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Embedded On-line System for Electrical Energy Measurement and Forecasting in Buildings

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***Abstract* — Fine grained measurement of electrical energy consumption in commercial buildings is essential for improved fault diagnosis and control with impact on the overall operation as well as user comfort. An open system architecture is presented for data collection, processing and communication of measured energy patterns at the local and aggregated level. The implementation is based on an embedded development board with current and voltage sensors, supported by open-source software and packages. Suitable user and programmatic interfaces allow reliable bidirectional connection to external automation equipment and information systems. such as the Building Management Systems (BMS). Recent advances in advanced algorithms for time series pre-processing and data-driven modelling allow good quality in situ predictions for the collected measurements. A relevant example consists of neural network based learning systems which are able to provide accurate hour-ahead and day-ahead predictions that contribute to reduction of peak demand with economic and environmental impact. Integration of such platforms in higher-level Cyber-Physical Energy Systems (CPES) is further discussed.**

Keywords* — *energy monitoring; internet of things; load forecasting; neural networks; smart buildings

I. Introduction

The Internet of Things (IoT) is composed of large numbers of embedded computing devices with network connectivity. These have enabled large scale granular monitoring of the physical world in many types of applications. This leverages a significant increase in capabilities along with a decrease in size of electronic components: microcontrollers, sensors, low-power radio transceivers, along with a decrease in cost and energy requirements. With regard to improved IoT-enabled intelligent systems, the devices provide high quality fine grained data that can be process by advanced algorithms for better control. Many learning algorithms are thus able to gradually identify simple to complex patterns in the measurement data streams, which are then leveraged to forecast future behaviour of the observed systems along with proper optimisation routines for their efficient and economic operation. With increased constraints on dependability, safety critical applications in the built environment, transportation and industry settings can be also instrumented through IoT.

The implementation of IoT systems in the energy field ranges from large scale deployments at the (smart) grid level down to consumer-facing implementation for commercial and residential units [1]. Of these, we are interested in exploiting the benefits of fine grained measurement, embedded learning and control for improving the energy management in large commercial buildings. For this scenario, small percentage gains in the accuracy and response time of the consumption forecast can lead to important savings for the building operator with positive impact on the grid stability and enabling participation of the building as a reliable entity in demand response (DR) schemes, including decision support for renewables integration [2].

The supporting IT infrastructure is currently being built up [3] that enables integration between closed-source proprietary Building Management Systems (BMS) with open-source software modules and hardware designs. Also, there is a large amount of good quality public datasets which can be used to learn black-box models of energy consumption patterns which can then be subsequently transferred to particular buildings with limited computational overhead for incremental training.

Main contributions of the work are listed next:

- development and enhancement of an embedded energy management system with the ability to run based on open-source technology;
- experimental results for day-ahead and week-ahead building energy forecasting, including anomaly detection, using previously trained and validated autoregressive neural network architectures.

The rest of the paper is structured as follows. Section 2 discusses relevant related work for energy monitoring and management devices for smart buildings. Section 3 presents the reference system architecture, based on a commercial device with extensions to support on-line learning methods for in situ forecasting of energy consumption. Section 4 illustrates the prediction of building energy consumption based on neural network learning algorithms. The paper is concluded in Section 5 with outlook on further experimental evaluation and deployment of the system.

II. Related work

Several related works are reported which broadly frame the current context and novelty of our contribution. [4] presents a control application for an IoT energy meter in a building. The authors describe in depth the physical realisation as well as the supported software primitives which allow integration with a higher level Building Energy Management System (BEMS). An alternative solution is described by [5] which uses industrial PCs in conjunction with commercial off-the-shelf energy meters, interconnected through standardised communication buses, RS485 serial connection in this case. The supporting IT infrastructure including database server, web server and front-end visualisation and energy management application is also described. Other types of designs have been identified in the recent scientific literature, both at the grid level [6] or as small scale embedded sensor nodes for energy measurements with low-cost, open-source components. Many of such systems can be assembled into networks of energy management devices at the neighbourhood level [7] with the potential of economies of scale and redundancy in the system design.

A user-driven domestic energy monitoring system is described in [8]. The system designed is aimed at raising awareness of end users by accurate reporting of energy consumption trends and events. An 8% reduction in consumption is achieved in the first week of deployment. For industrial applications, a remote energy monitoring unit design is provided by [9]. The unit is evaluated in a manufacturing scenario on a pilot flexible assembly line system for typical production energy optimisation in relation to existing key performance indicators (KPIs). [10] discusses the key aspects relating to feature engineering of input data for energy prediction. Various types of auto-encoder systems are evaluated to extract relevant features from historic energy consumption data in an automated fashion which automates and mitigates the challenge of unique building characteristics and inherent consumption variability. The potential which is highlighted aims at bridging the gap between black-box neural network models and domain specialist acceptance of the predictions.

The current work is also complementary to the previous contributions in [11], [12], [13] where extensive work has been carried out in deriving suitable black-box models. The techniques which were investigated ranged from conventional ARIMA system identification to neural network algorithms. In the current situation we aim at evaluating porting the algorithms on low-power embedded platforms for in situ forecasting with support from an external learning infrastructure.

III. System architecture

An energy management system is designed to improve the monitoring and control of energy-related usage, and local generation if applicable, leading to an increase in both energy and cost savings. Using an energy management system, problems of collecting, transmitting, saving, and controlling of the aggregate data in energy running processes can be solved by using different technologies such as smart meters, communication networks, software applications, as well as cloud databases for data storage.

The electrical load system architecture for an electrical power monitoring system is first discussed. Figure 1 presents a schematic diagram of the architecture of the electrical system monitoring in which data is collected from smart energy meter and displayed on web page. The proposed system is suitable for data collection and control the load. The monitoring system was installed in a building within the university with the goal of capturing aggregated loads that can be pre-processed and then input into a learning algorithm for pattern detection and forecasting.

The main components of the monitoring system are identified and further presented.

- **Voltage & Current Sensors** - current transformers (CT) sensors are used for measuring alternating current and they are particularly useful for measuring building electricity consumption. The sensors collect energy consumption data of electrical appliances every 10 seconds and send the data to the data collector.
- The **Smart Energy Meter** is an embedded system which incorporates a microcontroller in its implementation. The main purpose of the microcontroller is to simplify the system design and provide flexibility. The Smart Energy Meter that we used for the architecture is called emonPi and is an open-hardware Raspberry Pi 3 and also Arduino based web-connected energy and environment monitoring unit. EmonPi will collect electricity usage data from CT sensors and transfer data wirelessly to the main controller and a computer, cloud server or tablet/mobile phone. The hardware architecture of the emonPi consists of one AC Voltage Input designed for a 9V AC power adapter, Arduino compatible ATmega328P, RJ45 connector for connecting DS18B20 temperature sensors, IRQ pulse counting sensor, and access to power and spare I/O including analog and PWM, 433 MHz Radio send/receive module, I2C LCD (16x2) with control push button, Raspberry Pi Shutdown Button.
- **Real-time data processing and data analysis** - interprets data and stores in cloud server detailed overview of the energy consumption, interactive and customized graphs that give visual access to instant data. Also, using different analytical techniques, sev-

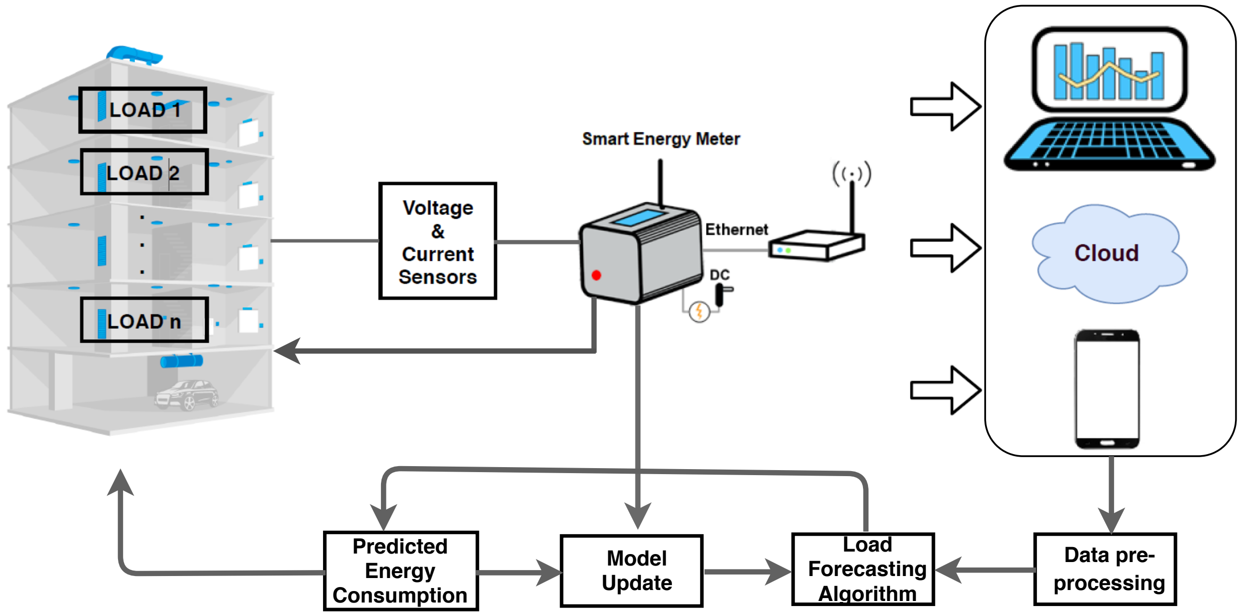

Figure 1: System architecture for electrical load monitoring

eral benefits become possible, such as gaining insight into individual equipment power use, identifying the equipment that is operating unnecessarily, reducing costs by eliminating unnecessary consumption or generating cost savings from demand analyses.

IV. Results with Neutral Network Forecasting of Electrical Loads

We present the reference neural network structure and experimental results on a building energy dataset with day ahead and week ahead prediction. The dataset contains the energy consumption in three university buildings from Zurich, Europe, over one year period. The sampling time for this dataset is one hour and the dataset consists of 8.760 data points. The main argument for choosing these buildings is that they allow a comparison between three types of dominant energy usage patters: offices - denoted as Building 1, classrooms - Building 2 and laboratories - Building 3, with the same type of underlying model structure for forecasting. The data is publicly available using the Building Data Genome repository [14].

For training a prediction model we chose a standard feed-forward Autoregressive Neural Network (NAR) with a sigmoid transfer function in the hidden layers and a linear transfer function in the output layer. The hidden layers outputs are calculated using the equation 1 [15]:

$$z = \sum_{i=1}^{n} w_i x_i + b_i, \tag{1}$$

where $X : x_i, i = 1 : n$ represents the input data set and $W : w_i, i = 1 : n$ represents the weight set, b_i represents the bias values of the network.

The hidden layer outputs are fed into an activation function to calculate the final value. The sigmoid function in the hidden layers represents the activation function that we use for our prediction models and is given by the following relationship:

$$\sigma(z) = \frac{1}{1 + exp^{(-z)}} \tag{2}$$

The network has the following structure: 1 input layer, 4 hidden layers with 8, 8, 16 and 16 neurons, respectively and 1 output layer with one neuron. The structure was chosen based on a previous study where the best performance for load forecasting in such buildings was obtained and validated for this configuration [13].

For training the network the Levenberg - Marquardt back-propagation learning algorithm (LMBP) was used. LMBP algorithm is robust and one of the most widely used optimization algorithms for neural network training procedures. The algorithm represents a combination of two methods: the gradient descent and the Gauss-Newton. In literature is demonstrated that for networks that contain up to a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence.

The update relationship is formulated as follows:

$$[J^T W J + \lambda diag(J^T W J)] h_{lm} = J^T W (y - \hat{y}) \tag{3}$$

where the values of λ are normalized to the values of $J^T W J$. This formulates a non-linear least squares problem with the goal of finding the optimal weights W that minimise the distance from the outcome across all training examples.

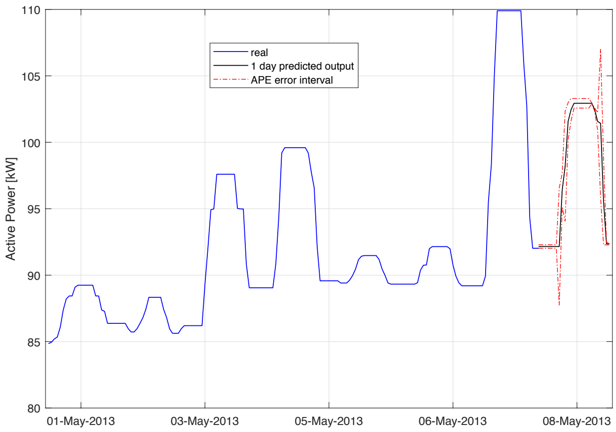

Figure 2: Predicted data - 1 day (Building 1)

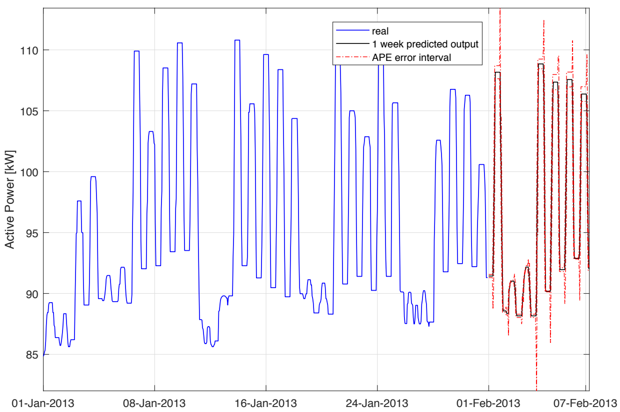

Figure 3: Predicted data - 1 week (Building 1)

Figure 2 and Figure 3 present two detailed plots with the evolution of predicted data for Building 1 short term load forecasting. The graphic illustrates also the absolute percentage error (APE) interval over one day and one week period of time. APE is calculated as:

$$APE = (real - predicted)/real * 100 \tag{4}$$

Figure 4 presents the correlation between active power, blue plot, and the outside temperature, red plot. This can offer useful information for building the forecast models especially in climates where conditioning the indoor air requires vast amounts of energy due to extreme outdoor-indoor temperature differences.

Regarding the model performance analysis we used the following metrics: Mean Absolute Error (MAE), Mean Squares Error (MSE), Mean Absolute Percentage Error (MAPE) and Mean Squared Percentage Error (MSPE). The metrics are described by the following equations:

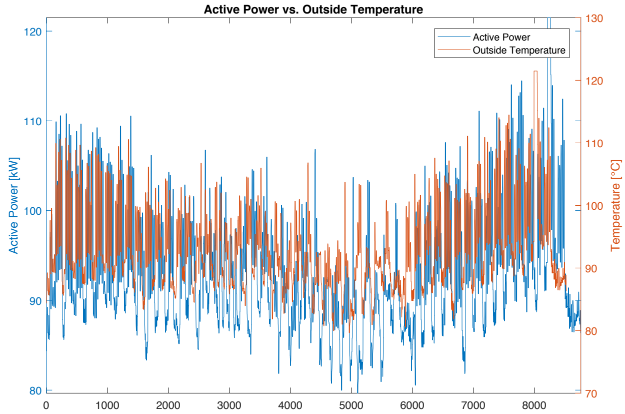

Figure 4: Active energy vs. outside temperature data sets

$$\begin{aligned} MAE &= \frac{\sum_1^n |Y_t - Yp_t|}{n} \\ MSE &= \sum_1^n \frac{(Y_t - Yp_t)^2}{n} \\ MAPE &= \frac{1}{n}\sum_1^n \left|\frac{Y_t - Yp_t}{Y_t}\right| 100 \\ MSPE &= \frac{1}{n}\sum_1^n \left(\left|\frac{Y_t - Yp_t}{Y_t}\right| 100\right)^2 \end{aligned} \tag{5}$$

where n represents the number of samples, Y_t the actual data and Yp_t the predicted data.

Table I presents the obtained values of each criteria for the three data sets. The first data set represents the evolution of energy consumption for the office dominant usage pattern, the second one is dominated by laboratory spaces and the third by classroom usage. Analysing the values of each error metric it can be easily noticed that the performance of the network can be considered good in terms of load forecasting for the first and third data set with 0.83% and 1.56% respectively. In case of the second data set the obtained error values are bigger, with a MAPE of around 4%. We can attribute this to the amplitude variations are steeper due to the classroom consumption pattern. This can be addressed by increasing the number of neurons in the hidden layers in a more complex network structure that could better capture the transitions in consumption from empty to full classes.

Table I: NAR forecasting performances

	MAE	MSE	MAPE(%)	MSPE(%)
Building1	0.8078	2.7618	0.8289	2.7226
Building2	2.7131	25.8681	4.0495	49.6436
Building3	0.9783	3.9365	1.5576	9.4545

Figures 5, 6 and 7 presents measured real data versus predicted data over 30 day period for the three buildings within a confidence interval CI defined by the following formula:

$$CI = MA \pm 1.96 * \sigma^2 \tag{6}$$

where MA is the moving average defined from the data set by taking the arithmetic mean of subsequences of 24 terms which means one day period dataset. σ represents the standard deviation of the sample:

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \hat{x})^2} \tag{7}$$

where, x_i are the observed values of the data set, $\hat{x}$ is the mean value of the observations and N is the number of observations in the data set. This results in the 95% confidence interval presented in Figures 5-7. It can be noticed that some values exceed the upper/lower limit which can be considered anomalies as a mismatch between the actual and predicted value. These prediction inconsistencies can be leveraged in order to improve the energy control strategies at the local level and contribute to the overall balancing of the grid, by mitigating peaks.

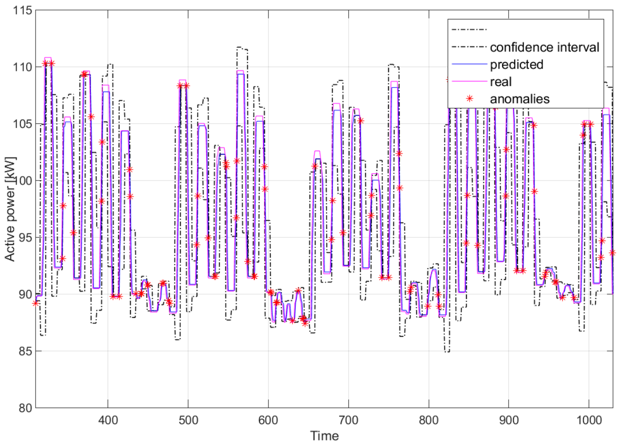

Figure 5: Real vs. predicted data (Building 1) - 95% confidence interval

All experiments of the current research has been performed on a 3.4 GHz i7 quad core processor and 8GB RAM and for the software implementation it was used Matlab. The integration with the embedded energy management device is realised through bidirectional data flows for updating the models based on newly collected data and for obtaining the forecasts that are then used to control energy intensive devices. A practical use case is related to the limiting of chiller power during hot summer days while accounting for user comfort decrease. Since Python is becoming a popular programming language for engineering and scientific applications and also because is increasingly used for technical computing and statistical learning for further research we intend to port to Python

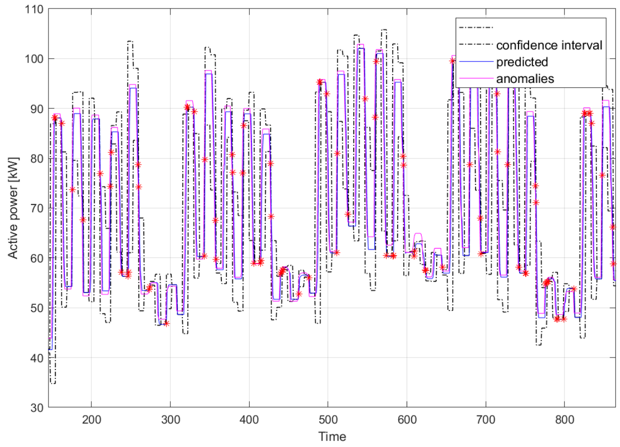

Figure 6: Real vs. predicted data (Building 2) - 95% confidence interval

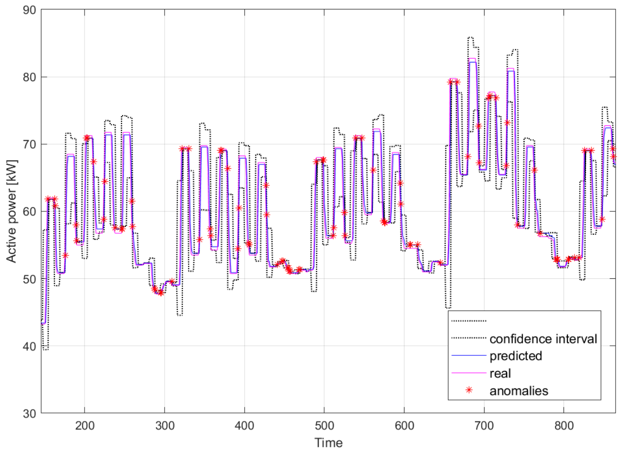

Figure 7: Real vs. predicted data (Building 3) - 95% confidence interval

and also from desktop PC to the embedded computing module.

V. Conclusion

The paper presented the concept of an embedded energy management device with load forecasting capabilities in large commercial buildings. The current design allows real-time data acquisition of energy consumption and, in connection with an external system for training models of energy consumption on large databases, can close the loop and partially control energy consumption in accordance to user-specified objectives. The models can also be used for tasks such as identifying certain top consumers [16] or recurring patterns that enable intelligent reduction of energy use. By moving the prediction closer to the source the lag associated to hierarchical and cloud levels of data processing and their cost can be mitigated.

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