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A generalization approach for reduced order modelling of commercial buildings

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Abstract

Grey-box techniques can counter the computational inefficiency and resource-intensive nature of the conventional complex white-box models. However, these approaches might tend to be too specific in their application and scalability is limited by network order. To overcome these challenges, this study proposes a generalized approach for selection of reduced-order RC network models for commercial buildings using the peak power consumption characterization. The devised methodology is used to design the RC networks of buildings connected to district heating network at University College Dublin. The close proximity between measured and simulated demand indicate the influence of power demand on RC network selection.

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Keywords: grey-box models; RC network models; energy management; optimization models; building simulation

1. Introduction

Energy efficient retrofits have become crucial in the building sector as approximately 80% of the buildings in developed countries are over 10 years old and consume a major portion of total energy demand [1]. Model based control techniques have been developed to ensure building equipment functions in an energy-efficient manner [2]. However, these control techniques need detailed building models, which require extensive monitoring and are not often the cost-effective solution [3]. This can be attributed to the fact that the nature of building operation is usually uncertain and depends on various factors, such as, usage and physical properties. Hence, simpler modelling approaches that relate the building's physical properties to its operating environment are required. Grey box modelling is one such approach, which has been used at a wide scale [2].

Grey box modelling combines the advantages of data-driven and physical modelling approaches. Therefore, these models are accurate and computationally efficient. The design approach of grey-box models is often application specific, for instance, the design approach for grey box modelling of commercial buildings differs on a case by case

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basis [3]. Furthermore, the scalability of these models is limited by the network order, which defines the level of complexity incorporated in the model. Reduced order grey box approaches counter these limitations by achieving a trade off between the network order and desired accuracy [2].

To address these challenges, this paper focuses on a generalized approach to create reduced-order grey box models for commercial buildings based on the characterization of the peak power consumption. Section 2 states the different types of modelling approaches along with insights into past literature of grey-box modelling. Section 3 describes the methodology implemented in the design of RC networks. Section 4 discusses the case study followed by results in section 5. Conclusions and future work are discussed in section 6.

2. Background

Building thermal behavior simulation requires extensive modelling approaches with different levels of detail [4,5]. The approaches differ based on the model structure, the intended area of application, the level of computation and the desired accuracy. Often these models are characterized by two thermal behaviors: static and dynamic [5].

2.1. Modelling approaches

The different techniques for energy modelling are divided into three categories based on the aforementioned factors. White box or forward modelling approach uses detailed physics based equations to model building components, sub-systems and systems [6]. These models use a detailed description of physical aspects to capture the system dynamics. The parameters are derived from the physical characteristics, the details of which can be obtained from the design plan, manufacture catalogue or on-site measurements. The model is then fed into white box software tools, such as EnergyPlus [7] and, TRNSYS [8], to analyze the energy consumption and building control and operational schemes [9]. However, the process is usually time consuming and requires large computational effort, which restricts its widespread use.

Black box or data driven models are derived using the relationship between inputs and outputs. These models do not require a description of the inner functioning of the building and hence, can be more easily setup.. These models use on-site demand measurements to train predictions of building operation and have been extensively used to design building control strategies [10]. Linear regression and self regression models, which define the statistical relationships among dependant variables, have been applied in practice to predict the monthly energy consumption of buildings [11]. However, the performance of these models depends on the input training data set and model identification is found to be inconsistent with physical reality when applied under hard conditions (sparse building data) [12].

Grey box models are a combination of the physics based white box models and the data based black box models and thus, offer a trade off between the level of computational speed and accuracy. These models integrate the simplified physical model of the building with a model identification process to identify the design parameters. Using simplified physical models reduces the requirement of training data sets and hence, the calculation time. Grey box approach utilizes trained simplified physical models, for instance RC networks, to represent the building physics.

2.2. Grey-box modelling

Grey-box models are quite popular in behavior prediction and control of a building or a group of buildings. Belic et al. analyzed a two storey family house by representing each wall inside the house with a different RC network in [13]. Ji et al. investigated the use of a lumped parameter model to estimate the hourly cooling load of a shopping mall in Shanghai [14]. Both the studies focused on finding the appropriate order of the network to maintain the energy prediction error below 10%.

Harb et al. [3] compared four grey box models in their ability to forecast the building indoor temperature and concluded that a two capacitor model structure with an additional consideration of the indoor air as a mass-less node enables the most accurate qualitative prediction of the indoor temperature. The models were treated with measurements from the buildings in normal operation and the case study included two residential buildings and one office building. Fux et al. [15] analyzed a series of RC network models (orders 1 to 4) designed to forecast the indoor temperature. The results identified that a first order model is able to predict the indoor temperature with a root mean

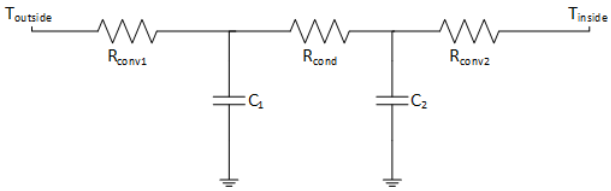

Fig. 1. RC equivalent network of a wall.

square error of 0.5^oC. However, the models were treated with data during unoccupied periods. Mejri et al. [16] identified the size of the model by testing a number of different orders for a small single floor office building and compared the resulting models in terms of their ability to simulate the thermal response. The study concluded that model order greater than two doesn't lead to any significant improvement in simulation results and over-parameterization was observed when increasing the model size. Model order reduction techniques were investigated by Goyal et al. [17]. The study implemented balanced truncation methods to compute the sparsity patterns for the non-linear part of the building dynamics. Another study by Deng et al. [18] proposed a methodology for model order reduction using aggregation of states using Markov chains. The simplified models were able to retain the physical intuition of the original model. However, the techniques did not take into account any scalability perspectives to allow for modelling a building cluster. Remmen et al. [19] developed a tool, called TEASER, to address the challenge of data acquisition required for dynamic modelling of buildings at an urban scale. The tool uses a data enrichment process for identification of the network model for various building archetypes. However, the tool still needs to be integrated with international statistical building stock data to extend its applicability to other countries.

3. Methodology

The objective of this work is to determine a generalized grey-box modelling approach applicable for all types of commercial buildings. The models designed using the approach should be able to predict the thermal behavior of a building or a stock of buildings.

RC network modelling approach employs RC networks to represent the heat transfer mechanisms, conduction and convection through internal and external walls, wall openings and roofs [20]. Besides conduction and convection, solar radiation adds to the heat transfer through windows and other openings. Also, heat gains result from the heat emitted by the occupants and the equipment.

Fig. 1 depicts the RC equivalent network of a building wall. The resistors signify the conduction and convection heat transfer resistances while the capacitors signify the heat retaining property or thermal mass of the wall. The network depicted is termed as a 3R2C equivalent model of the wall where R stands for thermal resistor while C stands for thermal capacitor. A similar network can be used to represent roofs. However, for simplifying the network, the entire building is sub-categorized as comprising of the building envelope (external walls and roofs) and the internal mass (floors, partitions, internal walls, furniture). This is followed by an aggregation of the parameters for the different components, particularly, external walls, roofs and internal mass [21]. Windows are represented as only resistors because the energy storing capacity is negligible for windows.

Different commercial buildings have different usage statistics, which deems it necessary to modify the RC network for each type. To develop a generalized approach to decide the RC network order, the peak power consumption of the buildings is analyzed as it would indicate the nature of building operation. Furthermore, the implemented methodology considers the thermal zoning of spaces inside the buildings. Thermal zones are assumed to possess similar thermal characteristics and hence can be represented by a single RC network. The overall methodology is summarized in Fig. 2 and implemented using the following procedure:

- Inspection of yearly peak power demand - a high order network (greater than two) is assigned to a building with high peak levels.

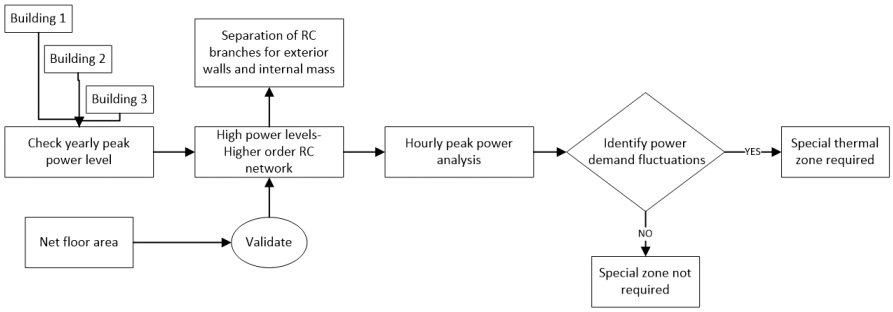

Fig. 2. Flowchart describing the process of RC network selection.

- Validation of network order with net floor area of building - higher peak levels might not always relate to the usage profile of the building as large buildings often have higher peak demands, which suggests that large buildings can be represented using low order networks.
- Hourly periodic fluctuations in peak power are analyzed against a base load to identify the presence of special thermal zones.
- Power fluctuations can be directly linked to a space inside the building that needs to be assigned a separate special thermal zone, thereby requiring a new RC branch altogether.

4. Case Study

Buildings connected to the district heating network on the University College Dublin campus were used as the methodology case study. The district heating network, as tabulated in Table 1, consists of different classes of buildings, namely, an energy centre, a library, several laboratory buildings with mixed uses, a student and a sports centre. The devised methodology aims to capture the dynamic design aspects of the buildings in consideration.

Table 1. Types of building in the district heating network.

Building Name	Building Type	Floor Area (m^2)
Agriculture Science Department	Laboratory Building	11008
Library	Group Rooms and Big Hall	23500
Newman	Classrooms and Offices	25605
Restaurant	Kitchen and Seating Area	4209
Science North	Laboratory Building	6778
Science West	Classrooms	7836
Sports Centre	Gym, Swimming Pool and Courts	6671
Student Centre	Leisure rooms and offices	4108
Sutherland Law School	Classrooms and Offices	6117
Tierney	Administrative Offices	5403

The buildings are analyzed based on the algorithm presented in Fig. 2. However, the RC network determination strategy of only three buildings from the table is presented here. The first building taken into consideration is the library to illustrate the importance of combining net floor area with peak power in the analysis. The power demand is analysed at fifteen minute intervals. The yearly maximum peak demand for the library building is 1960 kW. High peak demand would suggest a higher order RC network for the library. However, the net floor area for the library is the one of the largest amongst all the buildings. Hence, a further analysis of the peak power consumption is needed. Monthly and daily peak power consumption do not reflect the usage statistics of a building. Hence, an hourly analysis is done, shown in Fig. 3, to account for power fluctuations. The day chosen for the analysis is during occupied period and in the middle of the semester. As evident from the Fig. 3 , besides a high peak at 06:45 hrs, the fluctuations appears to be fairly constant during specific time periods. As the library consists of a big hall and group rooms, separate RC branches need to be considered for exterior walls and interior mass. Separating the roof from internal thermal mass

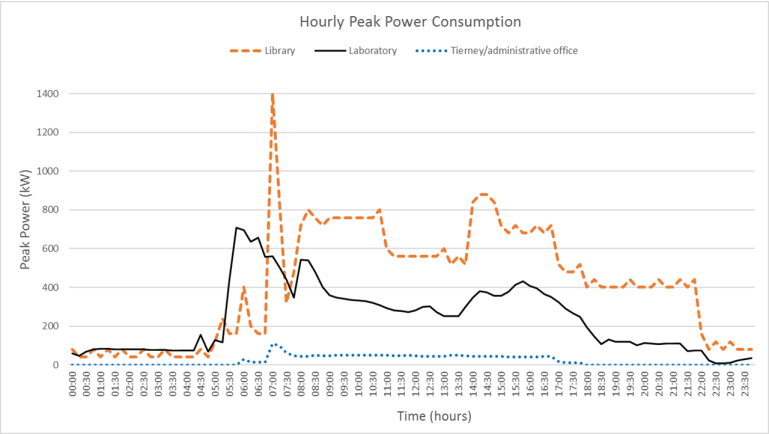

Fig. 3. Hourly peak power consumption data for library, Science North laboratory and Tierney/administration office building.

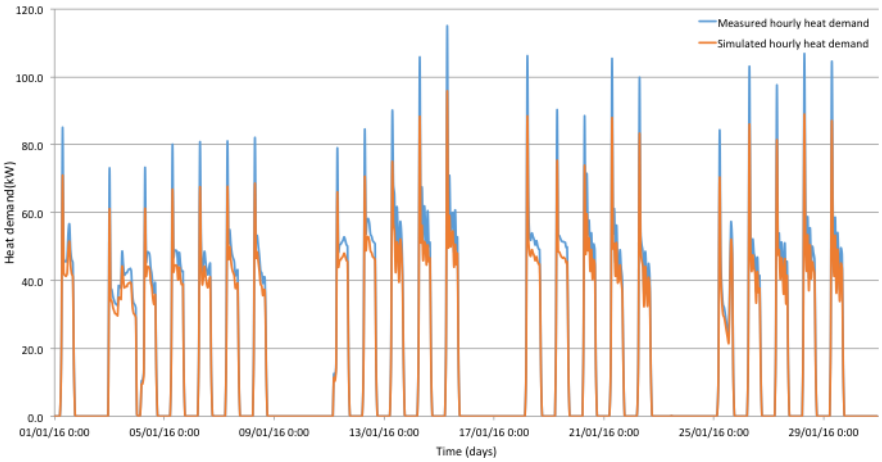

Fig. 4. Measured vs simulated hourly demand profile for the Tierney building.

might lead to over-fitting issues and thus unreliable estimates, owing to the simple nature of operation of library. If the 3R2C model is assumed for exterior as well as interior walls, this would result in a network of order four.

The second building considered for the analysis is Science North, which is a laboratory building. The maximum peak power demand of this building 6871 kW, which suggests a complex RC network. An analysis of the hourly peak power, Fig. 3, implies the presence of power fluctuations during fifteen minute intervals throughout the day, which can be linked to the presence of special thermal zones. Hence, the RC network would include separate RC branches for exterior walls, interior mass, roofs and a special thermal zone. The resulting order of the network would be 8.

The third building considered is the Tierney/administrative office building, which consists of administrative offices. Owing to the flat power demand curve, as depicted in Fig. 3, it can be inferred that a second order RC network would accurately represent the dynamics inside the building.

5. Results

An RC network model is built using Modelica[1] for the Tierney building. The model is used to simulate the demand profile for the month of January 2016. The measured and simulated profiles are shown in Fig. 4.

[1] www.modelica.org

6. Conclusions and Future Work

This paper has presented an approach for selection of RC networks for different types of commercial buildings. The power demand of the buildings is analyzed to decide the order of the network based on the devised algorithm. The algorithm is then implemented to design the RC network for the Tierney building, modelled using Modelica. The results indicate that the simulated profile is able to trace the measured profile. It can be concluded that peak power demand influences the selection of RC thermal network for buildings. However, the methodology still needs to be validated for all the buildings, which are more complex than the Tierney building. Furthermore, the integrated operation of the district heating network with all the buildings replaced as RC networks could be an extension to this work.

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