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PREDICTIVE MODELS OF THE ENERGY CONSUMPTION IN INTELLIGENT BUILDINGS

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Abstract: *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 generate predictive models of energy consumption in buildings. To verify the feasibility of this proposal, we apply our approach to a reference building for which we have contextual data from a complete year of monitoring. First, 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 of our reference building charged with estimating the energy consumption, given a concrete set of inputs.*

Key words: *big data, smart buildings, energy consumption, energy efficiency.*

1. Introduction

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. In recent 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 with the aim of enabling real-time systems anticipation and optimization of the energy consumption in buildings.

We propose a solution for data processing to generate energy consumption

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models of buildings which can be used to select the optimal measurements and strategies to save energy.

First, we analyze what the main drivers of the energy consumed in buildings are. For this analysis, we use the data measured by sensors installed in the building and thus generate the predictive model that estimates its daily energy consumption.

As a real case where energy saving must be achieved, we present an polyvalent sportive hall building with high levels of monthly energy consumption involved in thermal comfort provision.

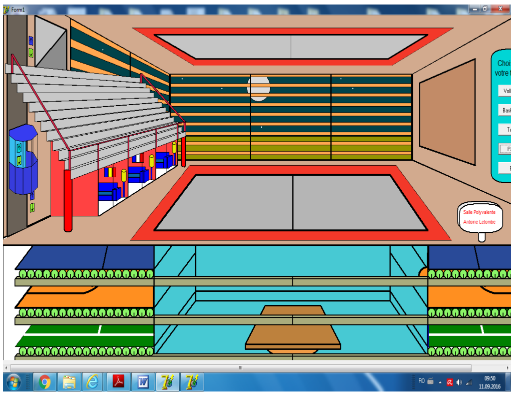

Fig. 1. *Virtual model of the polyvalent sportive hall building*

In this building, the first stages of experimentation have been already carried out following the approach proposed in this work. Analysis of the generated models has led to energy saving strategies being applied.

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 energy efficiency in buildings. Among these issues, relevant parameters affecting the energy consumed in buildings are described and proposed as input data of the building energy consumption model.

Finally, this section presents our approach to propose optimum strategies and actions to save energy in buildings. Section 4 details the energy usage characterization of our reference building, the process of generation of its energy consumption model and the analysis extracted from such models. 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 [2] 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 [3]. 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 [1]. Timers and motion sensors provide a useful tool to detect and respond to occupants, while providing them with feedback information based on real sensor data and contextual information [4].

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. We propose to generate accurate predictive models of energy building consumption to be used to select the best strategies for saving energy of the specific characteristics of each building.

3. Optimum Strategies for Energy Efficiency 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.

The CEN Standard EN15251 (British Standards Institution 2007) proposes criteria for dimensioning the energy management of buildings, while indoor environmental requirements are maintained [6]. 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.

During the monitoring phase, information from heterogeneous sources is collected and analyzed before specific actions are proposed to minimize energy consumption. Considering this, and taking into account the models for predicting the comfort response of building's occupants given by [5], we describe below the main parameters that must be monitored and analyzed before selecting optimum strategies to save energy.

1. *Electrical devices always connected to the electrical network.*

In buildings, it is necessary to characterize the minimum value of energy consumption due to electrical devices that are always connected to the electrical network.

2. *Electrical devices occasionally connected to the electrical network.*

Depending on the kind of building under analysis, different electrical devices must be included in the final system responsible for estimating the daily electrical consumption of the building.

3. *Occupants' behavior.*

Energy consumption of buildings due to the behavior of their occupants is one of the most critical points in every building energy management system.

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

5. *Information about the energy generated in the building.*

Information about the amount of daily energy generated and its associated contextual features can be used to estimate the total energy generated in the future.

6. *Information about energy consumed in the building.*

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. Therefore, the approach proposed to design optimum strategies of energy saving in buildings is the following:

1. Analyze the energy consumption profile associated to each service provided in the building. In this way, it is possible to identify variables affecting the energy consumption of each service.
2. Analyze the relation among the evolution of such variables and the energy consumed. Thus, it is possible to select variables with the most relevant impact in the energy consumption.
3. Provide behavior patterns of the variables identified as relevant, including their uncertainty.

4. Implement a predictive building model able to estimate the evolution of the energy consumption given such a set of inputs.

5. Design optimum strategies of control to save energy in the building based on the estimated evolution of the energy consumption. We propose a procedure based on applying different soft computing techniques according to the specific goal to be achieved.

After carrying out these steps, an estimator is able to predict the energy consumption in an on-line way.

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.* During this first stage, we collect data about outdoor/indoor temperature, humidity and pressure. The Energy Consumption (EC) is collected over short periods of time (each minute of every day during a year).

Such measurements are associated to specific vectors of environmental parameters ($Z(t)$) measured outside and inside the building. Thus, the building models generated will be sufficiently representative to cover different contextual conditions. So, the set of data pairs for the training of our building model is:

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

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. The different processing techniques applied in this stage are given 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 for every feature extracted from the initial dataset.
- *Feature selection*. We apply *principal components analysis (PCA)* in conjunction with a ranker search mechanism.

If we consider EC(i) as multi-dimensional observations vector and u as an arbitrary direction in this multi-dimensional space, the principal components are calculated by optimizing the following equation:

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

where multi-dimensional observations column vector is transposed in row vector.

With the aim of reducing the final computational load of the estimation method, we searched the optimum number of attributes to represent the energy consumption profile of our reference building.

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 is a statistical procedure that 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.

This transformation is defined in such a way that the first principal component has the largest possible variance and each succeeding component has the highest variance possible under the constraint. In our approach the number of features was reduced to 3, which will be denoted as $f\,1$, $f\,2$, $f\,3$.

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

$$\{[f\,1(t), f\,2(t), f\,3(t)], Z(t)\},\ t = 1, 2, ..., N. \tag{3}$$

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

3. *Clustering.* During this stage, the input data division according to the distribution of the values of these features is carried out, the data being 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* for each landmark is computed as regression technique [5].

Radial basis functions network 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:

$$P = \{p_i\},\ \forall p_i = [p1, p2, ..., pn], \tag{4}$$

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:

$$Z = \{z_i^k\},\ \forall z^k_i = [z^k_1, z^k_2, ..., z^k_n]. \tag{5}$$

Then, given the training values $\{(p_i, z^k_i), ..., (p_n, z^k_n)\}$, our goal is to find a function that will allow us to classify the monitored energy consumption (z_i), giving its vector of features ($p_i = [\,f\,1_i, f\,2_i, f\,3_i]$).

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:

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

where $\left\| p_j - c_i \right\|$ 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:

$$z(p_j) = \sum_{i=1}^{C} w_i . \frac{\varphi\left(\left\| p_j - c_i \right\|\right)}{\sum_{k=1}^{c} \varphi\left(\left\| p_j - c_k \right\|\right)}, \tag{8}$$

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:

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

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.

Therefore, our resulting *Radial basis function*, RBF avoids over-fitting. Subsequently, given a new vector of features p^l_j, the weights w_i are used during the estimation process to obtain an energy consumption estimate $\hat{z}$, according to:

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

5. Conclusion and Future Work

Our approach address to energy saving and energy efficiency in buildings based on using the data measured by sensors installed in the building. For the extraction of relevant knowledge from all the sensed data to model the energy consumption profile of buildings, we apply sophisticated Soft Computing techniques.

Once energy usage profiles have been extracted, we can design and implement actions to save energy. For the generation of predictive models, we use the data collected during a monitored period. Then, considering such models, we propose some measurements of control to save energy in the building taken as reference.

At present we are carrying out experiments to analyze the impact of implementing the strategies proposed to save energy in the building under experimentation.

As future work we will apply the approach proposed in this paper to other buildings, with the aim of demonstrating its applicability in different contexts.

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