CLIMA 2016 - proceedings of the 12th REHVA World Congress

volume 10

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Publication date:
2016

Document Version
Publisher's PDF, also known as Version of record

Link to publication from Aalborg University

Citation for published version (APA):
Heiselberg, P. K. (Ed.) (2016). *CLIMA 2016 - proceedings of the 12th REHVA World Congress: volume 10*. Department of Civil Engineering, Aalborg University.

Operational Load Shaping of Office Buildings Connected to Thermal Energy Storage Using Dynamic Programming

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Abstract

In the future we will pay for energy flexibility rather than energy consumption. This makes clear that we need to investigate and enhance the energy flexibility of buildings. Basically, buildings energy flexibility refers to the thermal mass and any other building integrated physical entity that can store energy. But the buildings energy flexibility is also associated with the applied control strategy. A promising strategy to increase the flexibility of the building energy demand is the use of model predictive control. The performance of the model predictive control strategy strongly relates to the formulated optimization methodology.

In this paper a generic optimization methodology using dynamic programming is successfully implemented. The method evaluates peak shaving and load shifting of building energy demand using a thermal energy storage tank. Simulations are conducted that investigate the optimal discharge of a thermal energy storage tank installed in a small scale office building.

The study also presents an approach to define the building to grid energy flexibility. In particular, the flexibility to limit the electricity consumption of the heat pump as heating source is investigated. Based on the optimization results of three cases (reference, peak shaving and load shifting case) the building to grid energy flexibility is calculated.

Keywords –thermal enery storage tank; office building; dynamic programming; optimization; peak shaving; load shifting; energy flexibility

1. Introduction

The increase of renewable integration is a challenge of balancing today's power grids and requires new strategies to avoid network congestion and power outage. Load shifting and peak shaving have been identified as promising strategies to shape the load and to modify energy consumption patterns of buildings [1]. A key element to change the energy usage of buildings is the application of thermal and electrical energy storages. By nature, buildings offer a great potential for storing energy, either by utilizing the available thermal capacity (building thermal mass) or by adding energy storages (water, ice, phase change materials, thermochemical materials, electrochemical materials etc.) [2]. In this study the operational load shaping of office buildings using a typical building integrated water tank as thermal energy storage (TES) is investigated. The objective is to show for different operational conditions (storage energy capacity, ambient conditions etc.) the amount of energy flexibility that can be provided to the power grid while modifying building demand patterns. In particular, the study investigates two key elements that aim to identify the energy flexibility of office buildings connected to thermal energy storage water tanks. The first element presents a generic method that concentrates on a day ahead optimization to find the optimal discharging strategy of the thermal energy storage. This optimization method contains a dynamic building and thermal energy storage model so that any information associated with temperatures and power flows is available for each simulation time step. The method is developed in such a way that it can be applicable to the model-based process control of buildings. Based on the introduced method the paper presents the second key element, the building to grid energy flexibility that is closely related to the flexibility of the electricity consumption for heating. The calculated flexibility is dynamic and different for each simulation time step. Depending on the optimization strategy the building can offer a day ahead hourly flexibility availability to the grid.

In chapter 2 we describe the implementation of the generic method (1st key element) by explaining the entire model including optimization methodology and building to grid energy flexibility definition (2nd key element). Chapter 3 shows simulation results for the reference, peak shaving and load shifting case and based on the results the building to grid energy flexibility.

2. Model description

The model contains 5 major blocks, weather & occupancy forecasting model, building & storage model and optimization model. We assume an office building that is located in the Netherlands. Typical weather data was acquired from a TMY database for De Bilt. The main parameters obtained from the TMY database were the ambient temperature and the solar radiation (Figure 1).

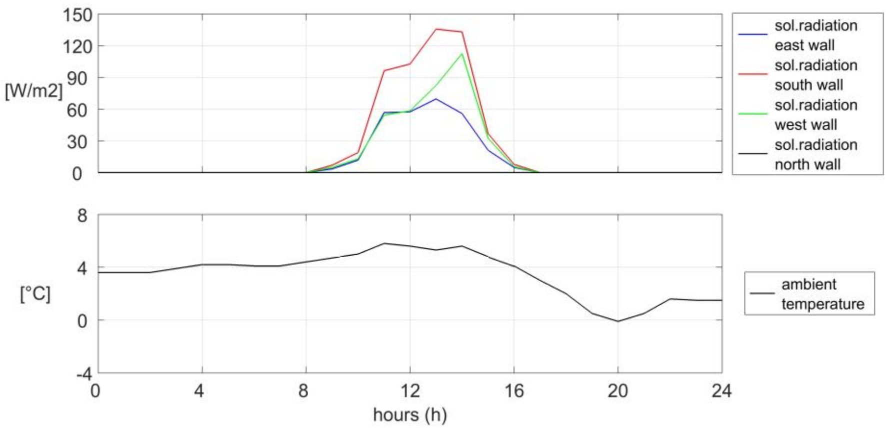

Fig. 1 Typical winter day – TMY weather data DeBilt, The Netherlands

Both parameters served as input for the building and optimization model. It is to emphasize that direct and diffuse radiation are used to compute the external heat gained by the building. The solar irradiation on the building accounts for horizontal and vertical south, west, east and north oriented planes.

The major source of internal gains is the presence of occupants. In order to predict their presence, a stochastic occupancy model was chosen. Such a model typically considers discrete occupancy states using Markov chains [3,4]. The Markov model is based on online occupancy measurements or offline occupancy data. Those data are used to build a transition probability matrix that provides the probability distribution of any discrete state. The occupancy model integrated in this study allows the implementation of Markov chains. However, sufficient occupancy data for office buildings in the Netherlands were not yet available, so that a hand-chosen occupancy probability (similar to [3]) was implemented (Figure 2).

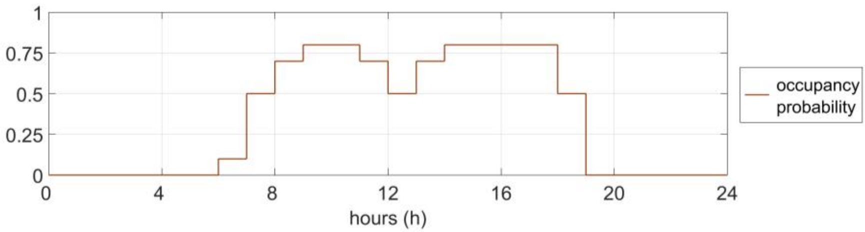

Fig. 2 Occupancy probability – small scale office building in the Netherlands

In the simulations the assumed probability affects the internal heat gains generated by lighting, computers and the human body. A probability of 1 refers to the maximum value of lighting 100 W, computers 400 W (50 W per computer) and the human bodies of 960 W (120 W per person). Those values were chosen for each of the 2 floors of the small scale office building with 135m² floor area and a maximum occupancy of 8 persons per floor. The structure of the building with 7 rooms per floor is composed of building elements (Table 1) containing concrete (0.73 W/mK; 921 J/kgK; 1920 kg/m3) and external mineral insulation (0.04 W/mK; 830 J/kgK; 90 kg/m3).

Table 1. Building structure

Building elements	**Materials**	**Thickness [m]**
External wall	Mineral insulation; concrete	0.05; 0.30
Internal wall	Concrete	0.15
Ceiling, Floor	Concrete	0.25

The building model was developed using the BRCM toolbox [5]. The basic approach of this toolbox is to represent a building model by an advanced resistance-capacitance (RC) network that considers an internal thermal model (zones, internal and external walls) and an external heat transfer model (ambient conditions). The building model physics include conduction in walls and convection plus radiation between walls and zones using predefined heat transfer values. The toolbox was successfully validated by comparing against EnergyPlus and only smaller discrepancies were observed [5].

The reason was found in the simplifications of the toolbox assuming constant heat transfer parameters, combined convection/radiation and a simplified window model.

We assume a building integrated water tank as thermal energy storage. Since the main focus of this study lies on the optimization methodology the TES model was integrated as a one-node model. However, since storage heat loss has been indicated as critical parameter, a value of 8 % daily heat loss [6] was added to the storage model.

Dynamic programming (DP) was chosen as optimization methodology because it allows the interaction with linear and nonlinear models. Any building and storage model might be used instead of the ones chosen in this study. The DP integrates building and storage as a function or object providing input and receiving output (state values). The state variables x_t integrated in the DP are the building zone temperature (one-zone model) with a resolution of 0.5 K and the thermal storage temperature with a resolution of 1.25 K. The decision variables u_t were defined as the zone and storage temperature at the next simulation time step. Based on the standard Bellman equation (equation 1) we want to find the best trajectory of temperatures u (equation 2) that satisfies the value function J_t over the planning horizon N where $t = 0,1,\ldots,N-1$ [3,7].

$$J_t(x_t) = \min_{u_t \in U_t(x_t) \varepsilon_t} E\left[g(x_t, u_t, \varepsilon_t) + J_{t+1}\big(f_t(x_t, u_t, \varepsilon_t)\big)\right] \tag{1}$$

$$u(x_t, t) = \underset{u_t \in U_t(x_t)}{\arg\min}\, E[g(x_t, u_t, \varepsilon_t, t) + J_{t+1}(x_{t+1}, t)] \tag{2}$$

In particular, the DP covers 2 objectives, minimizing the electricity demand for space heating and maximizing the thermal comfort. Heating can be provided by an electrical heat pump (with $COP_{HP}(T_{ambient})$) or by discharging the TES.

$$COP_{HP}(T_{ambient}) = \begin{cases} 4, & T_{ambient} = 293\ K \\ 2, & T_{ambient} = 273\ K \end{cases}$$

The comfort maximization problem was converted into a minimization problem (minimizing the deviation from the comfort reference temperature) and included in the cost-to-go function $g(x,u,\varepsilon)$ (equation 3)

$$g(x_t, u_t, \varepsilon_t) = \varepsilon_t\big(x_{zone,t} - \tau\big)^2 \alpha\, P_{HP}(x_t, u_t) + \theta_t\big(x_{zone,t}\big) + \omega_t\big(x_{zone,t}\big)$$

with $(x_{zone} - \tau) > 0$ (3)

where $P_{HP}(x_{zone},u)$ is the electricity demand of the heat pump, ε describes the expected occupancy probability and $(x_{zone} - \tau)^2$ is weighing the probability of occupancy by the square of the difference between zone temperature x_{zone} and comfort reference temperature τ [3,4]. $\theta(x_{zone})$ can penalize the expected discomfort temperature, called chance constraints [8]. $\omega(x_{zone})$ can be used as penalty to avoid any heating applied to the building during the off-peak period. Equation 3 considers a discomfort penalty of $\theta(x_{zone} < 293.5\ K) > 0$ and a reference temperature $\tau = 294.25$ K for $\varepsilon > 0.5$ and $\theta(x_{zone} < 292.5\ K) > 0$ and $\tau = 293.25$ K for $0 < \varepsilon \leq 0.5$.

The first objective (1st key element) of this study aims at investigating the optimal discharge of the TES by applying peak shaving or load shifting. For this reason a peak shaving and load shifting factor α was added to the cost-to-go function (equation 3) with

$$\alpha = \frac{P_{HP}(x_{zone}, u)}{P_{HP,max}} \qquad \text{for peak shaving} \qquad (4)$$

where $P_{HP,max}$ is the maximum electricity demand of the heat pump (here called reference case), and

$$\alpha = e^{-1/2\left(g_3 \frac{g_2}{(g_1-1)/2}\right)^2} \qquad \text{for load shifting} \qquad (5)$$

where g_1, g_2 and g_3 are the coefficients of a Gaussian window. We define g_1 as the duration of the load shifting period, g_2 as a vector representing the time steps within g_1 and g_3 as $g_1/t_{window,ls}$. The Gaussian window enables the implementation of load shifting preferences. Those are represented by a load shifting time $t_{ls} \in g_2$ and a load shifting window $t_{window,ls} \subset g_2$ with $-t_{window,ls}/2 \leq t_{ls} \leq t_{window,ls}/2$ as discharging preferences. Of course, the optimization methodology can consider several Gaussian windows when applying load shifting as optimization strategy.

The last part of the model (2nd key element) includes the definition and calculation of the building to grid energy flexibility. In this study we consider the flexibility to limit the electricity consumption of the HP at any moment in the future. In particular, the DP framework can optimize the use of the HP by adjusting set points and changing scheduling strategies over a certain receding prediction horizon. Based on the results of the chosen optimization strategy the model can simulate at each moment of the prediction horizon the flexibility to disconnect the HP from the grid or to limit the electricity consumption of the HP. This particular flexibility is expressed in hours and represents the prediction of limiting the HP while meeting thermal comfort of occupants.

3. Simulation results

All simulations were performed in Matlab with a simulation horizon of 24 h starting at midnight. A simulation time step of 1 h was chosen. An initiation simulation of 24 h was carried out and the results served as starting point for various cases using the predefined input as described in chapter 2.

The 1st simulation case conducted was the reference case that considered only the heat pump to cover the heating demand of the building (Figure 3). From this figure we can clearly see that the zone temperature is in good agreement with the occupancy probability and the thermal comfort constraints. A maximum comfort temperature is reached at 294 K (21.5 °C) at a maximum occupancy of 0.8. The zone temperature decreases during the lunch period and in the afternoon when people leave from work.

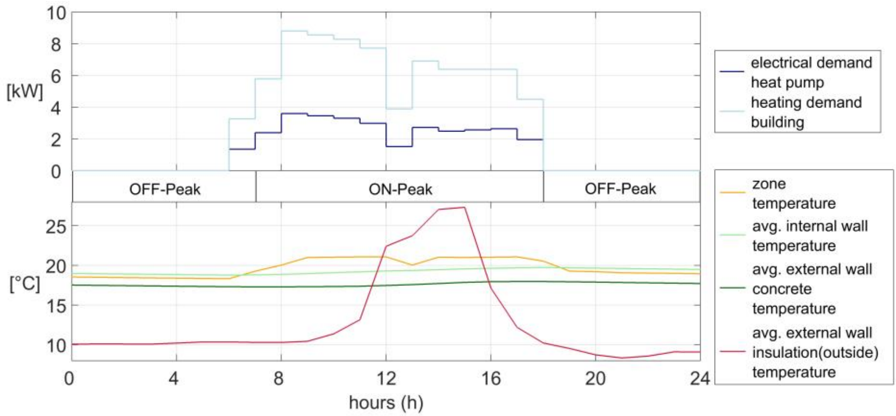

Fig. 3 Optimization results – reference case, upper diagram shows the power consumption of the HP and the heat transferred from the HP to the building, lower diagram shows building zone and wall temperatures

It is to emphasize at this point that this study does not assume the preheating effect of the building thermal mass (internal and external walls) within the optimization. The focus was set only on the optimized discharge of the TES tank. Therefore, we defined off peak (0.00 – 7.00 & 18.00 – 24.00) and on peak (7.00 – 18.00) periods (Figure 3). Discharge of the TES tank could only take place during the on-peak period to avoid preheating.

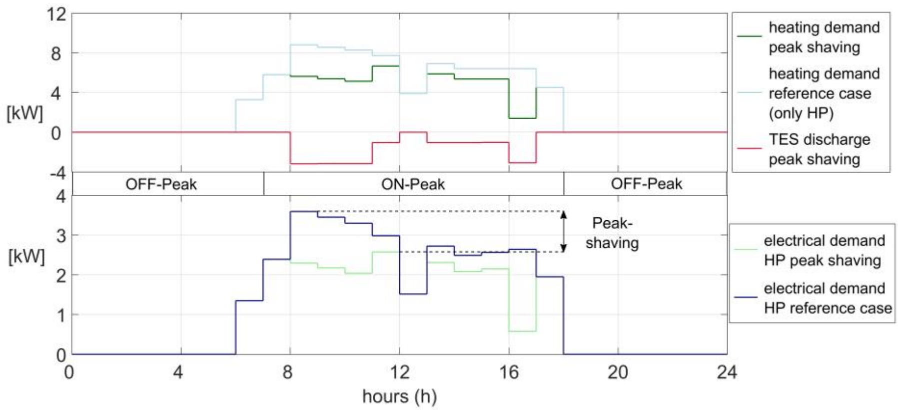

Fig. 4 Optimization results – peak shaving vs. reference case, upper diagram shows the heat transferred from HP to building for the reference and the heat transferred from HP and TES to building for the specific peak shaving case, lower diagram shows the power consumption of the HP for both cases indicating the peak shaving during on-peak period

The 2nd simulation case investigated the peak shaving of the reference case by optimizing the discharging of the TES (Figure 4). For the TES water tank a volume of 0.75 m^3 was chosen. The initial tank temperature was set to 40 °C and the tank temperature at the end of the discharging process to 20 °C (ΔT = 20 K).

Further simulations were performed considering various tank volumes (0.1 – 1m^3) to indicate the peak shaving potential of different energy storage capacities (Figure 5). It can be seen that a tank of 0.75 m^3 with ΔT = 20 K can significantly reduce the daily electricity peak load of a small scale office building to 72 % of maximum.

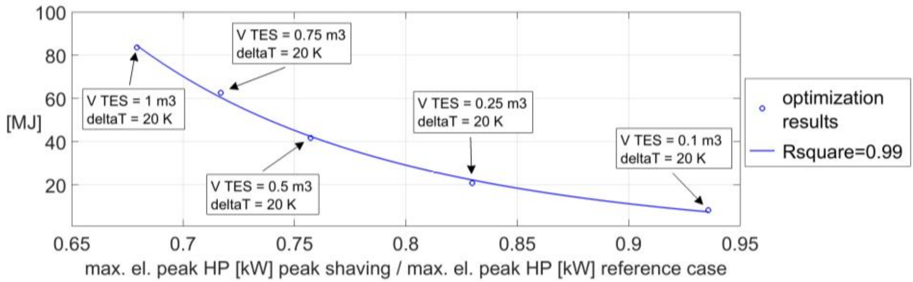

Fig. 5 Optimization results – peak shaving, the diagram shows the peak shaving potential for different energy storage capacities

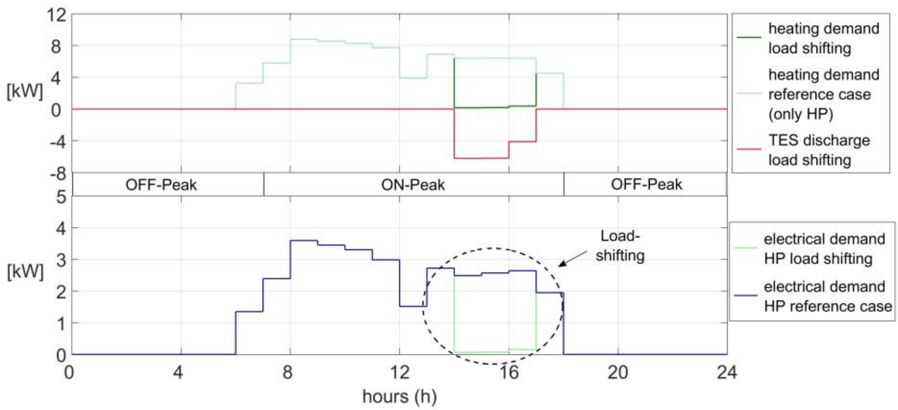

Fig. 6 Optimization results – load shifting vs. reference case, upper diagram shows the heat transferred from HP to building for the reference and the heat transferred from HP and TES to building for the specific load shifting case, lower diagram shows the power consumption of the HP for both cases indicating the preferred load shifting during on-peak period

As a second optimization strategy this study investigated the load shifting to the on-peak period. In particular, this strategy considers discharging preferences, t_{ls} as preferred discharging time and $t_{window,ls}$ as preferred discharging period within the on-peak period. As an example, figure 6 illustrates the load shifting for the case with one Gaussian window including the preferred discharging time 15.00 – 16.00 (equal to the simulation time step of 1 h) and a time window of 2 h (± 1 h). The discharging of a TES tank with 0.75 m^3 mainly takes place between 14.00 and 17.00 which is in a good agreement with the load shifting preferences. Those preferences were implemented in the optimization while meeting all constraints.

Based on the optimization results of the reference case, peak shaving case and load shifting case, the building to grid flexibility could be calculated. As introduced in the previous sections this particular flexibility is calculated at each time step (hourly) over the prediction horizon of 24 h. Figure 7 illustrates the day ahead prediction of the flexibility to disconnect the HP at each moment of the day.

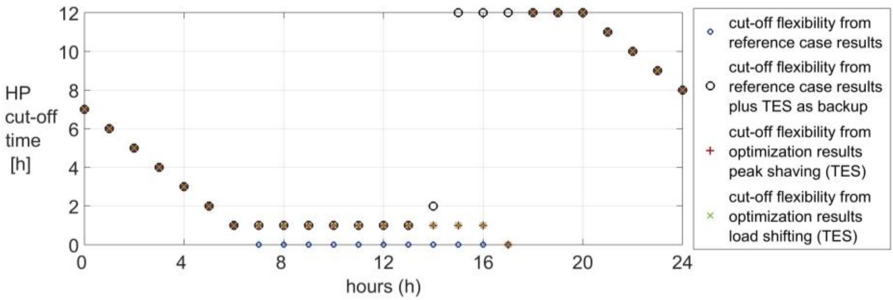

Fig. 7 cut-off flexibility based on the results of the optimization strategies shown in figure 3,4 and 6. The diagram describes the disconnection of the HP from the grid. At each full hour of the day the calculated flexibility represents the maximum duration of disconnecting the HP from the grid while meeting the comfort bounds. The possible maximum duration was determined not to extend the value of 12 h

The cut-off flexibility of the reference case with a fully charged TES (0.75 m^3 and ΔT = 20 K) as a backup achieves the highest flexibility at each moment of the day. This is as expected since all the other strategies include the same optimization constraints and either consume energy from the TES during the day (peak shaving and load shifting) or do not have a TES as backup (reference case without TES). At 14.00, for instance, the reference case without backup does not provide any flexibility, the peak shaving and load shifting case can provide a flexibility of disconnecting the HP for one hour. And finally, the reference case with TES backup enables a two hours HP cut-off flexibility without compromising thermal comfort of occupants.

4. Discussion

The introduced optimization methodology enables the simulation of peak shaving and load shifting for a small scale office building connected to a TES tank. The major advantage of this methodology is the exchangeability of building and storage models. The DP allows to connect different models that can be white, grey or black box models. The only necessity is to provide an interface to exchange information about state variables. The drawback of the DP is the number of state variables that can be applied.

The more state variables the model includes the higher the computational effort becomes. In this study the model considered 2 state variables (zone and storage temperature). The duration of a 24 h simulation was improved to last 24 min using Intel® Core™2 Duo CPU E8400 @3.00 GHz. The duration is also due to iterations of the building model updating the zone temperature as state variable. A possible solution to decrease the simulation time and to overcome the curse of dimension is the application of approximations. However, this will be subject of further investigations.

What has been barely discussed so far is the implementation into the process control of buildings. Since we introduced an optimization methodology and highlighted the major advantage of exchangeability of connected models, the methodology is flexible to be implemented. Still, a practical implementation has to show the control performance. This includes also benchmarking to other comparable model-based methodologies such as MPC (model predictive controller). This will be part of future publications.

So far, the simulations have been performed including a building model based on an advanced RC network. Since the BRCM toolbox enables the use of a well-developed and validated building model, the dynamics of a small scale office building are sufficiently represented. The use of a one node TES model is sufficiently representing the dynamics of a TES water tank since the focus was set on the optimization methodology. Using such a model in the framework of model-based process control is likely to cause underperformance of the model-based controller because TES heat transfer phenomena such as convection and conduction are not included. Therefore, a TES model of higher complexity needs to be connected. Further simplifications assumed in the simulations relate to the HVAC system. So far, the model only considers a heat pump as heating source. No other components such as pipes, radiators etc. have been connected.

We introduced and calculated a building to grid energy flexibility that can limit the electricity consumption of the heat pump. This is a very valuable information to optimize the balancing of the power grid that is dominated by intermittent renewables. Short-term changes due to the scarcity of solar and wind can be better matched knowing the flexibility to adjust building power consumption. Similarly, the building to grid flexibility enables matching of supply and demand when observing a surplus of renewables. In this case, the building is offered to take up energy from the grid. This might be done by charging any available thermal storage without compromising thermal comfort of occupants. This building to grid charging flexibility can be calculated using the same methodology as proposed in this study and will be part of future publications.

5. Conclusion

This study introduces an optimization methodology for a small scale office building connected to a TES tank using dynamic programming. The method is generic because of exchangeability of the building and storage models. Optimization results for peak shaving show that a 0.75 m³ water tank with a temperature difference of 20 K can reduce the daily heating electricity peak load to 72 % during a typical Dutch winter day.

We have successfully demonstrated peak shaving and load shifting of buildings energy demand by optimizing the discharge of a TES water tank. Based on the optimization results of various cases the study proposes a building to grid energy flexibility. In particular, the flexibility to limit the electricity demand of the heat pump while predicting and meeting thermal comfort of occupants was calculated. In future studies we will consider the flexibility of charging as well as the flexibility of other HVAC components and electricity devices such as lighting. It is to emphasize that calculating the flexibility based on optimization results is a valuable information of balancing the power grid. In future work, we will go a step beyond this approach and integrate the flexibility into the objective function. This will result in an integral optimization methodology including energy supply and demand.

Acknowledgment

This work has been supported by OTIB, PIT, BAM Techniek and EBC Annex 67 Energy Flexible Buildings.

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