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Climate responsive cooling control using artificial neural networks

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ABSTRACT

The building envelope is influenced by climatic factors as thermal radiation, solar radiation, convection heat and infiltration heat. Their peak occurs at different times. Obtaining an equivalent thermal resistance of the building envelope is a challenge considering heat loss/heat gain of building envelope towards climate responsive cooling control. Considering heat flow at the zone using EnergyPlus software brings climate responsive cooling control. The Artificial Neural Network (ANN) model was developed which deciphers the building envelope heat flow using data obtained from EnergyPlus. Using ANN, model predictive controller and Gray box model of the building cooling system, thermal performance was obtained by simulations using Simulink, MLE+, BCVTB and EnergyPlus. The ANN envelope heat load predictor improves energy efficiency over the temperature based model in which the climate heat flow is determined using the equivalent thermal resistance and the atmospheric temperature. An Energy saving of 6.25% with 1.05% error for Chennai 5.19% with 2.21% error for Trichy and 7.52% with 0.08% error for Shillong climate was obtained.

1. Introduction

Energy conservation results showed increased operational efficiency, reduced CO_2 emission and maximum utilization of energy sources [1]. N+1 numbers of air conditioners are used in telecommunication cooling system. Here N is the number of air conditioners designed for peak summer load and one is the standby [2,3]. Automatic sequencing and web based control of air conditioners are discussed in [4,5] not climate responsive. The air conditioner scheduling method discussed in [6,7] was suitable for human comfort. According to [8] it is not economical to increase the thermal insulation of the air conditioned building beyond a certain limit. To control the cooling system climate responsive atmospheric temperature has been tracked in [3] and using atmospheric temperature and finite difference method, thermal load has been estimated in [9]. According to [10] the temperature lags behind solar radiation. Hence it is not sufficient to track the varying atmospheric temperature, but it is necessary to get the building envelope cooling load which influence as the room temperature. This paper is organized as follows. In Section 2 related work is presented. Section 3 describes the methodology followed. Section 4 explores the RC modeling followed by Section 5 which examines the preprocessing simulations. Section 6 which details the ANN based learning method and the Section 7 reports on the Simulation based experiments. Section 8 discusses the results. Section 9 gives the concluding remarks and direction for future research that can be taken forward.

2. Related work

The thermal load computation is a complex issue. Software like EnergyPlus can be used to address this problem. EnergyPlus was used for the analysis of thermal performance of buildings. The EnergyPlus model was calibrated with occupancy schedule based data mining and empirical data [11]. The purpose was to get a more accurate EnergyPlus frame work for simulations and analysis. Price varying demand response controller has been discussed in [12]. ANN-GA based rule for heating system optimization was applied in [13]. Here, the building envelope was modeled in EnergyPlus software using ANN and GA control rules were developed for optimizing the heating system. For optimization of cooling capacity and control, the thermal load data is explicitly required by the controller. In [14,15] EnergyPlus was used for optimization of air conditioner ON with free cooling fans. In the control scenario, Fa Wang [16] used constant pressure and constant flow method along with the MPC controller and compared results with ON/OFF control scheme. Jie Zhao et al. [17] simulated and compared optimized-MPC control over the base line control for human comfort using predicted mean vote (PMV). Jan Siroky et al. [18] compared weather compensated controller and model predictive controller. Ma, Yudong. et al. [19] used model predictive controller with a thermal load estimator using atmospheric temperature and solar thermal load. Hu Chaowen et al. [20] used ANN along with DeST software and other parameters for predicting hourly thermal load. Compensation for thermal stratification was discussed in [21] with atmospheric

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temperature and kalman filter. From the literature survey it was found that the thermal load of building is not explicitly computed in whole year scale considering heat loss/heat gain of the building envelope for optimizing cooling capacity. The variable speed drive based air conditioner is gaining momentum nowadays [22–24]. This paper aims to address this research gap.

3. Methodology

The thermal load of the building is a function of wind speed and the atmospheric temperature and solar radiation etc. [25,26]. The sensible cooling load of the building (I_b) and infiltration heat (I_{inf}) has been obtained from EnergyPlus. The EnergyPlus gives a net building envelope heat gain at the zone level after incorporating the heat storage at the surfaces. In order to apply the same in control, ANN has been used to learn thermal load data with weather data of EnergyPlus. Measuring solar radiation is a complex issue. The data of 15 min sample of whole year for I_b and I_{inf} was segregated into monthly data. Monthly ANN was created and trained for both I_b and I_{inf}. This increased the accuracy of the ANN prediction without solar radiation. The trained ANN can predict the thermal load using present weather data viz. atmospheric temperature, wind speed, wind direction which can be easily measured for any building. This data will be used by the MPC controller to optimally schedule the variable capacity air conditioners. The MPC controller selects these monthly ANN in a time synchronized manner with climate. The time in seconds is counted cumulatively from 00:00:00 h of the first day January till the last second of December. The counted time is divided by 900 s for simplified handling and this is called a time sample. The monthly ANN is selected using the time sample. For example, if the time sample is between 0 and 2976, the January ANN is selected. If the time sample is between 23,329 and 26,208 then October ANN is selected by the controller. A real telecommunication building pertaining to Chennai, India latitude 13.0827°N, longitude 27.2707°E was considered for study. The climate was classified as tropical wet and dry climate. The building was modeled in EnergyPlus [11–15]. The input data file (idf) file used in our earlier work [27] was modified with a dual set point to EnergyPlus to consider both heat loss and heat gain of the building envelope so that this method can be suitably used for any climate. The Table A.1 of Appendix A show the parameter of the building.

4. RC Thermal modeling

Fig. 1 shows the heat flow in and heat removal out of the building. The building outside surfaces heat balance equation is given by

$$OSCH = OSCVH + OSTRH + OSSRH,$$

where

OSCH = Outside Surfaces Conduction Heat, OSCVH = Outside Surfaces convective heat, OSTRH = Outside Surfaces Thermal Radiation Heat, OSSRH = Outside Surfaces Solar Radiation Heat.

$$OSCH + ISCH + HS = 0,\ \ ISCH = -OSCH - HS,$$

where

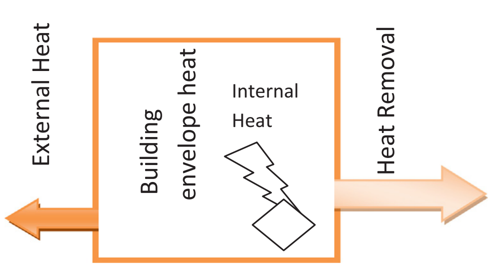

Fig. 1. Energy balanced heat removal.

ISCH = (Inside Surfaces Conduction Heat also called opaque surfaces conduction heat) = I_{OPQ},

HS = Heat Storage on surfaces.

The various formulas used by EnergyPlus in computing the surface heat is given at the end of Appendix A. The EnergyPlus gives computed energy values in joules. For 15 min samples these values can be converted into watts by dividing 900. Dividing by 900,000 gives kW for every 15 min. For the purpose of similarity EnergyPlus variable names were used throughout the paper. All the Energy values are used as kW.

Zone air system sensible cooling Energy $I_b = I_{OPQ}$ + window heat addition (I_w) + Infiltration heat(I_{inf}). The EnergyPlus gives the heat fluxes acting on the zone air system conducted through inside surfaces.

$$I_b = I_{OPQ} + I_w + I_{inf}$$

Zone air system sensible cooling energy -Zone infiltration sensible heat gain energy =

$$I_b - I_{inf} = \text{Surfaces Heat} = I_{OPQ} + I_w$$

The Resistance capacitance (RC) models are generally used for thermal analysis. [28–30]. This method uses the electric- thermal analogy called gray box modeling.

4.1. t-MPC RC model

The wall, floor, roof etc. are considered using 2R1C model represented by R_1 and R_2 and C_w as shown in Fig. 2. The C_R represents the room air thermal mass. The infiltration heat equivalent resistance of the building is given as R_3. P represents the air conditioner cooling output which draws thermal current opposite from the air thermal mass there as the room temperature V_o is maintained at the desired level. This model considers the climate influence as atmospheric temperature variations V_i. Eq. (1) an (2) represent the state space equation for t-MPC

The RC parameters of the building under consideration was obtained from the peak thermal load of the building which is indicated in Table 4.1.

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$$C_R\frac{dV_o}{dt} = \frac{V_i - V_o}{R_3} + \frac{V_w - V_o}{R_2} - P + I_L$$

$$C_w\frac{dV_w}{dt} = \frac{V_i - V_w}{R_1} - \left(\frac{V_w - V_o}{R_2}\right)$$

$$\frac{dV_o}{dt} = -\left(\frac{1}{C_R R_3} + \frac{1}{C_R R_2}\right)V_o + \left(\frac{1}{C_R R_2}\right)V_w + \left(\frac{1}{C_R R_3}\right)V_i - \frac{1}{C_R}(P - I_L). \tag{1}$$

$$\frac{dV_w}{dt} = \left(\frac{1}{C_w R_2}\right)V_o - \left(\frac{1}{C_w R_1} + \frac{1}{C_w R_2}\right)V_w + \left(\frac{1}{C_w R_1}\right)V_i. \tag{2}$$

The internal heat load $I_L = I_E + I_P + I_I + I_h$. The State space model using Table 4.1 is

$$A = \begin{pmatrix} -0.8274 & 0.4744 \\ 3.459 & -6.918 \end{pmatrix}, B = \begin{pmatrix} -0.301 & 0.353 \\ 0 & 3.459 \end{pmatrix}, C = (1\ \ 0),\ D = (0\ \ 0)$$

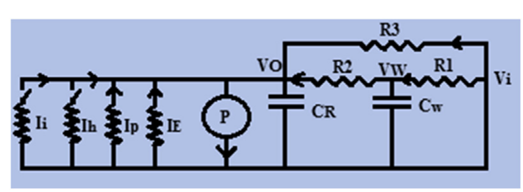

Fig. 2. RC model for t-MPC. $V_o(t)$ - Room temperature °C, $V_i(t)$ -Atmospheric temperature °C, I_E-Equipment Load (kW). I_P-Power plug Loads (kW), I_I-Lighting Load (kW), I_{h-} Human heat Load (kW), P-Air Conditioners (N nos.) in kW, R1,R2- equivalent wall floor ceiling resistances Equivalent Resistance °C/kW, R3-equivalent infiltration resistance in ^{0}C/kW,C_{w-} wall capacitances in kWhr/^{0}C C_{R-}thermal mass capacitance in kWhr/^{0}C.