluated in comparison with the produced ARIMA model.

Further work based on these results includes the minimization of the sampling interval, in order to obtain better reaction times and achieve an ultra-short load forecast, modeling more unusual activities or other grid problems.

RESULTS

Fig.6 depicts the posterior probabilities of the MMPA. The proposed algorithm successfully detects the changes between weekdays and weekends and the anomalies of the sample dataset, and rapidly increases the probability of the appropriate sub-filter to 1 while the rest tend to 0.

Also, from Fig.7a it is obvious that MMPA predicts the load demand and identifies the anomalies in a successful manner. Fig.7b shows that the produced ARIMA successfully identifies and forecasts the normal periodic load behavior but it is not as capable of forecasting sudden anomalies.

Figs.8a and 8b depict the sequence of the relative error for each one of the above-mentioned methods. The average error falls inside the current industrial upper limit, which is 2.5%. Table 1 summarizes the results as far as the error is concerned. The best results are indicated in bold.

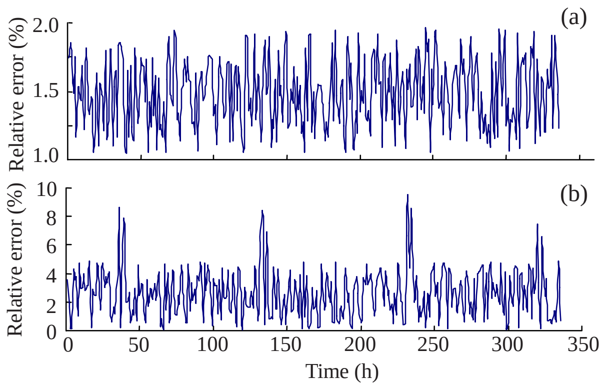

Fig.8 MMPA (a) and ARIMA (b) relative error for the two weeks' sample period

Table 1 shows that MMPA is successful in achieving good performance. The higher relative error of MMPA occurs during the weekend because the load characteristics are non-Gaussian (Huang and Shih, 2003). To be more specific, the maximum error occurred on Sunday 29th of January, the last day of the sample dataset, where a fault occurred.

Table 1 Relative forecast error for the two weeks' sample data

Method	Relative error (%)		
	Max	Min	Average
MMPA	**1.986**	**0.106**	**1.020**
ARIMA	9.132	**0.106**	2.680

The best results are indicated in bold

CONCLUSION

Effective short term load forecasting in power systems and efficient modeling are certainly complex tasks since they are affected by multiple seasonal and calendar effects, high volatility, etc. In this study a part of the real measured data supplied by the Hellenic Public Power Corporation S.A., Athens, Greece was used to produce an ARIMA that would be a successful representation. This data was altered by the addition of two peaks (high load demand) and two failures (blackouts). The produced sample dataset was used by the MMPA and the produced ARIMA model in order to test each method's performance under normal periodic load behaviour and during sudden, unexpected anomalies.

The proposed algorithm MMPA is shown to tackle successfully the problem, exhibiting low average errors, even at weekends where the load presents non-Gaussian behavior, forecasting the load demand quite accurately, and identifying very quickly any anomalies present. The performance of ARIMA is acceptable when the load demand behaviour is the normal periodic one but ARIMA was not able to perform equally well when anomalies are present. The current study can be useful in calculations that concern electricity consumption and electricity price forecasts, giving the possibility to electricity providers, retailers and regulatory authorities to supply uninterrupted energy at low cost.

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