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AN OPTIMIZATION METHOD BASED ON EVOLUTIONARY COMPUTATION USED FOR ESTIMATING THE ENERGY CONSUMPTION FOR HEATING IN A BUILDING

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Simplified mathematical models that can describe the real behavior of a building with relative small errors can provide useful information about the best operational methods of the HVAC (Heating, Ventilating and Air Conditioning) systems, energy demand for heating and cooling, etc. We developed a simplified mathematical model for computing the energy demand for heating and optimized it with a Genetic Algorithm, in order to minimize the error between the model and real data. The tested period (a month) showed that the optimization method is suitable for this type of applications and the relative error was 0.14 kWh.

Keywords: energy consumption for heating, building simplified model, Genetic Algorithm

1. Introduction

The current optimization of sensors, controllers and networking infrastructure, as well as the decrease in their manufacturing costs lead the way to the development of *smart* building features, such as continuous monitoring, controllers, diagnosis, optimal HVAC usage and cognitive learning facilities. For these kind of applications, it is desired to be able to compute and predict the transient energy required for heating and cooling, which accounts for more than

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50% of the total energy used in a specific building across European Union (EU) [1,2].

The building operation is the most important factor in order to decrease the peak demand in this energy sector, which is the largest end-use energy consumption in EU, with a total share of 40% [3,4]. Optimal building energy consumption and operation strategies offers an optimal alternative to reduce the energy consumption in residential and tertiary sectors. Transient models for buildings energy prediction are essential for developing control and operational strategies to increase the efficiency in energy consumption and improve the interior comfort.

The literature splits buildings modeling domain into two basic categories: forward and inverse modeling [5]. The forward models (*"white-box"*) represents a purely physical model, which requires a priori comprehensive knowledge about the building's construction materials, geometry, emplacement, type of HVAC system and so on, information which is not always available on site. This method is usually used for designing and optimization of the HVAC system. Due to their complexity, white box models are usually implemented within simulation tool such as EnergyPlus [6], ESP-r [7], TRNsys [8], which use synthetic environmental data and complex mathematical equations to determine energy requirements, energy production and interior comfort level. The synthetic data used in this type of models, implies a significant computing error, and cannot describe the real behavior of the tested building. Using this type of method generally entails large amount of time to develop the model and analyze the results, and usually requires trained personnel for utilization.

The inverse modeling is based on the empirical behavior of the building which implies data driven models. This refers to *black-box* models (e.g. artificial neural networks – ANN), which are purely empirical models. A black-box model requires on-site measured data, usually harvested over a long period of time, in order to be able to provide estimation of energy consumption under different conditions. The shortcoming is the large amount of data used in training and validation processes and the dependency on building operating conditions. If the training data does not cover large varying conditions in building's operational strategies and environmental conditions, or if there are major changes in the control strategies, or in occupancy schedule, it can lead to considerable forecasting errors [9].

In order to overcome the shortcomings of the previous two models, an inverse gray-box model was developed. This is basically a hybrid model that combines a simplified description of a building and it is trained with measured data harvested over a relatively short period of time. This type of approach showed a very good efficiency if it is optimized using different methods. The shortcoming is that it is necessary to implement an optimization algorithm in order to minimize the errors between the model's output and real, measured data.

For this, Braun et al. [10,11] developed an optimization and training algorithm which implies using two optimization methods: a global search algorithm (used to minimize the errors caused by the simplified representation of the building's elements) and a nonlinear regression algorithm (used to minimize the errors between the model's outputs and real measurements). The optimization method provided very good results, and it reduced the period to one to two weeks. The base mathematical method is to obtain a specific transfer function, starting from a state-space representation of the building's envelope. Usually, the state-space formulation has been used to analyze linear systems characterized by a large number of inputs and outputs

Wang and Xu developed a series of simplified gray-box models [12,13,14] for which they used a parameter optimization method based on Genetic Algorithm (GA) which can rapidly converge to the nearly optimal solution for a given problem. The GA estimator determined optimal values for desired parameters (Resistors and Capacitances) by minimizing the error between models and measurements. They also found relatively small errors between prediction and real data for a period of two weeks. Their method used as a base mathematical formulation a frequency domain method, which has its own shortcomings and can induce errors if the parameters are not chosen well.

2. Mathematical representation

In order to be able to compute the energy consumption for a building, the approach presented in [**Error! Bookmark not defined.**,**Error! Bookmark not defined.**,15] was adopted and improved by applying a customized optimization algorithm in order to reduce the errors between the model and measured data. The optimization algorithm is based on evolutionary computation theory and is described in chapter 3.

In order to generate the simplified mathematical model, first we represented the building, considering the main elements: exterior walls, roof, floor, windows and interior thermal mass (represented as interior walls). Each of these components is represented by a simplified analogous thermal network, composed of three thermal resistance (R) and two capacitances (C) – 3R2C. This simplified representation leads to eight thermal nodes, which are further analyzed in order to create the state-space representation.

The method used for computing the energy consumption for heating is based on a research made by Seem et al. [16,17]. This implies an algorithm for representing a transfer function starting from a state-space representation of the system. A simple state-space representation for continuous, linear, time-invariant system with *p* inputs, *n* states and *m* outputs has the following general form:

$$\frac{d\boldsymbol{x}}{d\tau} = \boldsymbol{Ax} + \boldsymbol{Bu} \tag{1}$$

$$y = \boldsymbol{c^T x} + \boldsymbol{d^T u} \tag{2}$$

where:

- $\boldsymbol{x}$ – The state vector containing temperatures from nodes;

$$\boldsymbol{x}^T = [T_{c,1}, T_{c,2}, T_{e,1}, T_{e,2}, T_{f,1}, T_{f,2}, T_{i,1}, T_{i,2}] \tag{3}$$

- $\boldsymbol{u}$ – The inputs vector containing all driving conditions which influence the zone energy consumption;

$$\boldsymbol{u}^T = [T_z, T_a, T_g, Q_{sol,c}, Q_{sol,e}, Q_{g,r,c}, Q_{g,r,e}, Q_{sol,w}, Q_{g,c}] \tag{4}$$

The input vector $\boldsymbol{u}$ contains the driving parameters which influences the zone's energy requirement: the zone's temperature (assumed constant in this study) - T_z, the exterior temperature - T_a, ground temperature - T_g, the solar radiation absorbed by the roof ($Q_{sol,c}$), exterior walls ($Q_{sol,e}$), radiative internal gains ($Q_{g,r,e}$ – on exterior walls, $Q_{g,r,c}$ – on celling), convective internal gains ($Q_{g,c}$) and solar radiation transmitted through the windows ($Q_{sol,w}$).

- $\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{c}, \boldsymbol{d}$ – Matrices and vector of constant elements obtained from thermal characteristics of walls.

The matrices coefficients are obtained by writing the dynamic energy balance in each node presented in the thermal network. This results in a system of eight differential equations in the following form:

$$C_{c1}\frac{dT_{c1}}{d\tau} = \frac{T_a - T_{c1}}{R_{c1}} + \frac{T_{c2} - T_{c1}}{R_{c2}} + Q_{sol,c} \tag{5}$$

The building's overall mathematical representation is obtained by adding the energy balance of the zone's internal node, represented by T_z temperature. The obtained system of nine differential equations is than written in matrix form, obtaining the coefficients of the $\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{c}, \boldsymbol{d}$ parameters.

- y – The energy used for heating/cooling.

The method presented in [**Error! Bookmark not defined.**] allows to obtain an equivalent transfer function, with the output at any time *t* of the form:

$$y(t) = \sum_{k=0}^{n} \boldsymbol{S}_k^T \boldsymbol{u}_{t-k\Delta\tau} - \sum_{k=1}^{n} e_k y(t - k\Delta t) \tag{6}$$

The $\boldsymbol{S}_k$ vectors and e_k scalars are the transfer function coefficients obtained from the constant coefficient matrices, while n is the number of states (eight in this representation). This transfer function computes the system's output at time *t*, using the present and past inputs values and past outputs. In this research, the time step $\Delta\tau$ is one hour.

3. Optimization algorithm

Genetic Algorithms (GA) have been around since the early 1970s, when John Holland created their theoretical foundations and proposed the first applications in his book, "Adaptation in Natural and Artificial Systems" [18]. Inspired from genetic evolution in biology, Holland proposed a universal model that could evolve by recombining information and passing it on to next generations, a search heuristic that proved very effective in a wide range of applications with a limited number of parameters that interact in complex, non-linear ways. Simply put, a genetic algorithm searches the given state space, in order to find the best fit for the desired solution [19], resulting in a robust adaptive search procedure. This is very effective as a global search heuristic used in optimization problems involving a fixed number of parameters for which one can estimate limit boundaries [20].

In order to model the problem with Genetic Algorithms, the first thing to do is to identify the parameters of interest. In this study, the parameters which need to be optimized are the thermal resistances and capacitances which compose the building's envelope. This parameters have a direct influence on the performances of the simplified model (equation 6) and their exact values are unknown. Usually, part of these parameters are fixed, and can be used directly, while the rest have to be varied in order to best estimate the solution. These parameters of interest form what is commonly known as a chromosome in the GA. A GA routinely starts by initializing randomly a population of individuals, each with their own chromosome, and proceeds to solve the problem for all individuals. After this step, all results have to be evaluated, using what is known as a fitness function, in order to identify which are the best individuals in the population.

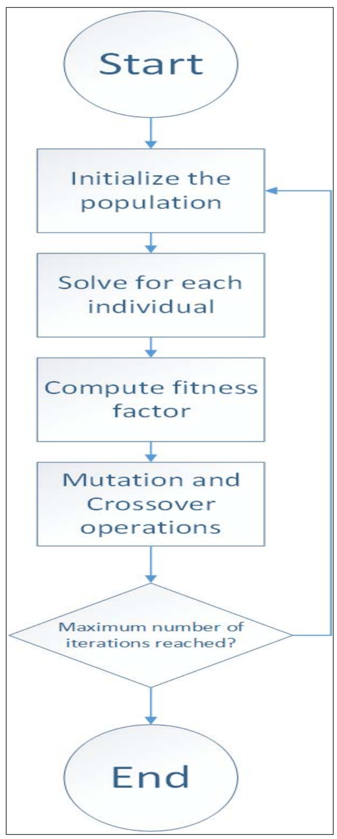

Fig. 1 GA flowchart

Moreover, genetic operators such as mutation and cross-over can be used in order to avoid converging to local minimums/maximums. For the scope of the algorithm, mutation represents changing one or more traits in the chromosome, whereas crossover represents interchanging one or more traits between two chromosomes within the population; these operators are only applied with a certain probability. Finally, these steps are reproduced for a fixed number of iterations, or until the error drops under a desired threshold. A flowchart of actions that typically occur in a GA can be observed in Fig. 1.

4. Implementation and results

For implementation we used the low-energy building from UPB campus, described in detail by Căruțaşiu et al. [21], and the considered period was December 2014.

First we computed the thermal resistances and capacitances, starting from the thermal conductivity, specific heat and density from each layer composing the building's envelope. The second step was to harvest parameters of interest in order to compute the input vector. These were obtained from the monitoring system mounted on the case study house and detailed in [ERROR! BOOKMARK NOT DEFINED.]. The outside and ground temperature were used as provided by sensors, while the zone temperature ($\boldsymbol{T_z}$) was computed as the main temperature inside the house (harvested from all sensors). The solar radiation absorbed by the opaque elements, such as roof and external walls, was computed using the algorithm presented in detail by Teodoroiu and Şerbănoiu [22]. In order to estimate the radiative and convective heat gains, we considered a constant occupancy schedule (from 9:00 AM to 17:00 PM in workdays, and no occupancy in weekends) and four habitants.

These values were used for computing the energy consumption for heating in December, using the non-optimized mathematical model. As shown in Fig. 2, the difference between the model and real (measured) data is very large. The average daily real energy consumption over the tested period was 17.2 kWh, while the pure model estimated an average value of 70.6 kWh, resulting an absolute error of 53.4 kWh and a relative error of 309%. This emphasizes the need of implementing an optimization algorithm.

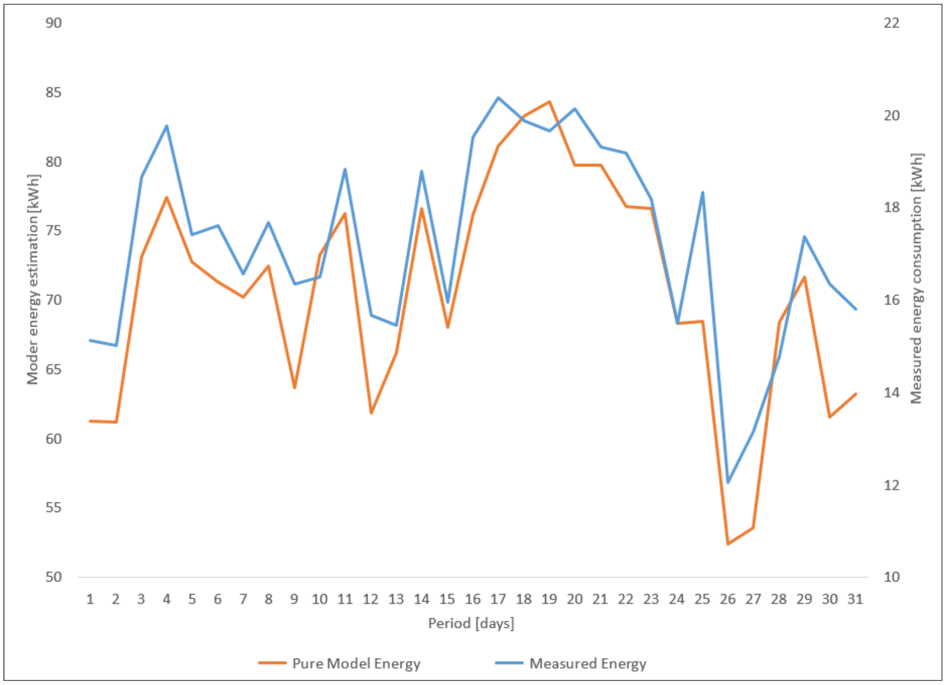

Fig. 2. The pure model energy estimation versus measured energy consumption

For implementing the optimization algorithm we used the Java programming language. A GA's population is composed of chromosomes, formed form the parameters of interest (thermal resistances and capacitances in this paper). We generated a population of 2000 individuals, each one taking random values in the imposed ranges (minimum and maximum values of the parameters of interest based on the materials composing the building). The mutation probability was set to 40%, while the crossover probability was set on 30% in order to increase the diversity among the individuals from the population. In order to reach convergence, only 5 iterations were needed, in which the survival rate from one iteration to another was made up from the best 50 individuals. The individuals were evaluated based on a fitness function which was considered to be the integrated root-mean-square error between the optimized model and measured energy (equation 7).

$$f = \sqrt{\frac{\sum_{k=1}^{N}(E_{model} - E_{real})^2}{N-1}}, \tag{7}$$

where N is the number of data points considered.

We recomputed the GA each 14th days (N = 14 days), in order to account for variations in the input data that could introduce errors in our system.

Using these Genetic Algorithm proprieties, the results of the optimized model is shown in Fig. 3. As observed, the implementation of the Genetic Algorithm minimized the errors between the measured data and the pure mathematic model. The average error was 0.14 kWh over the considered period. The fitness function varied from 0.6 to 3.5, meaning a very good approximation. The daily difference between the optimized model and real data varied from 0.02 to 1.95 kWh.

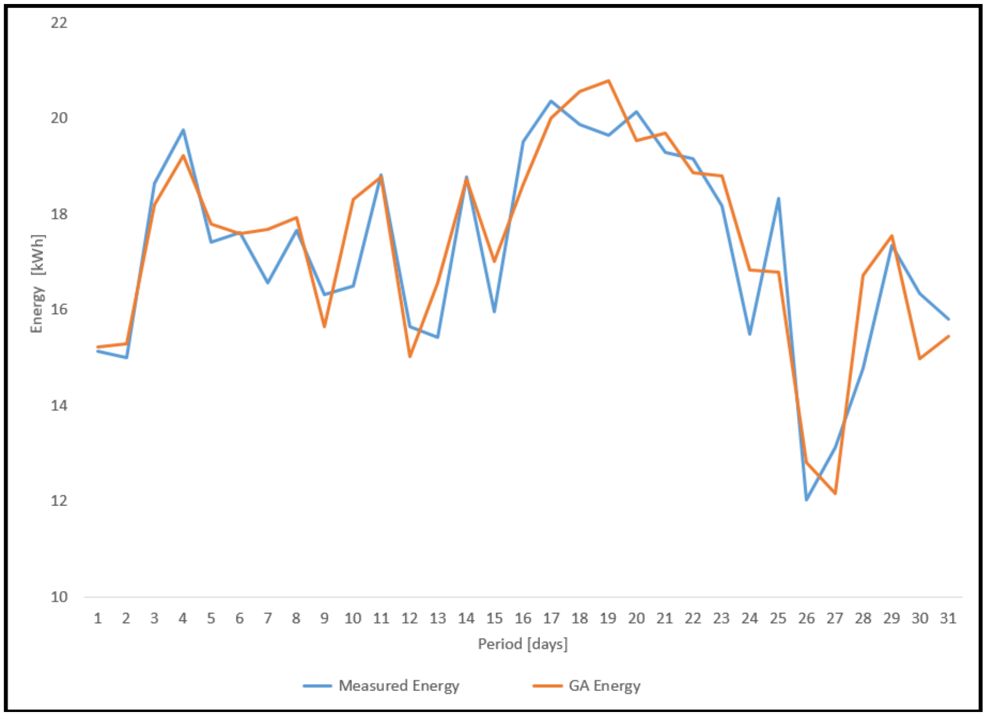

Fig. 3. Optimized model

5. Conclusions

Mathematical models which can estimate with high accuracy the energy consumption in buildings are a great challenge for engineers as research on new models and optimization methods are ongoing. The applicability of the optimized model varies from simple HVAC efficiency strategies to aggregation in smart buildings and smart grids.

The simplified inverse building model presented in this paper provides a new approach in terms of optimization algorithms used in this research area. The customized Genetic Algorithm implemented showed a very good efficiency in finding the optimal parameters in the imposed research space. These optimal parameters ensures the minimization between the model's energy estimation and real (measured) data. By creating a chromosome containing all 20 parameters which compose the thermal envelope of the building, the method can be applied even if the values are not known very well or are not known at all (energy auditors cases).

The daily average measured energy consumption in the studied period was 17.25 kWh, while the optimized model estimated 17.39 kWh, meaning a relative error of 0.85%, while the daily average difference between the two was 0.14 kWh, proving the applicability of the algorithm.

The simplified model only estimates with high accuracy the energy consumption for heating. The errors introduced by high oscillations in the exterior temperature involves the need of a new approach. As future work, we propose to implement a multi-model approach in order to be able to estimate the energy consumption for the test building during all seasons.

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