Cooling load estimation using machine learning techniques

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Abstract:
Estimating cooling loads in heating, ventilation, and air-conditioning (HVAC) sys- tems is a complex task. This is mainly due to its dependence on numerous factors which are both intrinsic and extrinsic to buildings. These include climate, fore- casts, building material, fenestration etc. In addition, these factors are non-linear and time-varying. Therefore, capturing the effect of these parameters on the cool- ing load is a complex task. This investigation combines forward modelling, i.e., physics based model simulated using energyPlus with deep-learning techniques to build a cooling load estimator. The forward model captures all the time-varying factors influencing the cooling loads. We use the long short-term memory (LSTM), a deep-learning method to provide forecasts of cooling loads. The advantage of the proposed approach is that cooling load estimations can be provided in real-time thus providing sort of soft-sensor for estimating cooling loads in buildings. The proposed approach is illustrated on a building of suitable scale and our results demonstrates the ability of the tool to provide forecasts.

Keywords:
Heating, Ventilation, and Air-Conditioning (HVAC) Systems, Cooling Load Estimation,
Long Short-Term Memory (LSTM), Building Controls, Deep-Learning.

1. Introduction

Space cooling consumes significant energy around the world and is expected to increase due to urbanization [1,2]. The HVAC energy consumption is highly influenced by cooling loads in the building. Modelling the cooling loads is a complex task due to their dependence on numerous extrinsic and intrinsic factors. Intrinsic factors include building construction material, orienta-tion, floor area, fenestration plan etc. Similarly, extrinsic factors are due to occupancy, climate,

opening of windows and doors, working days and others. Modelling cooling loads encapsulating all these factors is a complex task. In particular, providing multi-variate regression model is computationally intensive.

Conventionally, two approaches are used for capturing cooling loads: forward and backward. In forward models, the building is modelled and simulated using the knowledge on construction material, fenstration plan, orientation and other information. Then the energy consumption and cooling load are calculated. Usually this is done through software tools such as TRYNsys, energyPlus, and others. While these models provide detailed analysis on energy consumption and cooling load, they cannot be used online for estimating cooling loads. Contrary to this machine learning tools which use measurement data to fit a model provide an easy way to capture the dynamics. However, their model fidelity depends on historical data on which they are trained and usually obtaining such data is usually complex.

Two widely used approaches for modelling cooling loads in buildings are: forward and inverse modelling [3]. In forward modelling, the actual properties of the building system including geometry, orientation and others are modelled in a software to predict the energy performance. However, these require detailed explanation of the materials used, architecture etc., which are in general difficult to obtain. One drawback with forward approaches is that they cannot predict energy consumption in occupied buildings. Inverse modelling approaches use data-driven approaches and more accurate than forward ones. Widely used method in practice is the Air Conditioning and Refrigeration Institute (ACRI) load estimation form which is a static and off-line method. An empirical method which formalizes cooling load computation as a software was presented in [4]. Regression based analysis for predicting cooling load was presented in [5] to compute the cooling load using off-line data. The use of artificial neural network to model cooling loads in buildings has been studied in [3,8,9,12]. Data-mining techniques such as support vector machines (SVR), artificial neural networks, classification and regression tree, chi-squared automatic interaction detection, general linear regression, and ensemble inference model were studied for modelling cooling loads in [7]. Similarly, the investigation in [10] used support vector machines (SVM) to predict hourly cooling load in the buildings.

Of late the use of dynamical simulation tools such as DOE-2, EnergyPlus, TRNSYS, BDA, ESP-r, BLAST, IDA etc. [14] are being widely studied. The use of models to estimate cooling loads with two software Building Controls Virtual Test Bed (BCTVB) and EnergyPlus was studied in [?]. The estimation of thermal load in buildings by including factors such as construction, geometry, layout, climate etc., was proposed in [14]. In addition, the proposed method studied the use of artificial neural network to capture the cooling load in buildings. The investigation in [13] presented a model-based approach for estimating the cooling load in the buildings. The proposed approach used a reduced order state-space thermodynamic model and extended Kalman filter for estimating the cooling loads. The advantage of the method is the development of soft-sensor which can be used to measure the cooling load dynamically. However, the investigation had a restrictive assumption that the system is linearized around an operating point to design the EKF. Considering the multiple factors influencing the building

thermal dynamics and complex behaviours this may not be always possible. Further, requires linearisation during each computing epoch which makes their adoption in building automation systems complex. A method to maintain temperature bounds within user-defined comfort bands using nonlinear control theory was proposed in [6]. However, the paper does not consider recursive estimation of cooling-loads. Semi-parametric approaches for modelling building cooling loads have been studied in [15]. The use of recursive learning algorithm and parsimonious system identification has also been studied for modelling buildings using data driven approach in [18].

Machine learning approaches have been studied in the literature for heat-load estimation. The use of machine learning approach for modelling cooling loads in three types of buildings was studied in [16] and it was found that ANN gives satisfactory accuracy. However, one problem with the proposed approach is that it cannot be used as a real-time cooling load estimator, rather is a tool for modelling historical information. The investigation in [17] proposed single and ensemble model for heating and cooling load estimation. It's wholly a data-driven approach without capturing the forward modelling aspects of the building. The authors used support vector machines for regression. The authors in [7] used ensemble approaches for estimating the cooling loads in buildings and proved that it closely models the physical aspects found from simulations. However, typically heating loads have causal relation which depend on their past values, therefore recurrent neural network naturally fits the modelling framework. Contrary to this, the use of recurrent neural network for estimating cooling loads has not been fully studied in the literature.

This investigation overcomes the shortcomings in existing literature by combining the detail forward models with long short-term memory (LSTM), a deep-learning tool. The LSTM is a recurrent architecture which has the capability to learn from inputs with time-lags. This makes it suitable as a tool to model cooling loads which evolve as a function of many nonlinear occurences. As against existing approaches, we combine forward modelling of EnergyPlus with data-based modelling capability of LSTMs to provide a soft-sensor for cooling load estimation. The main contributions of the paper:

(i) An approach that combines forward modelling approach with data-driven approach for modelling cooling loads;

(ii) Show that the model can be used for real-time estimation of cooling loads;

(iii) Illustrate the proposed approach in a building of suitable scale.

The paper is organized as follows. Section 2 presents the problem formulation and the cooling load estimation methodology is presented in Section 3. Results obtained from a building data and using LSTM is presented in Section 4 and conclusions and future course of investigation are presented in Section 5.

2.   Problem formulation

The problem studied in this investigation is the estimation of cooling loads in buildings. While there are many methods for capturing building thermal dynamics, forward modelling is widely used and it provides detailed model about building materials, orientation, geometry and others. Usually forward modelling is a complex task and such models cannot be used for real-time cooling load estimation. On the other hand, building data-based approaches for estimating heating load is complex as the data-integrity will affect the model fidelity. Therefore, hybrid approaches combining forward and data-based models are very much required in building automation systems. However, to our best knowledge such models have not been investigated in the literature, this is mainly due to:

(i) Need for cumbersome first principle models and their simulation times to provide real-time data;

(ii) Absence of methods to combine forward models with data-based methods;

(iii) multi-variate nature of cooling load.

A method to overcome the challenges above and estimate the cooling load is proposed in the next section.

3.   Cooling load estimation methodology

The cooling load estimation methodology in the paper is based on combining forward modelling with data-driven approaches. The idea is illustrated in Figure 1. The forward model is created using EnergyPlus encapsulating various building parameters. Then the cooling load obtained are used to feed a LSTM which uses the forward model as the nominal one and starts estimating the time-series of the cooling load.

3.1.   Forward model

In the forward modelling phase, the buildings with its dimensions, orientation, fenestration plan, construction material, HVAC system architecture etc., is simulated in energyPlus. Within energyPlus the weather file for the specific region are added. In addition, the influences of occupancy external temperature, weather conditions, humidity are also captured. Solar gains through radiation and heating produced by loads are also used to compute the cooling loads in different zones of the building which are used as inputs to the LSTM model. The energyPlus provides a comprehensive model to capture the building dynamics and data required for generating soft-sensors for cooling load using data-driven approach.

3.2.   Long Short-Term Memory (LSTM)

The LSTM is an extension of recurrent neural network (RNN) which handles the exploding and vanishing gradient problems. Typically, RNNs use sequential information and stores their current output based on previous inputs. However, their backward traversability is limited by vanishing gradient problem. The LSTMs overcome this problem by introducing gates which control the gradient flow and preserve causal relationship with long-term inputs making them suitable for capturing cooling loads. The critical components that differentiate a LSTM from
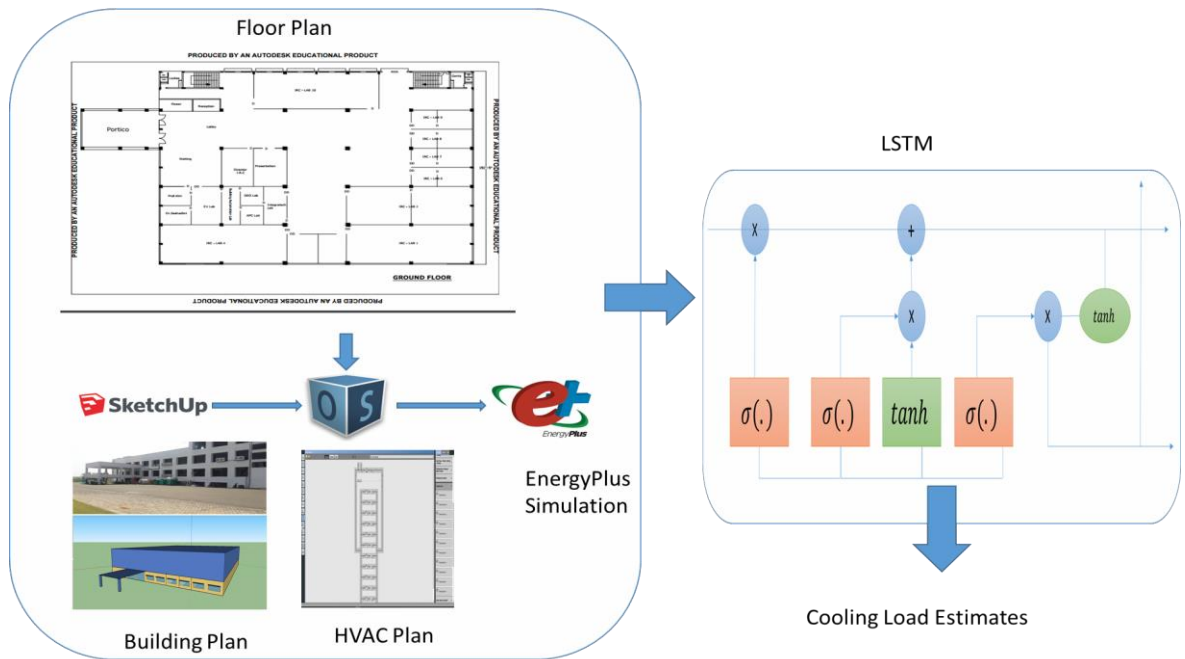
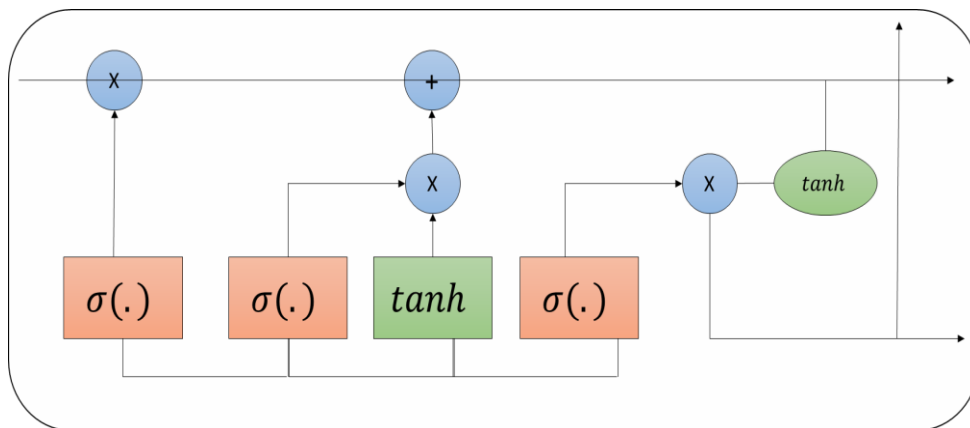*Figure 1 Cooling Load Estimation Methodology.*

Figure 2 LSTM Architecture.

RNN are the memory cells and gates as shown in Figure 2. The RNN models the input sequence u using the recurrence relation,

$$h_{t+1} = f(h_t, u_t) \tag{1}$$

where u_t is the input at time t and h_t denotes the hidden state. The gradient vanishing and explosion problem are solved by introducing gates, this leads to the LSTM states

$$I_t = \sigma(W_I).[h_{t-1}, u_t] + b_I \tag{2}$$
$$f_t = \sigma(W_f).[h_{t-1}, u_t] + b_f$$
$$o_t = \sigma(W_o).[h_{t-1}, u_t] + b_o$$
$$\tilde{C} = tanh(W_o.[h_{t-1}, u_t] + b_o)$$
$$C_t = f_t \} C_{t-1} + I_t \} \tilde{C}_t$$
$$h_t = o_t tanh(C_t)$$

where I, f, and o denote the input, forget and output gates, respectively. The weights W and parameter b are tuned in the LSTM unit. In addition, C_t denote the current cell state and $\tilde{C}_t$ denotes the new candidate values for the cell state. The sigmoidal functions on the gates are used to restrict their values between '0' and '1'.

4. Results

The proposed LSTM based soft-sensor for cooling loads was tested using the proposed methodology with data obtained from energyPlus. Our idea is to simplify the analysis and therefore, we use simple time-series which will incorporate the effects due to factors regarding building materials from the forward modelling. Our idea is to construct a deep-learning model using LSTM and forward model provided by energyPlus. We consider a simple case of three thermal zone building controlled using a HVAC system. The mass-flow rate to the zones are controlled using variable air volume (VAV) system and the energy consumption is influenced by the cooling loads. The occupancy is assumed to be varying nonlinear w.r.t. time and hence difficult to capture. In addition, there are electric loads such as lightings, computers, security systems and other stray loads which contribute to the heating load. Heat gains from weather through fenestration and building envelop are also captured by the forward model. The data is generated for every 15 minute duration is used in our analysis.

In the forward model we use energyPlus to generate about 248 different sets of data which influence the thermal load in buildings. Then out of which we illustrate the method on time-series evolution of heating load data obtained from simulations. While all the three zones cooling load distribution can be obtained with the proposed technique. To simplify our analysis, we restrict our study to cooling load estimation of single zone using LSTM based soft-sensor. The LSTM in our approach consists of 200 hidden units and the other parameters used in our approach is shown in Table 1.

The variations in root mean square error (RMSE) during training period of LSTM is shown in Figure 3. One can verify that the RMSE error comes down with an increase in samples showing

Table 1 LSTM Parameters.

Parameter	Value
Initial learning rate	0.05
Maximum iterations	250
Gradient Threshold	1
Schedule	piece-wise linear
Learning drop period	125
Learning drop factor	0.3
Number of hidden units	200

robustness of the proposed methodology. Moreover, the method provides good learning as seen from the RMSE plot. From the loss-function it can be observed that the error goes to zero with the number of iterations and reaches zero for 250 iterations during learning phase. The training curve for RMSE being smoothed and training phases are differentiated with bold and lighter colour to enable understand the smoothing action.
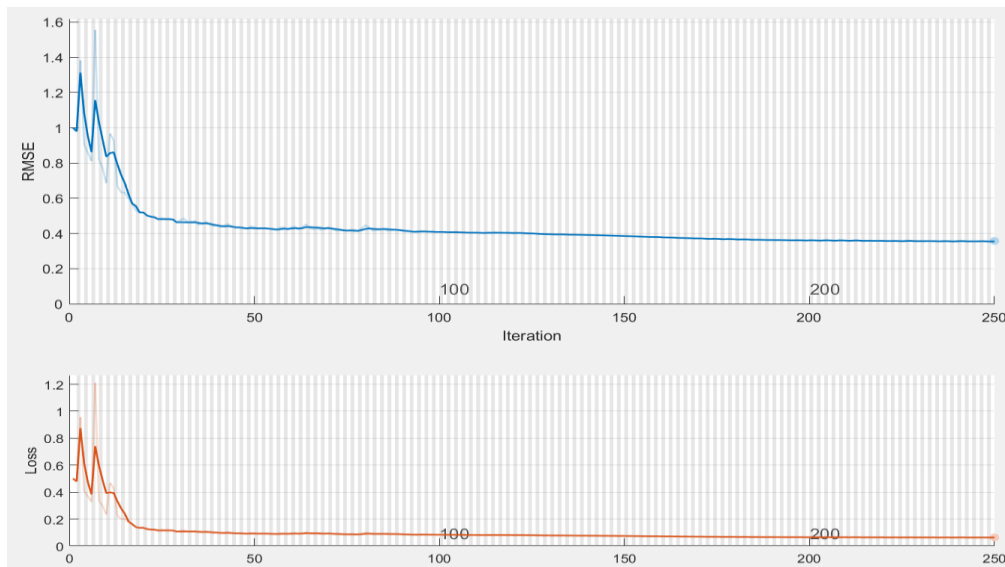

Figure 3 RMSE variations in LSTM during training.

A part of the time-series data is used for validation phase to compute the error metric and to find whether the soft-sensor has attained reasonable accuracy. The plot for actual measurements versus estimation obtained with the proposed soft-sensor is shown in Figure 4. One can see that the error with the LSTM is reasonable for the considered application. The maximum of error is around -500 Joules which over a period of 15 minutes is not considerable. Similarly, the error on the positive side is around 200 Joules. Moreover, the MAPE of the predictions is 4.2% signifying that the proposed method can be used for estimating cooling loads in buildings.
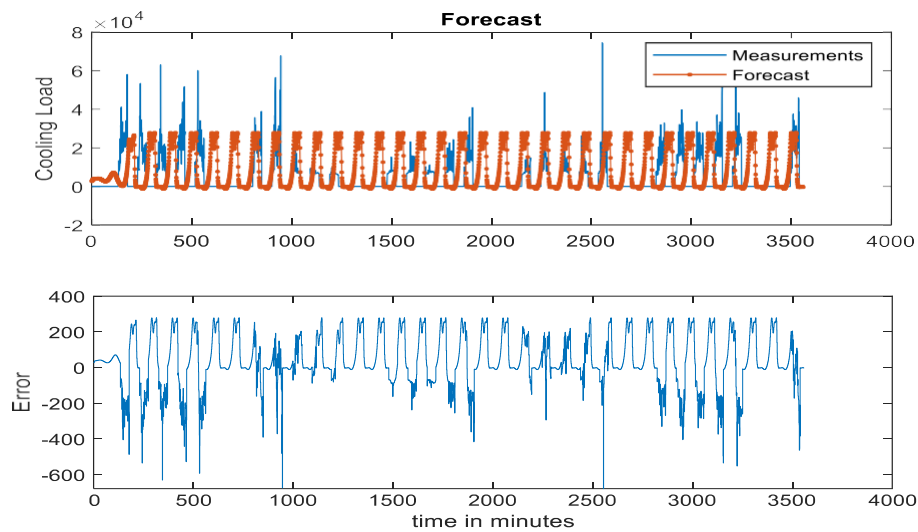
Figure 4 Predicted and Actual values of cooling loads with error.

Our results illustrate that by combining forward modelling and LSTM as soft-sensor for cooling load can be built without considering factors that are intrinsic to the buildings such as orientation, fenestration etc. Similarly, it could also account for extrinsic factors such as weather, occupancy, variations in ambient conditions and others. Therefore, the proposed model is simple and combines the advantages of both forward and data-based modelling. The results also suggest that the proposed method could be used for building soft-sensor for estimating cooling load in real-time by using the proposed technique. Moreover, the need for complex multi-variate analysis is simplified to computing a time-series forecast. We used the LSTM due to its advantages in capturing past-samples and accounting for delays which is very much required for buildings as their inertia is high. This means that the time taken to have a temperature change is large and often requires memory to remember the previous states and delays.

5. Conclusions

This paper presented an approach for estimating cooling loads in building combining forward modelling with data-driven approach. We used energyPlus based models for capturing the building and HVAC dynamics. This includes construction aspects such as building layout, geometry, orientation, material, fenestration plan and others. In addition, this also considered extrinsic influences due to weather, occupancy, control schedule etc. Using this model data was collected which trained a long short-term memory (LSTM) network. This is mainly due to the ability of LSTM to model outputs considering causal effect of the past values. The combined forward and data-based model was used to predict cooling loads and our results demonstrated that this method provides an efficient way to compute cooling loads in real-time which is very much required for designing optimal control strategies in building automation systems. Providing multi-variate LSTM models and statistical analysis of the proposed model

are future course of this investigation.

Acknowledgments

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