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Development of a building simulation model for indoor temperature prediction and HVAC system anomaly detection

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Abstract: In order to reduce global energy consumption, energy-efficient, green and smart buildings should be built. In addition to the application of other energy efficiency measures, effective management of heating, ventilation and air conditioning (HVAC) systems are also required. High-quality management and control of those systems ensures optimal occupant comfort, proper operation, rational energy consumption, and a positive impact on the environment. This is especially important for large buildings with complex systems such as hotels. As a contribution to the creation of appropriate tools for the management and control of HVAC systems in smart buildings, this paper presents the results of the development of a detailed dynamic simulation model based on data collected from a smart room system in a hotel in Zagreb, Croatia. The smart room system provides historical data on a set and actual room temperatures, occupancy schedule, windows openings, fan coil unit (FCU) operating status, fan speed, control valve opening, and heating or cooling modes with a time step of 5 minutes. The simulation model based on TRNSYS software uses part of the available data and predicts the room temperatures. A comparison of the predicted and measured temperatures at each time step shows that the deviations of the manually calibrated model are within acceptable standardized limits. The developed model has been applied to identify major anomalies in the operation of the FCU system, yielding promising results.

Keywords: *Anomaly detection, Calibration, HVAC system, Simulation model, Smart room, Validation*

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Nomenclature	
HVAC	Heating, Ventilation and Air Conditioning
FCU	Fan Coil Unit
cvRMSE	Coefficient of Variation of the Root Mean Squared Error
nMBE	Normalized Mean Bias Error

1. INTRODUCTION

The heating, ventilation, and air conditioning (HVAC) system is one of the largest energy consumers in buildings. Therefore, it is critical to identify strategies to reduce energy usage [1]. The first step to improve energy efficiency in buildings is to properly model the building performance with the corresponding HVAC systems. The developed models can be used to analyze energy consumption, as well as to discover anomalies and improve control logic [2]. There are three modeling techniques for building system simulation, white-box or physical models [3], black-box or data-driven models [4] and gray-box or hybrid models [5]. The advantages and disadvantages of these modeling strategies are discussed in the literature [6]. When creating a building simulation model, a calibration process is required due to the uncertainties and complexity of the models. Calibration involves changing the parameters of the building and its systems until the obtained results match the measured ones. Calibration can be performed manually [7] or automatically [8]. Optimization methods such as genetic algorithms can be used for automatic model tuning [9]. That the time period over which the calibration and validation processes are performed does not need to cover the entire data range, but only a few representative weeks can be sufficient in this regard [10]. There are standard metrics and techniques in the literature for validating the created models [11].

Most of the work in this area has focused on energy consumption analysis, and only a handful of papers deal exclusively with simulating the indoor air temperatures of specific zones [12]. Those often use large one-hour simulation time steps [13] or they are unable to accurately represent specific conditions such as human behavior [14]. In Ref. [15], TRNSYS energy modeling tools were used to study temperature dynamics in a naturally ventilated residential building. Parameters such as air infiltration rate and window functions were considered. The results provided values of normalized mean bias error (nMBE) between -6.7% and 7.6% and coefficient of variation of the root mean squared error (cvRMSE) between 5.3% and 8.7%. In a similar study, a white-box model developed in TRNSYS was used to predict indoor temperatures in a low-energy building and a cvRMSE of less than 7.5% was obtained [14]. In another study, a novel calibration method for building simulation models based on evolutionary algorithms was presented [16]. When applied to a college building, this method provided cvRMSE values of 4.5% and 5.4%, respectively, for two test rooms. Another paper reported the accuracy of an EnergyPlus model for a five-story office building and found that the calibrated model predicted hourly indoor temperatures for an entire year with a cvRMSE value of less than 2% and a temperature deviation of ±1.5 °C [13]. A multizone airflow model using TRNSYS for two test houses was developed in [17]. This model achieved an average cvRMSE value for the indoor temperatures of about 2.2%.

One way to detect anomalies in HVAC systems is to simulate the physical processes in the building and its systems [18]. A white-box simulation model predicts how the system will behave under both normal and fault conditions and calculates the residuals of the predicted and measured values [19]. If the results differ greatly, an anomaly can be detected. In addition to using white-box models for anomaly detection, there are other techniques based solely on data, such as data-driven, knowledge-based, or rule-based techniques [20]. Such techniques require only sensory measurements, and expert knowledge of the system, and are generally less computationally intensive and time consuming.

This study addresses the sub-hourly prediction of hotel room temperatures, an area that remains relatively unexplored due to the complexity of hotel HVAC systems, fluctuations in room occupancy, and unpredictable guest behavior. It describes the development of a white-box model to predict room temperatures and detect major anomalies in HVAC system operation in a hotel in Zagreb, Croatia. The hotel rooms are equipped with smart room technology providing a rich data set with real information about room occupancy, window openings, and HVAC system operation, particularly the fan coil unit (FCU) installed in each room. The model was created for a single floor of the building with a simulation time step of 5 minutes, which provided detailed insight into the temperature dynamics by using TRNSYS

18 software and the Google SketchUp 3D tool. After calibration and validation, the model was used to detect anomalies in the operation of the FCUs. Anomaly detection was based on the difference between model results and sensory measurements. The article is organized as follows: After introduction section, Section 2 describes and presents the building simulation model, collected data, validation metrics, and simulation process. Sections 3 and 4 present and discuss the results. Finally, in Section 5, the conclusions are reported and some guidelines for future work are given.

2. MATERIALS AND METHODS

The next subsections describe the hotel building used to develop the simulation model, the smart room system installed in the building, a dataset of multi-year records from each room, the weather data, and the methods of model development, calibration, and validation.

2.1. Case Study Building

The building for the case study is a hotel in the Croatian capital, Zagreb. The hotel has 166 rooms equipped with a smart room system. The smart room system enables controlling and monitoring of all systems in the rooms. Most floors of the hotel have 24 guest rooms, which are identical except for the rooms in the corners. The corner rooms have a floor area of 32 m^2, while the other rooms are 26 m^2. The height of the rooms is 2.6 m. A typical room consists of a resting or sleeping area and has a bathroom and at least one external window. The overall heat transfer coefficient (U value) of the exterior walls, ceilings between rooms and adjacent walls is 0.27 W/(m^{2}K), 1.02 W/(m^{2}K) and 0.21 W/(m^{2}K), respectively. Each window has an area of 8.65 m^2. Their overall heat transfer coefficient and solar heat gain coefficient are 1.10 W/(m^{2}K) and 0.33, respectively. The rooms do not have external blinds on the windows, only manually operated curtains. The HVAC system in each room consists of a four-pipe fan coil unit (FCU) that can heat or cool as needed. Each FCU has a rated heating and cooling capacity of 1600 W at nominal operating conditions. The water supply temperature in heating mode depends on the outdoor air temperature and is 70 °C at an outdoor temperature of -15 °C. In cooling mode, the water supply temperature is 9 °C. The FCUs recirculate the indoor air, and supply 60 m^3/h of conditioned outdoor air provided by the central mechanical ventilation system. The same amount of air is extracted from the bathrooms via the same central ventilation system.

2.2. Smart Rooms

The basis of the smart room idea is a microprocessor-controlled station that monitors and records all sensory measurements and intelligently controls all actuators to make a hotel room function better. Smart rooms have many benefits, such as reducing costs, improving guest satisfaction, increasing security, and centralized control that allows staff to work more effectively because they always have access to the latest information. The smart room system enables control of FCUs installed in the rooms, as well as lighting and shading. The system is also able to detect the opening of doors, thus registering the presence of people in the rooms. It can monitor all measured values such as room temperature, opening of windows or water on the bathroom floor in case of an accident. In addition, the system provides greater security through alarms, detection of unauthorized entry or malfunctions. Thanks to the centralized operation, the activities of the hotel staff can be monitored, which all improves the management and supervision of the entire system.

2.3. Dataset

The sensory measurements and outdoor weather parameters used for model development are listed in Table 1. The smart room system collected data from all rooms in the hotel. The sensory measurements were collected between 2013 and 2021, but only the data from 2018 were used to calibrate and validate the simulation model. The sampling rate of the measurements was 5 minutes. The data were preprocessed to eliminate problems that may have resulted from missing or erroneous values. The data of measured and set temperatures are integer values due to the design of the data acquisition system, while the temperatures predicted in the simulations are real values. The other signals are Boolean values. The lower values of each signal represent an empty room, a turned-off FCU, a closed window, and vice versa. Some sensory measurements were not used as inputs in the simulations. These data were FCU fan speed, control valve status, and HVAC system mode (heating or cooling regime).

Table 1. Description of the data used in simulations.

Variable	Type	Description
Set temp.	Integer [°C]	Desired temperature set by guests or hotel staff
Room temp.	Integer [°C]	Measured room temperature
Occupation	Boolean	Presence of persons in the room
Window	Boolean	Status of window (open/closed)
HVAC state	Boolean	Status of FCU (on/off)
Outside temp.	Real [°C]	Temperature of outside air
Irradiance	Real [kJ/h]	Solar irradiation on horizontal surface
Humidity	Real (%)	Relative humidity of outside air

Outdoor conditions recorded by the Croatian Meteorological and Hydrological Service at a nearby weather station and stored as hourly averages of 10-minute samples were also used. The outdoor environment data included ambient temperature, solar irradiation and relative humidity. The solar irradiation was processed individually so that each surface received the correct amount of solar energy according to its orientation and slope.

2.4. Simulation Model

The simulation model was created using TRNSYS software. The thermal zone model of the selected floor is presented in Fig. 1. The structure was designed with Google SketchUp using the Trnsys3d plugin.

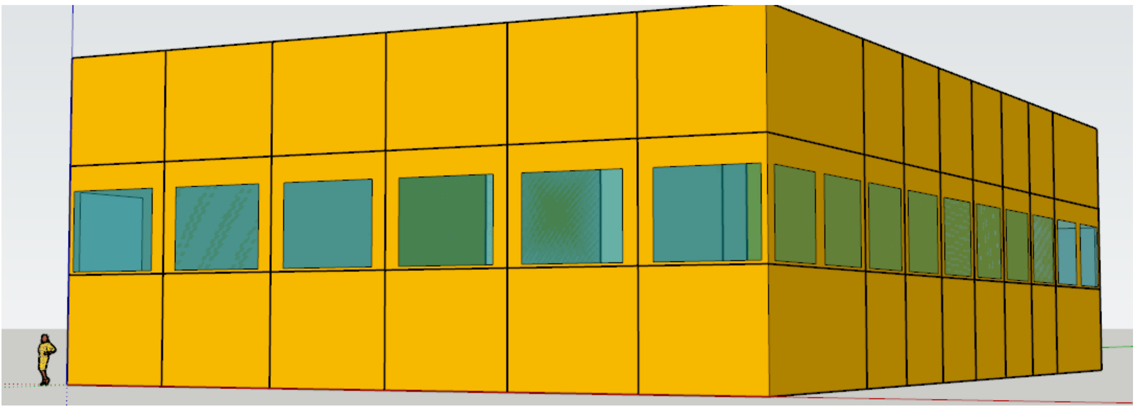

Figure 1. A representative floor of the building in Google SketchUp.

The dimensions were taken from the architectural descriptions of the building. Due to the size of the building and the complexity of its systems, only one representative floor was included in the simulations. There are 24 guest rooms on this floor, and each thermal zone in the simulations represents a room and its associated bathroom. Defining a common thermal zone for the bedroom and bathroom in each room was possible because there are no independent heating elements in the bathrooms and the temperature conditions are similar to those in the bedrooms. To encapsulate the heat exchange within the building, the adjacent spaces of the selected floor were included in the simulation model. However, these adjacent thermal zones were defined only to compute the heat exchange between them and the simulated rooms, not to predict the temperatures in them. Therefore, the temperatures of these adjacent zones in the simulations match the records of the smart room system. Once the shape of the zones was created, the model was inserted into the TRNSYS software. In TRNSYS, all zone properties such as wall and window properties, internal heat gains, infiltration, the FCU system, its control logic and ventilation were defined. In addition, weather data was also included in the simulations to represent real outdoor conditions. It was assumed that only guests present in a room generate heat and moisture gains (100 W and 35 g/h per person, respectively). Infiltration was defined as a constant inflow of outside air at 0.1 air changes per hour (ach), increasing to 3 ach when windows are open. The room ventilation was set to draw air from the FCU (depending on the fan speed) and air from the central mechanical ventilation system.

The data collected by the smart room system in the hotel used for the simulations were the set temperature, occupancy status, window status, and HVAC (FCU) status. This data is used to control the room temperature to the desired value, create more accurate occupancy schedules in terms of heat gains, model the exchange of outdoor and indoor air when the window is open, and model the activation and deactivation of the FCU as desired by the guests at that time.

Simple thermostats were used for the control logic in each room. The thermostats had 3 levels to control the fan speed of the FCU and thus the room temperature in cooling and heating modes. To develop a suitable model for the simulations, the FCU data was taken from the manufacturer´s technical specifications, taking into account the design water temperatures in heating and cooling modes given in Section 2.1.

Assumptions are an essential part of the modeling process of a building and its systems. Therefore, it was necessary to calibrate the model to match the measured data. The model was manually calibrated by changing the model parameters to achieve better results. The simulation time step was 5 minutes, which corresponds to the sampling rate of the data in the hotel.

2.5. Validation Metrics

The developed model is evaluated by comparing the simulated and measured temperatures for each thermal zone (room). Common metrics for evaluating a simulation model are the normalized mean bias error (nMBE) and the coefficient of variation of the root mean squared error (cvRMSE) [11]. The nMBE metric, represented by Eq. (1), reflects the bias error of the temperature prediction and yields either positive or negative results. A limitation of Eq. (1) is the possibility of error compensation by positive and negative values, which could lead to misleading results. The cvRMSE metric, calculated using Eq. (2), avoids this problem by implementing the squared temperature difference, ensuring that the results are always positive. The results of these equations are expressed as percentages, which facilitate comparison with other simulation features. Eqs. (1,2) are presented as follows:

$$\mathrm{nMBE}=\frac{\sum(y_m\text{-}y_s)}{\sum y_m}\cdot 100\ (\%) \qquad (1)$$

$$\mathrm{cvRMSE}=\frac{\sqrt{\frac{1}{n}\sum(y_m\text{-}y_s)^2}}{\frac{1}{n}\sum y_m}\cdot 100\ (\%) \qquad (2)$$

where y_m is the actual (measured) variable, y_s is the simulated variable, and n indicates the number of samples. In Eq. (1), the variable n is eliminated to simplify the calculations.

The standard criteria for evaluating the developed model are divided into monthly and hourly criteria. To confirm the validity of the model, the hourly criteria should be within ±10% for nMBE and less than 30% for cvRMSE [21]. The monthly criteria should maintain a range of ±5% for nMBE and less than 15% for cvRMSE [21].

3. RESULTS AND DISCUSSION

In this section, we present the results of the developed simulation model after the calibration process. Fig. 2 shows a comparison between the simulated and measured room temperatures, and relevant status signals such as occupancy, window opening, and FCU status for a particular room in January 2018 under standard operating conditions. The predicted temperatures largely reflect the observed trend in measured temperatures, albeit with some deviations due to uncertainties inherent in the model.

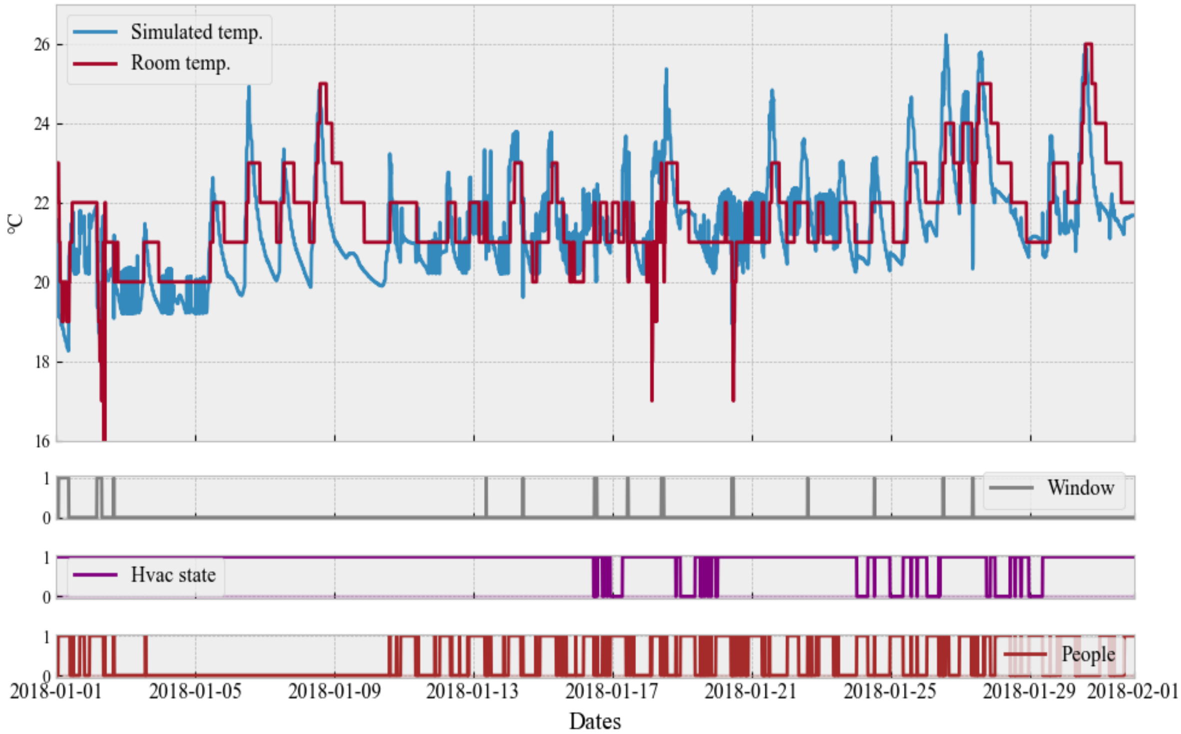

Figure 2. Comparison between simulated and measured room temperatures supplemented by the status signals of the FCU system during the winter season.

Although these additional signals do not directly evaluate the simulations, their impact on the results is significant and must be considered when analyzing the results. Occupancy status indicates how long the room has been occupied, but does not provide information about the number of occupants in the room. HVAC status and window status have a direct impact on FCU operation. An active window status means the window is open and results in automatic deactivation of the FCU unit. An open window facilitates air exchange between the indoor and outdoor environments, which typically results in a drop in indoor temperature during the winter season. The HVAC state and occupancy status signals equal to 0 also reflect periods when the FCU is disabled. When all of these signals are reset to their default values, the FCU unit resumes normal operation.

3.1. Model Validation

Fig. 3 illustrates the validation results of temperature simulation for all zones over a period of one month in winter and summer 2018 on a representative floor of the hotel building. The validation results for each thermal zone (room) are within acceptable limits and consistent with the criteria defined in the literature. The values of cvRMSE range from a minimum value of 3% to a maximum value of 7.3%, with an average value of 4.3% across the entire floor. Similarly, the nMBE values vary from a maximum error of -4.3% to an absolute minimum value of 0%, with an average error of 0.2%. It is noteworthy that zone Z1 has the highest error, with a cvRMSE of 7.3% and an nMBE of -4.3%. In contrast, zone Z6 has the lowest margin of error, with a cvRMSE of 3% and an nMBE of 0.17%.

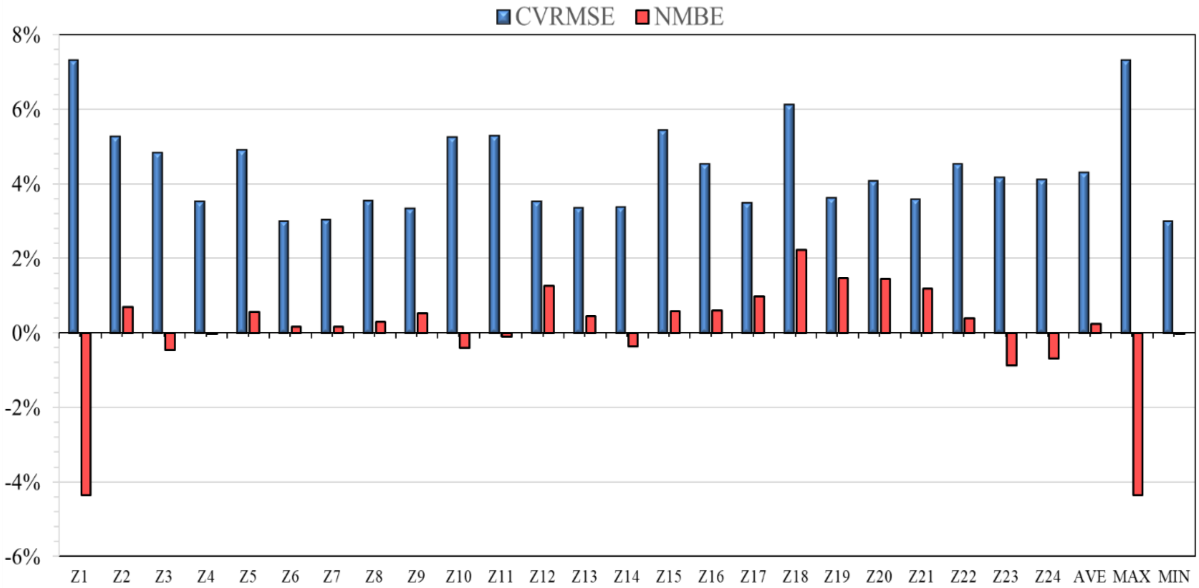

Figure 3. Accuracy of temperature prediction for all thermal zones, average, maximum and minimum of the representative floor of the building.

Fig. 4 illustrates the accuracy of the heating and cooling energy use prediction for the observed floor of the building. Using the cvRMSE metric, the mean of the prediction accuracy during the cooling season is 12.67% and has a standard deviation of 13.72%. In contrast, the mean prediction accuracy for energy consumption during the heating season is 21.21% with a standard deviation of 15.35%. On average, the overall accuracy across all individual periods is about 17%. It is worth noting that the simulation model tends to make less accurate predictions in winter than in summer, which could be due to factors such as opening windows that cause a significant temperature change and lead to an increase in space heating. Despite some outliers that show deviations of more than 50% in both seasons, certain zones show exceptional prediction accuracy with deviations of less than 5% according to the cvRMSE metric.

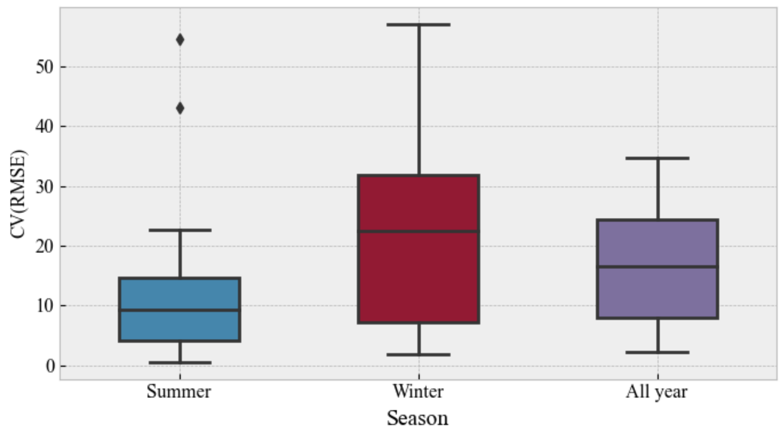

Figure 4. Accuracy of seasonal energy consumption prediction for the representative floor of the building.

3.2. Detection of Anomalies

Fig. 5 shows the temperature variations during an episode of FCU system anomalies in a single room during a summer period. Anomaly detection was based on the residuals of simulated and measured temperatures plotted over an extended period of time. The simulation predicted room temperatures that matched guest preferences. However, actual temperatures deviated from this prediction, indicating a problem with the FCU.

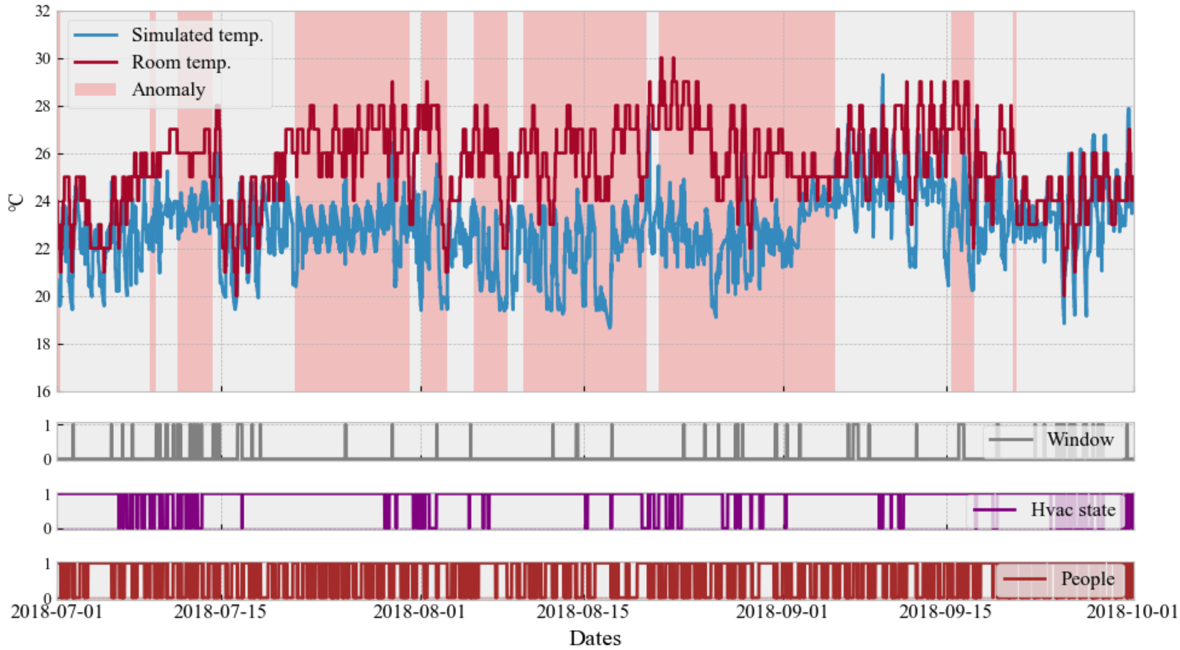

Figure 5. Comparison of simulated and actual temperatures in the observed room with highlighted periods of FCU faults during the summer season.

During the manifestation of the anomaly, guests were often present in the room. Only in some cases was the FCU turned off and the window occasionally opened, causing a slight disturbance in the room temperature. However, the simulation ruled out these disturbances as the cause of the temperature anomalies. Subsequent verification of other rooms with similar characteristics, such as shape, orientation, and function, showed that the system operated normally during the same period. This observation confirmed that the temperature fluctuations were not due to external conditions, such as intense solar irradiation.

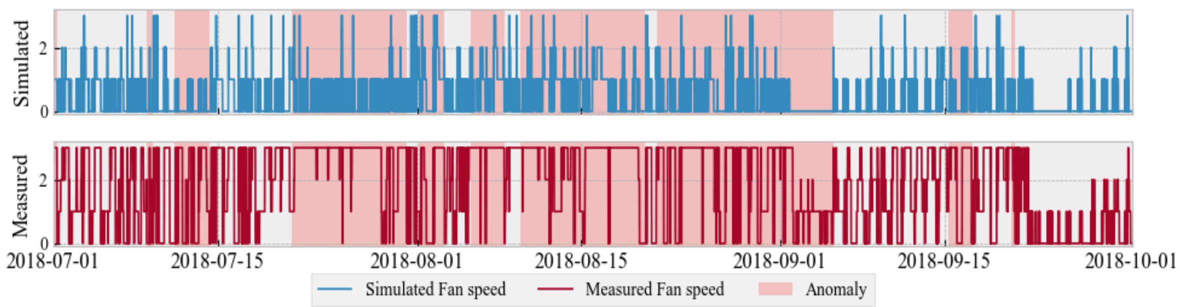

Figure 6. Comparison of simulated and actual fan speeds in the observed room with highlighted periods of FCU faults during the summer season.

Fig. 6 shows a comparison between the simulated and actual operation of the FCU, with the detected errors highlighted by the temperature deviations in Fig. 5. Throughout the period in which the anomaly occurred, the actual FCU performance exceeded its simulated counterpart. The actual system operated predominantly at higher fan speeds and for longer periods of time. Throughout the period in which the anomaly occurred, the FCU operated at full capacity and exhibited system disturbances only under extreme conditions, such as particularly hot days. Conversely, during periods of milder external conditions, the system managed to maintain thermal conditions even though it was operating below its full capacity. These FCU malfunctions negatively impacted occupant satisfaction due to the unsuitable room temperature.

The indoor air temperature in each room was simulated using a detailed white-box model of part of the building, which was calibrated and validated. The differences in validation results for each room are due to the assumptions made regarding the building fabric and system operating parameters, as well as the inability to model some specific conditions. In the validation results, the higher errors were recorded mainly in the periods with open windows, which caused large temperature shifts. The model could be calibrated at the level of a room or a group of rooms with similar characteristics to obtain better validation results or more accurate temperature prediction. Based on the detailed physical model developed, the temperature trends in each room can be determined for the normal operation of the system. One of the problems in performing the simulation and validation is the integer values of the recorded actual room temperatures, which were a source of uncertainty in the obtained results. Taking human behavior into account makes the simulations more accurate and valuable. Data collected in the field on occupancy, window opening, and HVAC state were used to model the human behavior that affects the simulations in terms of internal heat gains and ventilation rates, as well as FCU system operation. The problem with simulating window openings is accurately determining the air exchange rate and thus the temperature change. To determine the exact change, a more complex model of natural ventilation is required that takes into account wind speed and direction as well as the characteristics of the window opening.

A detailed simulation model developed in this way can also perform energy calculations, improve control logic, be used for model predictive control, and for anomaly detection. In this work, it was used for anomaly detection. Anomalies in the FCU system were detected using the residuals between the simulated and measured temperatures. If there are large temperature variations over a long period of time, there is a possibility that there are anomalies in the FCU system. At shorter intervals, there are smaller temperature deviations that later disappear. Temperature deviations can also occur due to some assumptions and unknowns in the system itself.

The simulations were performed only on one floor of the hotel, but other floors can be easily simulated since the construction of the floors is identical. By simulating only, a certain part of the building, savings in simulation time and modeling could be achieved.

Developing a model using the TRNSYS simulation program is quite labor intensive due to the inherent complexity of the physical processes. Compared to alternative techniques, such as data-driven modeling, detailed models often require more effort and deeper knowledge. This includes gathering specific information about the building fabric and HVAC systems. An essential step in modeling is calibration, an iterative process that aims to match the results of simulations with the collected field data. Such detailed simulation models are very computationally intensive, with a single simulation of the annual temperature data in this study taking up to 12 hours. However, there are advantages to using this simulation model. For example, it facilitates system analysis and modification and requires less training data from sensory measurements compared to other methods. For the purposes of this study, it was sufficient to select one month each of winter and summer operating data to accurately fit the simulation to the real data.

4. CONCLUSION

A white-box model capable of predicting room temperatures and detecting major anomalies in the HVAC system, particularly in the FCUs, was developed. The model was created using TRNSYS 18 software and Google SketchUp 3D tool for a single floor of a hotel in Zagreb, Croatia. A detailed 5-minute simulation time step was used to allow an in-depth study of the temperature dynamics. According to the cvRMSE metric, the accuracy of the created model was 4.3% for the temperature simulation and 17% for the energy consumption simulation. Our model operates within the acceptable accuracy limits specified by ASHRAE guidelines and uses a database of room-specific details. In addition, the model has accounted for human behavior, which is essential for realistic simulations. The inclusion of heat gain calculations, fan coil control in response to human input, and modeling of air exchange when windows are open helped create a simulation environment that closely resembles real-world conditions.

The model was not only able to simulate the indoor climate for a given space, but also to detect faults in fan coil units. This feature is based on the analysis of discrepancies between simulated and actual temperature measurements. Therefore, this study contributed to our understanding of temperature dynamics in hotel rooms and was also used to detect anomalies in the HVAC system. Future work includes development of automatic fault detection and diagnostics, advanced modeling of natural ventilation with windows open, and improvement of operational control as model predictive control.

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