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Occupant models for use in hybrid building models

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SAMENVATTING

Gebruikersgedrag kan de energieprestatie van gebouwen aanzienlijk beïnvloeden. Dit rapport beschrijft modellen voor gebruikersgedrag in kantoorgebouwen die in literatuur zijn gevonden en/of al worden gebruikt door TNO-experts. Het rapport richt zich op twee specifieke toepassingen: 1) foutdetectie van klimatiseringssystemen en 2) model predictive control om de energieflexibiliteit in gebouwen te benutten (energievraag te verschuiven en te veranderen). Vier soorten gedrag zijn in beschouwing genomen, namelijk aanwezigheid, aanpassing van de thermostaatinstelling, gebruik van elektrische apparaten en het gebruik van zonwering. Naast het literatuuroverzicht en de beschrijving van de meest geschikte modellen voor gebruikersgedrag voor de twee toepassingen, is een keuze gemaakt welke modellen worden geïmplementeerd en geëvalueerd in het hybride model (predictive twin) van het TNO kantoorgebouw aan de Stieltjesweg in Delft. De resultaten van deze evaluatie worden ook in dit rapport gepresenteerd. Op basis hiervan wordt een definitieve set van modellen voor gebruikersgedrag geselecteerd die geïntegreerd kunnen worden in de predictive twins die worden gebruikt in WP1 en WP2 van het B4B project.

SUMMARY

Occupant behavior can significantly affect the energy performance of buildings. This report describes the occupant behavior models in office buildings, which exist in the literature and/or are used already by TNO experts. The report focuses on two specific applications: 1) fault detection of HVAC equipment and 2) model predictive control to utilize the energy flexibility in buildings (i.e. to shift and alter the energy demand). Four types of behavior, namely occupancy, thermostat setpoint adjustment, appliance use and blind use have been considered. Besides presenting a literature overview and pointing out the most suitable occupant models for the two applications, a subset of the models were chosen to be implemented, and evaluated, in a digital twin of the TNO Stieltjesweg office building in Delft. Performance analysis of the implemented models is also presented. This will lead to a selection of a final set of occupant behavior models which can be integrated in the digital twins used within WP1 and WP2 of the B4B project.

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1 INTRODUCTION

Occupant behavior can significantly affect the energy performance of buildings (Piselli and Pisello 2019). Energy-related occupant behavior plays a key role in performance evaluation, fault diagnosis in HVAC systems and smart control. Generally, the occupant behavior can be divided into two categories (Mahdavi et al. 2017): adaptive behaviors (e.g. opening blinds, interaction with windows and thermostats, switching on the light etc.) which are triggered by adapting to the indoor climate to reach comfort, and nonadaptive behaviors which are not related to comfort (e.g. use of appliances, switch off the lights). Motivated by the importance of the occupant behavior, over the last decade a significant variety of quantitative models, aiming to generate accurate behavioral predictions, have been proposed in the literature. However, only a fraction of these works have elaborated on quantifying the potential improvement that these models can bring in energy performance prediction, as most of the models have not been implemented in an energy simulation software.

This report aims to present a selected collection of adaptive and non-adaptive occupant behavior models (including models existing in literature as well as models already used by TNO experts in other projects) which can generally be integrated in building energy simulators with a focus on two particular applications: 1) fault detection in HVAC equipment (WP1 of the B4B project), and 2) model predictive control in buildings to utilize the building flexibility, i.e. to shift or alter the energy demand (WP2 of the B4B project). Some HVAC equipment has a two-way interaction with the building; an air handling unit with heat recovery, for example, controls the indoor comfort in the building, but the heat recovery functionality depends on the extracted air from the building. In cases where the fault detection includes equipment subcomponents which interact with the building, the equipment model should be coupled to a digital twin of the building which also include occupant behavior. Similarly, model predictive control relies on a building model which is able to continuously generate prediction over a short time horizon. This also requires accurately predicting the occupant behavior and its effect on the control objective. It should be noted that models which are suitable for fault detection are not necessarily suitable for building control (see Chapter 2). Four different behavioral aspects are considered: 1) occupancy, 2) appliances use, 3) thermostat setpoint adjustment and 4) operation of the blinds. The interaction with the windows is not covered in this report as in many modern office buildings (including the TNO living lab) the windows cannot be opened. Among the four behavior types, occupancy is particularly important as it drives other behaviors such as the temperature setpoint adjustment and blind operation as well, and can also partially affect the appliances use. Each of these behaviors influence both the energy performance and indoor comfort of the building and are relevant to the two aims of this work. For each of the four behavior types considered, one or more of selected models were implemented and tested in a digital twin of the TNO Stieltjesweg office building in Delft that is used as living lab in WP1 and WP2 of the B4B project. This leads to the identification of the occupant behavior models which will be integrated in the above-mentioned digital twin.

In summary, this report addresses two research questions: 1) Based on literature and previous TNO projects, what are common modelling approaches which can be generally applied in office buildings, for each of the mentioned applications and behavioral aspects, and 2) what are the most feasible models for us to use in the living lab TNO Stieltjesweg in Delft for fault detection and model predictive control in buildings. Here the selection is made based on factors such as availability of data, the spatial resolution of the building model, and the application in question. The general methodology of this study is described in chapter 2, followed by four chapters each dedicated to one of the four behavior types mentioned above. The report closes with a discussion and conclusion.

2 METHODOLOGY

To decide which occupant models to use in fault detection and control applications in the living lab TNO Stieltjesweg, we used the following stepwise methodology for each of the four occupant behavior types, namely occupancy, appliances use, thermostat setpoint adjustment and operation of the blinds:

1. A literature review of various data-driven models is provided. The goal in this section is to cover a wide range of various approaches, and describe their characteristics, predictive potential and data requirements.
2. A subset of the reviewed models, as well as models already used by TNO experts in previous projects, are selected and described in more detail. The models are selected based on their potential to be coupled with a building energy simulator in a straightforward way, and to be generally applicable in digital twins of office buildings for fault detection in HVAC systems or model predictive control. We note that a predictive model which is suitable for fault detection, is not necessarily suitable for model predictive control: the former includes monitoring the HVAC systems by reproducing their operation in retrospect (i.e., in the near past) at regular timesteps, while in the latter case the models have to be able to predict the future. Other selection criteria include high predictive power, having a rather general scope to be applicable to different office buildings, and that the training data can be acquired easily.
3. One or more of the models which have been selected in step 2 are chosen to be implemented in a digital twin of the TNO Stieltjesweg office building that is used as living lab in WP1 and WP2 of the B4B project. The rationale behind the choice is discussed, which is mainly motivated by the available data, as well as by the spatial resolution (i.e., the zoning) of the building model and the application at hand.
4. Finally, the prediction outcomes of the implemented occupant behavior models are discussed, compared and, when possible, validated against the measured data in the TNO Stieltjesweg office building. This leads to final choices for occupant models to be used in fault detection and control applications in the living lab Stieltjesweg within WP1 and WP2 of the B4B project. This will also produce insights on steps to follow for implementing the occupant behavioral models in other office buildings.

3 MODELS FOR OCCUPANCY

3.1 Literature review

The reviewed papers on occupancy modelling can be generally divided into two categories (Ding et al. 2022), (Chen, Jiang, and Xie 2018) (Jin et al. 2021): 1) real-time estimation and 2) prediction.

3.1.1 Real-time estimation

In real-time estimation the model uses other measurable quantities (e.g., CO_2 concentration) to estimate the occupancy. This will pose a challenge for applying such models to predict the future, as the input parameters of the models should also be predicted. Moreover, occupancy changes the CO_2 concentration; not the other way around. In such cases it would be impossible to use such models for prediction, but they can be considered as soft sensors to detect the occupancy in real time. A wide range of various modelling techniques has been used for real-time estimation, including hidden Markov chains (Han, Gao, and Fan 2012), (Dong et al. 2010), (Ai, Fan, and Gao 2014), autoregressive hidden Markov chains (Ai, Fan, and Gao 2014), (Dong et al. 2010), and machine learning models (e.g., support vector machines (Dong et al. 2010), (Han, Gao, and Fan 2012), (Chen and Soh 2017), neural networks of various architectures (Dong et al. 2010), (Javed et al. 2017), (Milenkovic and Amft 2013), (W. Wang et al. 2018), (Yang et al. 2012), (Yang et al. 2012) (Zhang and Ardakanian 2019), (Chen and Soh 2017), regression and classification trees (Fajilla et al. 2021) and autoregressive integrated moving average (Chen and Soh 2017), (W. Wang, Chen, and Song 2017)). The CO_2 concentration has been frequently used, sometimes in combination with other sensor data, for real-time occupancy estimation. Data about appliance usage has also been used to infer occupancy patterns in office buildings (Sonta, Simmons, and Jain 2017). A fusion framework to apply machine learning models for occupancy estimation is presented in (Chen, Masood, and Soh 2016), which covers extreme learning machine (ELM), support vector machine (SVM), artificial neural network (ANN), K-nearest neighbors (KNN), linear discriminant analysis (LDA) and classification and regression trees (CART).

3.1.2 Prediction

The occupancy models which are suitable for prediction generally use historical occupancy data to predict future occupancy patterns. Therefore, after training the model on historical data, the model can predict the occupancy without requiring any external input, except time-related parameters (e.g., hour of the day, day of the week, etc.). The predictive models fall into two general categories: deterministic models, or stochastic models. Deterministic models are in fact static profiles based on the hour of the day and day of the week (Duarte, Van Den Wymelenberg, and Rieger 2013), (D. Aerts, J. Minnen, I. Glorieux 2012). They are easy to use, but fail to capture the randomness associated with the movements of single occupants. They are suitable to model occupancy of the buildings with large number of occupants. The stochastic models, on the other hand, are able to represent the random nature of occupancy behavior. The majority of stochastic models reviewed in this report are connected to inhomogeneous Markov chains, and represent the stochastic change in the occupancy of one or multiple zone(s), based on transition probabilities, which determine the probability of moving between well-defined states (e.g., moving from one zone to another, or entering/exiting a zone), and in general depend on time (e.g., hour of the day and/or day of the week). Training of the Markov chains involves estimating the transition probability matrices using historical occupancy data. The reviewed stochastic models mainly differ in their scope/number of states (e.g., single zone vs. multiple zones, single occupant vs. a population of occupants) and the type of the training data (e.g., measured data vs. surveys). A well-known example is the two-state model by (Jessen Page 2007) which models the absence/presence of an occupant, and can be parametrized by an hourly occupancy profile and a free constant parameter, referred to as the mobility, to characterize the "level of activity" of the occupants. The occupancy of the building at each time can be calculated by multiplying the expected total number of occupants by the probability of being at the present state. This model has been evaluated in (Mahdavi and Tahmasebi 2015), along with a deterministic model introduced in the same work, and another stochastic model by (Reinhart 2001). The model by (J. Page et al. 2008) has also been generalized by (Widén, Nilsson, and Wäckelgård 2009) to a three-state model (absent, active, inactive) and was used to model light use, and also to a four-state (present/absent, active/inactive) model by (McKenna, Krawczynski, and Thomson 2015). (Chen, Xu, and Soh 2015) redefined the Markov chain state as being the number of occupants in a zone, thereby proposed a multizone stochastic model which takes into account the movement of occupants between individual offices. On the other hand, (Salimi, Liu, and Hammad 2019) and (Salimi and Hammad 2020) used data on individual office occupants to construct occupant-specific inhomogeneous Markov chains (i.e., one Markov chain model per occupant) based on the time of the day and the day of the week. (C. Wang, Yan, and Jiang 2011) have proposed an event-driven Markov chain model. In this case the occupancy change is not driven by time, but by occurrence of a specific event. Although in principle this could constitute a more precise model, it has the drawback that the events need to be known/determined beforehand.

A novel approach to predict the occupancy number in offices based on an "adaptive" inhomogeneous Markov model has been proposed by (Li and Dong 2018), where at any time point the historical data of the recent past, falling inside a moving window, is used to continuously train the model. They compared this model with another original model based on hierarchal sampling, as well as the Page et al. (2008) model and two machine learning models developed in the same paper, and showed that the Markov chain model outperforms them all.

Aside from Markov chain models, the deep-forest machine learning approach proposed by (Zhou et al. 2022) is applicable to short-term prediction, as the input to the model is exclusively constructed from the historical occupancy data, including the multi-order transition probability vectors.

3.2 Potential options for modelling

3.2.1 Models for fault detection

If the occupancy is directly measured, it can directly be used in the fault detection application. Otherwise measured indoor environmental data (e.g., CO_2 concentration) can be used as occupancy estimators. Here supervised (e.g., artificial neural networks (Dong et al. 2010)) or unsupervised (e.g., hidden Markov chain (Han, Gao, and Fan 2012)) machine learning models can be used. It should be noted that these models require fine-grained historical training data (e.g., data on single-room level) measuring the occupancy estimators (and also the occupancy itself, if a supervised model is used). Similarly at the estimation phase the occupancy estimators should be continuously monitored as they are used as model input. Provided that such data is available, these models generate accurate estimations for occupancy at the single-room level.

3.2.2 Models for building control

If the goal of occupancy modeling is to predict the future occupancy state to be used in e.g., model predictive control, models which use the indoor environmental data as input are generally not applicable (see Section 3.1). Consequently occupancy predictive models are trained exclusively on historical occupancy data, and depend only on temporal variables (e.g., hour of the day, day of the week, etc.). The simplest models in this category are the deterministic profile methods. To capture the temporal variation of the occupancy to a sufficient degree, the profiles should be (at least) based on the hour of the day and the day of the week, and preferably take into account the holiday periods. Markov chain models present an alternative category of methods for occupancy prediction. Among these, the classical model by (J. Page et al. 2008) is particularly straightforward to be integrated in a building simulation software as it requires the least amount of training data. If historical timeseries of individual occupant states is available, the model proposed in (Li and Dong 2017) would also be an attractive choice due to its adaptive nature. The model by (Chen, Xu, and Soh 2015) is designed for a multizone building model and has the advantage of capturing the occupants' movement from one zone to another. This is achieved by using the change of occupancy as the Markov chain state, instead of actual number of occupants, to reduce the training computational load. It should be noted, however, that applying this method requires historical timeseries with high temporal resolution (e.g., less than ~ 10 minutes), as the model only considers changes of -/+1 in the occupancy of each office.

It should be noted that occupancy drives other behavior such as the temperature setpoint adjustment and blind operation as well, and can also partially affect the appliances' use. Therefore the selected modelling approaches for appliances use, blind use or thermostat setpoint have implications for the resolution and accuracy of the chosen occupancy model. This depends significantly on the spatial resolution of the building model: If the building is modeled at the level of small offices with low number of occupants, and an accurate prediction of the thermostat setpoint adjustments, blind operation and/or occupant-related appliances use is required at the same level. The occupancy model should in principle be able to accurately predict the behavior of individual office occupants, and to capture the stochastic nature of single-office occupancy. On the other hand, if the model contains large zones with typically high number of occupants, the coupling between the occupancy behavior (at the level of the individual occupants) and other types of behavior becomes weaker. In this case a simpler occupancy model which predicts the total number of occupants in each zone, such as a deterministic profile method, might be sufficiently accurate.

It should be noted that unsupervised occupancy estimation models, such as hidden Markov chains, can also be used to provide training data for occupancy prediction models if the occupancy cannot be directly estimated.

3.3 Selected modelling approaches for application TNO Stieltjesweg

In the TNO Stieltjesweg building no data on behavior of individual occupants is available. Furthermore, no direct data on occupancy of single offices is available (although in a limited number of the offices the occupancy can be estimated based on the measurement of indoor CO_2 concentration). The direct estimation of the occupancy data is possible on the floor level, by collecting and processing the gate data (using people counters). This leads to historical timeseries of the number of occupants per floor. The building model has a comparable spatial resolution: the basement (i.e., the labs) is considered to be one zone, and the other 3 floors are divided into two zones along the north-south direction, leading to in total 7 zones. Therefore, during the monitoring period, the number of occupants in each zone and at each moment in time can be estimated by distributing the occupancy of each floor between the zones based on the zone's floor surface area.

3.3.1 Models for fault detection

If the occupancy is monitored in real-time, the historical occupancy (rather than the model prediction) can be used for fault detection. Otherwise the model used for building control, as will be selected after testing and validation in Section 3.4, will be used also for fault detection.

3.3.2 Models for building control

Based on the measured occupancy data, deterministic and probabilistic models will be constructed:

- In the most simplest form, a deterministic model can be based on average occupancy profiles which are calculated from the historical measured occupancy data, and represent the average number of occupants per zone for each hour of the day, separately for each day of the week. Such a simple model might turn out to be insufficient, as it cannot capture the changes in the number of occupants due to e.g. holiday periods. In that case, a more elaborated approach can be considered, where the profile is dynamically adapted based on the near-past historical occupancy data.

  An adaptive profile method was developed as follows: part of the measured data covering a full week is used as the training data to construct a weekly profile, $N(wd,t)$, where wd is the day of the week and t is the hour of the day. The weekly profile is then normalized as

  $$P(wd,t) = \frac{N(wd,t)}{N_{max}}, \tag{1}$$

  where $N_{max} = \max[N(wd,t)]$ is the highest point in the weekly profile. Therefore the normalized profile $P(wd,t)$ is between 0 and 1. To use the adaptive model for prediction, Equation (1) can be inverted as

  $$N(wd,t) = N_{max} \times P(wd,t). \tag{2}$$

  It is then assumed that $P(wd,t)$, which describes the shape of the weekly profile, stays unchanged while N_{max} acts as a scaling factor and is updated regularly based on the available recent history of measured data via the following equation:

  $$N_{max} = \frac{\overline{N}}{\overline{P}}, \tag{3}$$

where the symbol $\bar{\ }$ denotes the exponential averaging over the available data history. The choice of performing exponential average instead of a normal average is motivated by the fact that exponential averaging is a weighted averaging method, where the weights decrease exponentially by moving further back in time. The speed by which the weights decreases can be controlled by a decay rate. Therefore the exponential average associates a higher importance on the most recent history.

- A probabilistic version of the adaptive profile method was also explored. In this model N_{max} is still estimated via Equation (3), while $P(wd, t)$ in Equation (2) is replaced by a stochastic representation, calculated using the Markov Chain technique. The Markov chain model is based on the two-state model by (J. Page et al. 2008), which describes the time evolution of a group of agents, each having a binary state (0: not present, 1: present). This model takes the normalized weekly profile (Equation (1)) as an input. It also has one free parameter which is called the mobility factor and is denoted by μ. The mobility factor determines how often the agents change their states. The probabilistic version of the adaptive profile method works as follows: given the normalized weekly profile and a fixed mobility factor, a large group of binary agents are simulated via a stochastic Markov process. At each simulation time step, N_{max} agents are randomly selected out of the whole population of agents, and the number of the selected agents which are present (i.e. are in state: 1) is reported as the occupancy during that timestep. As before, N_{max} is regularly updated via Equation (3).

3.4 Results application TNO Stieltjesweg

To validate and compare the models, they were incorporated in the hybrid building model developed by TNO[1] and the resulting indoor temperature profiles and energy demands were compared with a reference simulation which uses the actual measured occupancy timeseries as input.

Upon inspection of the measured data *of* occupancy, it becomes clear that in general the occupancy profile varies week by week (brown data in Figure 1). Especially, in the last two weeks of July, the occupancy is clearly lower, probably due to summer holidays. To capture this, *the dynamic profile method was used as explained in section 3.3.2.* The predictions of the adaptive profile method on the test data (i.e. the data which is not used to infer the normalized profile, Equation (1)) are shown in Figure 1 for different zones of the Stieltjesweg building (blue data). The results correspond to day-ahead predictions, where the prediction horizon covers 24 hours, and the data history is updated on the beginning of each day. The decay rate for the exponential averaging was also set to 24 hours, associating a higher weight on the data of the past day. It can be seen that the adaptive profile method successfully captures the decrease in occupancy during the summer holidays. Although there are occasional differences between the data and predictions, which occur because the normalized profile $P(wd, t)$ is not truly fixed, it was found that these differences have only a negligible effect on the zones temperature profile and cooling demand (Figure 2Figure 3).

[1] The hybrid building model developed by TNO is described in deliverable D2.1-2.2-2.3 “Building and building systems energy prediction models to enhance energy flexibility control” of the B4B project.

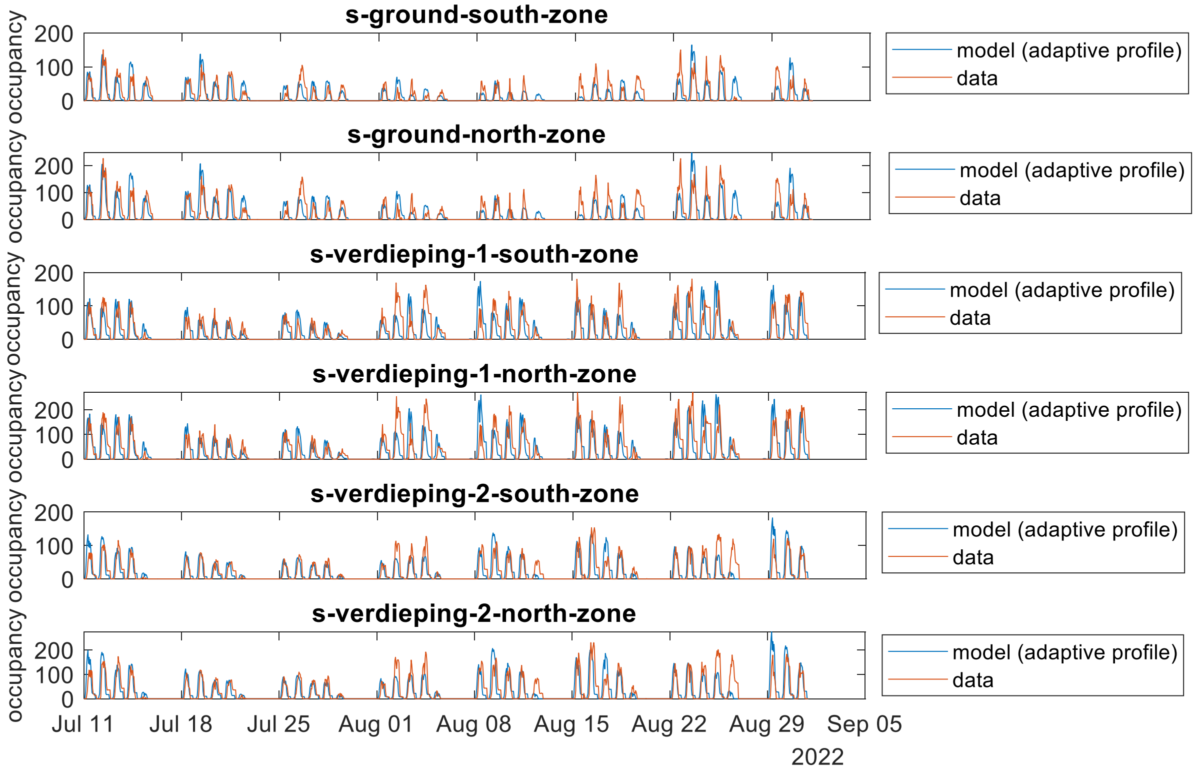

Figure 1: timeseries of occupancy in different zones of the Stieltjesweg building. Brown: measured data, blue: predictions of the adaptive profile model.

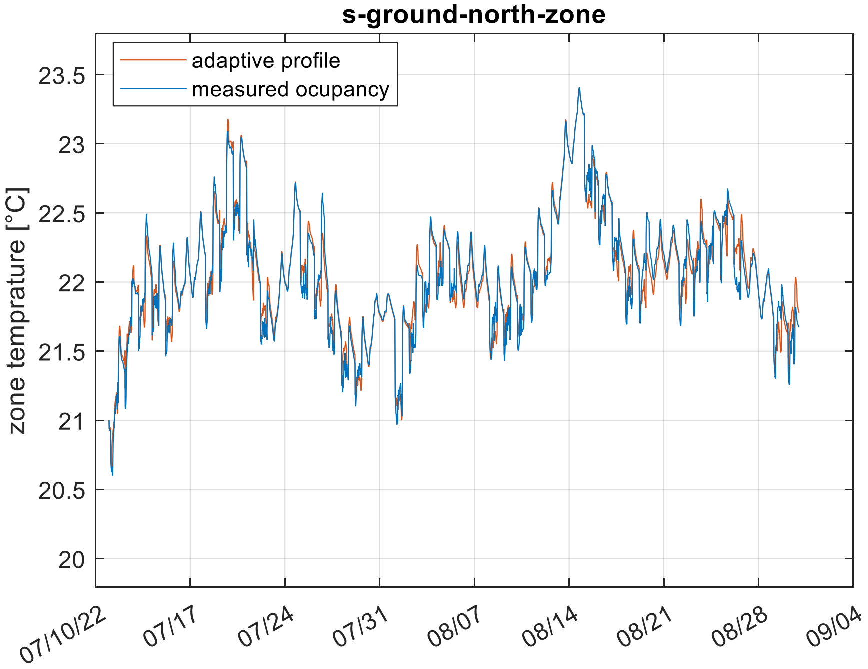

Figure 2: predicted indoor temperature in one of the thermal zones of the Stieltjesweg digital twin, with two different occupancy profiles: blue: measured occupancy, brown: adaptive profile method.

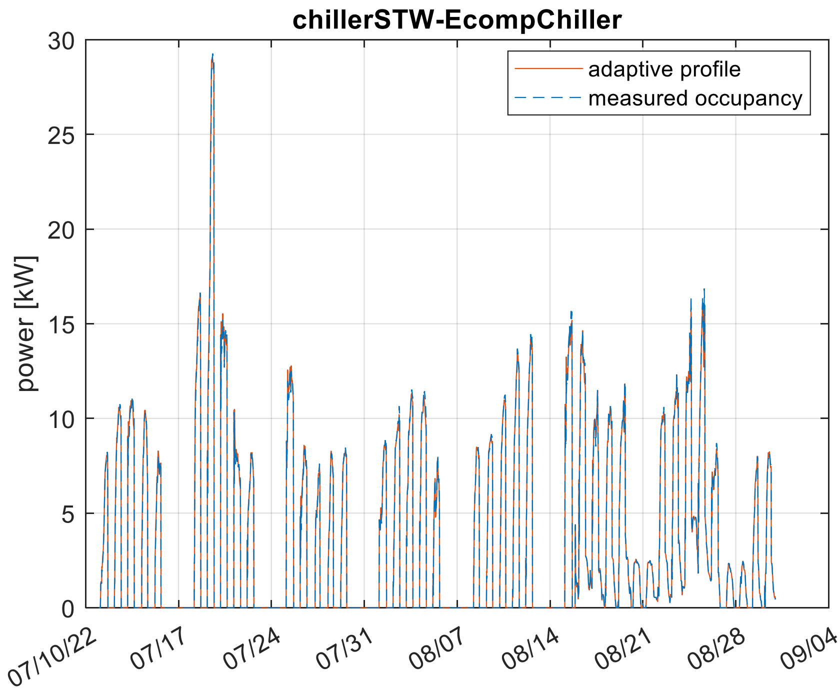

Figure 3: electricity power required for cooling, as predicted by Stieltjesweg digital twin, with two different occupancy profiles: blue: measured occupancy, brown: adaptive profile method.

Applying the *stochastic* adaptive model to the digital twin of the Stieltjesweg building, it turns out that the predictions remain very close to the predictions of the original adaptive model, even when μ varies in a wide range (see Figure 4). This is expected based on the law of the large numbers: with a large enough number of agents, the stochasticity tends to disappear. It can therefore be concluded that, for the Stieltjesweg building, a stochastic model is not required, because the number of occupants is quite high. The model might still be relevant in other use-cases, for example in a model with a large number of zones, where the average number of occupants in each zone is small.

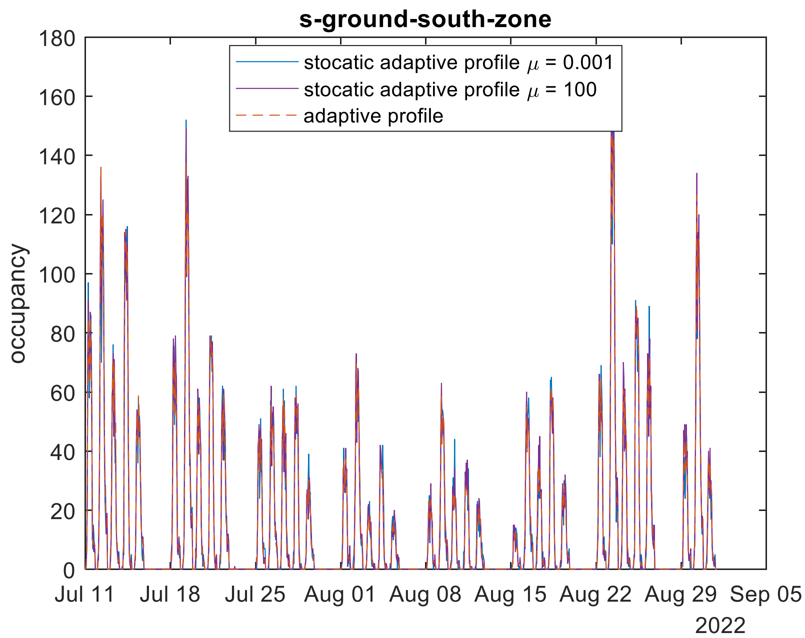

Figure 4: The predicted occupancy for one of the zones in the Stieltjesweg digital twin. Blue: stochastic adaptive profile model with $\mu = 0.001$, purple: stochastic adaptive profile model with $\mu = 100$, brown (dashed): adaptive profile model.

4 THERMOSTAT SETPOINT ADJUSTMENT

4.1 Literature review

The reviewed papers on predicting temperature setpoint adjustments by occupants can be generally divided into two categories: 1) statistical models and 2) reinforcement learning and agent-based models.

4.1.1 Statistical models

A common approach in occupant behavior modelling is to model binary action probabilities (e.g., opening/closing the windows or blinds) by logistic regression, where the influence of various (environmental) triggers are linearly combined. Such models have been applied in the literature to predict the action of changing the thermostat settings from one timestep to the next (Gunay et al. 2018). Using monitoring data from 11 residential buildings, (Belazi et al. 2019) constructed logistic regression models for three different levels of activity: active, normal and passive. The triggers considered in this study include indoor and outdoor temperatures, indoor and outdoor relative humidity, outdoor CO_2, wind speed and solar radiation. This method has been generalized by (Fabi, Andersen, and Corgnati 2013) and (Fabi et al. 2013): in addition to predicting the probability of changing the thermostat settings by logistic regression, a linear regression model was trained to predict the magnitude of change. Also in this work, three separate models are developed corresponding to three activity levels. Following the same principles (D'Oca et al. 2014) modelled two action probabilities, both for turning up and turning down the thermostat, for three activity levels. Notably, in this work the period of the day is included in the model inputs in addition to environmental triggers.

4.1.2 Reinforcement learning and agent-based models

Agent-based models (rule-based agents as well as reinforcement learning agents) have also been used to mimic occupants' interaction with the thermostat. For example, (Vellei, Martinez, and Le Dréau 2021) constructed and trained rule-based stochastic agents, using a novel dynamic thermal discomfort estimation which is based on a two-node thermophysiological model coupled with a dynamic thermal perception which is used to calculate thermal comfort. The inputs of thermophysiological model are the six basic parameters: air temperature, mean radiant temperature, air velocity, relative humidity, clothing insulation, and metabolic heat generated by human activity. User interaction data from about 9,000 connected Canadian thermostats was used to calibrate the model. The model was then used to predict occupants' override rates in reaction to typical demand-response-activated setpoint modulations in two residential buildings.

On the other hand, (Deng and Chen 2021) used reinforcement learning agents. The agents are trained using the Q-learning algorithm, where the change in thermal sensation vote (TSV)[2] is used as the reward function. After training, the model predicted the behavior of adjusting the thermostat set point with a R^2 from 0.75 to 0.8. in an office building. Most notably, it has been demonstrated that the trained reinforcement-learning (RL) agent has self-adaptation capability: transferring the behavior knowledge of the RL model to other office buildings with different HVAC control systems, the model predicted the occupant behavior with a R^2 from 0.73 to 0.8. Going from office buildings to residential buildings, the transfer learning model also had an R^2 over 0.6. Following the same principles, (Park and Nagy 2020) presented a reinforcement learning-based Occupant-Centric Controller for thermostats. Monitoring indoor air temperature, occupancy, and thermal vote, the agent learns the unique occupant behavior and indoor environments and calculates adaptive thermostat set-points to balance between occupant comfort and energy efficiency.

4.2 Potential options for modelling

4.2.1 Models for fault detection

Usually temperature setpoints in offices are continuously monitored. In this case the measured data can be used directly in fault detection. Otherwise a model is required to predict the behavior. Here agent-based models have the advantage that they explicitly model the occupants as active agents that perceive and react to the changes in their environment. For example, the self-learning agent developed by (Deng and Chen 2021)

[2] The calculation method for TSV is not presented in this paper.

can be an attractive choice due to its generalizability potential. However training and implementing these models requires estimating a comfort KPI which is typically related to a wide range of (indoor) environmental factors. Therefore application of these models to fault detection is heavily dependent on the availability of their required input data. In case the required data is not completely available, statistical models present an alternative, as they don't necessitate calculating a comfort KPI and thus are more flexible in terms of their required input data. The input for statistical models can be limited to factors which are known or measured (e.g., the outdoor weather and the hour of the day). Switching to a different type of model and limiting/changing model input parameters will of course have consequences for the accuracy of the model. To our knowledge the two modelling approaches have not yet been compared in the literature in terms of their prediction accuracy.

The basic principle behind both the agent-based and the statistical models is that occupants react to the environment to improve their comfort. While this certainly holds in general, and might explain the behavior of an active occupant quite well, occupants' habits can also play an important role. In previous research at TNO it turns out that when occupants' habits are the dominant factor (for example, if the occupants set their thermostat to a particular program and rarely change it), it is possible to already get quite a high prediction accuracy simply by looking at the trend in the near past. As an example, applying this approach to more than 20 Dutch households yielded a ~96% accuracy (Figure 5)[3]. In such a case one can expect that applying a statistical approach, such as ones proposed by (Fabi et al. 2013; Fabi, Andersen, and Corgnati 2013), without considering occupants' habits, would result in a less accurate prediction. It is therefore recommended to include the time-related features (e.g., hour of the day) as input in statistical models.

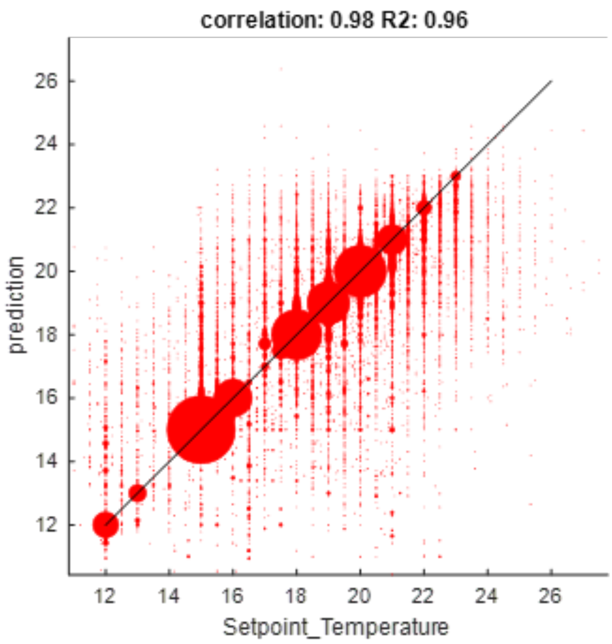

Figure 5: Prediction of the room thermostat position (the size of the circles is a measure of the number of individual points at that point)[3].

4.2.2 Models for building control

The considerations pointed out in Section 4.2.1 concerning thermostat setpoint prediction for fault detection also holds for building control. In the case of agent-based models there is an additional complexity, as the environmental factors needed to calculate the comfort KPIs should be predicted over a time horizon. This might make it practically challenging to use agent-based models for building control.

If limited training data is available, a possible approach would be to train a statistical model, including the time-related features in model input, as suggested in Section 4.2.1. If the setpoints are continuously

[3] Published in the internal TNO report "KIP2021 Energy & IEQ Performance - Literatuurstudie gedragsmodellering en vertaalslag naar predictive twins".

monitored, we propose to construct a predictive model based on the near-past monitoring data[4]. The model could be as simple as predicting the current value of the setpoint to be the same as what it was yesterday at the same hour. As mentioned in Section 4.2.1. such a simple model can already yield quite a high accuracy especially for inactive occupants. If a higher accuracy is needed a standard model for timeseries prediction, such as autoregressive integrated moving average or a LSTM network, can be used. These models can also take into account additional inputs, such as occupancy, day of the week and indoor/outdoor temperature.

4.3 Selected modelling approaches for application TNO Stieltjesweg

4.3.1 Models for fault detection

In the Stieltjesweg building, the setpoint temperatures in the offices are continuously monitored. Therefore, in the fault detection application, the measured setpoints are directly used as an input for the digital twin of the Stieltjesweg building.

4.3.2 Models for building control

Upon inspection, temperature setpoint data seems to be rather static (the timeseries vary ~ once a month). It would therefore be logical to use a simple model to predict the future setpoints, by assuming that the value of the setpoint for the coming hour is the same as what it was at the same hour yesterday.

4.4 Results application TNO Stieltjesweg

In the Stieltjesweg building, local setpoint temperatures are available in many rooms. While the measured time series show room-to-room variations, the setpoint temperature for any single room varies rarely in time, and remains unchanged for long periods (Figure 6).

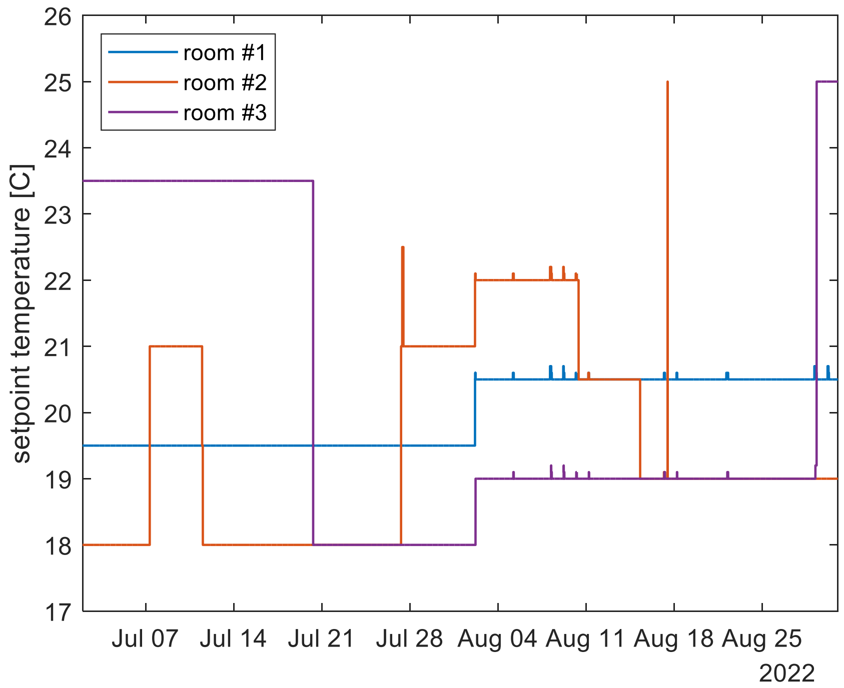

Figure 6: an example of measured timeseries of setpoint temperatures, for 3 offices in Stieltjesweg building.

Considering this, a simple model was constructed to predict the rooms setpoint temperatures during the working hours. In this model the predicted setpoint at each future hour is predicted to be the same as the latest past measured value. Figure 7A shows a comparison between measured and predicted setpoint temperatures for a single room vs. time, while Figure 7B shows the correlation between the data and

[4] The amount of the historical data to include in the model input is a design choice. It can include only the previous day, or it can cover a couple of weeks. The amount of the historical data can be determined via hyperparameter optimization, a common technique in machine learning, to reach the best prediction accuracy.

predictions across all rooms and during the whole measurement period (July-September 2022). The accuracy of the model is quite high, with a r-squared score larger than 99%.

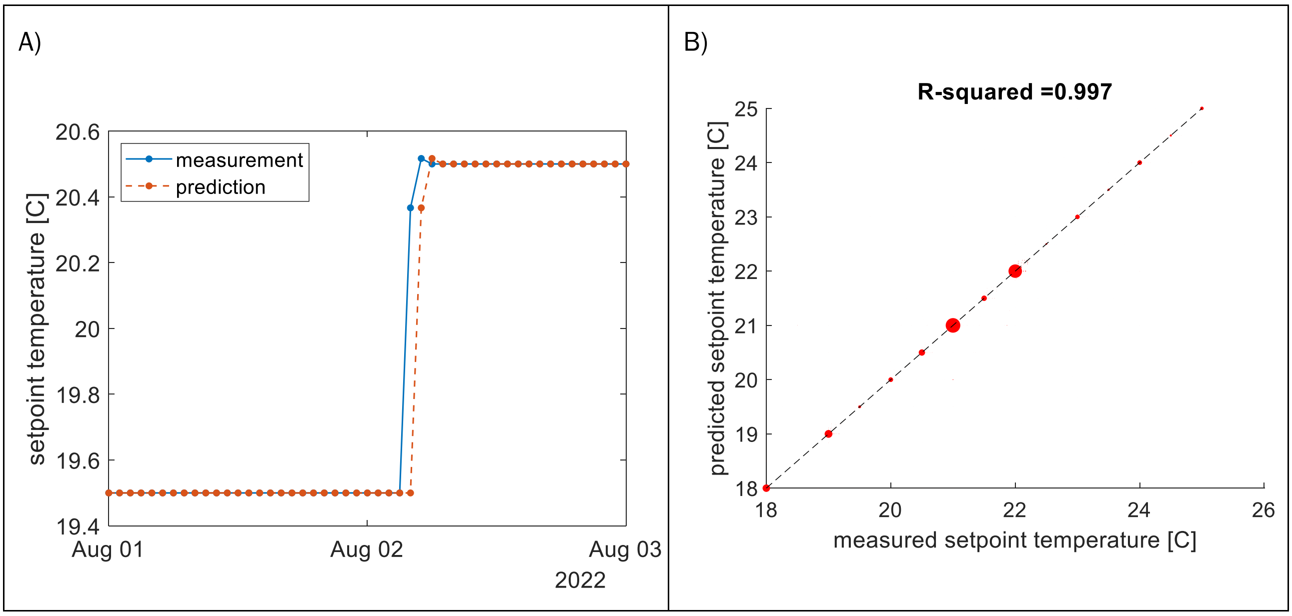

Figure 7: A) the predicted and the measured setpoint temperature in a single office room – only a period of two days is shown to clearly visualize the differences, B) the correlation between the measured data and predictions across all rooms and during the whole measured period.

To validate the prediction model for the setpoint temperatures, the digital twin of the Stieltjesweg building[5] was used to simulate the indoor temperature and the cooling demand using the actual and predicted setpoint temperature timeseries (see Figure 8Figure 10 for the whole simulation period, and Figure 9Figure 11 for a zoomed-in view). The two sets of simulation results are in general quite close. Therefore the proposed method to predict the setpoint temperature is accurate enough to be applied in a digital twin of the Stieltjesweg, building for building control. It should be noted that Figure 9 and Figure 11 zoom in on a particular time point, where the setpoint temperature is simultaneously increased by a couple of degrees in many offices at the beginning of the working day on 2nd of August, probably as a result of a change in the global setpoint value of an entire floor in the building management system. This leads to a spontaneous decrease in the morning cooling load (Figure 11 solid blue line). However, the predicted setpoints are one hour behind the real ones, which creates a higher peak (Figure 11 dashed brown line), and therefore leads to a momentary lower zone temperature (Figure 9). This is one of the rare instances where the setpoint prediction model makes a noticeable difference in the predicted cooling demand and indoor temperature.

It should be emphasized that the proposed model works well in the Stieltjesweg building because the changes in the temperature setpoints are quite infrequent. In case the occupant actively changes the schedule in response to certain environmental or temporal triggers, these should be included in the prediction model, for example in a statistical model as in (Fabi, Andersen, and Corgnati 2013). The choice of the suitable model is therefore dependent on the observable patterns in the measured data and should be done on a case-by-case basis.

[5] The hybrid building model developed by TNO is described in deliverable D2.1-2.2-2.3 “Building and building systems energy prediction models to enhance energy flexibility control” of the B4B project.

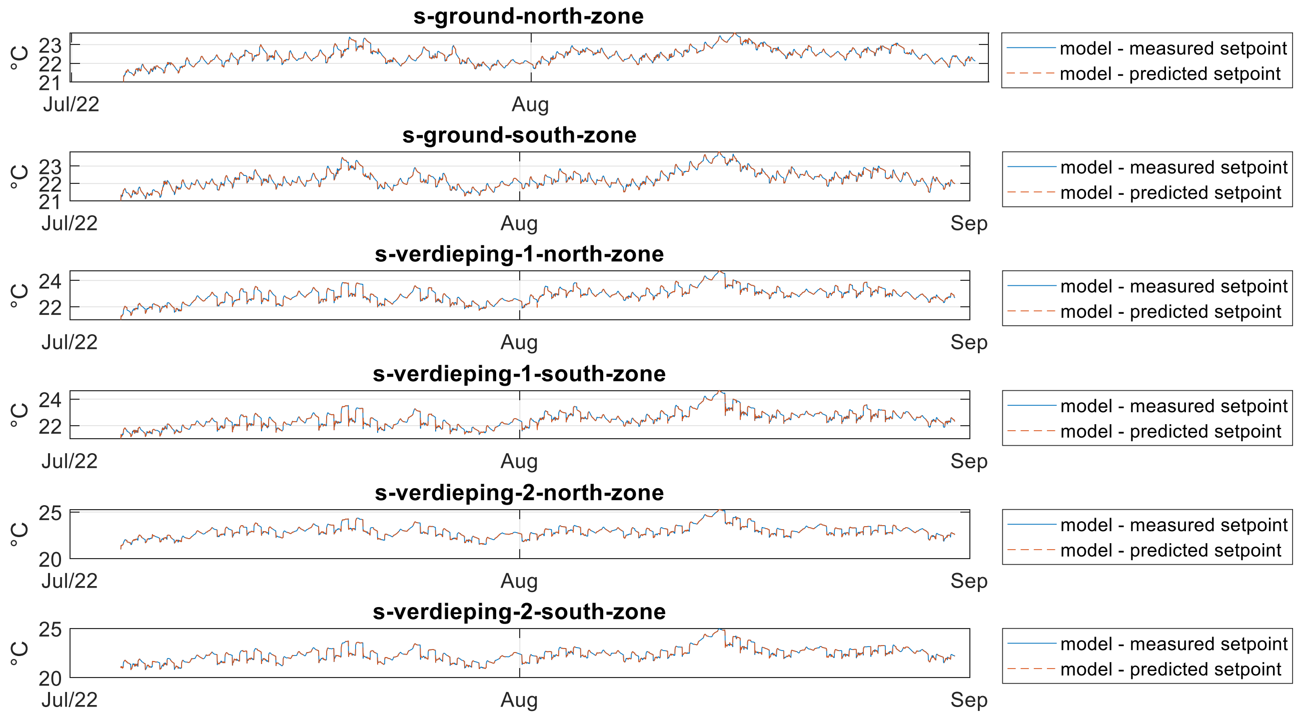

Figure 8: indoor temperature in different thermal zones of the Stieltjesweg digital twin, using the measured data (solid line, blue) and the prediction (dashed line, brown) for the room setpoint temperatures.

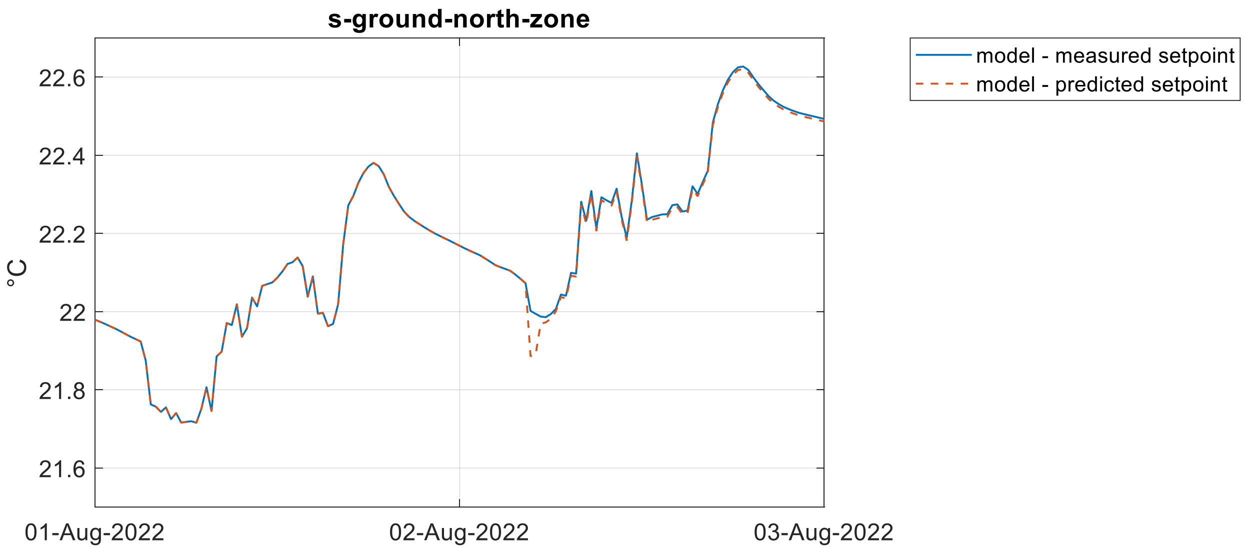

Figure 9: indoor temperature in one of the thermal zones of the Stieltjesweg digital twin, in a period of two days, using the measured data (solid line, blue) and the prediction (dashed line, brown) for the room setpoint temperatures.

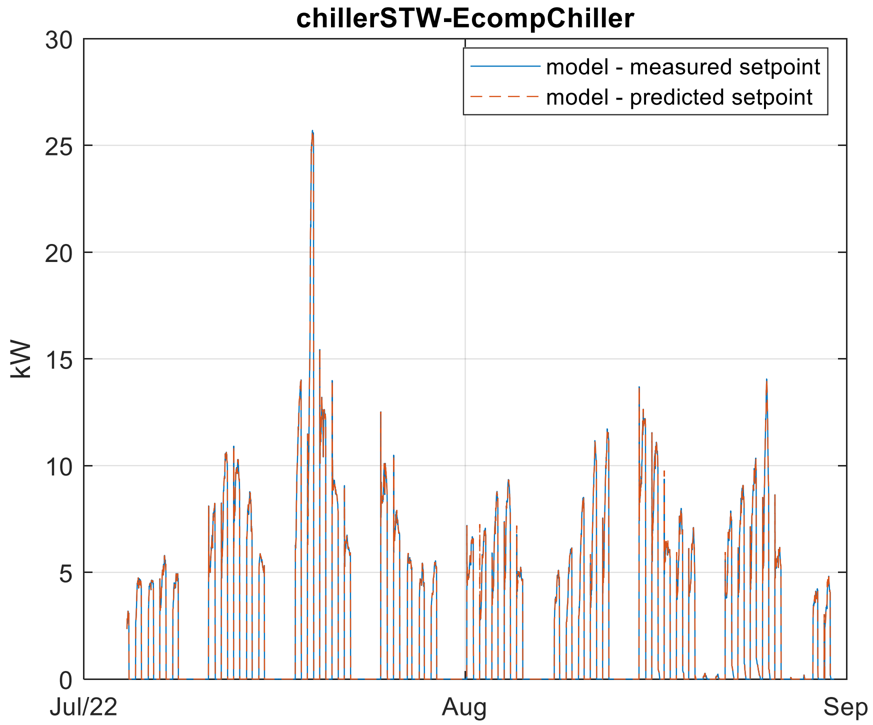

Figure 10: electricity power required for cooling, as predicted by the Stieltjesweg digital twin, using the measured data (solid line, blue) and the prediction (dashed line, brown) for the room setpoint temperatures.

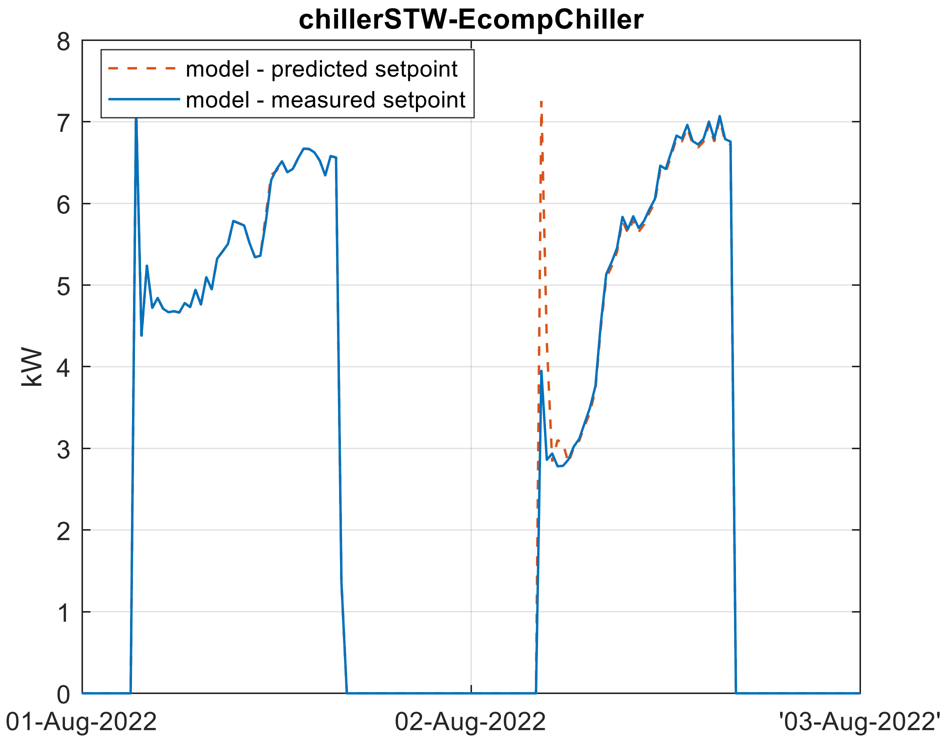

Figure 11: : electricity power required for cooling, as predicted by Stieltjesweg digital twin, for a period of two days, using the measured data (solid line, blue) and the prediction (dashed line, brown) for the room setpoint temperatures.

5 APPLIANCES USE

5.1 Literature review

The literature review reveals that the primary input to predict electricity use of appliances is the historical electricity use data. In most cases the models also take occupancy (either directly estimated or predicted by another model) as input, as the use of some appliances (e.g., laptops and screens) are proportional to the number of office occupants. The models can be generally divided into two categories: 1) statistical models and 2) machine learning models.

5.1.1 Statistical models

A common approach in the literature is to model the probability distribution of the electric power usage, dependent on time of the day or the occupancy. Then, to predict the electricity, a data point is randomly sampled from the probability distribution. An example of this approach is presented by (Gunay et al. 2016). In this work, five different situations related to occupancies were considered: (a) office occupied, (b) intermediate breaks, (c) weekday evenings, (d) weekends, and (e) vacations. In each case, the empirical probability distribution for the electric power usage is constructed from the historical data corresponding to the same period. To predict the future electricity use, first the occupancy is predicted to identify the relevant time period, then a datapoint is randomly drawn from the corresponding distribution. It has been shown that this approach preserves the statistical properties of the historical data in the generated predictions. A similar approach has been used by (Mahdavi, Tahmasebi, and Kayalar 2016), where a Weibull distribution is fitted to the histogram of the electricity power use. Also in this work, the power use is coupled to occupancy: three different occupancy regimes have been considered: 1) occupied periods or intermediate absences shorter than one hour; 2) intermediate absences longer than one hour; 3) outside working hours. For each regime a Weibull distribution is separately fitted to the historical data. In parallel, a deterministic model for appliances use has been constructed in the same work, which assumes that the electric power is linearly proportional to the occupancy. Regarding the occupancy input, (Mahdavi, Tahmasebi, and Kayalar 2016) considered and compared three different cases: direct estimation, and occupancy prediction by a model (J. Page et al. 2008) with two different values for the mobility factor. It was concluded that the deterministic model is better at predicting the total annual load, while the stochastic model is better at predicting the annual peak load. The performance of both models has been evaluated in this work: using the measured occupancy, the deterministic and stochastic model both resulted in a normalized root mean squared error (NRMSE) of about 13%. For the stochastic model, using predicted occupancy increase the NRMSE to ~16%. It should be noted that these numbers should be considered with caution, as they are likely to be situation dependent: in another study with a different use case a NRMSE as high as 30% has been reported for the stochastic models, although this could be partially due to the fact that the model is not fully recalibrated to the new use case.

In (Obrien, Abdelalim, and Gunay 2019) a rather different statistical approach was presented: the hourly schedule of the power use is assumed to have the same general shape every day: starting at a constant low level at midnight, the power use profile linearly increases to a higher level during a limited period (in the morning), then stays unchanged for some time, until it is linearly decreased during a limited period (in the evening) to a lower level. The profile can thus be expressed as a six-parameter five-section linear piecewise equation (two values for the two levels plus four time values). The parameters for the power use profile are different for any given day, and are sampled from a multi-variable Gaussian distribution. In this way stochasticity is introduced to the model. The mean and the variance of the Gaussian distribution are estimated from historical data. A mixed-effect modelling approach is exploited here, capturing not only the total power use in the building, but also the variations in the electricity use of individual occupants. This model is applied to a 17-storey office tower for right-sizing HVAC equipment.

5.1.2 Machine learning models

Machine leaning models have also been used to predict the appliances electricity use. This includes long short-term memory (LSTM) neural networks (Markovic et al. 2021) (Z. Wang, Hong, and Piette 2019), Locally Weighted Learning (LWL), Support Vector Machine (SVM), and C4.5 decision tree algorithms (Lasternas et al. 2014). In particular (Markovic et al. 2021) developed a LSTM model using monitored data from a research building located in Abu Dhabi, United Arab Emirates (UAE). In order to test the generalization capabilities of the proposed method, the model was evaluated using data from two additional buildings, a bank office building located in Frankfurt, Germany, and a university building in Ottawa, Canada. The results showed that the developed LSTM is applicable to the tested buildings without the need for occupant-wise or building-wise calibration. The model predicts the appliances electricity use over the following 24 h, based on the measured data over the past days. The duration of the input sequence was treated as a learned hyperparameter based on the experimental results. Here, the investigated input sequence ranged between 1 and 7 days. Taking the occupancy as an additional model input turned out to improve model predictions, although in 2 out of 3 use cases the improvement is minor (less than 1% reduction in NRSME). It was shown that the model outperforms the models by (Gunay et al. 2016) and (Mahdavi, Tahmasebi, and Kayalar 2016), although the difference between the models depends on the use case: among the 3 use cases, the difference between the NRMSE values of the LSTM model and the recalibrated version of (Gunay et al. 2016) model ranges from 1 to 10%.

5.2 Potential options for modelling

5.2.1 Models for fault detection

If the electric power use of appliances is continuously monitored, this data can be directly used in fault detection. Otherwise any of the predictive models used for building control can also be used for fault detection.

5.2.2 Models for building control

Literature review revealed two important categories of models: 1) statistical methods, and 2) machine-learning approaches. The advantage of models in category 1) is that in principle they are able to reproduce the statistical characteristics of the distribution of the electric power usage. This includes capturing the occasional spikes which typically show up in the power use signal, and whose occurrence appears to be random (i.e., is hard to predict). However, these models do not capture the temporal correlations between the datapoints. On the other hand, the models in category 2) have the ability to incorporate the temporal correlations along the electricity power signal, while they might result in predictions which are smoother than what is in reality. Among the reviewed papers, the work by (Gunay et al. 2016) is a representative for the models in category 1), while the LSTM model proposed by (Markovic et al. 2021) represents category 2). Both of these models are good candidates to be applied in office buildings. It should be noted however, that in general predicting the appliances electricity use, especially that of a single house or a single office, is challenging. In such a situation it is not a priori clear which of the two above-mentioned models is more accurate in any particular use case, and to what extent they differ from each other in terms of their influence on the building performance prediction. Therefore, in a first attempt to predict the appliances use, it is meaningful to consider a rather simple model to act as a baseline. The baseline model could be a fixed profile for each hour of the day and the day of the week, which is also linked to occupancy similar to the deterministic model in (Mahdavi, Tahmasebi, and Kayalar 2016). This approach is applied in the TNO Stieltjesweg building (see Section 5.3.2 for details). A more advanced option is to make the profile adaptive, by constructing it using only the "recent" historical data which falls inside a moving window (e.g., to predict the appliance use at a particular hour of a certain day, the historical data for the past 4 weeks is collected, and then the datapoints corresponding to the same hour and weekday is averaged). Characterizing the performance of the baseline model, one can then consider more complex models. Using a more advanced model is only justified if it significantly outperforms the baseline.

5.3 Selected modelling approaches for application TNO Stieltjesweg

5.3.1 Models for fault detection

In the TNO Stieltjesweg office building electric appliances are not continuously monitored, but measurement data in a limited time period is available for certain appliances such as laptops and computer screens, lamps, coffee machines, vending machines, etc. As continuous monitoring of all appliances is not present, the appliance use should be modelled in the same way in the case of fault detection as in the case of building control. It is therefore proposed that the same model is applied in both cases. The suggested model is thus described in Section 5.3.2.

5.3.2 Models for building control

The proposed model follows the same basic principle of the deterministic model by (Mahdavi, Tahmasebi, and Kayalar 2016). At the first step, the limited measured data is used to construct profiles of electric power use, per hour of the day and per day of the week, for each monitored component. Then the profiles are combined with proper proportionality factors (e.g., the typical power use of a laptop is multiplied by the number of occupants in each zone, the power use of a lamp is multiplied by the number of lamps in each zone) to yield the full profile for appliance electricity use per zone.

5.4 Results application TNO Stieltjesweg

Based on the limited measurement data the following models were constructed to predict the electrical power use for various appliances in the Stieltjesweg building:

- For laptops and monitors, mean power use in the active and standby modes was estimated from the available measurement data. The total number of laptops in each zone is estimated by calculating the expected number of desks in all offices within the zone based on their floor areas. It is further assumed that all of the present occupants in every zone are using laptops. This is a logical assumption because all the zones in the models only include offices and no labs. All the unused monitors are assumes to be in standby mode. Taken all together, the total power use of all laptops and monitors in each zone can be estimated.
- Measured data was used to derive average power use profiles, for each day of the week and each hour of the day, for vending machines, coffee machines, fridges and printers in each zone.
- No direct measurement of the electric power use for lighting was performed at the Stieltjesweg building. Therefore the power use for lighting was modeled based on the following information/assumptions: total number of lamps and their nominal power use were determined by direct inspection of the building. It is assumed that on average a certain number of lamps will be on for each present occupant in each zone. (this can be determined by counting the number of single lamps above each desk). Despite this being a plausible assumption, it make break down if a large number of people are present, when the estimated number of lamps in the on state exceeds the total number of existing lamps. Therefore the estimation is limited by the total number of lamps per zone.

Applying the model as described above, the total appliances heat gain for each zone in the digital twin of the Stieltjesweg building can be estimated. The result is shown in Figure 12.

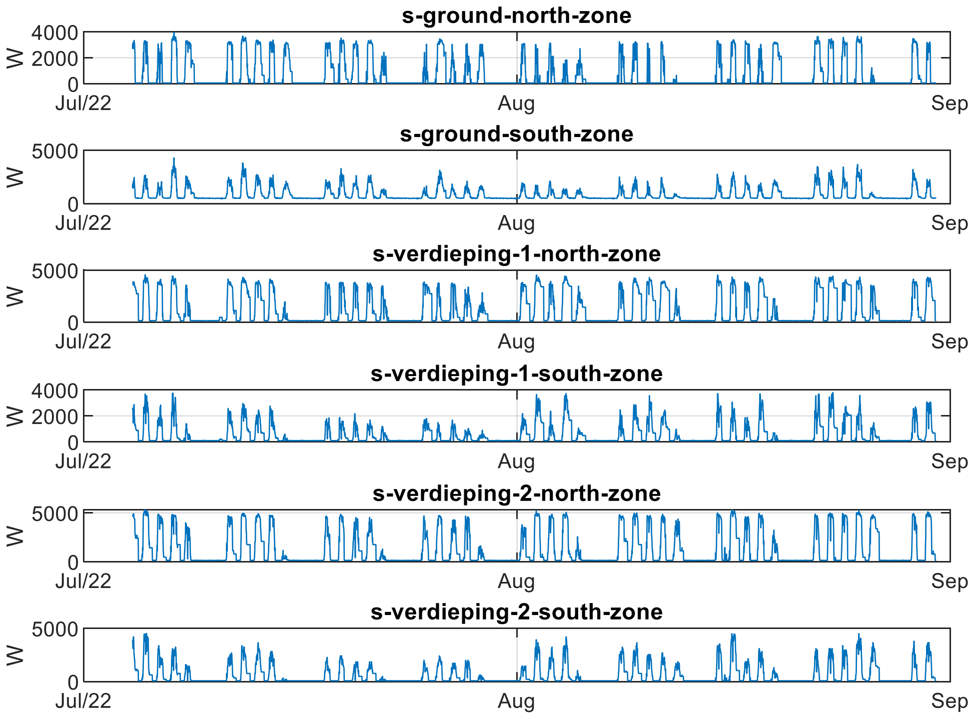

Figure 12: estimation of the total appliances heat gain for each zone in the digital twin of the Stieltjesweg building.

6 BLINDS

6.1 Literature review

Visual comfort of the occupant, as quantified by indoor illuminance, luminance, glair indices and solar radiation/ external illuminance, are considered as a principal trigger for closing the manual blinds. This is established in an overview by (Da Silva, Leal, and Andersen 2012). This review reveals that the action thresholds for closing the blinds vary in different studies. In addition, it turns out that generally there are not much literature available on manually controllable blinds, and most of the previous works have focused only on blind closing and not on blind opening. Two studies were found in the literature which use logistic regression to model the probability of both actions, where the trigger factors for taking an action are linearly combined. The study by (Gunay et al. 2017) mainly focuses on proposing and testing a control scheme for opening the blinds and turning off the light (closing the blinds and turning the lamps on remains to be done manually). This is done by constructing statistical models for closing the blinds and turning the lamps on, to find out setpoints for indoor illuminance to safely (i.e., without violating occupants' comfort) close the shading and turn the lamps off. This has been done separately for individual offices. As a byproduct of this work, the statistical correlations between the outdoor solar radiation and the blind opening and closing actions have been quantified. These can be used for modelling the manual shading behavior. An important modelling point is that interaction with the blind occurs only when the office is occupied (this is taken into account both during the training and application of the model). This can reproduce the observation that once the blinds are closed, they can stay closed for days before they are opened again (see Figure 5 in (Gunay et al. 2017)). The second study by (Haldi and Robinson 2009) uses a similar technique to model occupants' interaction with two types of manually controllable blinds in 14 south-facing individual offices in an office building. Three separate models were constructed depending on the occupancy status: arrival, intermediate occupancy and departure. The contribution of various environmental triggers was tested, including indoor and outdoor temperature, indoor and outdoor illuminance, global horizontal radiation, beam and diffuse radiation, whether the lighting is on (a binary variable), and the current position of the blinds. Forward feature selection was employed to select the most influential triggers for inclusion in the final model. The dominant triggers found are dependent on the type of blinds, type of action, and the occupancy regime. Nevertheless, the current position of the blinds and the indoor illuminance always ranks on top. Based on the constructed logistic regression models, (Haldi and Robinson 2009) also implemented a Monte Carlo algorithm to simulate the blind usage. They showed that the model is generally able to capture the statistical properties of the actual behavior, although occasional deviations were also observed.

6.2 Potential options for modelling

6.2.1 Models for fault detection

Similarly to the other three behavior types, if the manual interaction with the blinds is continuously monitored, the data can be directly used for fault detection. However this is rarely the case. Usually a model should be used to predict the behavior. There are two options:

1. If a historical dataset is available, logistic regression models for blinds closing and opening can be constructed in the same way proposed by (Haldi and Robinson 2009). The trigger factors included in the model should be either monitored or predicted in some way, so that the model can be applied in practice. The data should include some information about the shading, e.g., preferred (i.e., most probable) positions of the blinds when the closing/opening actions occur.
2. If there is no data on blinds usage, its influence on solar shading has to be indirectly estimated. This can be done by matching the predictions of a digital twin of the building, e.g., of indoor temperature and/or energy use, with actual data.

6.2.2 Models for building control

The two modelling options for fault detection, as presented in Section 6.2.1, are also applicable to building control. In case option 2 is chosen, the model input should be limited to the ones that can be predicted, such as outdoor solar radiation.

6.3 Selected modelling approaches for application TNO Stieltjesweg

6.3.1 Models for fault detection

In the Stieltjesweg building, there are two possibilities for shading control: automatic shading devices located outside the windows, and shading devices in the inside of the windows which are manually controlled by the occupants. Furthermore, there is a considerable external shading from surrounding buildings which was calculated by a data-driven software tool developed at TNO. It should be noted that, since the automatic shading also reacts to the outdoor radiation, it is difficult in practice to separate the contribution of manual shading from the automatic shading, especially because the manual shading might be less effective: the manual blinds are inside the building, so from an energetic point of view their effectiveness depends on their ability of reflecting back the sunlight which has already entered the building. Based on the above considerations, the choice has been made to only model the combined effect of manual and automatic shadings, using a deterministic model with a single set of radiation thresholds for closing and opening actions.

As there is no data of the use of the internal or automatic shading, their resulting shading effect should be indirectly estimated following option 2 in Section 6.2.1, by matching the predicted zone temperatures with the measured data, as part of the calibration of the digital twin of the Stieltjesweg building[6]. This can be done by assuming that the closing and opening actions are triggered by outdoor radiation, as determined by two radiation thresholds (a higher threshold for closing the blinds and a lower one for opening them). This approach is in fact similar to the statistical model by (Gunay et al. 2017): due to the fact that each zone in the building model covers roughly half a floor and contains many offices, it is expected that the stochasticity in the interactions of individual occupants with the blinds are averaged out to some extent. Therefore using two deterministic thresholds instead of a statistical model can be sufficiently accurate.

6.3.2 Models for building control

The model used for fault detection, as described in Section 6.3.1, will also be used for building control.

6.4 Results application TNO Stieltjesweg

The Stieltjesweg building is oriented in the north-south direction, As the transmitted solar load from the south-facing windows is dominantly larger, only the shading operation for the south-facing windows is modeled. The radiation thresholds were estimated via manual calibration, i.e. by matching the measured and predicted indoor temperatures in different zones. The calibration results are shown in Figure 13, which correspond to the radiation threshold of 200 W/m^2 for closing the shading devices, and 170 W/m^2 for opening them.

[6] The hybrid building model developed by TNO is described in deliverable D2.1-2.2-2.3 “Building and building systems energy prediction models to enhance energy flexibility control” of the B4B project.

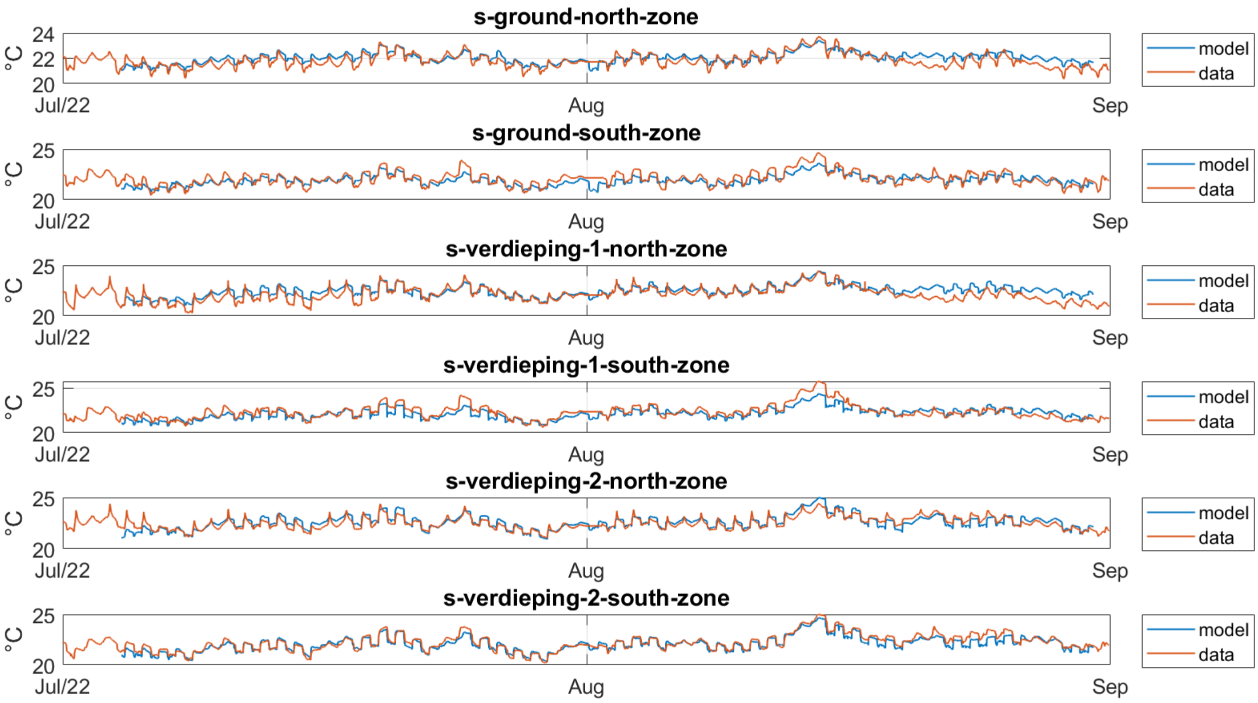

Figure 13: measured (brown) and predicted (blue) indoor temperature in different thermal zones of the Stieltjesweg building, where the radiation thresholds to operate the shading devices are estimated by matching the predicted and measured indoor temperatures.

7 CONCLUSION

This report describes the occupant behavior models, which exist in the literature and/or are used already by TNO experts, that are potentially applicable to fault detection of HVAC equipment and model predictive control in office buildings. Four types of behavior, namely occupancy, thermostat setpoint adjustment, appliances use and blinds use have been considered. Besides presenting a literature overview and pointing out the most suitable occupant models for fault detection and predictive control, a selected subset of the models were implemented in a digital twin of the living lab TNO Stieltjesweg in Delft[7]. Performance analysis of the implemented models was also presented, leading to a selection of a final set of occupant models which are suitable for the digital twin of the Stieltjesweg building. A summary of the insights derived from the literature review, as well as an overview of the potential models chosen for implementation and their performance analysis, is given below.

For occupancy modelling, two general categories are identified: occupancy detection, which relates the occupancy to environmental factors such as CO_2, usually using machine learning techniques, and occupancy prediction using profiles or Markov chain models. For the Stieltjesweg building, it was proposed that measured historical occupancy data will be directly used for fault detection, while for building control, the data is used to construct both deterministic adaptive occupancy profiles as well as a probabilistic version of the adaptive model based on the Markov chain formalism by (J. Page et al. 2008). Both models were compared and validated against measured data. It was concluded that the deterministic adaptive profiles can successfully capture the week-by-week variations of the occupancy, while the probabilistic version did not bring an additional advantage: due to the large number of the occupants in the Stieltjesweg building, the stochasticity of the model is averaged out. The probabilistic model might still be relevant in other use-cases, for example in a model with a large number of zones, where the average number of occupants in each zone is small.

Models for the temperature setpoint adjustment include statistical models based on logistic regression as well as the agent-based models. The former can be more easily implemented for building control. Emphasizing on the importance of taking into account occupants' habits and routines in the model, it has been proposed that models for timeseries predictions, which predict the future trend based on the near-past history might perform better in building control applications, especially for passive occupants. Particularly, based on the observation that the temperature setpoints rarely change at the TNO Stieltjesweg offices, a simple model was implemented which predicts the future setpoint values based on the last measured previous value. The model was validated against the measured data at the Stieltjesweg offices, and it was shown that it can predict the setpoint temperature with quite a high accuracy (r-squared of more than 0.99). It should be emphasized that the proposed model works well in the Stieltjesweg building because the changes in the temperature setpoints are quite infrequent. In case the occupant actively changes the schedule in response to certain environmental or temporal triggers, these should be included in the prediction model. The choice of the suitable model is therefore dependent on the observable patterns in the measured data and should be done on a case-by-case basis.

Based on the literature review, the models to predict appliances use include both statistical models, which sample from electric power usage distributions at different occupancy regimes, as well as the machine learning models which learn the future trend based on historical data. As discussed in the report, both approaches have their advantages and disadvantages, and their accuracy varies across use cases. At the TNO Stieltjesweg office building only the power use of some electrical appliances has been measured during a limited period, which in turn limit the modelling possibilities. It has been proposed to use the measured data to construct an average profile for electricity use of appliances at each zone, for each hour of the day, and day of the week. The profiles are related to occupancy similarly to what is suggested in (Mahdavi, Tahmasebi, and Kayalar 2016), and are used both for fault detection and building control. The resulting profiles were presented in the report and included in the digital twin of the Stieltjesweg building to model the appliances gain.

Statistical models based on logistic regression have been proposed in the literature to capture both closing and opening of the blinds. Although this is a valid modelling approach, it cannot be used to model the blinds

[7] The hybrid building model developed by TNO is described in deliverable D2.1-2.2-2.3 "Building and building systems energy prediction models to enhance energy flexibility control" of the B4B project.

use behavior at the TNO Stieltjesweg office building, as there is no measured data to train the models. Instead, the combined shading factor associated with both manually controlled blinds and external shading devices was inferred from measured indoor temperature, as a part of the calibration of the digital twin. This approach will be used both in fault detection and building control. Provided that measured data on the blind use (and possibly on indoor illumination) is available, and the control logic of any existing shading device is known, then the blind use can be explicitly modeled, for example using the statistical approach proposed in (Gunay et al. 2017).

In general, the results of this report highlight the importance of data availability: in case of occupancy and setpoint temperature, sufficient data was available from the Stieltjesweg building, which allowed for construction and validation of data-driven models. On the contrary, with a limited data on appliance use and no measured data for blind use, both the modeling approaches and validation possibilities are limited. Therefore collecting high-quality measured data on occupant behavior is recommended.

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