Office Heating Modeling Using an HVAC Power Step Response Experiment

Mikko Nykyri, Saku Levikari, Mohammad Seyfi, Samuli Honkapuro
LUT University
Lappeenranta, Finland
Email: mikko.nykyri@lut.fi

***Abstract*—Indoor air quality is an important aspect in office buildings. Poor air quality leads to people feeling unwell and working inefficiently. However, heating, ventilation and air conditioning cause a significant expenditure in large building complexes. Automation systems that are widely installed in buildings in many places around the world allow control of the ventilation, which can be utilized in reduction of energy consumption. Still, utilization of the control systems needs knowledge of the system dynamics, which may be a troublesome task to accomplish with insignificant return. This paper presents a method for indoor temperature modeling using a gray box model and a step response experiment for data gathering to obtain a means of predicting indoor air temperature with adequate accuracy with low effort compared to more complex modeling endeavors. When testing the model, the maximum error between the actual and predicted air temperature was 0.270°C and the absolute error value of the prediction was 0.112°C.**

***Index Terms*—Smart Buildings, Temperature Control, HVAC Control, Smart Cities, Predictive Modeling**

I. Introduction

Energy saving is a hot topic worldwide as people seek methods to reduce their energy use. This is motivated both by ambitions to reach carbon neutrality (e.g. the 2050 net-zero greenhouse gas emissions target of the European Union), and the desire to gain economic benefit by reducing the amount of money spent in energy. This trend is visible in both domestic and commercial settings: people try to cut down their energy spending in their homes, and their employers seek to benefit economically by reducing their energy expenditures. Buildings that promote the efficient use of resources, also known as green buildings, have become a topic of interest as green building certification programs have been implemented [1]. However, even if green buildings are something that is aspired, the implementation of them may not be trouble-free. Even if energy savings are reported, in some cases, the air quality in the building can be affected negatively [1].

Many people work in office buildings, where a significant amount of energy is used in just to keep the space suitable for people to work in. Energy is consumed in, e.g., heating, ventilation, and air conditioning (HVAC). The HVAC system in office buildings is a crucial part of the building infrastructure as people can not work well if the conditions are inadequate. This is emphasized with strict requirements that can be imposed for the air quality inside the work area. The air needs to be ventilated to keep the temperature, carbon dioxide (CO_2), and humidity levels in control. Especially in hot climates, HVAC systems are considered an integral role of building infrastructure [2]. High air temperature and humidity will lead to people discomfort, but high air humidity can also lead to property damage like mold or electrical equipment failure as the water condenses to different surfaces. In colder climates, the importance of heating is obviously crucial so that the temperature stays warm. Poor air quality in terms of high CO_2 concentrations affects decision-making in some populations and causes various functions to be slower [3]. In [4], the CO_2 concentration of air is used to label the air quality into roughly three categories of good, moderate, and poor.

All this means that the HVAC system has to be used and it cannot be turned off or tuned too low for energy saving reasons, but questions are raised whether the HVAC systems could be optimized to run so that they use less energy or use less money to perform the task that the system is required to do.

Dynamic energy pricing, i.e., electricity price that changes over time depending on the market, is becoming more and more common, which affects the way people get billed for their energy use. Dynamic energy pricing promotes engaging in demand response, which is a concept where the usage of electrical energy is shifted away from undesirable or nonoptimal moments of time. This can mean, e.g., that electrical energy use is minimized during times when the cost of electrical energy is high, and increasing the usage during times when it is low. The possibilities for engaging in demand response can be further enhanced with a battery energy storage system and local energy production, if those systems are installed.

When considering demand response in an office building, gaining economic benefit from shifting HVAC utilization requires knowing how the air quality of the building changes when the HVAC power is controlled. This means that the dynamics of the air quality need to be known in order to have an insight on what happens when the input power of the HVAC changes. To obtain an accurate understanding of the building dynamics, a complex model would need to be implemented requiring to have multiple air quality measurements around the building collecting data over time that are used to make a virtual representation of the actual building. Making this kind of model can be troublesome, and requires a significant

Authors would like to thank Business Finland for the funding for project "Smart edge-computing based building energy management enabling electric transportation - SmartE3".

979-8-3315-1278-1/25/$31.00

amount of work [5].

As data is collected for the model development, more data tends to lead into more accurate model for the building where it is applied to. However, the advantage gained from increasing the amount of data may be negligible, if the model accuracy is only improved by a small margin. When considering the indoor air temperature, there is not one "sweet spot" where the temperature is just right, but rather there is a temperature range where the cognitive performance is unaffected by the surrounding temperature [4]. Therefore, instead to targeting to model a space to reach temperature accuracies of, e.g., one-tenth of a Celsius degree, but rather to reach an adequate accuracy of, e.g., one degree.

This paper studies the possibility of modeling the air quality dynamics of an office building with a gray box type model (like described in [6]). The problem is approached with a simple step response experiment where the building air quality dynamics are studied with measurements around the building during an experiment where the HVAC power is first reduced and then raised back again. This paper presents how a step response experiment can be used to obtain a model for predicting office indoor air temperature with adequate accuracy. Defining what is adequate accuracy is not a straightforward thing to accomplish. However, in terms of this paper, adequate means that the prediction is able to follow the trend of the actual temperature and the numerical value is not off than ± 1 °C.

II. Background

Since HVAC is a significant contributor of energy consumption in buildings, modeling of HVAC system dynamics in order to pursue energy savings is a field of on-going research interest. In [7], it is said that research has been active for decades. The task of HVAC modeling can be approached from different angles depending on the sub-type of model that is pursued. In [6]–[8], three sub-types of HVAC models are described: data-driven models, physics-based models, and semi-physical "gray box" models. Data-driven models are purely based on measurement data and can be a good fit, but they have to be tailored in each setting individually [6]. These models are sometimes also called "black box" models. They are based on data analytics and machine learning models, such as neural networks [8]. Physics-based systems are said to be more versatile, but provide less accuracy to data driven models [6]. Their logic is based on fundamental laws of physics, such as heat transfer and mass balance [8], some even focusing on modeling airflow dynamics [9]. These models are sometimes called "white box" models, and they can also utilize, e.g., resistance and capacitance as analogy for heat transfer between rooms [10]. Gray box models are hybrid models, and lay somewhere between the two being based on both data and physics [6], [8].

Gray box models have some advantages over physics-based and data-based models. They are said to provide more accuracy than physics-based models, and also better generalization potential than data-driven models [6]. However, they are also said to be the hardest to develop and they may need retuning if the operating conditions change from the conditions that were present during data collection [6]. Physics-based models are also said to be difficult to develop, which has raised interest in building data-based models [7]. When developing a model, the required amount of knowledge of the phenomenon that is modeled (e.g. the air quality of a building) depends on the sub-type of the model. When building a data-based model, only the data is required and little knowledge of the phenomenon itself, but in a physics-based model, detailed knowledge is required [6]. Grey box models, again, have their requirements for knowledge in between physics-based and data-based models [6]. On the other hand, the hybrid nature of the models may allow for capturing of effects that would have otherwise been left out when modeling the equations for the dynamics of the modeled phenomenon [6]. Grey box models are also said to be more robust than black box models when against weather changes [11].

III. Methods

The model is created by first composing the equation for temperature behavior by assessing the factors that effect the change of temperature over time $\frac{dT}{dt}$. Then, data is collected from the building to have data for the machine learning model to have for determining the values of the coefficients of the equation.

A. Temperature behavioral

The temperature of the air inside the office is dependent on the HVAC system power setting. As the system power increases, it causes a change to the temperature in the system if there is a difference in the thermal energy of the air that is input to the office space Q_{in} and the energy that is exhausted Q_{out}:

$$mc\frac{dT}{dt} = Q_{\mathrm{in}} - Q_{\mathrm{out}} \tag{1}$$

where m is the total mass of the air inside the building (constant) and c is the specific heat capacity of air (constant). Q_{in} is considered as a positive value, and Q_{out} a negative value. The sum of all energy exchanges $\sum Q$ in the building can be expressed with

$$\sum Q = Q_{\mathrm{cond}} + Q_{\mathrm{HVAC}} + Q_{\mathrm{DH}} \tag{2}$$

where Q_{cond} is the conducted heat exchange, Q_{HVAC} is the heat exchange of the HVAC system, and Q_{DH} is the heat input by the district heating (if applicable). The conducted heat exchange Q_{cond} is calculated with

$$Q_{\mathrm{cond}} \cong k_{\mathrm{cond}}(T - T_{\mathrm{amb}}) \tag{3}$$

where k_{cond} is the thermal conduction coefficient, T is the current air temperature, and T_{amb} is the current ambient (outside) air temperature. The HVAC heat exchange Q_{HVAC} is calculated with

$$Q_{\mathrm{HVAC}} \cong k_{\mathrm{HVAC}}\dot{m}(T - T_{\mathrm{amb}} + T_{\mathrm{preheat}}) \tag{4}$$

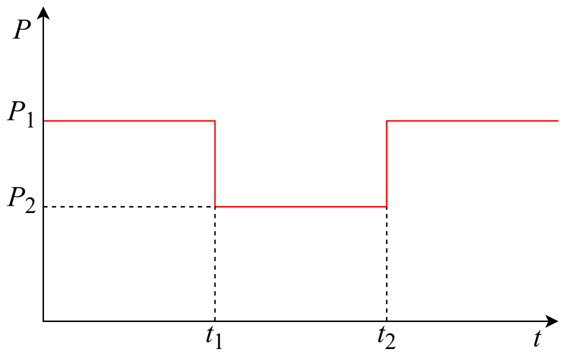

Fig. 1. The step response experiment of the HVAC system. The HVAC power setting is lowered from P_1 to P_2 when $t = t_1$, and raised back to P_1 when $t = t_2$.

where k_{HVAC} is the HVAC coefficient, $\dot{m}$ is the mass flow of the HVAC system, and T_{preheat} is the set point of the HVAC pre-heat (constant). Finally, if district heating is present, the district heating heat exchange Q_{DH} is calculated with

$$Q_{\text{DH}} \cong \max(0, T - T_{\text{set}}) \tag{5}$$

where T_{set} is the set point of the air temperature in the building. By substituting Q_{cond}, Q_{HVAC}, and Q_{DH} in Eq. 2 using Eqs. 3, 4, and 5, the equation can be expressed as

$$\begin{aligned} \dot{m}c\frac{dT}{dt} &= k_{\text{cond}}(T - T_{\text{a}}) \\ &+ k_{\text{HVAC}}\dot{m}(T - T_{\text{amb}} + T_{\text{preheat}}) \\ &+ \max(0, T - T_{\text{set}}) \end{aligned} \tag{6}$$

Then, the change of temperature over time $\frac{dT}{dt}$ can be solved:

$$\begin{aligned} \frac{dT}{dt} &= \frac{k_{\text{cond}}}{mc}(T - T_{\text{amb}}) \\ &+ \frac{k_{\text{HVAC}}\dot{m}}{mc}(T - T_{\text{amb}} + T_{\text{preheat}}) \\ &+ \max(0, \frac{1}{mc}(T - T_{\text{set}})) \end{aligned} \tag{7}$$

Because the mass flow $\dot{m}$ is dependant on the power setting of the HVAC system P_{HVAC}, we can substitute $\dot{m} \approx P_{\text{HVAC}}$. Then, if we substitute coefficients $\frac{k_{\text{cond}}}{mc} = \alpha_1$, $\frac{k_{\text{HVAC}}\dot{m}}{mc} = \alpha_2$, and $\frac{1}{mc}(T - T_{\text{set}}) = \alpha_3$, we can express the equation as a function of features α_1, α_2, and α_3, because all the other terms of the equation are measurable temperature values or set points:

$$\begin{aligned} \frac{\delta T}{\delta t}(\alpha_1, \alpha_2, \alpha_3) &= \alpha_1(T - T_{\text{amb}}) \\ &+ \alpha_2 P_{\text{HVAC}}(T - T_{\text{amb}} + T_{\text{preheat}}) \\ &+ \max(0, \alpha_3(T - T_{\text{set}})) \end{aligned} \tag{8}$$

B. Data collection

To obtain data for calculation of the features α_1, α_2, and α_3 of the behavioral models, a step response experiment is performed where the HVAC system power is suddenly dropped when $t = t_1$ from P_1 (75 kW) to P_2 (40 kW), and the value of air temperature is monitored and logged (Fig. 1). When $t = t_2$, the HVAC is powered back up, keeping the data logging active. The step response test was performed in an office building located in Lahti, Finland. The data is collected using the automation system of the building, which controls and monitors the HVAC system.

The office building where the model is applied consists of mainly similar rooms that have indoor working space. Each room has a temperature sensor for data collection, and the data is collected using these sensors from every room in 10 minute intervals. Since the rooms have similar characteristics, the model can be simplified by averaging the temperature data across all rooms so that one value represents the temperature of the whole building. The building consists of two levels and a basement. In the ground level, there is a storage room, light laboratory testing facilities, four small offices, one medium-sized office, and personnel facilities (e.g. break rooms, changing rooms, and restrooms). The upper level consists of one large office room and four medium-sized offices.

C. Model training

The model training was performed using Python and its libraries numpy, pandas, and scikit-learn. Using these libraries, a linear regression algorithm was applied to the temperature data. A simple linear regression model from scikit-learn was utilized, which uses the least squares method for the linear regression modeling.

IV. Results

When using the model to predict room temperature over time, the temperature profile follows the trend of the actual values (Fig. 2). Although the trend of the temperature is followed, there is some error in the actual and predicted values. The maximum error of the values is 0.270 °C. Besides the maximum error, the mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE), and the coefficient of determination (R2) were calculated and rounded into three decimals (Table I). The MAE and MAPE values of 0.112 °C and 0.509% can be considered good, because as discussed above, the predicted temperature values are precise enough for indoor air temperature assessment. However, the R2 value of 0.134 can be considered a bit low, but this is due to the prediction not following the trend of the actual temperature curve aggressively enough.

The main benefit of the presented method for model training over purely physics of data-based models is the simplicity of the modeling process. The low effort needed to perform the training can be considered to outweigh the inferior performance of the model, if the accuracy is good enough for its use case. Many buildings have an automation system that collects

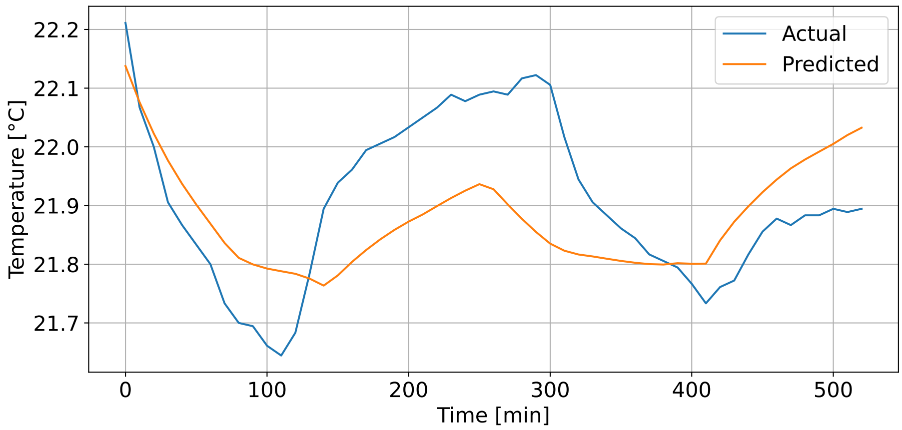

Fig. 2. The actual and predicted temperature in the building. The temperature values are averaged across all rooms in the building measured in 10 minute intervals. The predicted temperature follows the trend of the actual temperature.

TABLE I
THE PERFORMANCE METRICS OF THE MODEL

Metric	Value	Unit
Mean Absolute Error (MAE)	0.112	°C
Mean Squared Error (MSE)	0.016	°C
Maximum error	0.270	°C
Mean Absolute Percentage Error (MAPE)	0.509	%
Coefficient of Determination (R2)	0.134	n/a

data, and therefore there may be no need for new infrastructure like measurement devices to obtain the data for modeling.

V. Discussion

When considering the model performance in predicting the indoor air temperature, the results suggest that the model can reach adequate accuracy in following the actual temperature trend in the building. This can allow the model to be used in, e.g., planning to implement a smart HVAC system that optimizes the system utilization with the electrical system by engaging in demand response. This can be implemented by, e.g., boosting the HVAC use when the cost of electricity is low, and reducing it when the cost is high. Still, the air temperature has to be kept within reason, and employee comfort and performance should not be affected with cost savings.

However, as discussed earlier, the temperature of the indoor air is not the only metric of air quality. In [12], it is said that many methods that pursue high energy savings tend to focus so heavily on thermal comfort management so that the end result is in poor indoor air quality, even if the temperature is kept within range. For example, the amount of CO_2 in indoor air is an important factor in air quality. People generate CO_2 in the indoor air when they exhale and the amount of CO_2 in the indoor air depends on the number of people in the space. The amount of CO_2 a person generates depends on their physical activity and metabolism, which is dependent on different aspects, including age, body mass, and sex [13]. People of different ages and physical properties work in an office setting, but their level of physical activeness can be considered similar. In [13], it is estimated that in an office space, on average, each person generates CO_2 with a rate of 0.0048 l/s.

The removal of CO_2 from an office space is done mainly with the exhaust of the HVAC system. Keeping this in mind, the power setting of the HVAC system should be kept high enough that also CO_2 concentration in the space is kept low enough so that the air quality is not unsuitable for work. This suggests that CO_2 could also be used as a variable to consider in the modeling, or that there needs to be a method for ensuring this, e.g., a hard limit on the lowest possible power setting for the HVAC. On the other hand, similar kinds of hard limits should be in place as a backup for temperature control as well.

VI. Conclusion

In this paper, a method for office indoor air temperature dynamics modeling was presented using a step response experiment. In the experiment, the power setting of the building's HVAC system was dropped from 70 kW to 40 kW, and after a while, it was raised again to 70 kW. Temperature data was collected to train a gray-box model of the temperature dynamics of the indoor air. The results show that a simple experiment can be used to obtain adequate model performance; when testing the model, the maximum error between the actual and predicted air temperature was no more than 0.270°C. Furthermore, the mean absolute error value of the prediction was 0.112°C. When considering the temperature control of an indoor office space, this magnitude of error can be considered not very meaningful if it allows for efficient HVAC system utilization with, e.g., demand response to gain monetary benefit from using less energy on ventilation during times when the cost of electrical energy is high. On the other hand, the air quality must be kept within limits to ensure proper conditions for people working in the building.

Since the accuracy of the prediction can be considered acceptable, the predictions could be utilized in, e.g., a reinforcement learning model training to pursue smart building systems with intelligent HVAC control to both achieve greater energy efficiency. When combined with smart grid solutions such as energy storages and dynamic energy pricing, the building owners can also pursue monetary benefits with less effort than more conventional and precise modeling of the building thermal dynamics.

REFERENCES

[1] A. Steinemann, P. Wargocki, and B. Rismanchi, "Ten questions concerning green buildings and indoor air quality," *Building and Environment*, vol. 112, pp. 351–358, 2017.

[2] M. Fasiuddin and I. Budaiwi, "HVAC system strategies for energy conservation in commercial buildings in saudi arabia," *Energy and Buildings*, vol. 43, no. 12, pp. 3457–3466, 2011.

[3] B. Du, M. C. Tandoc, M. L. Mack, and J. A. Siegel, "Indoor CO2 concentrations and cognitive function: A critical review," *Indoor Air*, vol. 30, no. 6, pp. 1067–1082, 2020.

[4] S. Dimitroulopoulou, M. R. Dudzińska, L. Gunnarsen, L. Hägerhed, H. Maula, R. Singh, O. Toyinbo, and U. Haverinen-Shaughnessy, "Indoor air quality guidelines from across the world: An appraisal considering energy saving, health, productivity, and comfort," *Environment International*, vol. 178, p. 108127, 2023.

[5] F. Massa Gray and M. Schmidt, "A hybrid approach to thermal building modelling using a combination of gaussian processes and grey-box models," *Energy and Buildings*, vol. 165, pp. 56–63, 2018.

[6] A. Afram and F. Janabi-Sharifi, "Review of modeling methods for HVAC systems," *Applied Thermal Engineering*, vol. 67, no. 1, pp. 507–519, 2014.

[7] S. Wu and J.-Q. Sun, "A physics-based linear parametric model of room temperature in office buildings," *Building and Environment*, vol. 50, pp. 1–9, 2012.

[8] Z. Afroz, G. Shafiullah, T. Urmee, and G. Higgins, "Modeling techniques used in building HVAC control systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 83, pp. 64–84, 2018.

[9] Y. Bian, X. Fu, R. K. Gupta, and Y. Shi, "Ventilation and temperature control for energy-efficient and healthy buildings: A differentiable pde approach," *Applied Energy*, vol. 372, p. 123477, 2024.

[10] H. İbrahim Tol and H. B. Madessa, "Development of a white-box dynamic building thermal model integrated with a heating system," *Journal of Building Engineering*, vol. 68, p. 106038, 2023.

[11] T. Hauge Broholt, M. Dahl Knudsen, and S. Petersen, "The robustness of black and grey-box models of thermal building behaviour against weather changes," *Energy and Buildings*, vol. 275, p. 112460, 2022.

[12] Y. Yang, S. Srinivasan, G. Hu, and C. J. Spanos, "Distributed control of multizone HVAC systems considering indoor air quality," *IEEE Transactions on Control Systems Technology*, vol. 29, no. 6, pp. 2586–2597, 2021.

[13] A. Persily and L. de Jonge, "Carbon dioxide generation rates for building occupants," *Indoor Air*, vol. 27, no. 5, pp. 868–879, 2017.