Implementation and demonstration of an automated energy modeling framework for scalable and adaptable building digital twins based on the SAREF ontology

Jakob Bjørnskov¹, Muhyiddine Jradi¹
¹SDU Center for Energy Informatics, University of Southern Denmark, Odense, Denmark

Abstract

The building sector is currently seeing rapid digitalization through IoT sensor and smart meter networks as well as the development of more advanced building operation algorithms. In this work, a framework for automated energy model development is developed and assessed as a backbone for effective building digital twin applications. The framework is based on the SAREF ontology and its extensions, SAREF4BLDG and SAREF4SYST to represent the most important devices and components in the building, how they behave, and how they interact. Each component is associated with a data-driven model that is calibrated through operational data collected from the building. The framework is demonstrated and evaluated in a case study building considering a teaching room, where continuous commissioning and scenario testing are investigated as services.

Key innovations

1. The implementation of an innovative energy modeling framework based on the SAREF ontology is demonstrated in a real case study
2. A physics-informed LSTM model for indoor temperature forecasting is proposed and implemented to enable better generalization and accuracy
3. Two digital twin services are proposed and demonstrated in the context of the case study

Practical implications

The structure and relations provided by the SAREF ontology can effectively be used in combination with data-driven modeling and parameter estimation techniques to form a flexible and scalable energy model suitable for digital twins.

Introduction

The increasing availability of operational data from buildings favors the use of scalable and automated data-driven modeling methods. In this regard, recent studies introduced the concept of a Building Digital Twin Lu et al. (2019); Zhao et al. (2022), serving as a digital replica that senses and adapts according to the behavior of the actual building using the installed IoT devices. Such digital twins can be used to deliver various services such as performance monitoring, fault detection, advanced operational planning, and optimization.

In recent years, the potential of digital twins in yielding useful insights and delivering crucial services has been demonstrated in multiple sectors. However, there is still not a clear consensus on how a digital twin for a building application should be represented and which services it should deliver. Although Building Information Models (BIM) have played a major role in the digitalization of buildings, it is argued by Boje et al. (2020) that status quo BIMs are not compatible with IoT-integration due to their legacy data standards and originally intended use during the design and construction phase.

This work demonstrates the implementation of an innovative framework that builds upon the SAREF ontology, which spans across multiple domains including smart cities. The proposed framework is implemented and assessed by considering a case-study of a classroom in a university building. The building is serving as a living lab, with very detailed submetering on various levels. The classroom is equipped with various sensors and monitoring devices, measuring damper, shading, and radiator valve positions as well as temperature and CO₂ concentration. The collected data is used to automatically calibrate the components associated with the space. This includes a space model that accurately predicts indoor temperature, as well as models for valves, space heaters, and controllers.

The work presented in this paper is part of the international research project 'Twin4Build: A holistic Digital Twin platform for decision-making support over the whole building life cycle'. The developed platform targets three high-level services; I) A user-friendly interface allowing building owners to better understand how their building behaves and performs; II) Automated Performance monitoring and continuous commissioning for improved building operation and smarter facility management; III) Model-based scenario testing and operational optimization to enable planning support.

Case study

The considered case study is a classroom located on the second floor of a Danish university building as shown in Figure 1. The building was built in 2015 and attained the Danish building class 2020 as one of the first buildings in Denmark. It has a total floor area of 8500 m² with four stories of which the ground, first, and second floor contains...
The building is divided into four symmetrical quadrants each supplied by a balanced ventilation system. Each system has one heat recovery unit, one heating coil, and the supply air temperature is under normal conditions controlled based on the exhaust air temperature according to a piecewise linear curve. Similarly, the supply water temperature to the radiators is controlled based on the outdoor air temperature measured by a weather station placed on the roof of the building.

The considered classroom is heated with radiators and the supply air flowrate is controlled through Demand Controlled Ventilation (DCV), where the damper opening is actuated based on the measured CO₂ concentration in the room. Shades are installed on the building facade to avoid overheating during the summer months. The actuation signal of the space heater valves, dampers, and shades is controlled centrally by the Building Management System (BMS).

The classroom is equipped with multiple sensors, namely, temperature, CO₂, valve position, damper position, and shade position. In addition, a heat consumption meter is installed on the radiators.

**Modeling framework**

Through the presented case-study, this paper aims to demonstrate the implementation of an energy modeling framework suitable for digital twins of buildings. The modeling methodology builds upon earlier work by the authors Bjørnskov and Jradi (2023), where the Smart Applications REFerence (SAREF) ontology is used as a backbone and semantic structure. SAREF was developed by Daniele et al. (2015) in close collaboration with the industry to rectify the interoperability issues encountered in the IoT-domain. The ontology has a focus on devices, e.g. a light switch or a sensor with extensions covering multiple domains, e.g. SAREF4BLDG Poveda-Villalón and Garcia-Castro (2020), SAREF4CITY Poveda-Villalon et al. (2020), SAREF4SYST Lefrançois (2019), SAREF4ENER Daniele (2020), etc. Here, SAREF4BLDG is an ontology extension dedicated to the building domain, which classes are a subset of the Industry Foundation Classes (IFC) standard. This is considered a significant advantage as it potentially allows for direct mapping of properties and design values for the different building components such as coils, space heaters, dampers, etc.

In Figure 2, the overall Digital Twin concept is shown with its high-level components. The digital twin concept considered in this work follows the definition used by Grieves (2015) and Boje et al. (2020), i.e. that the digital twin concept is composed of three main constituents; the physical system, the virtual system, and a flow of data between these systems. The physical system is the asset to be managed, where the IoT devices play a major role, as they allow for continuous and automated data collection and feedback that can be processed in the virtual system. The role of the virtual system is to mimic the physical system as closely as possible through an accurate dynamic simulation model to enable different services such as continuous commissioning, operational optimization, and scenario testing. For the implementation presented in this work, the virtual system consists of three tightly linked components; the model library, the simulation model, and the semantic model.

The semantic model contains information about system topology, relations, and properties using concepts from the SAREF core ontology as well as the SAREF4BLDG and SAREF4SYST extensions. For instance, it might be specified that a space heater of class s4bldg:SpaceHeater is located inside a space of class s4bldg:BuildingSpace through the s4bldg:isContainedIn property.

The model library shown in Figure 2 consists of different component model classes that represent the dynamic behavior of the SAREF and SAREF4BLDG devices contained in the semantic model. Each model class inherits design properties from the SAREF4BLDG device classes and has tuneable parameters that can be adjusted based on data collected from the physical system.

The simulation model also (Figure 2) is obtained through the system topology and relations contained in the semantic model to connect inputs and outputs for the different component models. For the case study classroom, the information flow for the obtained simulation model is shown in Figure 3.

The Out/In labels at the edges shows the translation of output to input between models. As shown in the graph, virtual sensors and meters are placed in the model (green components), e.g. the Space temperature sensor or the Heating meter. Readings from these virtual measuring devices can be directly compared with readings from actual sensors and meters placed in the physical system.

**Component Modeling and Calibration**

In this section, the modeling and calibration of different model components is described in relation to the case study.

Each model is calibrated based on collected data on the
model inputs and outputs from the physical system. For parameter estimation of the air-to-air heat recovery, temperature controller, and space heater, a least-square optimization approach is used. The models are described in...
detail in Bjørnskov and Jradi (2023).

**Air to air heat recovery**

The employed air-to-air heat recovery model has four parameters, \( \varepsilon_{75\%} \), \( \varepsilon_{100\%} \), \( \varepsilon_{75\%} \), \( \varepsilon_{100\%} \), each denoting the efficiency for 75% and 100% airflow for heating and cooling mode. The inputs are supply and exhaust airflow, exhaust flow temperature, supply flow temperature setpoint, and outdoor temperature. The model output is the supply outlet temperature. The results are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>After calibration</th>
<th>MAE (°C)</th>
<th>RMSE (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varepsilon_{75%} )</td>
<td>0.849</td>
<td>0.28</td>
<td>0.47</td>
</tr>
<tr>
<td>( \varepsilon_{100%} )</td>
<td>0.851</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \varepsilon_{75%} )</td>
<td>0.828</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \varepsilon_{100%} )</td>
<td>0.822</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Temperature controller**

The indoor temperature controller model is based on the simple Proportional Integral Derivative (PID) controller. The model has three parameters \( K_p \), \( K_i \), and \( K_d \) and takes indoor temperature and indoor temperature setpoint as inputs with valve position as output. The calibration results are shown in Table 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Obtained value</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>( K_p )</td>
<td>0.438</td>
<td>0.0083</td>
<td>0.027</td>
</tr>
<tr>
<td>( K_i )</td>
<td>0.251</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( K_d )</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As shown in Table 2, the obtained value for the derivative gain \( K_d \) is 0 and the identified controller is thus a PI controller.

**Space heater**

The space heater model has two parameters, the overall heat transfer coefficient \( UA \)-value, and the thermal capacity \( C_r \). The model represents an aggregated model of 5 space heaters placed in the classroom. Model inputs are inlet water temperature, indoor temperature, and water flowrate while the output is aggregated heat consumption. The calibration results are shown in Table 3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>After calibration</th>
<th>MAE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>( UA )</td>
<td>83.3 W/K</td>
<td>1.09</td>
<td>1.37</td>
</tr>
<tr>
<td>( C_r )</td>
<td>( 2.73 \cdot 10^6 ) J/K</td>
<td>1.09</td>
<td>1.37</td>
</tr>
</tbody>
</table>

**Space**

The model used in this paper, for predicting indoor temperature, is based on earlier work by the authors where Long Short-Term Memory (LSTM) architectures were used Bjørnskov et al. (2022); Bjørnskov and Jradi (2022). LSTMs are a variant of Artificial Neural Network (ANN) architectures which are designed to account for transient and time-dependent behavior due to the cell state vector \( c \in \mathbb{R}^n \) and the hidden state \( h \in [-1,1]^n \), which carry information between time steps. In addition, the use of Physics-Informed Neural Networks (PINN) has recently also widened the application of ANN models for thermal control applications Gokhale et al. (2022), due to the increased generalization and robustness of the obtained models. In these models, the model is guided during training by imposing physics-based loss terms in the loss function.

A diagram of the used architecture for this work is shown in Figure 4. The model consists of four units responsible for modeling certain heat transfer mechanics, namely, Gain, Spaceheater, Ventilation, and Radiation. Unit G models the heat gained from the surroundings of the space, which is mainly the heat transfer through external walls. Unit S models the heat gained from the space heaters placed in the room. Unit V models the heat gained from the ventilation air flows and unit R models the heat gained from solar irradiation.

Each unit has two sequential LSTM units, A and B, where LSTM_A receives the model inputs for timestep \( t-1 \), and outputs its hidden state \( h_{A,t} \) for timestep \( t \). This hidden state is then used as input to LSTM_B, which outputs its hidden state \( h_{B,t} \), i.e. the indoor temperature change caused by the heat transfer mode modeled by the unit. Finally, all four temperature change predictions are added together to obtain \( \Delta T_{i,t} \). In order to impose physical constraints on the model, a physics-based loss term is associated with each of the units, G, S, V, R.

\[
\mathcal{L}_{G,t} = \text{ReLU}\left( \frac{\partial h_{B,G,t}}{\partial T_{i,t-1}} \right) + \text{ReLU}\left( -\frac{\partial h_{B,G,t}}{\partial T_{o,t-1}} \right) \quad (1)
\]

The first term in Equation 1, penalizes the model if the indoor temperature change caused by the surroundings...
h_{B,G,t} grows with indoor temperature \( T_{t,j-1} \). The second term in Equation 1, penalizes the model if \( h_{B,G,t} \) decreases with outdoor temperature \( T_{a,j-1} \). ReLU is the Rectified Linear Unit function, which is defined as \( \text{ReLU}(x) = \max(0,x) \).

The two inputs of unit S are \( T_{t,j-1} \) and a feature describing the inlet water flow energy to the space heater, \( Q_{S,t-1}^z = T_{a,j-1}u_{a,j-1} \), where \( T_{a,j-1} \) is the inlet water temperature and \( u_{a,j-1} \) is the valve position of the space heater. Under the assumption that water flow is proportional to inlet energy, this feature is equivalent to inlet energy after min-max scaling.

\[
\mathcal{L}_{S,t} = \text{ReLU} \left( \frac{\partial h_{B,S,t}}{\partial T_{t,j-1}} \right) + \text{ReLU} \left( \frac{-\partial h_{B,S,t}}{\partial Q_{S,t-1}^z} \right) + \text{ReLU} \left( - h_{B,S,t} \right) \quad (2)
\]

In Equation 2, the first term penalizes the model if the indoor temperature change caused by the space heater \( h_{B,S,t} \) grows with indoor temperature \( T_{t,j-1} \). The second term in Equation 2, penalizes the model if \( h_{B,S,t} \) decreases with the energy added to the space heater \( Q_{S,t-1}^z \).

Unit V has two inputs, and similar to the space heater, the two inputs describe the inlet air flow energy \( Q_{V,t-1}^z = T_{a,j-1}u_{a,j-1} \) and outlet air flow energy \( Q_{V,t-1}^z = T_{t,j-1}u_{d,j-1} \), respectively. Here, \( T_{a,j-1} \) is the supply air temperature, and \( u_{d,j-1} \) is the damper position. The associated loss with unit V is given in Equation 3.

\[
\mathcal{L}_{V,t} = \text{ReLU} \left( \frac{\partial h_{B,V,t}}{\partial Q_{V,t-1}^z} \right) + \text{ReLU} \left( \frac{-\partial h_{B,V,t}}{\partial Q_{V,t-1}^z} \right) \quad (3)
\]

In Equation 3, the first term penalizes the model if the indoor temperature change caused by ventilation \( h_{B,V,t} \) grows with removed energy \( Q_{V,t-1}^z \). The second term in Equation 3, penalizes the model if \( h_{B,V,t} \) decreases with added energy \( Q_{V,t-1}^z \).

\[
\mathcal{L}_{R,t} = \text{ReLU} \left( - \frac{\partial h_{B,R,t}}{\partial \Phi_{t-1}} \right) + \text{ReLU} \left( - h_{B,R,t} \right) \quad (4)
\]

From Equation 4 it follows that the model is penalized if the indoor temperature change caused by solar irradiation \( h_{B,R,t} \) decreases with solar irradiation \( \Phi_{t-1} \), while the second term penalizes the model if \( h_{B,R,t} \) becomes negative.

The total loss for a given time sequence with the number of time steps \( N \) is then expressed in Equation 5 as the sum of unit losses and the squared residual of the observed temperature change \( \Delta T_{t,j} \) and predicted temperature change \( \Delta \hat{T}_{t,j} \).

\[
\mathcal{L} = \frac{1}{N} \sum_{t=1}^{N} \left[ (\Delta T_{t,j} - \Delta \hat{T}_{t,j})^2 \right] + \mathcal{L}_{S,t} + \mathcal{L}_{V,t} + \mathcal{L}_{R,t} \quad (5)
\]

With the loss function defined in Equation 5, the model has been trained and evaluated on winter data using the same preprocessing and testing methods as used in earlier work Bjørnskov and Jradi (2022). In Table 4, the performance is shown on the test set on temperature prediction. Note that these performance measures are for temperature prediction on 24-hour horizons using a closed-loop configuration of the architecture shown in Figure 4.

**Digital twin service applications**

In this section, it is demonstrated how the obtained model for the case study can be used to deliver different services. The services explored in this paper are continuous commissioning and scenario testing.

**Continuous Commissioning and performance monitoring**

To demonstrate the utility of the modeling framework for continuous commissioning, a period of 2 weeks has been selected, which includes a significant change in the operation of the case study building and classroom. This change in operation is caused by the current energy crisis in Europe and the resulting 19 \(^\circ\)C indoor temperature policy of public buildings recently introduced by the Danish government. One major implication for the considered case study building and classroom is that the indoor temperature is reduced from 21 \(^\circ\)C to 19 \(^\circ\)C and the supply air temperature setpoint is reduced to constant 19 \(^\circ\)C during the chosen period.

The results for the commissioning case are shown in Figure 5. For all four plots, the red line indicates the time stamp where the supply air temperature setpoint was changed to constant 19 \(^\circ\)C in the physical system. In Figure 5a, Figure 5b, and Figure 5c the upper plots show the readings from the physical and virtual temperature sensors, while the lower plots show the performance gap represented through a moving average of the residual with a window size of 1 day. This moving average is used to obtain a more robust and stable metric for anomaly detection than the raw residual and avoid stochastic fluctuations. Figure 5d shows a binary anomaly signal which is 1 if the moving average is outside of the 1\(^\circ\)C error band and otherwise 0.

Generally, as seen from Figure 5a, Figure 5b, and Figure 5c, readings from the virtual and physical sensors...
are in agreement during the first four days with a performance gap within the 1°C error band. However, after the change of operation, the performance gap between the Indoor temperature and the Heating coil sensor starts to drift outside of the error band. For the virtual space, the simulated temperature is higher due to the warmer temperature of the supply air, while the physical space receives colder air due to the change in supply air temperature. These differences in supply air temperatures are evident from Figure 5c.

Figure 5d summarizes these observations through the binary anomaly signals. As shown, the anomaly signal changes to 1 for the space sensor directly after the change in supply air due to the unexpected drop in temperature, which continue for about 1 day. Afterward, the signal returns to 0 until Thursday in the second week when the anomaly signal again changes to 1. For the Heating coil temperature sensor, the anomaly signal switches to 1 after approximately two days when the measured temperature falls below 21°C. The signal does not switch on right away because there is a transitioning period of approximately a week before the supply air temperature reaches 19°C.

Although the detected anomaly is not a fault, the commissioning case presented in this study demonstrates the potential of the data-driven model and its capability in capturing anomalies and performance drifting as soon as it occurs. This is translated into shorter reaction times and resource savings. In addition, the presented approach can form a basis for a building’s continuous commissioning process on different levels, serving as a backbone for effective and robust fault detection and preventive maintenance.

Scenario testing

The second application of the modeling framework and the obtained case study model is scenario testing, which aims to compare different candidate operational scenarios in a zero-risk virtual environment.
During the winter periods, the building has a heating set-point of constant 21 °C. A common strategy for reducing energy consumption in buildings is to decrease the temperature setpoint in periods with no occupancy, e.g. during nighttime. This strategy is called **night setback**, which must be implemented such that the building is pre-heated before occupation in order to avoid thermal discomfort. However, buildings behave differently under different weather and operational conditions. Exploration of different setpoint strategies and their impact on energy consumption and indoor comfort is therefore important.

In this work, we explore four scenarios, the baseline constant 21 °C setpoint of the classroom, and three variations of night setback scenario with a varying setpoint. The investigated night setback scenarios are to change the setpoint schedule to 21 °C from xx:00 to 17:00 and 20 °C otherwise, where the starting hour xx is varied between 05, 06, and 07. To measure the impact on indoor comfort, we use the same aggregated metric as proposed by Arendt et al. (2020) for measuring thermal discomfort in Kelvin-hours, which captures both the duration and intensity of setpoint violations. Thermal discomfort is only aggregated for hours with occupancy which is assumed to be between 08:00 and 17:00.

The results for the scenario testing are shown in Figure 6. Figure 6a shows the virtual temperature readings for the baseline (top) and the 07 AM night setback scenario (bottom). The baseline also includes the actual measurements from the physical temperature sensor during the period as a reference. As shown, the baseline virtual readings (as well as physical readings) fluctuate around the 21 °C setpoint. In the night setback scenario, the temperature is allowed to drop during the night until 07:00 where the temperature setpoint is again increased to 21 °C. Figure 6b shows the resulting difference in heating consumption (top) and discomfort (bottom). As shown there is a clear tradeoff between reduced energy consumption and discomfort for the chosen scenarios. The sooner space heating is initiated, the lower the energy consumption. However, this comes at the cost of higher discomfort levels. Typically, maintenance of thermal comfort levels is valued higher than decreases in energy consumption. Therefore, the most viable of the three-night setback alternatives is the 5 AM scenario, which impacts the thermal discomfort the least by 0.29 Kh but saves around 12 % in heat consumption.

### Conclusion

In this paper, the implementation of an innovative energy modeling framework was demonstrated in a case study. The framework builds upon the SAREF ontology and its extensions to form the backbone of a digital twin platform. The building digital twin is considered as a collection of components such as spaces, heaters, controllers, fans, etc., that can be directly related to their real counterparts, enabling detailed performance monitoring and fault detection at both component and systems-level. This further enables building owners to test different operational strategies, and how they affect the building before they are implemented. Employing the framework, two digital twin services were demonstrated. Continuous commissioning and performance monitoring was demonstrated on individual components by comparing virtual and physical sensor and meter readings, i.e. predictions and measurements for a certain period. Here, anomaly behavior was correctly detected on a period with a change in building operation. As a second service, scenario testing was demonstrated by comparing baseline operation with three alternative operation strategies in terms of indoor comfort and consumed energy.

This work provides a proof-of-concept of the modeling framework and the potential applications and services it can deliver. The use of a well-established ontology ensures the scalability of the approach and that the de-
veloped framework could potentially be expanded and adapted to clusters of buildings or cities in the future. For future work, it is intended to further scale up the efforts leading to the development of a whole-building digital twin of the case-study building. In addition, it is expected that the delivered services could be expanded to consider also operational optimization and automated actuation of components or change of setpoints at a later stage.

Acknowledgment

This work is carried out under the ‘Twin4Build: A holistic Digital Twin platform for decision-making support over the whole building life cycle’ project, funded by the Danish Energy Agency under the Energy Technology Development and Demonstration Program (EUDP), ID number: 64021-1009.

References


