Coupling Building Thermal Network and Control System, the First Step to Smart Buildings

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***Abstract*—Buildings are one of the main energy consumer and carbon emission sources in European countries. Population growth in cities may be effective for economic growth, but by considering overpopulated cities, making new efficient buildings and optimizing energy consumption in older ones may be a good solution for energy management and carbon reduction in them. For doing this one needs to collect buildings data for months to get an idea about the energy consumption in a building. On the other hand, computer simulations may not provide very accurate results, but they can give a crude idea about energy consumption in buildings. There are many different tools to simulate energy consumption in buildings, among all of them simplified models provide fast and accurate results. Developing building model based on lumped capacitance method by means of resistance-capacitance (RC) circuits provides good results and a comprehensive schematic about the heat transfer in the building. In this paper, the application of thermal networks for building load calculation is introduced and it will be shown how effectively it can be used in control systems to make a smart building.**

Keywords—Energy management; Simplified model; Thermal networks; System identification

I. INTRODUCTION

Thermal engineers try to develop reliable methods to quantify energy consumption in buildings. The energy consumption of a building can be determined through three main methods. Experimental data provide the main accepted results, although they are very time consuming and it might be expensive to perform measurements in every building [1]. Another method which is called top-down method considers each building in the district as a sink and it is not concerned with end users. It calculates the energy consumption of the whole district based on collected energy values for a specific period of time, and top level variables such as micro economic indicators, population growth, unemployment, etc. In contrast to top-down method, there is bottom-up method. It determines the estimated energy consumption for the town and city scale by aggregating the energy consumption of a set of buildings to determine energy consumption for the region. This approach consists of two different methodologies: statistical method and engineering method [2].

Building simulation methods are applied as a tool for energy management and environmental assessment of buildings [3]. The building thermal performance and its physics can be investigated, statically or dynamically [4]; this can provide a suitable tool to study thermal comfort, predicting energy performance, and sizing HVAC systems of buildings. Furthermore, the generated simulation models must be reliable to insure engineers that extracted results can be used for further designs.

For having a better comprehension about the calculation of heating/cooling load in housing stocks, it seems necessary to have a quick description about solving energy equation for a building [6]. Peng and Wu present a quick description of four conventional methods, which are used for calculating energy consumption in a building as: Numerical method (Lumped capacitance method), Harmonic method (Can be used if there exists harmonic boundary conditions), Response factor method, and CTF (Conduction transfer functions [7]).

Harmonic and Laplace methods have been considered specifically in Peng's work and he [6] compares each method result for three various types of walls. Peng considers Laplace method as the most accurate model, and by calculating D value, as the deviation from Laplace method, he shows that thermal network has the smallest deviation from Laplace method.

For introducing the history of thermal network's application for calculating dynamic heat transfer it should be mentioned that in 1985, Hassid used the first 2R1C model for simulating dynamic heat transfer in a plane wall. Then Seems used a two node model for representation of plane walls with 3R2C [8]. 3R2C arrangement is widely used for modeling of transient heat transfer in building envelopes since that time. More recent types of RC models are 3R4C and 4R5C by Fraisse [9]. The next important progress in simulating building energy demand was including internal mass effect by considering 1R1C [10] and after that 2R2C by Wang [11]. Development in computer programming with high speed of calculation encourages designers to use different algorithms such as genetic algorithms for determining building parameters [12]. In a more sophisticated work Wang uses genetic algorithms for determining internal mass parameters [11]. Electrical analogy draws a parallel between heat transfer and electrical current conservation equation at corresponding nodes. Fraisse [13] provides a brief explanation in this area by introducing the calculation method for resistors and capacitors. The other interesting work in building simulation by RC circuit has been done by Gonzalez and Eames [14]. They present an analytical method for creating parameters of a second order lumped parameter model. As it has been shown in their paper 3R2C, model is the most accurate method for simulating multi-layer walls if dominant layer approximation is considered for determining the thermal circuit parameters. In another study which has been done in France, Park and Ruellan [10] propose a generic thermal model of electrical appliances in order to evaluate the influence of their thermal gain on low energy buildings. Thermo-electricity analogy is an intuitive approach, and it simplifies developing a systematic formulation and solution of buildings thermal performance by means of RC circuits. Even though the idea of a simple RC network is quit crude, but it can provide a very helpful tool for designers to estimate the warm-up and cool-down times corresponding with thermostat setback and setback recovery [15], which can be very helpful for controllers because most of them are working with similar circuits.

One of the attempts to categorize modeling techniques has been presented in [5]. It categorizes the available methods and comments on the applicability and limitations of each modeling technique. As shown in table 1, the modeling methods are distinctly divided into three categories: the "white box" method, the "black box" method, and a combination of both, the "grey box" method. Thermal networks can be used in white box and grey box modeling. If one can define the parameters in the thermal network according to physical properties of the construction, then it will be a white box model and if a set of data is used to estimate the parameters in the model then it will be a grey box model. There are two main ways to make data sets. The first one is to use experimental data which may not be available for every building. The second one is to use commercial software which has strong libraries which contains different used materials and structures for buildings with detailed thermodynamics properties of them. In this work TRNSYS software is used to provide training data for the simplified thermal model.

TABLE I. COMPARISON BETWEEN 3 SIMULATING METHODS [5]

Building simulation methods	**Models description**		
	Building Geometry	***Training Data***	***Physical interpretation***
white box	A detailed description of the building geometry is required	No training data is required	Results can be interpreted in physical terms
black box	A detailed description of the geometry is not required	A large amount of training data is required	Difficulties to interpret results in physical terms
grey box	A rough description of the building geometry is enough	A small amount of training data is required	Results can be interpreted in physical terms

In the next section of this paper thermal network method is introduced. For calculating internal temperature of a building a simple thermal circuit is considered. After presenting the governing equations, identification procedure is explained briefly. After that in results and discussions section the accuracy of results in different periods of the year will be shown and finally the model features and future studies will be described in conclusion section.

II. BUILDING'S THERMAL NETWORK MODEL

A. *Assumptions*

In thermal networks approach, the main assumption is that, a building has been made of a finite number of parts n, called nodes. Each resistance between two nodes represents the walls or windows or any other material between two different spaces, thus forming a thermal network. In addition, there may be direct heat input at each node, from various heat sources such as solar radiation, lights, occupancy, appliances, etc. By analogy with electrical circuits it is convenient to represent thermal networks by diagrams. If resistances and capacitances are not dependent on temperature gradients, then this approach is suitable for any linear thermal system. This assumption is compatible for the envelopes of buildings because the range of temperatures is small enough to permit designers to describe buildings by linearized equations. Therefore, any building can be modeled as a thermal network, to be more specific, any building can be represented as system of coupled first-order differential equations in time [16].

The first step is to decide the model order which introduces the number of capacitance in the model. The next step is to define the input and output parameters according to the problem. After that, the number of parameters which is dependent on model order and input and output of the model. The final step to produce a completely constrained grey box model is to connect all the parameters and data together by physical equations. In the case of this paper the input data contains outdoor temperature (T_{out}), total radiation (Q_{rad}) on building which is divided into two parts : the part which is absorbed by the external wall (Q_{rad1}) and the part which passes through the windows (Q_{rad2}) by considering the windows to wall ratio, and ground temperature (T_g), heat transfer by ventilation and infiltration (Q_{inf}, Q_{vent}) are considered as the input (known) information about the outdoor conditions. On the other hand internal temperature (T_{in}) and heating load (Q_{heat}) can be considered as input information too. One important fact in this selection is the model application. If the model is going to calculate the heating load (output of the model) in a building, then the indoor temperature must be considered as an input to the model and vice versa.

B. *Model Production and Governing Equations*

The model must be capable to convey all the physics of the problem according to input and output data. For a data provided in previous section, the first assumption is that to consider the first order model. It means that wall temperature (T_w) is calculated just in one point of the wall. More detailed wall construction can be considered too, but in this step this first order model seems enough. For a first order model with one output and six inputs at least 4 resistances and 2 capacitances are required to cover all different boundary conditions of the problem as shown in figure 1.

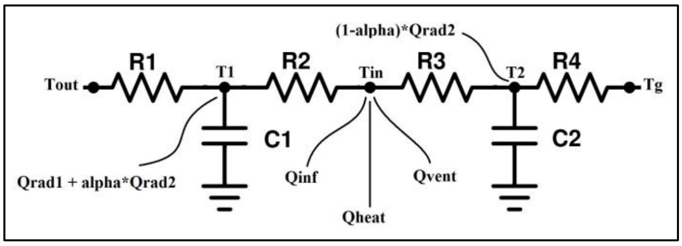

Fig. 1. 4R2C model for making the simplified building model

$R1$ and $R2$ represent the total thermal resistance between outdoor temperature and indoor temperature. $R3$ and $R4$ represent the total thermal resistance between the ground temperature and indoor temperature. $C1$ is the wall capacitance (in fact it contains all the capacitance of the building envelope, for more detailed models, different capacitances should be considered in different parts of the thermal circuit) and $C2$ represents ground capacitance. As it is shown solar radiation is heating the wall and some part of it passes through windows and heats the ground, and the heating load is affecting the indoor temperature directly. This model has the capability to show all the building properties by considering input data. Therefore, the state equation for this model is as shown in equations 1 and 2. The other equation for calculating indoor temperature or heating load is given in equation 3.

$$C_1 \frac{dT_1}{dt} = \frac{T_{out}-T_1}{R_1} + \frac{T_{in}-T_1}{R_2} + Q_{rad1} + \alpha Q_{rad2} \tag{1}$$

$$C_2 \frac{dT_2}{dt} = \frac{T_{in}-T_2}{R_3} + \frac{T_g-T_2}{R_4} + (1-\alpha) Q_{rad2} \tag{2}$$

$$Q_{heat} + Q_{inf} + Q_{vent} + \frac{T_1-T_{in}}{R_2} + \frac{T_2-T_{in}}{R_3} = 0 \tag{3}$$

III. PARAMETER IDENTIFICATION OF THE THERMAL NETWORK

Model identification is the process to determine physical properties of unknown systems according to some experimental data or training data. As shown in previous section the model structure for a 4R2C model, to calculate building thermal performance, includes 6 different unknown parameters ($R1, R2, R3, R4, C1, and\ C2$).

A. Training data

The building which is used in this work is a detached (4 fronts building) south faced building. The dimensions of the building are 10×5×3 m3. There are 2 windows on south wall: each of them has a width of 2 meters and a height of 1 meter. There is one window on the west and one on the east wall too, each of them has 1-meter width and 1-meter height. Overall area of the windows will be 6 m2, in which 30% of total area is the frame. In addition, as it is an office building the schedule for heating and cooling is organized as mentioned in table 2. The minimum allowed temperature in the building is 15°C and the heating system will be off if the indoor temperature is higher than 22°C. The infiltration and ventilation loads can be calculated from equations 4, 5, 6, in which ρ is the air density, V is the inside volume of the room, c_p is the air specific heat capacity, n is the infiltration rate (here n is 0.2 [h^{-1}]), and q_v is the air volumetric flow rate. The building is simulated as a heavy structured building and the material properties are represented in table 3. The EPB (Energy Performance of Buildings) regulation imposes Umax values that are far from the one used in the present work. In addition, the assumed building is a very simplified one and it doesn't pretend to represent the actual housing or office stock in Belgium. It is a kind of "virtual case study" to test the method.

TABLE II. BUILDING SCHEDULE FOR HEATING SYSTEM AND VENTILATION

Schedule	00:00 – 8:00	8:00 – 18:00	18:00 – 24:00
Working day	0	1	0
Weekends	0	0	0

$$Q_{inf} = \rho n V c_p (T_{out} - T_{in}) \frac{1}{3600} \tag{4}$$

$$q_v = \frac{(3.4 \times Schedule + 0.6) \times V}{3600} \tag{5}$$

$$Q_{vent} = \rho c_p q_v (T_{out} - T_{in}) \tag{6}$$

TABLE III. HEAVY STRUCTURE BUILDING MATERIALS

		Material (*inside → outside*)	Physical properties	
Wall	U value = 0.582 W/m^2K	Concrete	Thickness(cm)	19
			Conductivity(W/mK)	1.3
			Capacity(J/kgK)	800
			Density(kg/m^3)	1900
		Mineral wool	Thickness(cm)	5
			Conductivity(W/mK)	0.045
		Air gap	Thickness(cm)	2
			Resistance(m^2K/W)	0.17
		Heavy brick	Thickness(cm)	9
			Conductivity(W/mK)	0.75
			Capacity(J/kgK)	1000
			Density(kg/m^3)	1500
Roof	U value = 0.273 W/m^2K	Mineral wool	Thickness(cm)	15
			Conductivity(W/mK)	0.045
		Wood	Thickness(cm)	2
			Conductivity(W/mK)	0.12
			Capacity(J/kgK)	2500
			Density(kg/m^3)	400
Ground	U value = 2.648 W/m^2K	Plaster	Thickness(cm)	1.2
			Conductivity(W/mK)	1.38
			Capacity(J/kgK)	1000
			Density(kg/m^3)	200
		Hollow brick	Thickness(cm)	16
			Conductivity(W/mK)	1.23
			Capacity(J/kgK)	650
			Density(kg/m^3)	1300
		Concrete	Thickness(cm)	4
			Conductivity(W/mK)	0.58
			Capacity(J/kgK)	880
			Density(kg/m^3)	1300
Windows	U value = 1.1 W/m^2K	Double glazing	South wall win A(m^2)	4
			West wall win A(m^2)	1
			East wall win A (m^2)	1

B. *Identification results*

In this section some results are presented for parameter identification of the 4R2C model produced in previous section. For making the identification, Matlab system identification toolbox is used which has very powerful functions and algorithms for estimating black box and grey box models. According to equations 1,2 and 3 for determining the heating load for the building, wall capacitance, ground capacitance, wall and windows resistance and the ground resistance must be estimated ($R1, R2, R3, R4, C1, and\ C2$). In figure 2 the heating load model for the first 150 hours of the year is presented and in figure 3 the results are shown for the first 1500 hours. As it is shown in figures 2 and 3, the system simulation data has more than 86% of fitness comparing to training data out of TRNSYS software.

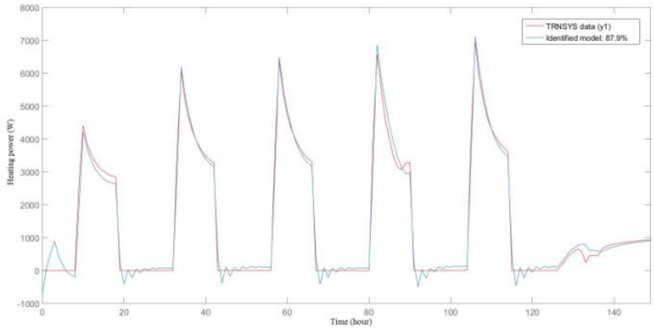

Fig. 2. 150-hour time response comparison for heating load

The estimated parameters resulting from each identification problem are provided in table 4 and they are compared with real values which were calculated according to thermodynamic properties of the materials presented in table 2. The identified parameters are given for three different sets of data: 150 hours, 1500 hours and 3000 hours of data are used to identify the parameters in the model. Because of the compactness of results for 3000 hours the figure is not presented here but the identified parameters are shown in table 4.

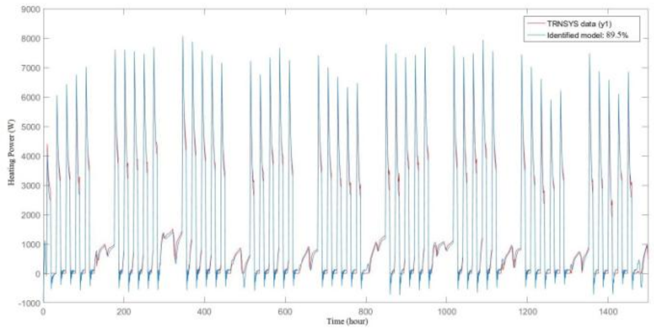

Fig. 3. 1500-hour time response comparison for heating load

The parameter R4 gets a value which is much more than its real value for 150 hours data. The other parameters are a bit different for 150 hours data but the difference is not as large as it is for R4. The parameters get almost a consistent value when the training data is more than 1500 hours. Almost all parameters in the last 2 columns of table 4, have equal values. According to table 4, one can conclude that the parameter identification of a 4R2C model for a building needs at least 1500 hours data to estimate physical values (mainly for R values). For this identification problem the time step of one hour was chosen. By reducing the time step to 15 minutes the estimated parameters for 150 hours data get more realistic values as shown in table 5.

TABLE IV. IDENTIFIED PARAMETERS FOR 4R2C MODEL WITH DIFFERENT DATA SETS

	TRNSYS data	150h data	1500h data	3000h data
		fitness = 86%	fitness = 89%	fitness = 89%
$R1$	0.0144	0.00046	0.00005	0.00007
$R2$		0.00286	0.01470	0.01436
$R3$	0.0067	0.00148	0.00114	0.00115
$R4$		10	0.00421	0.00436
$C1$	24259200	722000	207400	234400
$C2$	10248000	2023	4263	4221

TABLE V. IDENTIFIED PARAMETERS FOR 4R2C MODEL 150 HOURS DATA AND 15 MINUTES TIME STEP

	$R1$	$R2$	$R3$	$R4$	$C1$	$C2$
150 h data	0.00001	0.0017	0.0010	0.0036	360100	4179

After the identification has been done, the parameters for modeling the building are available. One can use this model to simulate heat transfer inside the building. To do this a control algorithm is developed. The developed control algorithm fixes the maximum and minimum allowed indoor temperature and in addition it decides about the turning on and off time of the heating system. In next section, the results will concentrate on the model capability to work with the control system to simulate heating load and indoor temperature.

IV. RESULTS AND DISCUSSION

The building control system is the main key to the future of the idea of smart building. It should be able to manage heating and cooling load, indoor temperature, relative humidity, and some other factors too keep the comfort inside the building as high as possible while it keeps the energy consumption at the least possible amount. Thermal networks provide accurate and fast results which can help to achieve the idea of smart buildings.

In this section the identified 4R2C thermal network accuracy will be checked for an office control system with turning on and off profile as shown in table 1. The occupancy effect is not considered in the model. In addition, the minimum allowed temperature inside the building is 15°C. The maximum allowed temperature is 22°C when the heating system is working. The control system is just working for controlling the heating system and it will not provide any results for cooling load (the building indoor temperature may be higher than 22°C during the hot season). Finally, it must be mentioned that the parameters out of 1500 hours data are used to make the building model. By using these assumptions, the following results are achieved.

The results for the first week of the year are shown in figures 4, 5, 6, and 7. In figure 4, and 5 the heating load and indoor temperature are compared to TRNSYS results. The model provides very good results for this period. In figures 6, and 7, the hourly error is presented. The results for the first 24 hours are not very accurate but after that the error is lower. The average error is around zero and for heating load the maximum error is around 1 kW and for temperature it is less than 1°C.

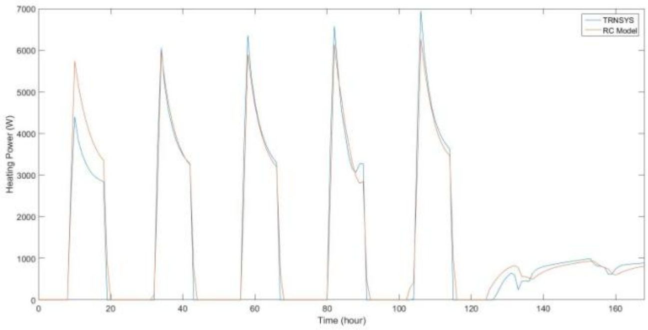

Fig. 4. Heating load for RC model comparing to TRNSYS

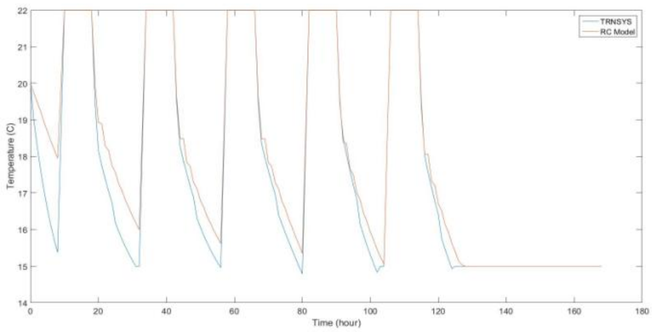

Fig. 5. Temperature for RC model comparing to TRNSYS

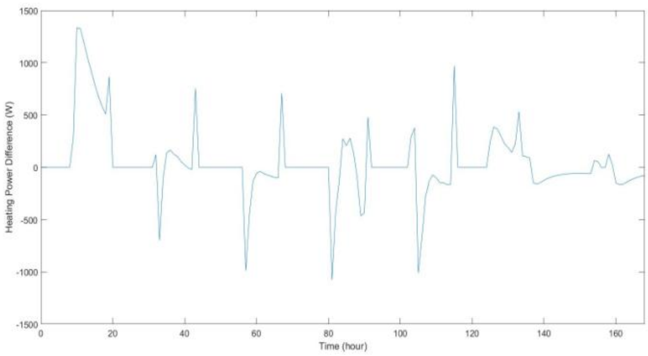

Fig. 6. Heating load error for RC model comparing to TRNSYS

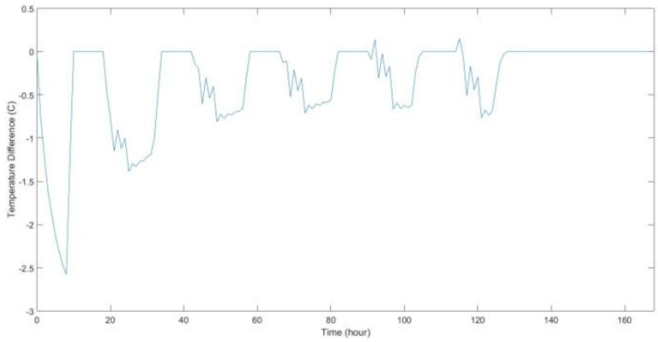

Fig. 7. Temperature error for RC model comparing to TRNSYS

Calculating the results for one week and comparing them with TRNSYS data seem interesting but the important point is that the model was trained with 1500 hours data (so the first 168 hours data were of course included in the data set). In next step the accuracy of the model is checked for data which were not used as training data.

This time the results are presented for the whole year. It means that the model was trained with 1500 hours data and is asked to predict energy consumption for 8760 hours. The results for this is presented in figures 8 and 9.

Considering results shown in figure 8, the model is able to predict energy consumption for whole year with high accuracy and the similar result is achieved for temperature model. The hourly heating load error is less than 2 kW and the average error is near to zero. For inside temperature prediction the hourly error for one year is less than 1°C for the whole year.

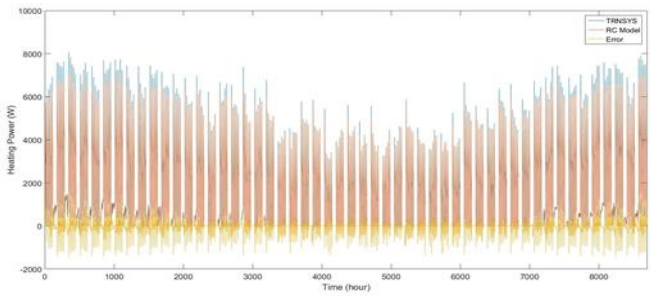

Fig. 8. Heating load for RC model comparing to TRNSYS for one year

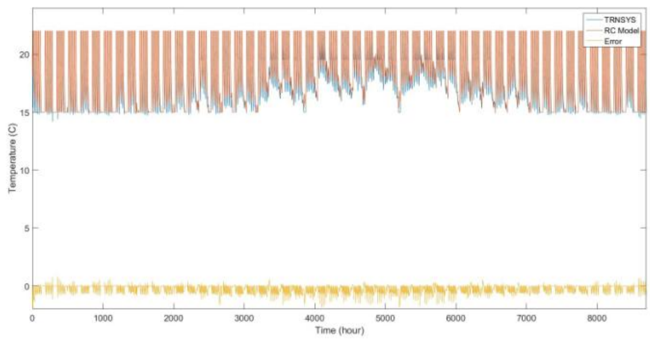

Fig. 9. Temperature for RC model comparing to TRNSYS for one year

V. Conclusion

This paper tried to show how effectively thermal networks can be used to predict the heating load and indoor temperature in buildings. The RC thermal networks have been introduced and then a 4R2C model used to simulate heating load and indoor temperature. The parameter identification has been done for 3 different sets of data and it shows how data set can have an influence on the accuracy of estimated parameters. The optimistic point about capacitance values is that at least their values are almost equal in two different identification problems. Although, the capacitances values are still far from the real values but the resistances are acceptable.

Finally, this RC model was used to predict heating load and indoor temperature of the building. For the first set of results the model simulates heating load for some part of the training data and it provides acceptable results when it predicts heating load and indoor temperature for hours which weren't part of the training data and the results were accurate enough.

The advantage of this method is the simplicity of the model for identifying thermal network parameters and its accuracy. In addition, using RC networks makes it easier to couple the building model with control system. In future works, one can develop a smart control system: it collects the data each hour and after collecting 1000 hours data (for example) for its training, it estimates the parameters of the building. Then it uses next data (for example the next 2000 hours) to train again and is able to update the thermal model of the building used in the control system.

Until now the model has been developed for a simple heavy structured building. It must be validated for various types of buildings with different functionalities and in different climates to prove its capability as a strong model of buildings. By means of this method we can generate intelligent building control systems to be the early step to smart buildings.

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