Field Programmable Gate Array based Smart System for Short Term Electric Load Forecasting and Load Scheduling for Smart Grid Applications

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***Abstract*-The paper proposes Field Programmable Gate Array (FPGA) implementation of a novel algorithm for short term electric load estimation and hardware implementation of load scheduling algorithm from the dataset generated by load estimation algorithm. The algorithm proposed in this paper uses load consumption and temperature of previous few days as parameters for estimation and this forecasted data is used for scheduling purpose. The information of load consumption can be obtained from smart meters already installed in smart grid. Estimation is done separately for Weekdays & Weekends/Public Holidays. The approach proposed applies all these parameters as coefficients for Kalman Filter algorithm to estimate hourly loads. Using the proposed algorithm the load was estimated with absolute mean percentage error of as low as 1%, which is better than using Artificial Neural Network technique where the absolute mean percentage error has been found to be around 2.2%, and the algorithm for load scheduling has been successfully implemented on the logic of FPGA.**

Keywords: Load Forecasting; Load Scheduling; Kalman Filter; Mean Absolute Percentage Error (MAPE); Smart Grid; FPGA

I. INTRODUCTION

Load forecasting refers to prediction of the load that will be consumed by the consumer. With accurate forecasting, the amount of power loss is reduced as the amount of power required is already estimated, hence not only the efficient power generation but also efficient load scheduling can take place [1]. Recently, a lot of emphasis is being given on efficient power transmission to each household. Smart grids are being set up in various countries across the globe, using which power can be efficiently and reliably generated, transmitted and consumed over conventional electricity systems [2 - 4]. With the smart grid, by combining the electricity grid with the communication network, a dumb grid becomes smart by sensing, communicating, exercising control and continually adjusting through feedback [5]. The current work targets one of the major aspects of smart grid, electric load forecasting and load scheduling. The smart grid is supposed to be equipped with smart devices and meters that provide the power consumption data of the current hour for a particular region/section [6-8], and this data is accumulated from the entire devices and meters then recorded on a centralized server. In addition to this, temperature values can also be obtained from weather department of that particular geographical region. With the knowledge of the mentioned parameters the power consumption electric load can be predicted quite accurately for the next hour. Once the power consumption data is predicted with a good efficiency, the load scheduling is performed with minimum switching between various load units with low switching power loss.

The paper proposes an efficient load forecasting algorithm with simulations and results separately for weekdays and weekend/holidays along with the FPGA implementation of scheduler for load scheduling based on the outcomes of load forecasting algorithm.

II. LOAD FORECASTING ALGORITHM

The main parameters involved in load forecasting are

- Electric power consumption over past few days,
- Temperature (Maximum, Average and Minimum values), and
- Whether the day is a holiday or not.

These parameters are applied as input parameters in Kalman Filter algorithm to provide the short-term estimation of power consumption. The criteria for selection of parameters are mentioned and provided in the following sub-section.

A. Selection of Parameters

The current section focuses on the selection of parameters needed for load forecasting. The load has been forecasted based on previous power consumption dataset, effect of temperature of surroundings and the type of the day (i.e. holiday or working day) [9].

1) Previous Power Consumption Dataset:

The peak power consumption comes at almost same time daily [10]. Meanwhile, it can be seen from the graph that minimums also occur at almost same time daily. This paper uses both temporal and spatial approach to select the parameters. The power consumption of current hour depends on the power consumption of the same hour yesterday, the day before yesterday and so on. However, effects due to days earlier than the day before yesterday are neglected as seen in Fig. 1. This completes our temporal approach for selection. In addition, the power consumption of the current hour depends on the power consumption of the previous hour, the previous hour to the same hour yesterday, the next hour to the same hour yesterday and similarly for the day before yesterday. This completes our spatial selection process.

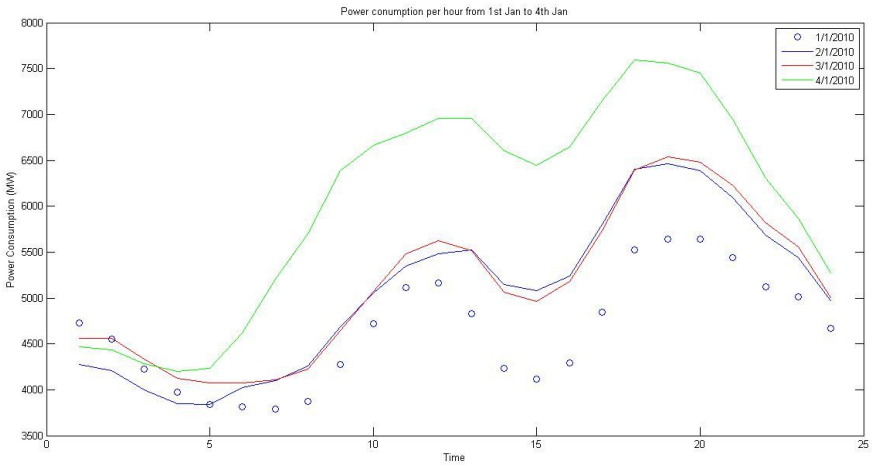

Fig. 1 (a) Power consumption for 1st – 4th Jan 2010 vs Time (01:00 hours to 24:00 hours)

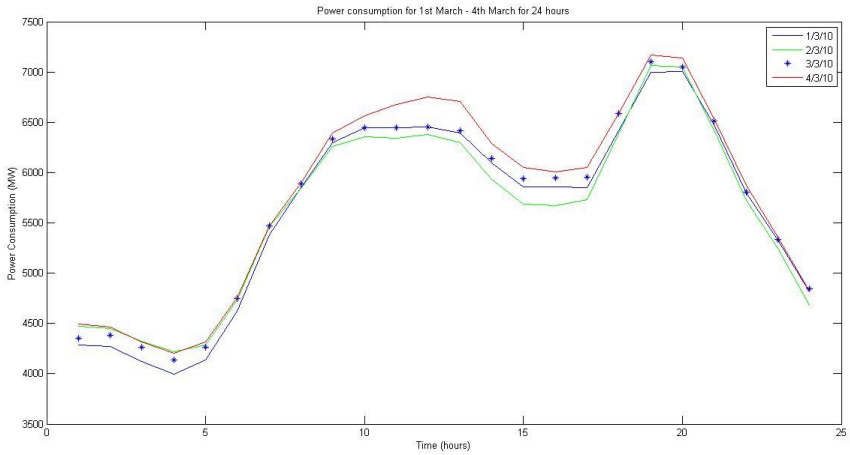

Fig. 1 (b) Power consumption for 1st – 4th March 2010 vs Time (01:00 hours to 24:00 hours)

2) Temperature:

According to Fig. 2 and Fig. 3, it is observed that the power consumption is more when temperature is lower or higher than a specific range, and less when temperature is within the certain range [11]. The approach proposed uses the average, maximum and minimum values of the temperature of the respective day till this hour for estimation. It is observed that with the decrease in temperature in January 2010, the power consumption increases which is visible, from 1st Jan to 5th Jan. Maximum power consumption is seen on 25th January for that month when temperature is minimal. When average temperature is between 120C & 300C, the power consumption is considerably low. If the average temperature is above 300C, it is observed that the total consumption increases again.

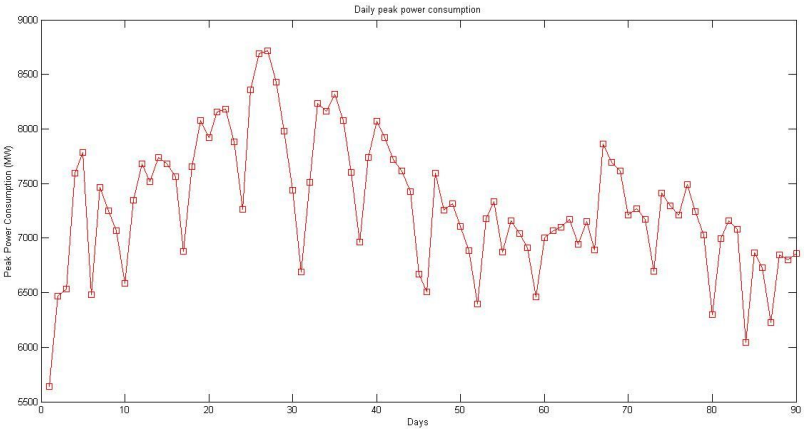

Fig. 2 Daily power consumption Jan 2010 to March 2010

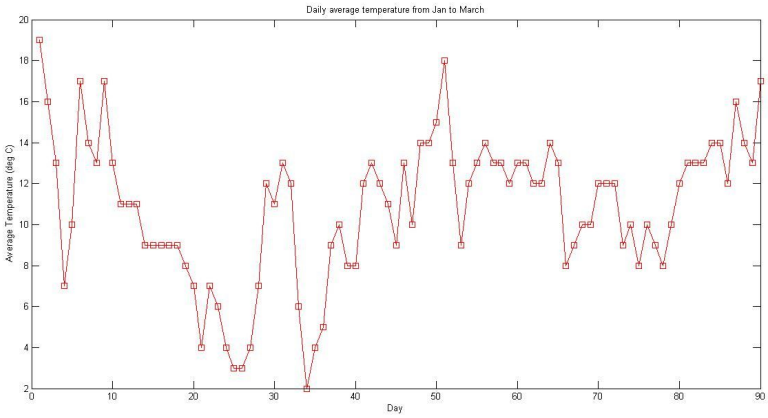

Fig 3 Daily average temperatures Jan 2010 to March 2010

3) Type of Day (Working day / Holiday):

According to the Fig. 4, it can be observed that power consumption is considerably less on Sundays and public Holidays.

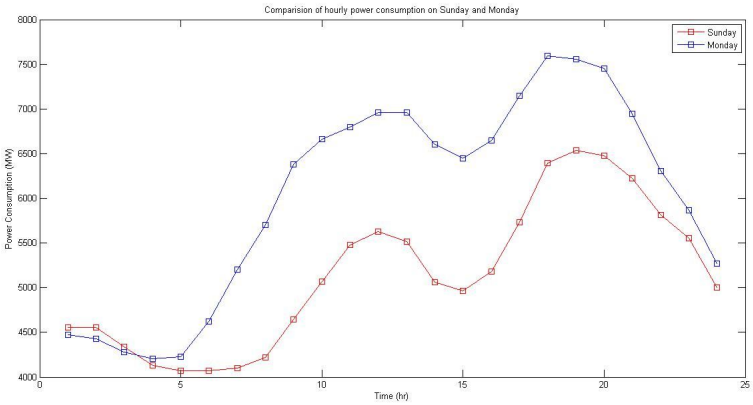

Fig. 4 Comparison of power consumption on any given Sunday vs. Monday

The current approach involves estimation of coefficients that are to be fed in the Kalman filter to get the final output.

B. Kalman Filter

Kalman filter operates on estimating states by using recursive time and measurement updates over time. Noise effect in the system is decreased due to recursive cycles that are expected to lead to true value of measurement. The Kalman filter algorithm is divided into two sections - time update, also referred to as prediction state, and measurement update, also referred to as correction state [12].

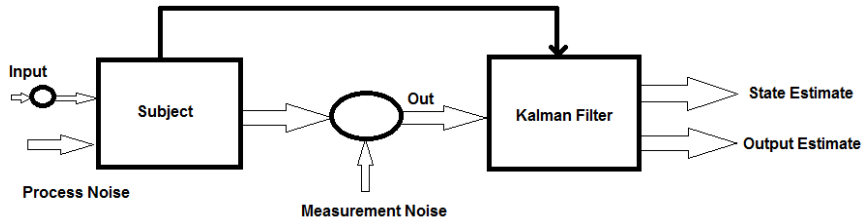

Fig. 5 Block diagram showing functioning of Kalman filter

Let us assume that input is xt at iteration t, control process is ut at iteration t, wis the process noise and v is the measurement noise [13]. The noise sources are assumed to be uncorrelated with each other with normal probability distribution. The Kalman filter equations are given by time update also known as prediction state and measurement update also known as correction state.

1) Time Update – (Prediction state):

$$\hat{x}_t^- = A\hat{x}_{t-1}^- + Bu_{t-1} \tag{1}$$

$$\hat{x}_t^- = A\hat{x}_{t-1}^- + Bu_{t-1} \tag{2}$$

In Equations (1) and (2), Q is the process noise covariance, i.e. p (w) ~ N (0, Q), the process noise p(w) is assumed to be normally distributed with mean 0 and variance Q; $\hat{x}_t$ is the state estimate at iteration t given by the results from former iterations; $\hat{x}_{t-1}$ is the state estimate at iteration t given by measurement yt (where yt = C xt + vt); Pt- is the a priori error covariance and Pt is the a posteriori error covariance.

2) Measurement Update – (Correction State):

$$K_t = P_t^- C^T (CP_t^- C^T + R)^{-1} \tag{3}$$

$$\hat{x}_t = \hat{x}_t^- + K_t(y_t - C\hat{x}_t^-) \tag{4}$$

$$P_t = (I - K_t C)\, P_t^-; \tag{6}$$

In the above equations, R is the measurement noise covariance, i.e. p (v) ~ N (0, R) and Kt is the Kalman gain. The above equations represent Kalman filter implementation for a generic linear discrete system. The time update predicts forward state estimate and error covariance. The estimates are then put into measurement update, which acts as correction mechanism and corrects the estimated values. As the above cycle takes place multiple times turn by turn, the noises are reduced and the error covariance Pt becomes closer and closer to zero.

C. Electric Load Forecasting Using Kalman Filter

One of the most important tasks in forecasting load demand is to develop an appropriate load model because it determines the prediction accuracy [14]. For implementing the Kalman Filter algorithm the inputs should be defined initially. For simplicity A & B constants are assumed to be unity. C is defined from the parameters selected in section 2. C is a 1 X 10 matrix to estimate all 10 coefficients which will serve as $\hat{x}_t$ for iteration t [15].

C = [C1 C2 C3 C4 C5 C6 C7 C8 C9 C10],

where C2 and C5 are selected temporally and C1, C3, C4, C6 and C7 are selected in space near those temporal parameters and hence can also be referred to as spatial parameters. The significance of coefficients C1, C2, …, C10 are described below.

C1 = Actual value of the previous hour consumption.
C2 = Actual value of the power consumption 24 hour ago.
C3 = Actual value of the power consumption 23 hour ago.
C4 = Actual value of the power consumption 25 hour ago.
C5 = Actual value of power consumption 48 hour ago.
C6 = Actual value of power consumption 47 hour ago.
C7 = Actual value of power consumption 49 hour ago.
C8 = Minimum value of temperature throughout this day till now.
C9 = Average temperature of this day throughout till now.
C10 = Maximum temperature of this day throughout till now.

$\hat{x}_t$ is a 10 X 1 matrix, with coefficients corresponding to these parameters.

$\hat{x}_t$ = [a1 a2 a3 a4 a5 a6 a7 a8 a9 a10]^T.

Pt is the error covariance and is given as (C*R*CT)-1, where R is given as difference between actual value yt and C* $\hat{x}_t$, and Q is the process noise in this case and follows a pattern similar to Gaussian curve. Initially, training of coefficients a1, a2, …, a10 takes place. For every hour of the day, a1,…a10 are plugged in as unknowns and multiplied along with the coefficients C1,…, C10 for that hour and equated to the actual power consumption for the same hour. This is done for the same hour of previous 10 days which gives 10 equations and 10 unknowns, and solving them gives us the values of all these 10 coefficients. These coefficients for one particular hour constitute the input $\hat{x}_t$ of the Kalman filter for that hour. The same is done repeatedly for 24 hours to get the coefficients value. Thus, for each day these values are again found out and process proceeds. After finding out $\hat{x}_t$ the value is plugged in to get R and Pt and thus correspondingly values are plugged in Equations (1) to (5) and iterated till Pt reaches close to zero.

III. LOAD SCHEDULING ALGORITHM

According to the previous section, efficient load forecasting is performed and a dataset is generated for the predicted load. Once the load is predicted, the scheduling technique is applied to effectively perform the load scheduling.

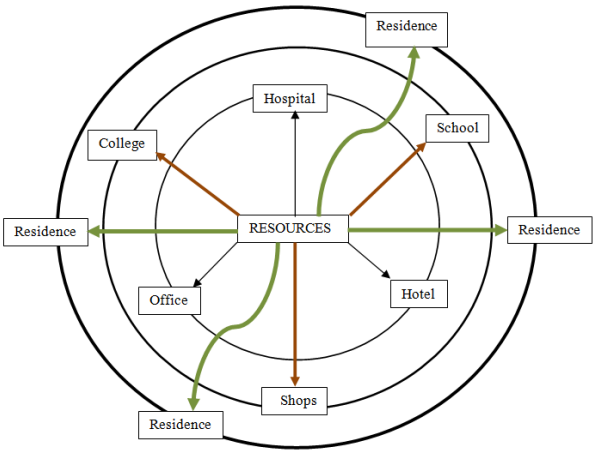

Fig. 6 Load segments distribution according to various categories and their alignment with respect to Resources

There are seven load segments, which are further classified into priority-based categories. The loads are arranged according to their priorities. The highest priority is given to hospitals, offices and hotels/hostels. The second in priority are schools, colleges and shops. The third/least priority is give to residences. The priority is defined according to the harmful effect it might cause in case no electric power is supplied to that load section.

According to the diagram, ospitals, Hotels and Offices come under Category 1 with the highest priority. Schools, Colleges and Shops come under Category 2 while Residences come under Category 3, i.e. with the lowest priority. Power consumption for each hour from various consumers is aggregated in their corresponding load segment, which is further classified based on their categories. The resource will be considered at the center of 3 concentric circles, each circle is made of several points with the same priority, i.e. all the loads that belong to the same category belong to the same circle. Any further load addition will be in any of these 3 categories on the corresponding circle. The circle for category 1, i.e. the one closest to the resource, will lie at a radius of unit distance, the second circle lies at a radius of 2 unit distance while the 3rd circle lies at the radius of 3 unit distance. Any further addition to resource will be added to a centralized resource section and the combined resource will be used to satisfy requests of various categories of loads.

If load from category 1 makes a request, the request will initially go to the resource, if the resource is unable to satisfy the complete requirement, then other resource available will fulfill that requirement, and the remaining request will go through resource to category 3. Now gradual degradation takes place at that category. If category 3 is able to fulfill the requirement, then that amount of load will be allotted directly from there, otherwise that amount will be allotted by category 3 and the remaining requirement will be taken from category 2.

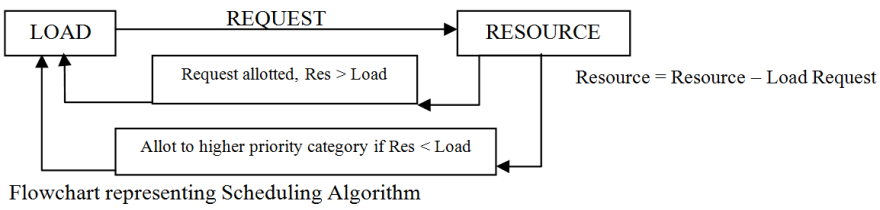

Fig. 7 Flowchart representing Load Scheduling Algorithm

For example, if the total resource available is 5 MW for t instance and the load requirement is 6 MW, also let the load be hospital (requirement 1 MW), school (requirement 1 MW), offices (1 MW) and residences (requirement 3 MW for 3000 houses), then 1st load requirement from category 1, i.e. hospitals and offices, will be calculated, which comes out to be 2 MW < 5 MW (available resource), and 2 MW will be allotted directly, the remaining resource (3 MW) will now be compared with the remaining load (4 MW). Now, school comes under higher category, hence 1 MW will be directly allotted to the school and the remaining 2 MW will be divided to 3000 houses as such each house gets electricity for 2/3 t instant of time causing power cut for t/3 instant of time. Moreover, if some additional load is added of higher category then power will be taken from lower category but if some load is removed then the power will first be provided to highest category and gradually passed to lower category in a round robin fashion.

IV. SIMULATIONS AND RESULTS

Simulation studies were performed in MATLAB using the data from ENTSO-E, Greece for the year 2010. Weekday and Weekend simulations were performed separately.

Power was calculated using the electric load consumption data as shown in section 2.3 and estimated coefficients using the algorithm.

$$\text{Power} = [C1\ C2\ C3\ C4\ C5\ C6\ C7\ C8\ C9\ C10]\ X\ [a1\ a2\ a3\ a4\ a5\ a6\ a7\ a8\ a9\ a10]^T. \quad (6)$$

A. Simulation for Weekdays

Figure 8 below shows the actual vs. estimated power consumption for the last Wednesday of all the 12 months or the year.

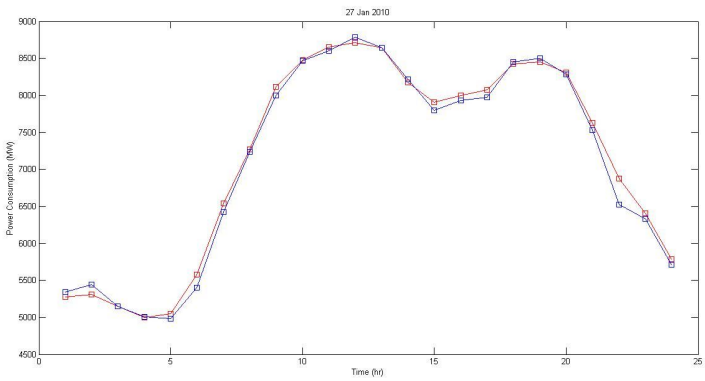

Fig. 8 (a) Actual vs. Estimated consumption for the last Wednesday of Jan 2010

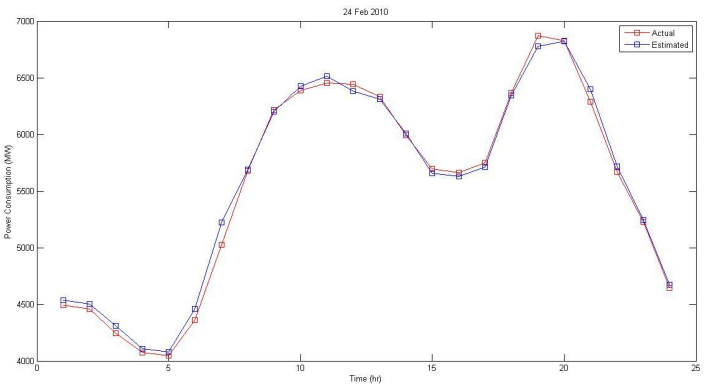

Fig. 8 (b) Actual vs. Estimated consumption for the last Wednesday of Feb 2010

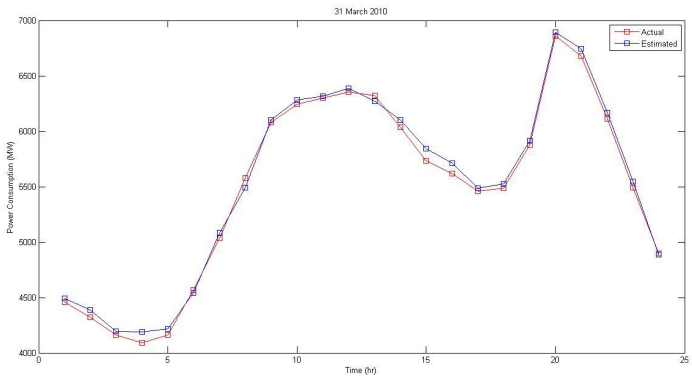

Fig. 8 (c) Actual vs. Estimated consumption for the last Wednesday of March 2010

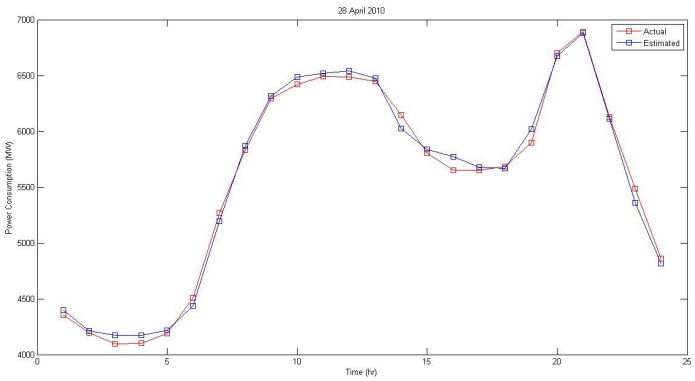

Fig. 8 (d) Actual vs. Estimated consumption for the last Wednesday of April 2010

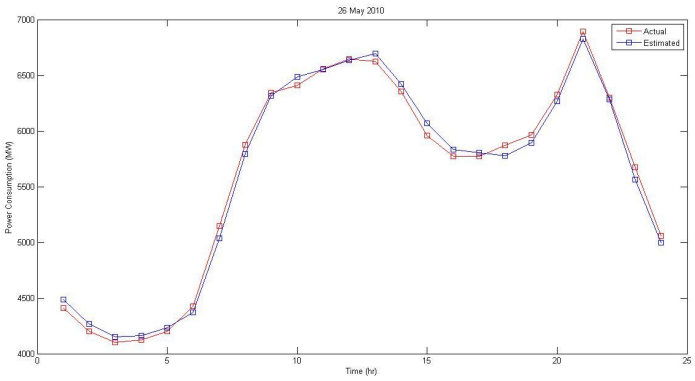

Fig. 8 (e) Actual vs. Estimated consumption for the last Wednesday of May 2010

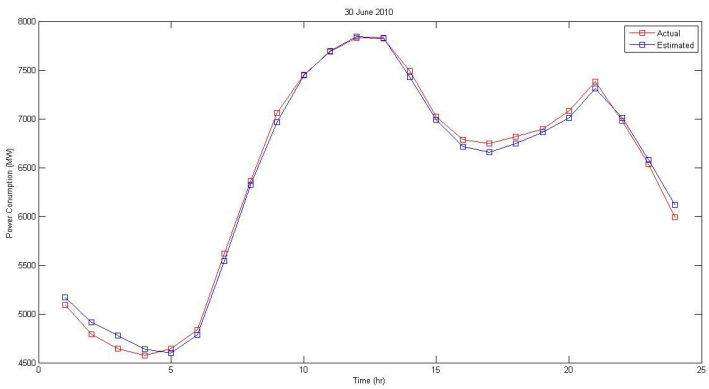

Fig. 8 (f) Actual vs. Estimated consumption for the last Wednesday of June 2010

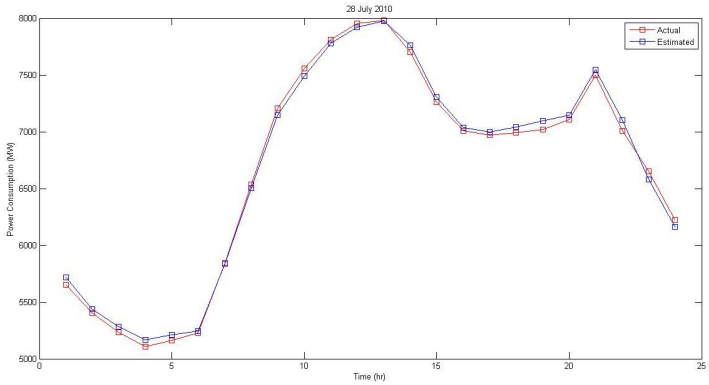

Fig. 8 (g) Actual vs. Estimated consumption for the last Wednesday of July 2010

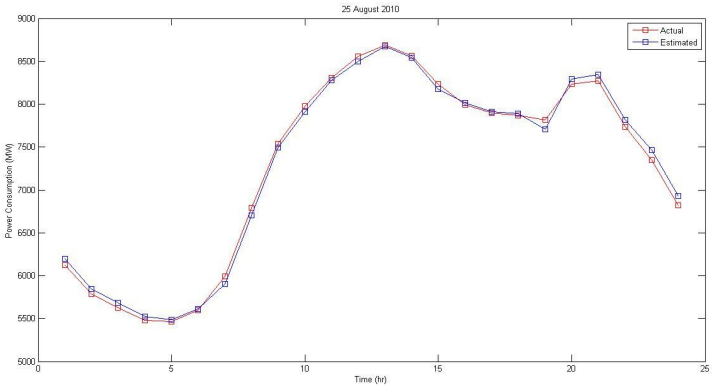

Fig. 8 (h) Actual vsEstimated consumption for last Wednesday of August 2010

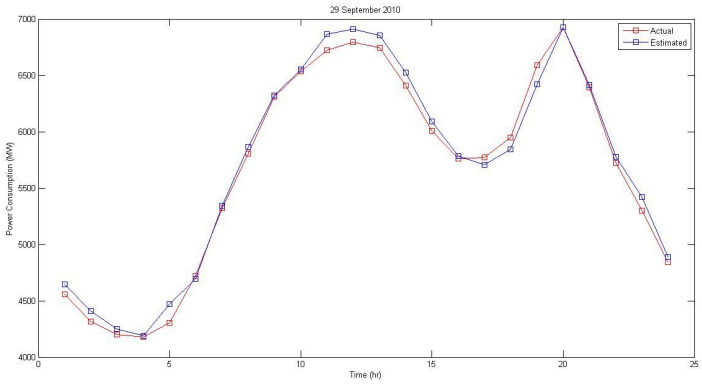

Fig. 8 (i) Actual vs. Estimated consumption for the last Wednesday of September 2010

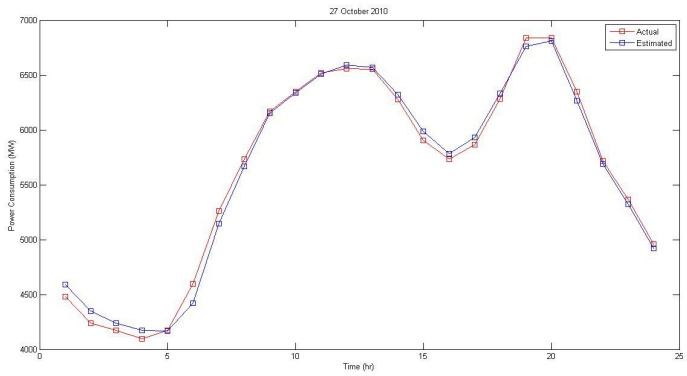

Fig. 8 (j) Actual vs. Estimated consumption for the last Wednesday of October 2010

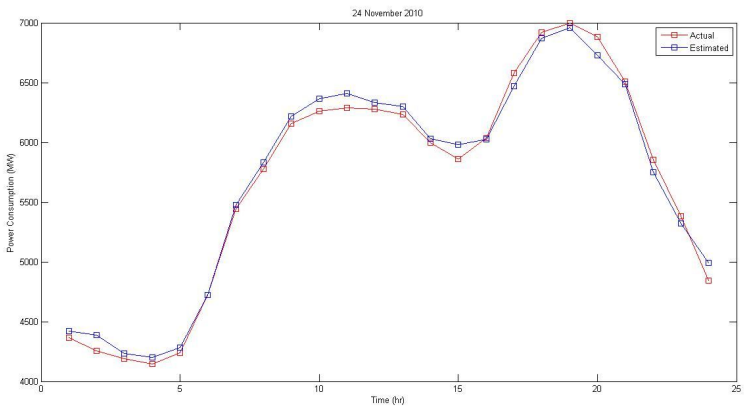

Fig. 8 (k) Actual vs. Estimated consumption for the last Wednesday of November 2010

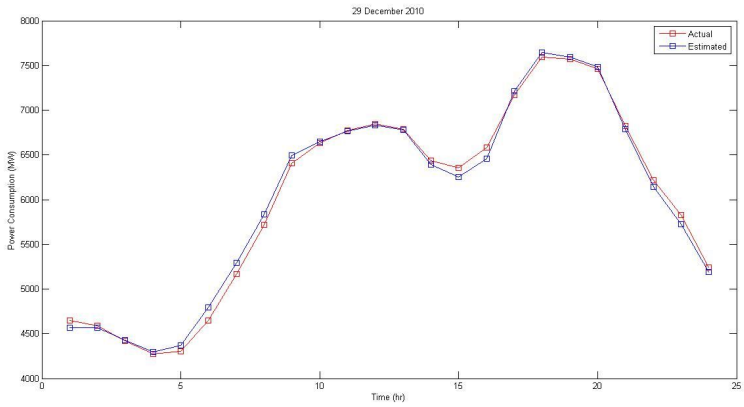

Fig. 8 (l) Actual vs. Estimated consumption for the last Wednesday of December 2010

Mean Absolute Percentage Error (MAPE/M) [16] is the measure of accuracy of a method for constructing fitted time series values. If At is the actual value, Ft is the forecast value and n is the number of samples considered, then M is defined by the formula:

$$M = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t} \tag{7}$$

Using the error percentage between actual and estimated values of power consumption, Mean Absolute Percentage Error (MAPE) is also shown for the last Wednesday of every month in 2010 in Fig 13. Figure 9 below compares the actual vs. estimated load for weekdays. Figure 13 represents the Mean Absolute Percentage Error for the last Wednesday of every month and Figure 14 represents that for weekdays.

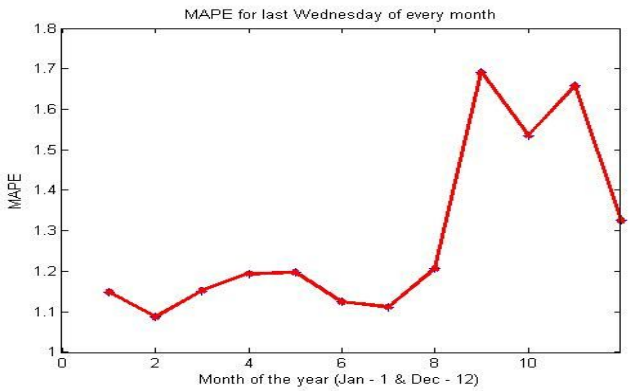

Fig. 13 MAPE for Last Wednesdays (every month)

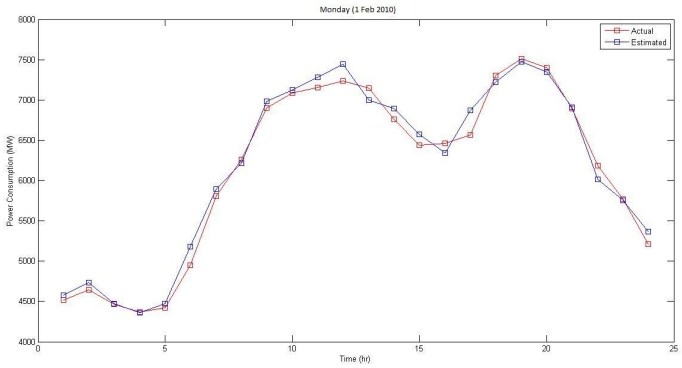

Fig. 9 (A) Actual Load vs. Estimated Load for Mondays

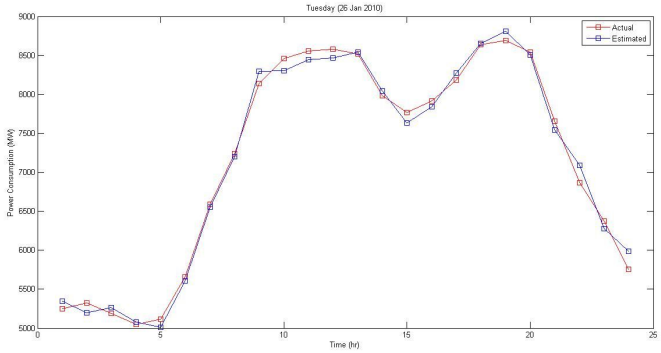

Fig. 9 (B) Actual Load vs .Estimated Load for Tuesdays

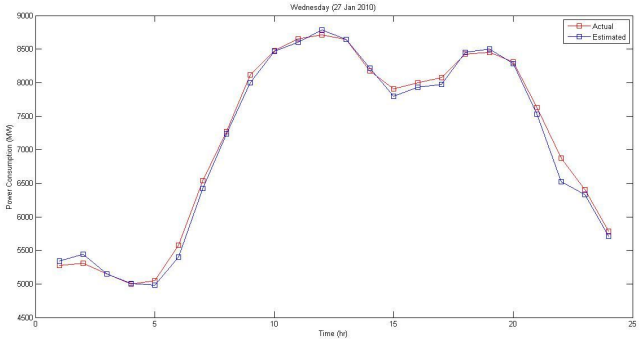

Fig. 9 (C) Actual Load vs. Estimated Load for Wednesdays

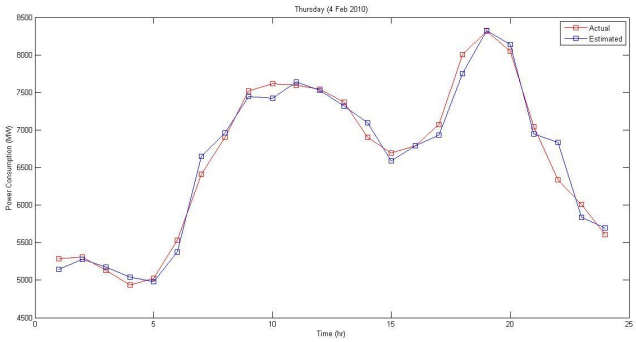

Fig. 9 (D) Actual Load vs. Estimated Load for Thursdays

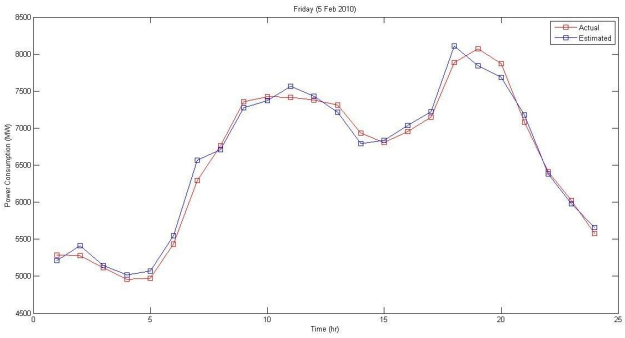

Fig. 9 (E) Actual Load vs. Estimated Load for Fridays

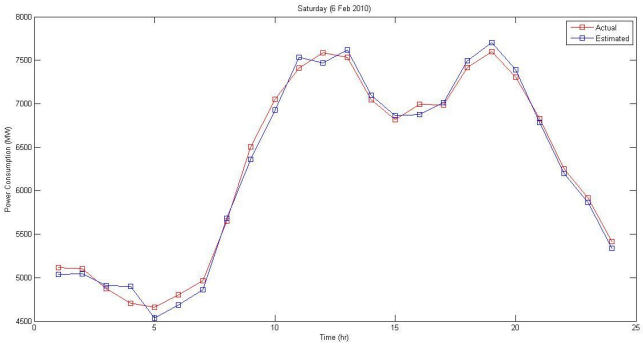

Fig 9. (F) Actual Load vs. Estimated Load for Saturdays

B. Simulation for Holiday / Sunday

Figure 10(A) represents the actual vs. estimated load for Sunday 14th March 2010 and Figure 10(B) represents the actual vs. estimated load for 25th March 2010 (a public holiday in Greece). Mean absolute percentage errors for these two days are given in Figure 14.

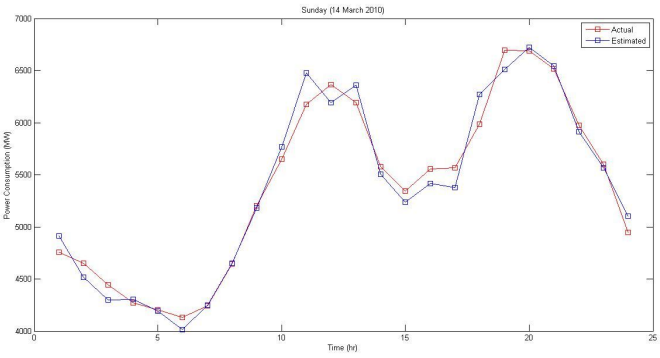

Fig. 10(a) Actual Load vs. Estimated Load for Sundays

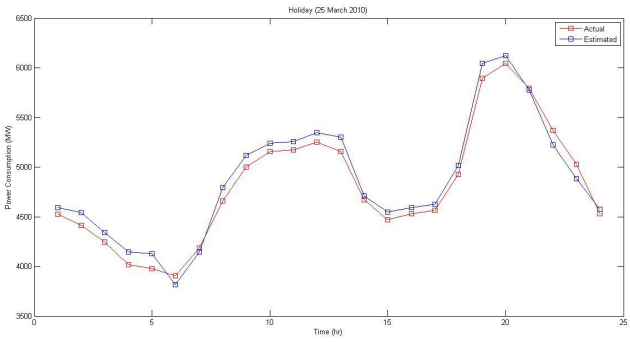

Fig. 10 (b) Actual vs. Estimated Load for a public holiday

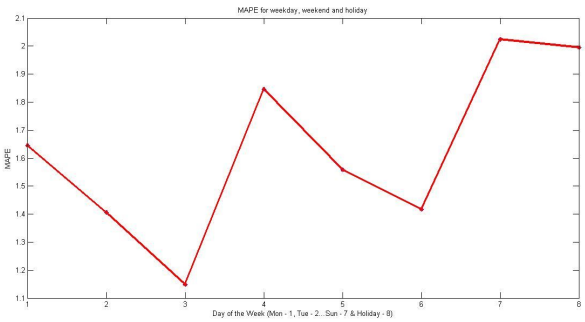

Fig. 14 MAPE for Weekdays, Sundays and Public Holidays (with Monday as 1, Tuesday as 2,…, Sunday as 7 and holiday as 8)

The mean absolute percentage error is found to be between 1% and 2% for all the days of the week.

C. FPGA Implementation for Load Scheduling

The load scheduling algorithm was implemented on Altera Cyclone II EP2C20F484C7 FPGA board. The load from each of the 7 load segments is aggregated for each hour so for each day there are 7 X 24, i.e. 168 inputs for the whole day, however for hourly scheduling there are 7 inputs one for each of the segment.

The figures below represent RTL and post mapping layout of the scheduler.

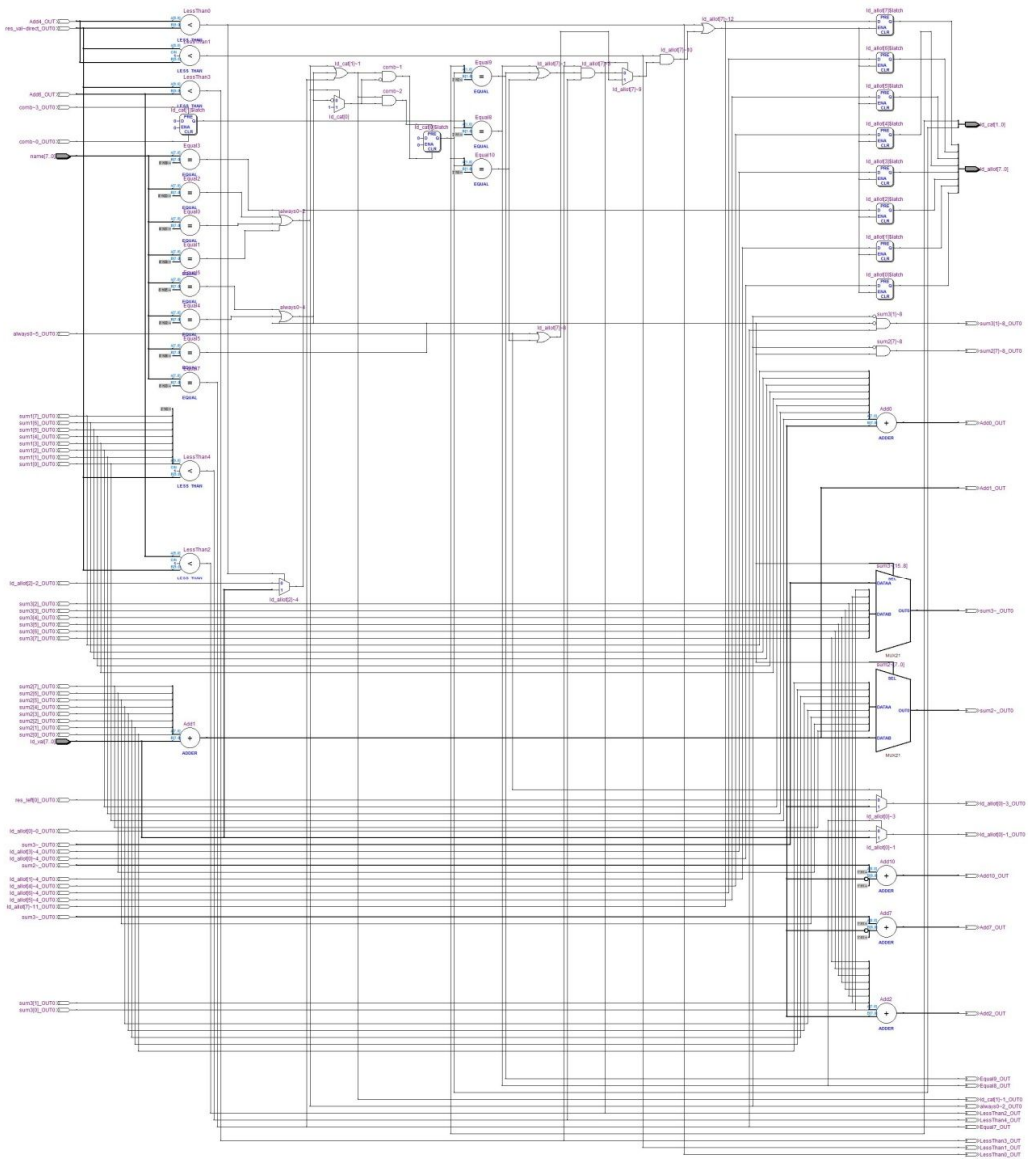

Fig. 11 RTL of the scheduler implemented on FPGA

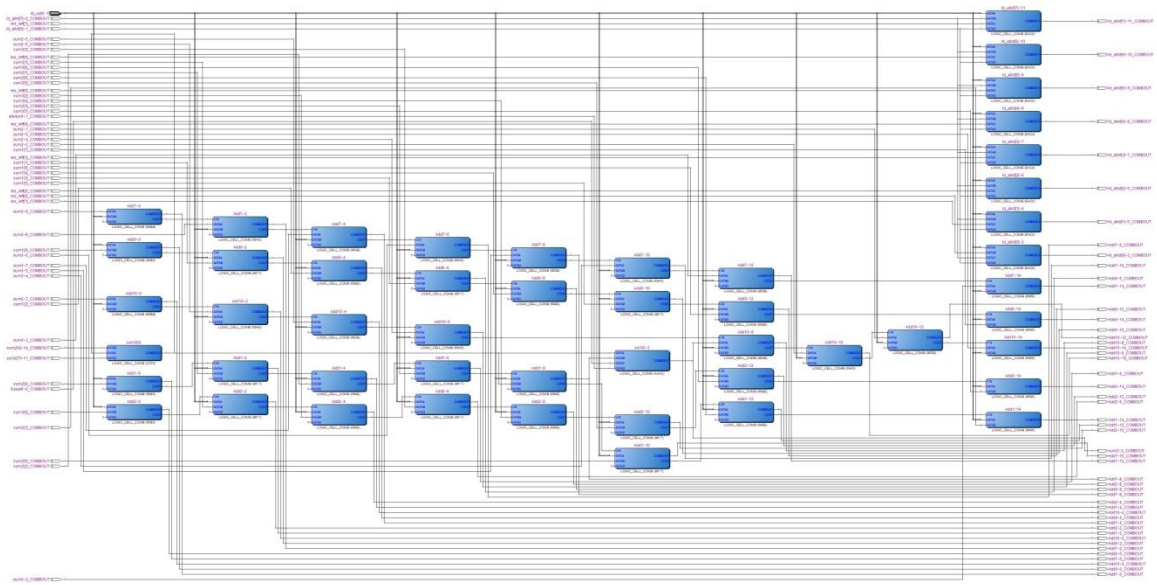

Fig. 12 Post mapping layout

Total number of logic elements utilized by the scheduler is 249 and the pin count is 36.

The resources used in FPGA based scheduler are very few and FPGA based scheduling provides additional benefit of parallelism and reconfiguration, which means very little time is required for data processing for scheduler and reconfiguration that enables to add the exceptions in power consumption, which would occur sometimes during a particular hour or a particular day.

V. CONCLUSION

In this paper, short-term electric load forecasting using Kalman filter algorithm was proposed. The estimated load was represented as linear combination of previous power consumption data and temperature with simulations carried out separately for weekdays and weekends for Greek electric power system. The proposed method performed estimation as fast as CPU clock rate as estimations were carried out using MATLAB 2009. Error percentage was as low as 0.08% in some cases. The mean absolute percentage error was found to be 1% to 2% for all the days of the week, which is less than using artificial neural network technique where MAPE is around 2.5% [17]. The scheduler was implemented on reconfigurable hardware, i.e. Cyclone II FPGA, and this load scheduling technique utilizes only 249 logic elements.

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