Un-Wrapping the development and the potentials of the Grey Box modelling approach

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ABSTRACT

With the growing increase in the population and comfort demands of people, the world's energy consumption and associated CO_2 emissions are increasing rapidly. Taking that into account, several energy efficiency measures in buildings are required during Building life-cycle concept. However, once the building operates, it shows the existence of mismatch between the predicted and real energy consumption, which is known as "Energy Performance Gap". Hence robust prediction of building energy consumption is crucial for improved decision making towards building energy consumption and CO2 emissions.

This paper describes the development and uptake of the data driven thermal network building simulation approach and its applications for making simplified thermal models of buildings by means of RC network, thermal resistances (R) and capacitances (C). Through critical literature review, the study investigates the advantages, disadvantages, and improvements of different building energy simulation approaches. Further, within the framework of lumped parameter RC approach, we conclude some new proposals to expand the application of the lumped parameter RC modelling approach to other engineering and energy management fields.

INTRODUCTION

People spend approximately 90% of their lives indoors. Thus, it is very important to maintain safe, healthy and high level of comfortable conditions in buildings–our living and working environments. However, to maintain these comfortable thermal conditions in buildings, a substantial portion of the world's energy consumption is required. In fact, approximately 40% of the world's energy consumption and nearly a third of greenhouse gas (GHG) emissions are associated with the building sector(Zuo et al. 2012). The EU's total energy consumption can be reduced by 5-6% and lower CO2 emissions by about 5% by renovating existing buildings (BPIE 2011). And therefore, prediction of energy consumption is very much crucial for improved decision making towards policy maker, reducing energy consumption and to fulfil the EU ambitious energy efficiency targets. However, building energy forecasting remains to be a challenging task due to the various factors which effect the consumption, for instance the physical properties of the building, the outdoor weather conditions, the installed equipment/s, and the behaviour of the occupants (Kwok 2011). And sometimes, it might lead to performance gaps (De Wilde 2014) which are caused by over estimation of the input values, poor assumption or lack of data , lack of proper knowledge and skills in construction industry, facility managers etc.(Burman et al. 2014)(Bordass et al. 2004)

Broadly, building simulation approach is widely used to predict the energy consumption in the various buildings stock. And generally BES approach is broadly divided in two main categories i) Physical models (Fundamentals 2013)/engineering methods (Zhao & Magoulès 2012)/ white box models (Coakley et al. 2014). ii) Data Driven approach , also known as inverse modelling approach (Foucquier et al. 2013). Further, and we have discussed BES approaches in detail in the section 2.

White box models are suitable when the physical knowledge of the system is known and that's why they are also known as "Physical model", and are based on detailed building environmental parameters such as building construction details, operation schedule, HVAC design information etc. And are most suited in the early design analysis phase of the building and for new construction (Hootman 2012). However, problem arises to this approach is when detailed data is not available to the users at the time of simulation and then failure to provide accurate inputs causes poor prediction. Additionally, the computational cost of these software is relatively high.

On the other hand, Data-driven building energy modelling approach rather learns from the available data for prediction. This approach is useful for existing buildings, old buildings. Nevertheless of having possible limitations(Discussed in the section Building Energy Simulation), Data-driven building energy modelling approach has gained a lot of research attention in building sector in recent years (Dimitriou, Steven K Firth, et al. 2015)(Westphal & Lamberts 2004). In response, several review studies have been published on Data-driven approaches. For instance recently (Amasyali & El-Gohary 2018) focussed on the machine learning algorithms, SVM (support vector machines, ANN (artificial neural networks, decision trees and other statistical algorithms. Prior to this study, Fumo (Fumo 2014) summarized the classification of various building energy prediction methods and focussed on the review of model calibration and verification and weather data used for modelling. Before Fumo, Zaho et al. Classified building energy prediction methods as engineering methods, simplified engineering methods, statistical methods, ANN methods, SVM, statistical methods and grey box models (Zhao & Magoulès 2012).

Despites of these rigorous efforts, there still a lack of review studies that analyses the lumped parameter modelling approach and its potential towards the building community. To address this gap, this paper offers a review of grey box lumped parameter approach. This paper describes the development and uptake of the thermal network and its applications for making simplified thermal models of buildings by means of RC network, thermal resistances (R) and capacitances (C). Through critical literature review, the study investigates the advantages, disadvantages, and improvements of different building energy simulation approaches. Further, within the framework of lumped parameter RC approach, we conclude some new proposals to expand the application of the lumped parameter RC modelling approach to other engineering and energy management fields.

BUILDING ENERGY PERFORMANCE SIMULATION

The Energy performance calculations are mostly done by Building Energy Simulation (BES) and the key essentials of the BES are prediction, cost and reliability as shown in the Figure 2.

As shown in the Figure 1, Generally, there exist two types of BES approach a) physical modelling approach/ White Box and b) data-driven approach/ Inverse Modelling (Fundamentals 2013)(Foucquier et al. 2013). Physical models (also known as engineering methods or white-box models) rely on thermodynamic rules for detailed.

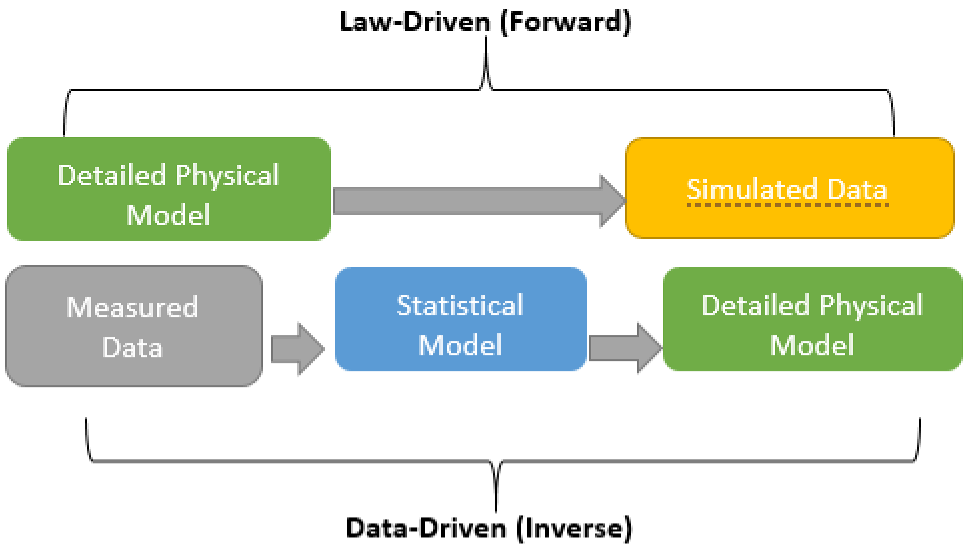

Figure 1 Explanation of Law-Driven and Data Driven (adapted from (Coakley et al. 2014)*).*

Energy Plus, e-Quest, and Ecotect are some software which uses physical modelling approach and are mostly used in the design phase (refer Figure 2).These types of software calculate building energy consumption based on detailed building and environmental parameters such as building construction details; operation schedules; HVAC design information; and climate, sky, and solar/shading information (Zhao & Magoulès 2012).

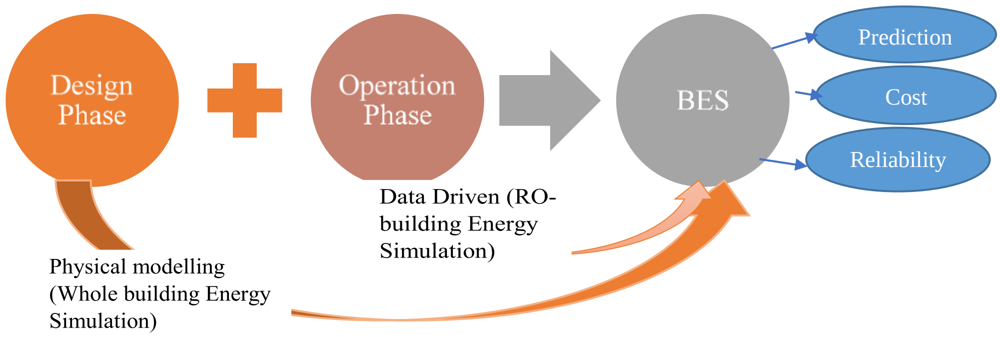

Figure 2. Role of BES approaches in building construction phase.

On the other hand, Data-driven building energy modelling (refer figure 1) approach, does not perform such energy analysis or require such detailed data about the simulated building, and instead learns from historical/available data for prediction. And are mostly used in the operation phase of the buildings. Data-driven energy consumption prediction has gained a lot of research attention in building sector in recent years (Dimitriou, Steven K Firth, et al. 2015)(Westphal & Lamberts 2004) . It can more accurately capture as- Built system performance because of deduction of model parameters from actual building performance. Forward modelling is extensively used for building modelling and design optimization generally suitable for design phase of the Building. Data Driven modelling is being used for existing Building for establishing the baselines and calculating the retrofit savings.

For both approaches**, forward and data-driven**, the models can be **steady-state or dynamic** (Figure 3)and are the two main approaches for determining the annual energy consumption of buildings. Steady-state models do not consider the transient effect of variables and is good for analysis in time steps equal or greater than 1 day. On the other hand, Dynamic models can track peak loads and are useful to capture thermal effects.

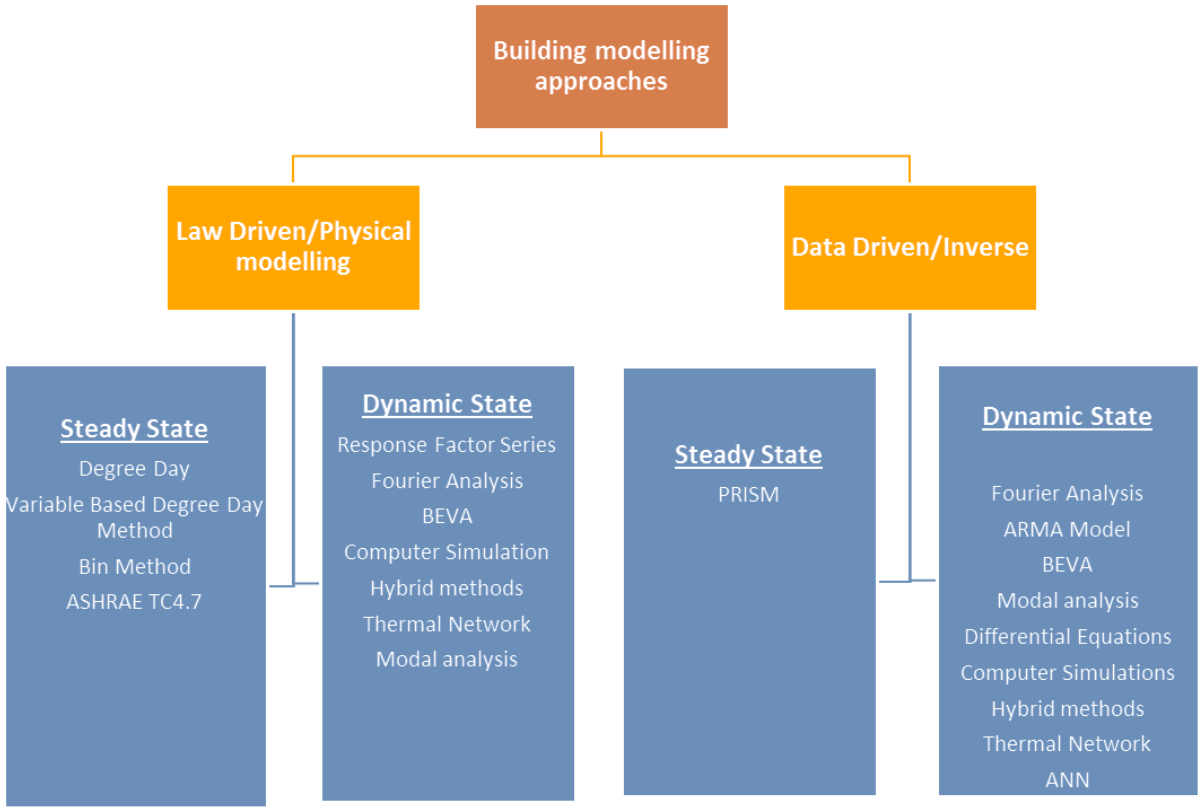

Figure 3. Commonly used methods for physical and data driven building modelling approaches

The stationary heat balance equation is a well-known approach for making steady-state models. This method provides a summary of the outside temperature's effects on the building's constant indoor air temperature. While, in some specific cases, the heat loss coefficient and the efficiency of the HVAC system are affected by the outside temperature, the steady-state model is considered for different temperature intervals and time periods: this is called the Bin method (White & Reichmuth 1996).

The dynamic approach generally includes the thermal network method, modal analysis, differential equations, autoregressive moving average modelling (ARMA), Fourier series, and Hybrid methods etc (Foucquier et al. 2013)(Zhao & Magoulès 2012)(Belić et al. 2016).

Black-box modelling bases the model solely on response data (monitoring of the building) The most popular black-box approaches for prediction and forecasting at building level are (Swan & Ugursal 2009): simple regression model (SRM), multiple linear regression (MLR), decision trees (DT), artificial neural networks (ANN) and support vector machine (SVM). Although physical insight is not required for making a black-box model, a model structure must be chosen, and this often involves making assumptions about the system (Foucquier et al. 2013).

Grey-box based approaches (Kämpf & Robinson 2007) combine prior physical knowledge with information from data sources. Usually grey-box models have a hybrid structure combining first principle physics and data driven approaches. They have some advantages but also limitations of the white and black-box models. In most of large scale models, the building stock is represented based on analogy with an electrical circuit, where a reduced order resistance- capacitance (RC) circuit can describe the energy behaviour of the building (Nielsen 2005). Grey Box modelling approaches has been used to predict energy consumption from a building level to the urban scale

APPROACHES OF THERMAL NETWORK

Intense research shows that the thermal network method is becoming popular among researchers to make accurate building models in most reliable way. Based on the literature we have presented the development of the thermal network RC method over the years which can be seen Table 1 below. It further concludes that, the application of thermal network varies from, energy prediction, parameter estimation to optimization of heating and cooling loads.

The literature evidences that this approach was used in 1980s to calculate the transient heat transfer in the wall (Hassid 1985). In 1985 Hassid (Hassid 1985) investigated the first thermal network resistance capacitance 2R 1C model for energy savings calculation.

Braun et al (Braun & Chaturvedi 2002), used 3R 2C thermal network configuration to identify optimal parameters using a nonlinear regression algorithm. The model and training method were extensively tested for different buildings and locations using data generated from a detailed simulation program. And they found that one to two weeks of data are sufficient to train a model so that it can accurately predict transient cooling or heating requirements.

Along with the parameter estimation (Ramallo-González et al. 2013)(Ogunsola & Song 2015) , some studies also show the application of thermal network in calculating indoor temperature(Bagheri et al. 2016). (Dimitriou, Steven K. Firth, et al. 2015) Vanda et al in their study also showed the importance of parameter estimation using grey box modelling approach which is also a form of lumped parameter modelling.

(Fraisse et al. 2002), they applied simplified approach to develop the building model using electrical analogy including heat floor. They compared the wall by developing the 3R 4C, 2R 1C and 3R 2C thermal network and found that the 3R 4C results are equivalent to 3R 2C model. Additionally, they modelled the heating floor by means of 2R 1C network. And hence detailed model is not necessary for further application of thermal network.

Another application of thermal network resistance capacitance was prediction of energy consumption (Ginestet et al. 2013) and additionally he optimised the thermal insulation, the heat capacity of the wall and the heating load of the building.

With the consideration of the climate factors, solar radiation plays an important role in energy assessment of the buildings and few recent literature studies show that the researchers have developed different methods to implement this important factor by means of thermal network. For instance (Yan et al. 2015), developed simplified analytical model to evaluate the solar radiant effect on heating and cooling load. Ogunsola (Ogunsola & Song 2015) in his study used solar air temperature instead of solar radiation in 3R 2C network.

Table 1. Thermal Network approaches and applications for different purposes

Author	**Network Configuration**	**Purpose**
(Braun & Chaturvedi 2002)	3R2C for a wall	optimal parameters are identified using a nonlinear regression algorithm.
(Fraisse et al. 2002)	3R 4C, 3R 2C	Convective and longwave exchanges with linear model
(Kämpf & Robinson 2007)	RC two node method	Study flows of energy within an urban district
(Underwood & Yik 2008)	3R 2C	Thermal network for wall
(Bueno et al. 2012)	RC	The model is used in a series of parametric analyses to investigate the impact of the (Urban heat Island Effect) UHI effect on the energy consumption of buildings for different building configurations. It is also used to investigate the dominant mechanisms by which the indoor environment and the energy performance of buildings affect outdoor air temperatures.
(Bagheri et al. 2016)	4R2C	to simulate heating load and indoor temperature. The parameter identification has been done for 3 different sets of data to show the influence of it on the estimated parameters.
(Danza et al. 2016)	3R 2C	Evaluating, controlling and managing heat energy fluxes in buildings.

CONCLUSION

In this research study, different modelling approaches, from white box models to black box models, were discussed and compared. Each of the individual modelling types have been discussed e.g. methods for short-term weather forecasting for building energy modelling were also introduced. Among them the most popular nowadays, are neural network models, linear parametric models and lumped thermal network models (RC-networks).

Based on the discussions of different modelling approaches in building operation and optimization a few conclusions are summarized as follows:

1. Detailed physical (white-box) models require high no. of parameters and subsequently high no. of iterations, which makes the estimation accurate. For operation strategy assessment, these models are very useful and informative. However, they might not be useful for online building operation.
2. Statistics also known as (black-box) models need large number training data, and completely rely on the measurement data of the input and output variables. And the training data should cover the forecasting building operation range, which is bounded by the building operation schemes. Fortunately, those operation data can be provided by detailed physical models. One of the drawback of these types of model is that they are not flexible and if something needs to be changed then whole model needs to be revised.
3. Simplified grey-box models are better for practical building model-based operation application. As they are combination of the physical and the data driven model, they use the physical laws to define the structure of the models and use measured data to find the parameter of these models. They have less parameters to determine and need shorter computation time, which has proved to be a huge potential in building energy model for energy and cost saving.

The literature review of the thermal network method has also been provided to cover different research studies. Further RO modelling approach is the most popular approaches of Grey Box modelling and mostly the research has mainly dealt with thermal network approach

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