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# Application of a simplified thermal network model for real-time thermal load estimation

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ABSTRACT

Heating and cooling loads are the major reasons for energy use in buildings. Buildings are usually subject to schedules and set-points which are not optimized in response to the dynamic weather conditions, internal loads, and occupancy patterns. The thermal network model has been widely applied for real-time building load estimation, which is crucial for optimizing the operation of the HVAC system. However, there has been limited exploration of the capabilities of the thermal network model due to constraints imposed by the solution method adopted. In this paper, the exponential matrix method was adopted to simplify the state space equations and solve the thermal network model analytically. This enhances the applications of a simplified thermal network model for investigation of multiple scenarios of HVAC system operations and equipment sizing, and for more accurate estimation of heating and cooling loads. This study also proves that the analytical solution method is asymptotically stable regardless of time step. A typical office was used as a case study and the predicted building loads are compared with measured data and numerical results from EnergyPlus. For the case study, the model demonstrated better accuracy and is seen to be robust for thermal load estimation for cooling season.



## 1. Introduction

The overall function of an HVAC (Heating, Ventilation and Air Conditioning) system is to compensate for building load in order to provide thermal comfort. The building load is the rate at which heat must be extracted from (or delivered to) the building to maintain the desired set-point, i.e., the rate at which heat is converted from (or to) the zone air. According to a study by Daum and Morel [1], buildings consumed 40% of total primary energy in the USA in 2008, with commercial buildings holding a share of 18.4%. Globally, around 40% of primary energy consumed in buildings is used for HVAC. It is not surprising that regulations and national policies are being developed and implemented to encourage or mandate reduced building energy consumption or prescribe increases in efficiency for relevant building components, such as building envelope elements, HVAC systems and equipment, and lightning equipment.

Buildings are usually subject to absorption and delayed release of radiation, thermal mass effects, infiltration, dynamic internal schedules and other phenomena which are either difficult to model or not accounted for by most models. Likewise, plant and building set-points often follow prescribed schedules which are not optimized in response to dynamic conditions, weather, internal loads, occupancy patterns, and so on. These conditions make building load calculations and optimization challenging. Since buildings account for significant portions of global electricity and energy use, real-time control and forecasts of the building load are important to minimize building electricity use and energy consumption. Oldewurtel et al. [2] predict a 5% delivered energy consumption increase in the building sector by 2035 if building technology from 2009 is used. Therefore, research in energy conservation in the building sector is highly important and accurate forecasting of dynamic building load is essential from a control, environment, and energy standpoint.

There have been several studies on building performance and load calculations. Pang et al. [3] developed a simulation-based framework for real-time building performance assessment. The framework allowed for a comparison of a building's actual performance and expected performance in real-time. However, several factors and variables such as HVAC operational schedules, control set-points, and weather data, e.g., solar radiation, relative humidity, wind speed, and direction, have to be updated at each time step. Causone et al. [4] developed a calculation procedure for cooling loads using the Heat Balance method and the Radiant Time Series (RTS) method, which are well described in the ASHRAE Handbook of Fundamentals [5]. These models need calibration to accurately reflect system performance. Braga et al. [6] developed a statistical

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**Nomenclature**

| | |
|---|---|
| $\rho$ | density |
| $\lambda$ | thermal conductivity, eigenvalue |
| $t$ | time |
| $sa$ | supply air |
| $l$ | length |
| $in$ | indoor |
| $i,j,k$ | counter |
| $h_i$ | inside convective heat transfer coefficient |
| $h_o$ | outside convective heat transfer coefficient |
| $amb$ | ambient |
| $U$ | input |
| $TMY$ | typical meteorological year |
| $T$ | temperature |
| $RC$ | resistance–capacitance |
| $R_{win}$ | window resistance |
| $C_{in}$ | indoor air capacitance |
| $A_s$, $B_s$, $C$, $D$ | state space matrix |
| $a_{ij}$ | $i$th row and $j$th column entry of matrix A |
| $b_{ij}$ | $i$th row and $j$th column entry of matrix B |
| $Q_r$ | half of total radiation from windows and radiative part of internal load |
| $Q_o$ | incident solar on outside surface |
| $Q_{conv}$ | convective part of internal load |
| $C_p$ | specific heat |
| $\alpha$ | solar radiation absorptivity |
| $I$ | global solar irradiance |
| $\Delta Q_{ir}$ | extra infrared radiation due to difference between the external air and apparent sky temperature |
| $h_o$ | convection coefficient on the external surface. |

process to model and estimate the energy consumption profile of a building during a cycle, e.g., one week. The statistical model was used to monitor and control energy consumption patterns. Using EnergyPlus, Feng et al. [7] compared the cooling load differences between radiant and air systems under the influence of factors such as level of insulation, thermal mass effects, internal heat gains, and solar exposure of floors and ceilings. Chen et al. [8] also assessed the effects of appliance level on real-time and historical energy use in buildings by separate measurements of the appliance plug loads, heating and cooling loads, and lighting loads through the use of energy meters and proxy sensors. Xuemei et al. [9] developed an algorithm for forecasting the cooling load, using a support vector machine (SVM) model, a machine learning technique whose parameters are determined from measured data. Duanmu et al. [10] developed the Hourly Cooling Load Factor Method (HCLFM) for cooling load prediction. The method assumes certain linear relationships between the cooling load components and variables such as temperature and enthalpy differences between indoor and outdoor air. Schiavon et al. [11] developed a calculation method for cooling loads in underfloor air distribution (UFAD) systems. Using EnergyPlus simulations, regression methods were developed to transform cooling loads from traditional overhead mixing systems to UFAD systems. However, the method is only suitable for design cooling load estimation.

The thermal network model of Resistances and Capacitances (RC) model is commonly used to describe the thermal delays caused by a building envelope and internal thermal mass effects, and provides robust and accurate estimates of the cooling load based on measured data. Although there have been many improvements in the RC model over the years, the three resistances and two capacitances (3R2C) arrangement is widely used for modeling transient heat transfer in building envelopes [12,13]. More recent versions of the RC models are 3R4C and 4R5C by Fraisse [14]. The RC model has also been used to investigate thermal coupling among building elements, estimate the cooling load for thermally activated building construction, and compare thermal zone aggregated methods [15–17].

The RC model represents the building envelope and internal mass using lumped capacitors and resistors, as developed by Xu [18]. The envelope RC parameters are usually found using theoretical properties of the building construction in frequency domain, or from construction materials. The internal mass RC parameters are determined by minimizing the differences between the building loads calculated using the model and the actual building loads. This avoids the lengthy calibration process which is necessary in other models, and compensates for errors in the input parameters of the model. The RC parameters have been traditionally estimated using a genetic algorithm and by solving the integrated RC model numerically using Runge–Kutta methods or other classical methods [18,19]. In a recent study [20], a time series model was deduced from the simplified RC model. Compared with pure statistical models, such as autoregressive models, the time series was deemed superior because it has less sensitivity to outliers and the ability to track sudden input changes such as abrupt air temperature drop or sudden changes in control strategy. However, current solution methods such as the time series and numerical solutions permit limited exploration of the capabilities of the thermal network model. For example, numerical solutions suffer from stability and convergence issues, which are often caused by the need to consider different time steps. For the time series, the previous four (or more) time intervals are needed as inputs. The needed measurements are sometimes unavailable or unreliable due to sensor malfunction or data quality assurance issues. Similarly, in previous RC model studies, there are no documented methods on the search space for the best fit of the internal mass parameters, particularly when the envelope and internal mass components are decoupled. Unreasonable initial guesses and/or bounds could lead to slow convergence. There have also been noticeable spikes in the cooling load prediction by the time series [20]. The identified issues with the current solution methods limit the general applicability of the thermal network model.

Therefore, the aim of this study is to solve the simplified RC thermal model using an analytical solution method and to apply the model to a typical office building. This model requires fewer inputs, depends only on initial (or any previous) time step data and current conditions, is capable of simulating floats in temperature for investigating thermal storage opportunities or for simply comparing several HVAC systems operation modes, and is consistent. This study also aims to investigate and ascertain the unconditional and asymptotic stability of the thermal network model for all feasible values of envelope and internal mass parameters by applying stability criteria to its resulting state space model. Latent load prediction is not included since latent heat gain instantaneously converts to latent cooling without a time delay.

The paper begins with a general description of the analytical solution to the simplified RC model, after which the stability of the thermal network model is investigated. The stability analysis is crucial and needed because of concerns about the feasible search region of the envelope and internal mass parameters that cause the model to become unstable. Satisfaction of asymptotic stability is highly important for the thermal model to correctly depict the physical and thermal behavior of the building system, since temperatures and heat fluxes are expected to remain bounded at all times. The RC model is then tested on a case study of an office, and compared with field measurements and simulation results from EnergyPlus. Various scenarios of parameter estimation are investigated, with the goal of choosing the most accurate and representative parameter set for forecasting the building load. Finally,