2015 Tenth International Conference on Ecological Vehicles and Renewable Energies (EVER)

Energy Consumption Prediction Methods for Embedded Systems

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***Abstract*—Human surrounding environment parameters are gathered regularly from electrical signals which are converted to digital signal using ADC converters and performing necessary data transformations. The gathered environment data can be estimated as a time series to apply standard statistical models. In this study, there are analyzed statistical models that help understand data and find consistent patterns-trends to make predictions depending on all previous data. Energy consumption data processing prediction methods were analyzed and presented. Dependency on time series analysis' results when using task management with prediction parameters is the special feature of designed measurement system. Transition from one state to another includes not only estimates of the previous and current states, but also a prediction state.**

***Keywords*—data acquisition; energy consumption; energy forecasting; Kalman filter; ARMA model.**

I. Introduction

In time series analysis ARMA autoregressive moving average models and discrete Kalman filter are widely used when data is linearly dependent [1-2]. Artificial Neural Network prediction is also one of the techniques that can be successfully applied [3-4]. In order to autonomously estimate which method should be applied during the run time of the system, the initial data analysis must be performed: time series stationary estimation, integration sequence tests execution. Time-series stationarity can be estimated by dividing measurements into separate groups by calculating mean, covariance and standard deviation. Time-series are analyzed as a strict and weak stationary and non-stationary series.

For dynamic process monitoring data momentary measurements must be acquired in different time or place. For time series statistical analysis and forecasting, ARMA models can be used successfully. ARMA model consists of two parts: the main principle is to combine auto-regressive and moving-average models. Autoregressive process explains new observations in time series using previous observation data:

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t \tag{1}$$

where Y_t is time series observations, $\varphi_1, \ldots, \varphi_p$ are autoregressive model parameters, ε_t is stochastic error, p is autoregressive process rank.

Moving-average process explains time series observations using Y_t model errors:

$$Y_t = \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{2}$$

ARMA (p, q) model:

$$Y_t = \sum_{i=1}^{p} \varphi_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{3}$$

ARMA model can be applied for stationary and weak-stationary time series only. Stationarity can be verified using statistical methods. Composed model must describe time series for not only known data but also it can give opportunity to predict future time series values depending on previous observations. ARMA models are used frequently because method of estimation is relatively simple and results can be obtained fastly. To ensure that model can be applied for data, time series stationarity must be calculated first. If stationarity is stronger, then there is a better chance that model can be fitted correctly to a given time series.

Kalman filter is a powerful tool to control noisy systems and widely used in object trajectory prediction, control, tracking, collision-warning systems, image processing, sensor fusion and other fields. Kalman filter is also used as a prediction algorithm in different areas [5 - 6].

II. Task Management Sub-System

The whole idea of the study is to develop an energy consumption and data processing system that ensures energy demand and resource predictions. The presented results describe the system as follows: development of data network transfer system; implementation of data acquisition system; the processing of stored monitoring data; comparison and conclusions of applied methods will be presented in order to achieve the best prediction results of energy demand and resources.

The accomplished research combines main integrated control, energy consumption data acquisition and processing concepts that allow the prediction of energy demand. Electrical energy consumption monitoring takes place with specialized equipment that uses standard data transfer protocols to communicate with e-service database server. For data storage, SQL database was selected. Network nodes are responsible for specific premises monitoring and has access to e-service gateway device that ensures data integrity.

Collected data will be used for energy consumption analysis and prediction. Large amount of information is stored in real-time during the experiment, therefore it is important to prepare appropriate relational database structure that is intended for large data analysis. Energy consumption analysis shows trends and correlation between data samples. The aim of prediction algorithm is to ensure the lowest measurement error. Measurement equipment nodes ensure essential parameter collection for the whole system, data transmission and integration into information concentration system.

Main human environment e-service management is implemented in main controller of the developed system. If device and laboratory lecture schedule plans are known, depending on human demand rules and command queries task management queue can be prepared in main microcontroller for real-time operations. In main core of system, specific task management algorithms must be implemented. When tasks must be accomplished in real-time, one of the task management principles must be adopted: cooperative task management, foreclosing task management, cooperative management with possibility to pause tasks. Real-time operating systems (RTOS) can also be applied successfully. For developed system, task management flexibility is important, therefore simple cooperative task management algorithm was developed. Task management subsystem was developed in previous work of authors adopting new features to incorporate forecasting state definitions [7 – 10].

In this work, task management queue consists not only from planned to execute tasks, but also involves prediction results and additional automatically acquired environment parameters (Fig. 1).

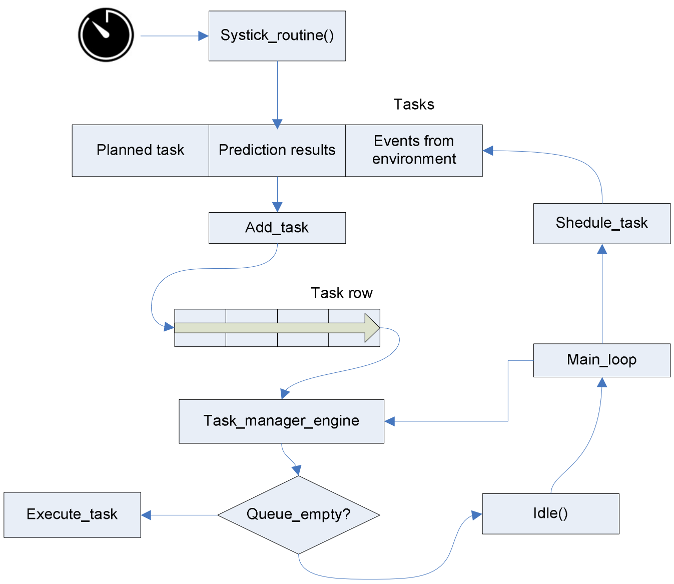

Fig. 1: Task management system with prediction parameters

In the previous work, related to energy monitoring system [11] authors investigate cooperative task management for embedded systems with a possibility to delay tasks. In current implementation row, there appear additional parameters that describe predicted state. When tasks queue is not empty, currently executed task must estimate prediction state and adopt task execution order. Each task is executed after indicated amount of time and algorhythm can obtain data structure of the stored system states from microcontroller memory to make further decisions. Depending on stored states, task will be executed at the first possible processor idle state.

III. Experiment Results

Most common approach is to prepare a queue, when using parameters defined for task declaration: task priority, expected execution time, time when task was started, task state. In proposed system task queue is analyzed in different manner – to use definitions of resource usage plans and estimated results of task execution in prediction state. Prediction state variable is used to estimate energy usage result before task is executed. User receives information about predicted results with proposed more effective usage scenario, depending on predefined user-customizable rules. For example, for testing purposes, scenario with dimmable RGB LED light source can be used with developed system. Depending on task priority to get comfort artificial lightning in user environment, system can propose what duty cycle must be applied to get sufficient lightning and power consumption, based on prediction results.

When monitoring energy consumption data, quantization period of one day was selected. There were

144 averaged observations, energy consumption data were grouped by 10-minute intervals ($\Delta t = 10$). In every hour, six averages were calculated every ten minutes. Depending on data observation scale, prediction must be less than or equal to one day ahead – to predict one period – T. The monitoring scenario always have determined and stochastic parts. Device usage plan and real energy consumption at the given time interval are presented in figure 2.

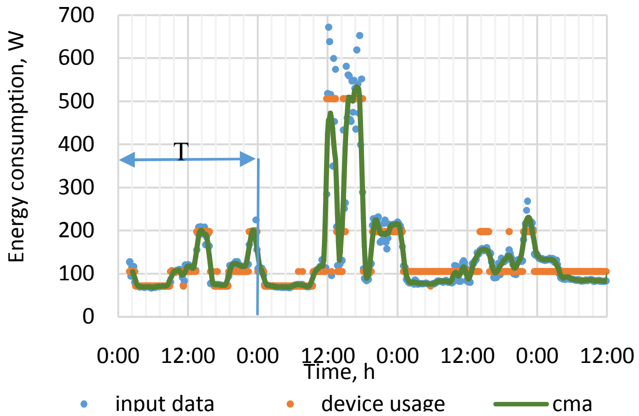

Fig. 2: Device usage schedule plan and real energy consumption

In this paper, data collected from university laboratory were used. Data consists of energy consumption in laboratory in real-time. Some periods (several consecutive days) were chosen for visual explanation of research results. Energy consumption data were acquired only using devices from developed system database list. For every device average power consumption was experimentally determined and device usage schedule was described in database. For testing simplicity there were only few devices used. For device usage automatic schedule plan generation there were used different main sockets to know where exactly device is connected. In this work, device usage schedule plan was used for two main purposes: to graphically visualize device usage plan when Y axis shows average energy consumption; to supplement ARMA model with determinable energy consumption data.

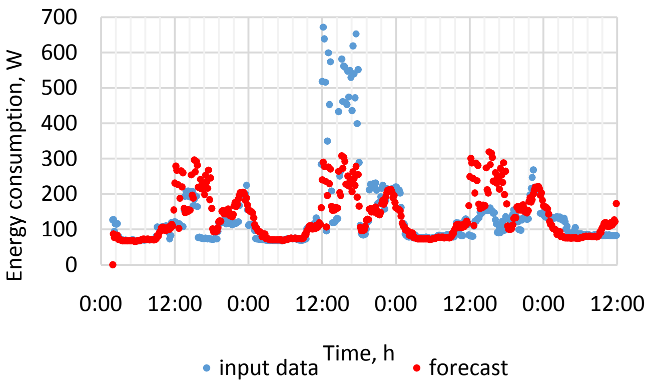

Fig. 3: Prediction using ARMA model

Two different approaches with ARMA model has been made. Prediction using only energy consumption data as an input (figure 3) and prediction that depends on device usage schedule plan (figure 4).

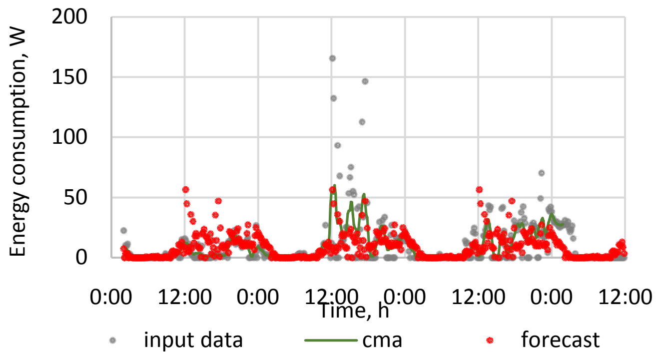

Fig. 4: Prediction using ARMA model with schedule plan

Observation values are normalized, when device schedule plan is used. Only larger than average usage values are taken into consideration. New values are equal to real observation difference from average estimated usage.

Kalman filter (KF) is a recursive algorithm and in this case it is applied for acquired energy consumption data. KF consists of prediction (known as process model) (4-5) and update (known as measurement model) (6-8) steps:

State prediction $\hat{x}_k$:

$$\hat{x}_k = A\bar{x}_{k-1} + w_k \tag{4}$$

State covariance $\hat{P}_k$ prediction:

$$\hat{P}_k = A\bar{P}_{k-1}A^T + Q \tag{5}$$

Gain K_k calculation to correct state prediction $\hat{x}_k$:

$$K_k = \hat{P}_k\, H^T\left(H\hat{P}_k\, H^T + R\right)^{-1} \tag{6}$$

State estimate $\bar{x}_k$ update using measurement z_k:

$$\bar{x}_k = \hat{x}_k + K_k(z_k - H\hat{x}_k) \tag{7}$$

Covariance $\bar{P}_k$ update:

$$\bar{P}_k = (I - K_k H)\hat{P}_k \tag{8}$$

where $\hat{x}_k$ is state prediction vector affected by noise w_k; $\bar{x}_k$ is update vector; $z_k = Hx_k + v_k$ is measurement vector affected by noise v_k; $w_k \sim N(0,Q)$, $v_k \sim N(0,R)$ are process prediction and measurement update independent Gaussian noises, respectively; $Q = E\left[w_k w_k^T\right]$, $R = E\left[v_k v_k^T\right]$ are independent process and measurement noise covariance matrices, respectively; A is state transition matrix; $\hat{P}_k$, $\bar{P}_k$ are prediction and update state covariance matrix, respectively; H is measurement matrix; I is identity matrix.

In update step, the difference between measurement and prediction states is compensated and new estimates are determined. Kalman filter convergence rate depends on Q and R matrices. Decreased value of Q or R shows the confidence in either process or measurement steps. In this energy consumption scenario, we observe only one state. Therefore, the following Kalman filter coefficients (matrices) are used: $A = 1$, $H = 1$, $Q = 0.005$, $R = 0.1$, $\overline{\mathrm{P}}_{\mathrm{k-1}} = 0.025$. Initial covariance matrix $\overline{\mathrm{P}}_{\mathrm{k-1}}$ is estimated empirically as it converges over time. Initial state $\bar{x}_0$ in prediction equation is set to value according to schedule's first value. If the efficiency of Kalman filter is low, for instance, time delay in convergence, parameters related to model A, H, Q and R need some adjustments, as the other internal variables $\bar{x}_k$, $\hat{x}_k$, $\bar{P}_k$, $\hat{P}_k$, K_k are recalculated or acquired externally as a measurement z_k. Kalman filter experiment results are presented in figure 5 and figure 6.

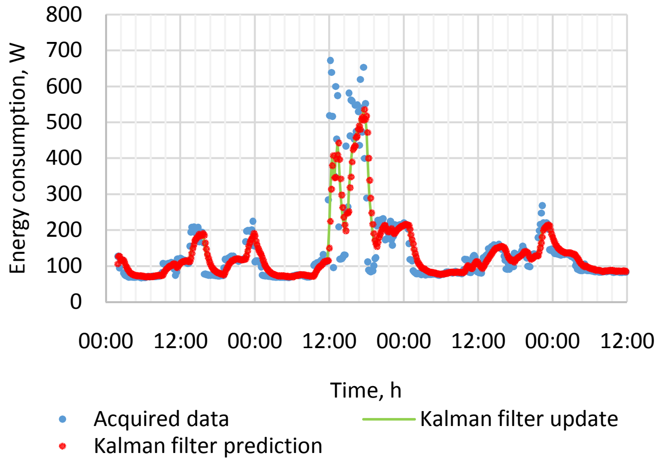

Fig. 5: Prediction using Kalman filter

Figure 6 shows prediction using only differences in energy consumption from device usage plan.

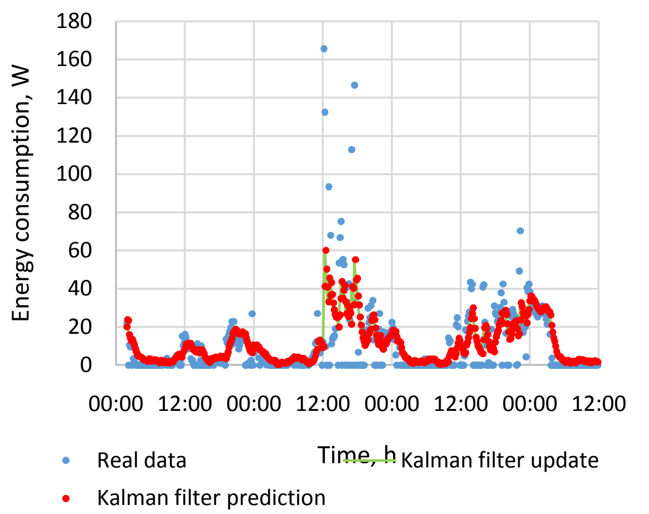

Fig. 6: Prediction using Kalman filter with schedule plan

For prediction results root mean square (RMS) value was calculated for each approach. RMS value of energy consumption curve in time is square root of sum of each observation distance squared. If there were n observations, RMS formula with observations $\{x_1, x_2, \dots, x_n\}$ can be expressed:

$$x_{rms} = \sqrt{\frac{1}{n}(x_1^2 + x_2^2 + \dots + x_n^2)} \tag{9}$$

Additional estimate was calculated to get average percentage distance between real observations x_i and device plan values p_i at the same moment:

$$E_d = \frac{1}{n}\sum_{i=1}^{n} \frac{|x_i - p_i|}{\max(x_i, p_i)} \tag{10}$$

TABLE 1: PREDICTION RESULTS COMPARISON

	ARMA	ARMA + schedule	Kalman filter		Kalman filter + schedule	
			Prediction	Update	Prediction	Update
RMS	84,534	29,251	62,115	49,681	31,537	29,267
$\mathrm{E_d}$	0,203	0,120	0,031	0,113	0,114	0,106

The higher RMS value or percentage distance $\mathrm{E_d}$, the lower the accuracy of prediction.

Kalman filter and ARMA model for prediction tasks can be applied differently as algorithms has different advantages and disadvantages. Kalman filter better fits to the current data, but prediction is limited to only Δt sample (one measurement ahead), according to the data acquisition scenario described in this paper. ARMA model reflects regressive curve properties and seasonality, also it can perform prediction of period T – further than KF algorithm. However, ARMA model demands that time series would be stationary, in this way algorithm is of limited usage.

IV. FUTURE PERSPECTIVES

Real-time energy consumption prediction is only one of the possibilities using developed system. Ecological vehicle can be managed with pre-calculated demands and command queries for future prediction. Depending on historical data, device usage plan can be estimated and consumption of different parameters can be predicted: traffic estimation and fuel consumption. Another possible application of the system is to predict gathered alternative energy from various sources: solar, wind, geothermic energy, etc. Predictions are possible because energy consumption data have trend and seasonality components. After more investigation, system can be adopted to use neural network time series prediction algorithms.

V. Conclusion

Depending on problems being solved, forecasting algorhythms can be adopted for automatic task management for different smart service systems. When properly adjusted, system can give information about task result before it started and offer some suggestions. Sequential periods of energy consumption data were used for ARMA model and Kalman filter prediction differences. Results show that forecasting accuracy is improved when device schedule plan is used. If device usage is not deterministic, forecasting of energy consumption becomes harder. Therefore, developed system uses database about laboratory devices. Otherwise, database can be filled with data automatically, with assumption that device power socket is predefined before system service is started and measured devices are powered on.

Acknowledgment

The authors thank The Ministry of Economy of the Republic of Lithuania and The Agency of Science, Innovation and Technology for the possibility to complete a scientific research ("Innovation voucher", Project „Creating of energy consumption system", Subsidy contract No: VP2-1.3-ŪM-05-K-03-711, 2014-2015).

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