Bulletin of the *Transilvania* University of Braşov • Vol. 9 (58) No. 2- 2016
Series I: Engineering Sciences

ESTIMATION OF THE ENERGY CONSUMPTION IN INTELLIGENT BUILDINGS

M. FRATU[1] L. CARSTOLOVEAN[1]

Abstract: *Everyday, building designers face exciting new challenges in incorporating new and innovative technologies in designing an efficient integrated intelligent building in areas of the building structure and its mechanical and electrical systems. The innovative technologies would need to ensure that the end users achieve the utilization of its abilities in optimization of there home space.*

In this work we present a novel approach to energy saving in buildings through the identification of the relevant parameters and the application of Soft Computing techniques to estimation of energy consumption in buildings. We characterize the building in terms of its contextual features and energy consumption, and then select the most appropriate techniques to generate the most accurate model charged with estimating the energy consumption.

Key words: *Big data, Intelligent building, Energy consumption, Energy efficiency*
.

1. Introduction

The definitions of an intelligent building can be systemically classified by the information and control services that serve the needs and expectations of the occupants. A smart home appears "intelligent" because its computer systems can monitor so many aspects of daily living; with just a single touch total control is always at our fingertips. Coded signals are sent through the home's wiring to switches and outlets that are programmed to operate appliances and electronic devices in every part of the house.

One way to reduce resource consumption is to design a home environment that controls environmental conditions. The home's occupant informs the system via some type of user interface that he or she wishes to stay comfortable while saving as much energy or money as possible.

The intelligence of the home is evaluated according to the level of systems integration. In order to achieve an intelligent building, various building systems, example lighting system, air-conditioning system, communication system and others, are required to equip in the building.

The intelligent buildings must be capable of not only providing mechanisms to minimize their energy consumption (even integrating their own energy sources to ensure their energy sustainability), but also improving occupant experience and activity efficiency.

[1] Dept. Installations for Construction of Transilvania University of Braşov (Romania).

In last time. different approaches have addressed the energy efficiency of buildings using predictive models of energy consumption based on usage profile, climate data and building characteristics.

The integration and development of systems based on Information and Communication Technologies (ICT), and more specially, the Internet of Things (IoT) are important enablers of a wide range of applications, for the general population, helping make intelligent buildings a reality. The IoT has provided vast amounts of data that can be analyzed deeply to reveal interesting relationships, which can be used to generate models able to anticipate and respond efficiently to certain events.

Big data and IoT are a perfect combination that can be applied to Smart Buildings scenarios for energy efficiency.

The approach of this paper involves applying insights from Big data algorithms to sensed data in intelligent buildings. We select the most suitable soft computing techniques to manage these data.

We propose a solution for data processing to generate energy consumption models of buildings which can be used to select the optimal measurements and strategies to save energy.

The structure of this paper is as follows: Section 2 reviews some related work proposed in the literature. Section 3 describes the key issues involved in intelligent buildings. Section 4 details the energy usage characterization of reference building, the process of generation of its energy consumption model. Finally, Sect. 5 provides conclusions and future directions of our work.

2. Related Work

As regards the analysis of buildings to understand how energy is consumed, initial solutions were mainly focused on using non-deterministic models based on simulations. A number of simulation tools are available with varying capabilities.

In [5] a comprehensive comparison of existing simulation tools is provided. This type of approach relies on very complex predictive models based on static perceptions of the environment. For example, a multi-criteria decision model to evaluate the whole life cycle of a building is presented in [6].

The authors deal with the problem from a multi-objective optimization viewpoint and conclude that finding an optimal solution is unreal, and that only an approximation is feasible.

With the continual progress made in the field of ICT and sensor networks, new applications based on using extensive number of different sensors to monitor building environments are being proposed to improve energy efficiency of buildings through the integration of massive volume of data [3].

The approach of this paper involves predictive models based on a combination of real data and predictive patterns that represent the evolution of the parameters affecting energy consumption in buildings.

Optimizing energy efficiency in buildings is an integrated task that covers the whole life cycle of the building. Herein after, we refer only to electrical energy consumption since other kinds of energy such as fuel oil, gas or water are beyond the scope of this work.

3. Intelligent Building

An intelligent building must perform three conditions. They are:

- The building should have advanced automatic control system to monitor various facilities, including air-conditioning, temperature, lighting, security, fire etc. to provide a comfortable working environment for the tenants.

- The building should have good networking infrastructure to enable data flow between floors
- The building should provide adequate telecommunication facilities.

An intelligent building must be smart enough to vary the environment and also to provide various means of communication or network regardless of whether it is internal or external. A room is the entity into which buildings are structured and used. Buildings are regarded as a collection of rooms. All analysis on smart house is done in the context of a particular room.

Room intelligence starts with monitoring and controlling information services known as Room Automation System (RAS) [1]. RAS is able to optimize environmental and safety aspects in an economical way. This can be achieved by using computers, together with function distribution control techniques, to optimize the usage of various pieces of equipment within the building such as the electrical facilities, the air-conditioning systems, fire-prevention equipments and security devices.

3.1 Room Automation System (RAS)

The overall goal of the RAS is to satisfy the inhabitants of the building. This is achieved with changing certain aspects of the room accessible volume, before a human inhabitant needs to manually instruct the building to do so.

Room Automation System (RAS) is based, on all sensory, regarded as being related to one single room. This is also valid for decisions taken by the system. Room Automation System (RAS) comprises of electronic equipment that automatically performs specific facility functions.

The commonly accepted definition of a RAS includes the comprehensive automatic control of one or more major building system functions required in a facility, such as heating, ventilating, and air conditioning system, lighting, power, lifts, security and more.. RAS includes a collection of sensors that determine the condition or status of parameters to be controlled, such as temperature, relative humidity, and pressure.

3.2 **Building Automation Network (RAS LAN)**

Building Automation Network provides the lowest level network structure interconnecting various LAN Controllers for electrical system. All LAN controllers are connected directly on to the RAS LAN. Once configured, controllers operate autonomously with no interaction required from other system. All the control application modules (power failure, auto restart time schedules, optimal start stop, etc) are resident in LAN controller memory for individual operation [2].

The Room Automation System (RAS) is an important part of the overall Intelligent Room Management System (IRMS) [7]. It not only shows the energy consumed in the building, it also provides monitoring and controlling functions of all the building services within the building.

The energy performance model for buildings proposed by the CEN Standard EN15251 (British Standards Institution 2007) proposes criteria for dimensioning the energy management of buildings, while indoor environmental requirements are maintained [8].

According to this standard, there are static and dynamic conditions that affect the energy consumption of buildings. Therefore, it is first necessary to identify the main drivers of energy use in buildings. After monitoring these parameters, we can model their impact on energy consumption. The main idea of this approach is to provide anticipated responses to ensure energy efficiency in buildings.

The RAS Workstation is loaded with Supervisory Control and Data Acquisition (SCADA) software along with the necessary drivers to interface to the controllers for monitoring and control [4].

Parameters such as temperature, humidity, pressure, and natural lighting have a direct impact on the energy consumption of buildings.

From this set of parameters affecting energy consumption, we can extract the input data to be included in the estimation of the target building energy consumption model.

Based on all these parameters, it is possible to design optimum strategies to save energy.

4. Generating the Energy Consumption Models of the Reference Building

Due to the features of our reference building, we focus on modeling its energy consumption associated to the time periods in which the building is occupied. We describe the computational techniques as follow:

1. *Data collection.* The Energy Consumption (EC) is collected over short periods of time (each minute of every day). Such measurements are associated to specific vectors of environmental parameters (*Z(t)*) measured outside and inside the building. So, the set of data pairs for the training of our building model is:

$$(\mathrm{EC}(t), Z(t)), \quad t = 1, 2, \ldots, N \tag{1}$$

where N is the number of data instances collected during 1 h of monitoring.

Electrical Energy Consumption, EC(t) refer to the environmental parameters vector associated to the energy consumption measured at the instant t.

2. *Pre-processing.* The pre-processing unit is responsible for transforming the measured data as follows:

– *Transformation* based on the raw dataset collected. During the transformation, compact representations of the input data, namely features, are extracted, which will be used later for energy consumption estimation.

– *Filtering.* During this process a filter is applied that removes features extracted from the training data set that does not vary at all or that varies too much.

– *Normalization*. All values in the given dataset are normalized during this phase. The resulting values are in the [0,1] interval.

– *Feature selection*. We apply *principal components analysis (PCA)* in conjunction with a ranker search mechanism. If we consider EC(i) as multi-dimensional observations and u as an arbitrary direction in this multi-dimensional space, the principal components are calculated by optimizing the following equation:

$$\frac{1}{m}\sum_{i=1}^{m}(EC(i)^{T}.u)^{2} \tag{2}$$

After this analysis, we found that outdoor temperature, humidity and pressure were the features selected by the ranked feature combination technique used by the Principal component analysis (PCA).

PCA mechanism uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

In our approach the number of features was reduced to 3, which will be denoted as

$f1, f2, f3$.

Considering this vector of features, Eq. (1) can be rewritten as:

$$\{[f1(t), f2(t), f3(t)], Zt\}, t = 1, 2, \ldots, N \quad (3)$$

At this point, we generate the maps of the building based on the selected features.

3. *Clustering.* The data are grouped according to the identified clusters, whose centroids are associated to landmarks.

4. *Landmark classifier*. After classifying the energy consumption landmark for each new measurement, we can focus on the outdoor temperature characterization of such landmark.

5. *Energy consumption estimator* For consumption estimation, the interpolation algorithm *Radial basis functions network* [5] uses all training data associated to every landmark. The input space P of our *Radial basis functions*, RBF is the vector of the mean values of the outdoor environmental parameters.

These data can be denoted as:

$$P = \{p_i\}, \forall p_i = [p_1, p_2, \ldots, p_n] \quad (4)$$

where n is the number of measurements gathered and classified within the chosen subset associated to a landmark.

The target class Z ($Z \in R^k$) represents the energy consumption. This is denoted as:

$$Z = \{z_i^k\}, \forall z^k_i = [z^k_1, z^k_2, \ldots, z^k_n] \quad (5)$$

Then, given the training values $\{(p_i, z^k_i), \ldots, (p_n, z^k_n)\}$, our goal is to find a function that will allow us to classify the monitored energy consumption (z_i), giving its vector of features ($p_i = [f1_i, f2_i, f3_i]$).

The vector p_j is provided as input to all functions of our *Radial basis functions*, RBF network, and the output $f(p_j)$ is given by

$$f(p_j) = \sum_{i=1}^{C} w_i.\varphi(\|p_j - c_i\|) \quad (6)$$

where $\|p_j - c_i\|$ is the Euclidean distance between p_j and the *Radial basis function*, RBF with center c_i.

The number of *Radial basis functions*, RBFs is C, and w_i are the weights of the network.

Thus, given a target vector of features p_j associated to the energy consumption z_j, the output of the *Radial basis functions*, RBF network may be expressed as a weighted sum of normalized basis functions:

$$z(p_j) = \sum_{i=1}^{C} w_i \cdot \frac{\varphi(\|p_j - c_i\|)}{\sum_{k=1}^{c} \varphi(\|p_j - c_k\|)} \quad (8)$$

where w_i are one-dimensional weights.

The parameter w_i may be determined to obtain a good approximation by optimizing the fit represented by the difference between the input values of the reference data and the test targets [Eq. (8)].

Thus, we form the following set of equations:

$$z(p_k) = \sum_{i=1}^{C} w_i.u(\|p_k - c_i\|), \quad k = 1,\ldots,L \quad (9)$$

We calculate w_i by solving the system of linear equations based on Eq. (9) and using the reference values of the database and their corresponding energy consumption estimations.

Subsequently, given a new vector of features p^i_j, the weights w_i are used during the estimation process to obtain an energy consumption estimate $\hat{z}$, according to:

$$\hat{z}(p^i{}_j) = \sum_{i=1}^{C} w_i.u(\|p^i{}_j - c_i\|) \quad (10)$$

After the off-line phase, energy consumption can be estimated using the building maps generated during the off-line stage.

5 Conclusion and Future Work

Intelligent building, with the use of automated control system such as RAS, enables both building owners and occupants enjoy the benefits of financial gain and enhanced accommodation /management quality.

Based on the data measured by sensors installed in the building, for the extraction of relevant knowledge from all the sensed data, we apply sophisticated SC techniques to model the energy consumption profile of buildings. Once energy usage profiles have been extracted, we can design and implement actions to save energy.

As future work we will apply the approach to analyze the impact of implementing the strategies proposed to save energy in the building under experimentation.

References

1. Agarwal Y, Balaji B, Gupta R, Lyles J, Wei M, Weng T (2010) *Occupancy-driven energy management for smart building automation*. In: Proceedings of the 2nd ACM workshop on embedded sensing systems for energy-efficiency in building. ACM, pp. 1–6.
2. Scott J, Bernheim et al: *Preheat: controlling home heating using occupancy prediction*. In: Proceedings of the 13th international conference on ubiquitous computing. ACM, pp. 281–290
3. Lu J, Sookoor T, Srinivasan V, Gao G, Holben B, Stankovic J, Field E, Whitehouse K (2010) *The smart thermostat: using occupancy sensors to save energy in homes*. In: Proceedings of the 8th ACM conference on embedded networked sensor systems. ACM, pp. 211–224.
4. Patel, S., Robertson, T., Kientz, J., Reynolds, M., Abowd, G. (2007) At the Flick of a Switch: Detecting and Classifying Unique Electrical Events on the Residential Power Line. UbiComp 2007: Ubiquitous Computing. Lecture Notes in Computer Science. Vol. 4717, Springer Berlin Heidelberg, pp. 271-288.
5. Moreno, M.V., Dufour, L., Skarmeta, A.F. et al. *Big data: the key to energy efficiency in smart buildings*. In: Soft Computing, May 2016, Volume 20, Issue 5, pp. 1749–1762.
6. Robles, R.J., Kim, T. (2010) *Applications, Systems and Methods in Smart Home Technology: A Review.* In: International Journal of Advanced Science and Technology, Vol. 15, February, pp.37-47
7. Nakajima, T., Satoh, I. (2006) *A software infrastructure for supporting spontaneous and personalized interaction in home computing environments.* In*:* Journal of Personal Ubiquitous Computer, Vol. 10, no. 6, p. 379-391
8. Directive 2010/31/UE related to Energy Performance of Buildings. Official Journal of the European Union on 18/06/2010.