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Reducing peak load of renewable energy at district level with predictive twins

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Abstract. One of the major challenges in the energy transition of the built environment is how to integrate energy-producing neighbourhoods into the existing energy infrastructure. The aim is to avoid the peak load of local renewable energy by consuming it at district level as much as possible. The energy transition puts an increasing burden on the local energy grid, because of the increasing electrical load on the demand side by heat pumps and electrical vehicle charging, but also because of the increasing intermittent supply of energy through solar power and wind turbines. With a predictive twin, a digital representation at building and neighbourhood level, supply and demand can be better balanced, so more solar power is used locally and peak load is avoided. The predictive twin "SirinE", developed by TNO, is a hybrid scalable model consisting of both a physical model for the building and installations, and an AI (Artificial Intelligence) model to describe the user behaviour. In the Horizon 2020 project syn.ikia, we are deploying this predictive twin in a model predictive controller (MPC) to use a temporary excess capacity of on-site solar energy as efficiently as possible. In this paper we present the model structure and the first simulation results for the energy prediction needed for the MPC.

1. Introduction

By 2050, the entire built environment must be energy neutral. A major challenge in the energy transition of the built environment is how to integrate energy-producing neighbourhoods into the existing energy infrastructure. The exponential increase of heat pumps and electric vehicles will lead to higher peaks in electricity demands. Intermittent availability of different renewable energy sources with associated trade platforms [1] will require energy systems to switch between energy sources fluently and at short notice. To ensure stability and security of supply, the energy network will need to incorporate a mix of different commodities (electricity, heat and possibly hydrogen networks) [2] and be capable of smart balancing energy supply and demand on a district level to avoid network congestions. Building level energy management (in houses, offices, hotels, etc.) can play an important role in the reduction of peak demands by distributing energy demand over time and over the different commodities. Building models can play a role in this increasing need for load balancing. The challenge is to develop a building model that not only plays a central role in optimizing energy efficiency at the individual building level, but can also - and more importantly - serve as a prime actor in balancing energy at the district level. The aim is to avoid the peak load of local renewable energy by consuming it at district level as much as possible.

To be able to balance the energy production within the capacity constraints of the local energy grid a reliable prediction or forecast of both decentralized renewable energy production and energy use of a building is needed. To be able to choose the right control scenario for a controller to balance energy, we need to be able to make short-term predictions based on different control scenarios. Therefore the application of the model is to produce a short-term (1 day ahead) prediction of the building energy demand and of the decentralized renewable energy prediction.

Occupant behaviour shows to be a major factor in the energy demand of a building and therefore it is essential that the consequences of behaviour on the energy use can be predicted by the model. Furthermore, the involvement of occupants may lead to changes in the occupant behaviour. As a consequence the prediction model must adapt itself continuously to reflect these changes.

The current state of the art in research in this field follows two directions. The first one focuses on smart district level control using Artificial Neural Networks and agent technology or Model Predictive Control [3, 4, 5]. Representation of individual building level energy requirements and performance in these models is simplistic and static, using simple fixed demand/supply curves. The second research direction focuses on single building scheduling and control studies using physical models simulated in specific tools, e.g. TRNSYS or Energy-Plus [6, 7] or RC networks [8]. Over the past few years, the academic focus in this research area has shifted from black box models to hybrid models because the latter give better predictions and achieve higher robustness [2]. The current generation of hybrid models of buildings is mostly focused on a single type of building and mainly uses fixed user profiles to model the heating demand.

2. Hybrid building model SirinE

SirinE is a hybrid predictive digital twin model for buildings and consists of a physical building model which solves the heat flow balance equations, and a data-driven occupant model which models the interaction of the occupants with the building components (e.g. thermostats, windows, electric appliances, etc.) and includes the effect of occupants actions in the heat flow balance equations. The unique aspect of SirinE is that it is a scalable model, which is currently not available. The current state of the art clearly shows the need for uniform scalable and more realistic building models which can tackle multiple functions and model interactions with the grid [9].

The building model of SirinE consists of a heat balance network that is automatically derived from the Building Information Model (BIM) that describes the geometric configuration and construction properties of the building (consisting of all spaces, walls, windows, doors, roofs, etc.) and the Building Energy Model (BEM) describing the building heating, cooling and ventilation equipment and its controllers. With the automatic generation of the heat network, the simulation model can be easily adapted to different building types, such as apartment buildings, row houses and office buildings. Furthermore the data used to calibrate the model makes use of the standardized ontology of Haystack. The simulation model is therefore easily scalable for different building typologies and the initialization time is short.

A generic occupant module (framework) has been created within SirinE which is responsible for reproducing the interaction of the occupants with the building. The occupant module contains distinct submodules, each associated with a certain occupant behaviour such as occupancy, interaction with windows or interaction with a thermostat setpoint. The implementation is quite flexible, in the sense that each of the submodules could be connected to a various set of predictive models, ranging from simplistic approaches (e.g. fixed hourly profiles) to complex AI algorithms. Receiving the state of the building at each timestep from the building simulator, along with weather information (figure 1), the occupant module predicts the occupant behaviour for the next time step and sends it back to the building simulator. The AI-based occupant module, in combination with the physics-based building simulator, makes SirinE a hybrid digital twin.

The building heat balance model dynamically interacts with the occupant model. This has been implemented in an agent-based framework. All individual users (or groups of users defined as a user role) are agents that interact with the heat balance model in a dynamic simulation over the prediction horizon. The occupant models that have been implemented (simple hourly schedules, models for thermostat and appliances based on sliding averages, Markov chain models for window opening behaviour) highlight the hybrid nature of SirinE. At the same time, the emphasis should be made that this is a general framework that can be coupled to any occupant model.

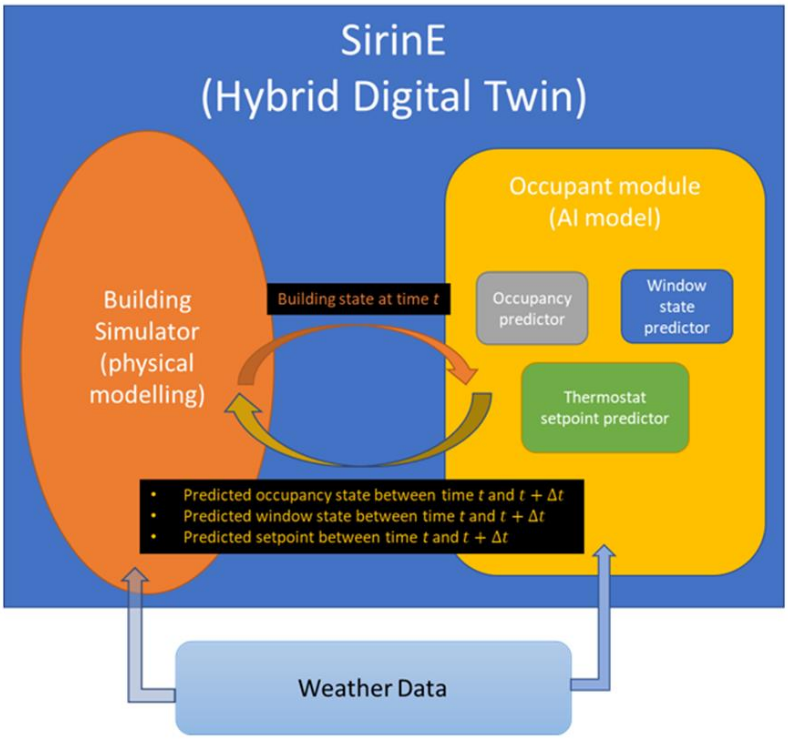

Figure 1. Interaction between the occupant model and the building simulation model within SirinE.

3. Hybrid building model SirinE for load balancing of an energy positive neighbourhoud

In the Horizon 2020 project syn.ikia, we are deploying the predictive twin SirinE in a model predictive controller (MPC) to use a temporary excess capacity of on-site solar energy as efficiently as possible. This MPC is applied in a demo Sustainable Positive Energy Neighbourhood (SPEN) in Uden. This neighbourhood consists of an apartment building with 39 apartments, each having its own PV panels and ground source heat pump for domestic hot water and space heating, and common neighbourhood PV and Electrical Vehicle charging stations.

To shift the energy load of the apartments to better utilize the energy generated by the photovoltaic panels, we calculate the optimal time to start heating the buffer vessel for domestic hot water and the time to start the space heating. We can shift the start time of space heating quite easily because the dwelling is both well insulated and has a large building mass in the floors and walls. Therefore the building will react quite slow to cooling down and heating up the rooms.

To develop a model predictive control for load balancing, a multizone model for the apartment building in Uden was constructed, where each room was considered a thermal zone. Each zone z_i is represented by a temperature node T_{zi} in the heat network. Each physical layer of boundary surfaces (i.e. walls, floor, ceiling and roofs) constitutes a temperature node in the heat network. For kth layer of the jth boundary surface $S_{j,k}$ ($k = 1$ corresponds to the innermost layer, $k = n$ to the outermost one), a temperature node $T_{Sj,k}$ is added to the heat network. In addition all boundaries (outdoor environment, ground etc.) are represented by a temperature node. The heat flow balance equations can be summarized as follows:

- For the zone z_i:

$$C_{zi} \frac{\partial}{\partial t} T_{zi} = \sum_{S_j \in z_i} A_j h_{\text{int}}^{\text{surf}} (T_{Sj,n} - T_{zi}) + Q_{zi,vent} + Q_{zi,int} + Q_{zi,sol} + Q_{zi,heat/cool} \quad (1)$$

- For the innermost surface layer $S_{j,1}$ of the boundary surface S_j which is in direct contact with the zone z_i:

$$C_{Sj,1}\frac{\partial}{\partial t}T_{Sj,1} = A_j h_{\text{int}}^{\text{surf}}\left(T_{zi} - T_{Sj,1}\right) + A_j h_{2,1}^{(j)}\left(T_{Sj,2} - T_{Sj,1}\right) \tag{2}$$

- For the internal layers of the surface S_j:

$$C_{Sj,k}\frac{\partial}{\partial t}T_{Sj,k} = A_j h_{k,k-1}^{(j)}\left(T_{Sj,k-1} - T_{Sj,k}\right) + A_j h_{k+1,k}^{(j)}\left(T_{Sj,k+1} - T_{Sj,k}\right) \tag{3}$$

- For the outermost surface layer $S_{j,n}$ in contact with the outside environment:

$$\begin{aligned} C_{Sj,n}\frac{\partial}{\partial t}T_{Sj,n} = {} & A_j h_{n,n-1}^{(j)}\left(T_{Sj,n-1} - T_{Sj,n}\right) + A_j h_{\text{ext-conv}}^{\text{surf}}\left(T_{out} - T_{Sj,n}\right) \\ & + A_j h_{\text{ext-rad}}^{\text{surf}}\left(T_{out} - T_{Sj,n}\right) + A_j F_{sky_j} h_{\text{ext-rad}}^{\text{surf}}\left(T_{Sky} - T_{out}\right) \\ & + Q_{Sj,sol} \end{aligned} \tag{4}$$

The parameters in the above equations are defined as:

C_{zi}: thermal mass of zone z_i.
$C_{Sj,\text{k}}$: thermal mass of surface layer $S_{j,k}$ of the boundary surface S_j.
A_j: the area of the boundary surface S_j.
$h_{\text{int}}^{\text{surf}}$: the internal surface heat transmission coefficient, including both the convective and radiative transmissions.
$h_{\text{ext-conv}}^{\text{surf}}$: the external convective surface heat transmission coefficient.
$h_{\text{ext-rad}}^{\text{surf}}$: the external radiative surface heat transmission coefficient.
$h_{k+1,k}^{(j)}$: conductive heat transmission coefficient between the kth and $(k+1)$th layers of the boundary surface S_j.
T_{out}: outdoor temperature.
T_{Sky}: apparent sky temperature.
F_{sky_j}: view factor to the sky for the boundary surface S_j.
$Q_{zi,vent}$: ventilation heat flow for the zone z_i. In SirinE this is calculated by solving the steady-state airflow balance equations.
$Q_{zi,int}$: internal heat flow for the zone z_i due to occupants and household appliances.
$Q_{zi,sol}$: solar heat flow for the zone z_i via the windows.
$Q_{Sj,sol}$: absorbed solar power by the external boundary surface S_j.
$Q_{zi,heat/cool}$: heating or cooling flow delivered to zone z_i via the floor heating system. In SirinE this is calculated by modelling a plant loop system, which includes a heat pump, a source-side pump, a load-side pump and a ground heat exchanger and solving the steady-state flow and heat flow balance equations.

In addition to the Building model, a combined tank and heat pump model is used to simulate the production of the domestic hot water (DHW). The model solves the heat flow balance equations between the layers of hot water inside the tank taking into account the heat stratification in the water volume.

To calculate the losses due to ventilation and infiltration TNO has developed a multizone airflow model, AirMAPs [10]. Similar to COMIS [11] it is based on a network model. Each zone in the building is considered homogeneous for temperature and is represented by a node. The nodes are linked in a network to model the airflows. This network consists of all the openings, ventilation grills, cracks, fans and other air flow components. This model not only takes into account the airflows induced by fans but also includes the effects of wind and buoyancy resulting from temperature differences. Furthermore, the additional airflows due to the turbulent air exchange of large openings of windows and doors are modelled This airflow model interacts with the heat network model within SirinE. At one timestep the temperatures of the heat network are passed on to the airflow model, while on the following timestep the calculated airflows are passed on to the heat network model.

4. First simulation results for the prediction

As an input for the model predictive controller a reliable prediction is necessary for both the temperature in the different zones and the energy use of the heat pump. The simulation is performed using a heat pump control comparable to the real installation control, which uses an on-off controlled heat pump for both space heating and for heating of domestic hot water.

We have simulated the indoor temperatures and the energy use of the heat pump during a year. In the summer of 2022 the tenants moved in to the apartments, and from that date we can validate the SirinE simulation results and we can start implementing the model predictive controller. Figures 2 and 3 show the simulated temperature profiles as well as the electric power consumption by the heat pump during a whole year for one of the apartments in the apartment building in Uden.

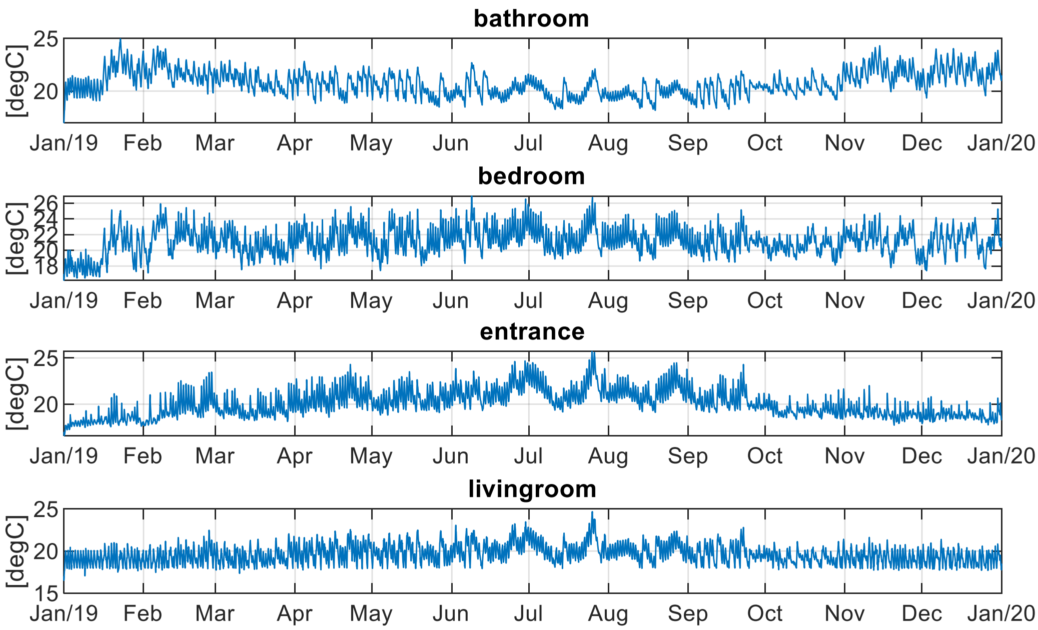

Figure 2. Simulated temperature profiles during a whole year for all rooms in one of the apartments in the apartment building in Uden.

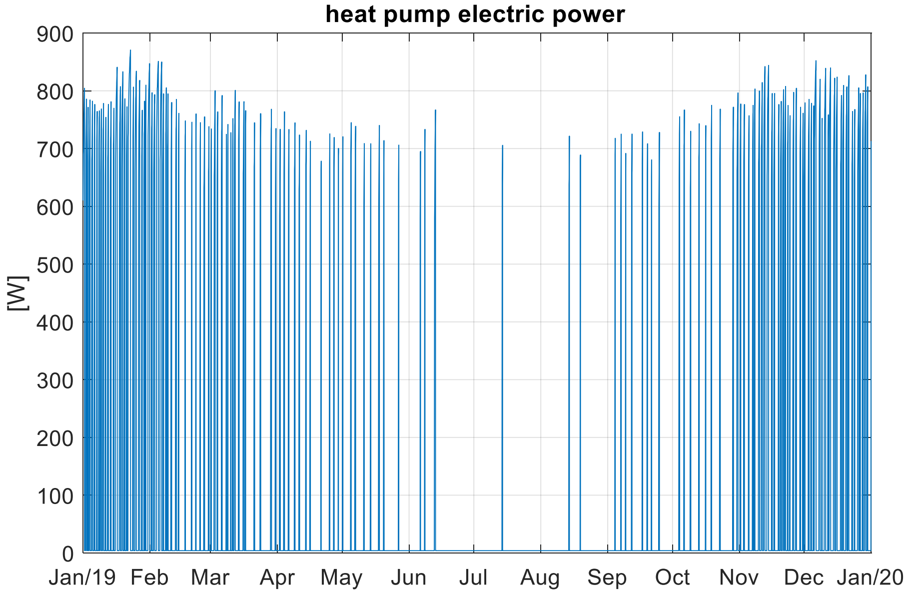

Figure 3. Simulated electric power consumption by the heat pump during a whole year for one of the apartments in the apartment building in Uden.

5. Conclusion

The paper provides an overview of a novel hybrid modelling approach for buildings. A challenge with models that are based on heat networks is that they can be slow. With the SirinE model we are able to perform predictions of several scenarios for future control, within the time constraints of the control problem A unique quality is that the building model uses a standardized data format for both the BIM (gbXML) and the building data (Haystack), therefore the model is scalable and quick to initialize. Next step is to implement and test the model predictive controller in the Sustainable Positive Energy Neighbourhood (SPEN) in Uden.

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