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Optimal Solar Energy Utilization in Building Operation under Weather Uncertainty

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ABSTRACT

In this paper, we present an emulator that is built to evaluate the closed-loop operation of an integrated solar system under uncertain solar irradiance forecast. The energy system includes (i) A building-integrated photovoltaic/thermal (BIPV/T) system; (ii) An air-to-water solar-assisted heat pump; (iii) A thermal energy storage (TES) tank; (iv) A radiant floor heating system used to condition an open-plan office space. The outlet air from the solar collector of the BIPV/T system serves as the source side for the heat pump, the load side of which is connected to the TES tank. We model the solar irradiance as non-Gaussian stochastic disturbance affecting the cost and constraints, using a probabilistic time-series autoregressive model that takes sky-cover values from an external weather forecast service provider. Approximate dynamic programming methodology is deployed in the controller to solve the stochastic optimal control problem, and achieve good solution quality. The emulator couples the physical system models in TRNSYS with the stochastic model predictive controller developed in Python and MATLAB. The results show that the proposed approach saves up to 44% of the electricity consumption for heating in a winter month, compared to a well-tuned rule-based controller.

1. INTRODUCTION

Building-integrated solar technologies allow onsite collection of solar power and heat, which can be utilized by HVAC systems (Chen et al., 2010). Compared to conventional heat pumps, solar-assisted heat pump (SAHP) systems with thermal energy storage (TES) devices are able to utilize solar heat and achieve higher energy efficiency (Chu and Cruickshank, 2014). Due to the ease of maintenance/installation, as well as the high efficiency of the system, indirect series systems are suitable for cold climate applications (Chu et al., 2014). Model predictive control (MPC) has been proven as an effective strategy to operate solar energy systems with thermal storage (Candanedo and Athienitis, 2011; Pichler et al., 2014). In typical control-oriented models of heat pumps, the dependency of the coefficient of performance (COP) and capacity on the load and source side temperatures is an important feature (Verhelst et al., 2012). Thus, in the case of indirect series systems, the COP and capacity depend on the thermal storage tank temperature and solar irradiance, which is stochastic by nature and imposes challenges by introducing uncertainty on the cost and constraints.

For solar systems, considering the uncertainty in solar irradiance forecast enables decisions with improved risk tolerance and system performance (Petersen and Bundgaard, 2014). Stochastic model predictive control (SMPC) is a promising approach as it directly accounts for the uncertainty in weather forecast, and enables the use of chance constraints representing conditions that are satisfied with a predefined probability (Oldewurtel et al., 2012). However,
this approach requires up-to-date disturbance forecast information for every prediction horizon. Also, forecast models need to (i) incorporate the physical nature of the disturbances; (ii) take advantage of existing information such as recent measurements and external forecast; and (iii) entail a certain level of fast computation for implementation in actual controllers (Lazos et al., 2014).

In this paper, we demonstrate an emulation framework for optimal solar energy utilization of an integrated solar-system. We present a probabilistic time-series autoregressive model that takes sky-cover forecast values from an external weather forecast service to predict uncertain solar irradiances. Stochastic model predictive control is implemented to account for the uncertainty in solar irradiance forecast and minimize net energy consumption while maintaining thermal comfort.

2. METHODOLOGY

2.1 Emulator

Figure 1 shows the system emulation diagram. The test-space is one of the Living Labs located in Herrick Laboratories building at Purdue campus. A building-integrated photovoltaic/thermal (BIPV/T) system with a corrugated unglazed transpired solar collector (UTC) is installed on the top section of the south façade of the Living Lab, allowing on-site generation of solar power and heat. The outlet air from the UTC provides heat to the source side for an air-to-water solar-assisted heat pump, while the load side of the heat pump is connected to a TES tank, which supplies hot water to the radiant floor (RFH) system. Physical models for the building, BIPV/T system, RFH, and TES tank are built in TRNSYS and details for the model settings are presented in Li et al., (2015). The data-driven heat pump model is developed in MATLAB.

The predictive controller is developed in Python and it is coupled with TRNSYS Type 155 using MATLAB as middleware. While the building and energy system in TRNSYS receive real time measured weather data, the predictive controller reads the up-to-date weather forecast to quantify the solar irradiance uncertainty based on sky-cover forecast. Also, real time updates from the system in TRNSYS are sent to the predictive controller as feedback. Based on the weather forecast and the feedback, the controller predicts the optimal heating power to implement in the system for the upcoming hour.

![System emulation diagram.](image)

2.2 Solar Irradiance Forecast Model

A solar irradiance forecast model is incorporated in the predictive controller to predict the global horizontal irradiance ($I_{g,t}$) at a future time $t$ given a sky-cover forecast ($s_{ct}$). We assume that the forecast values obtained from the National Oceanic and Atmospheric Administration (NOAA) are accurate for a 24-hour horizon. We model the cloud variability over time using an autoregressive process while using a probabilistic model to classify the sky condition as clear ($c_t = 1$), partly-cloudy ($c_t = 2$), and overcast ($c_t = 3$) based on the hourly-updated sky-cover forecast. The form of our model is:

$$I_{g,t}(a_t, c_t) = I_{dir, dir,t} \cdot \left(\text{sgn}(a_{1,t})\right)^{1-l_1(c_t)} 1_{\{1,2\}}(c_t) + I_{dir,diff,t} \cdot \left(\text{sgn}(a_{2,t})\right)^{1-l_2(c_t)}$$  \hspace{1cm} (1)

The clear-sky direct ($I_{dir, dir,t}$) and diffuse ($I_{dir, diff,t}$) horizontal irradiance can be obtained from a model developed by Bird and Hulstrom, (1981). When $c_t = 1$, the direct ($I_{dir,t}$) and diffuse ($I_{diff,t}$) horizontal solar irradiances are equal to
clear-sky direct and diffuse horizontal solar irradiance, respectively. When \( c_i = 2 \), the direct and diffuse horizontal irradiances are only a fraction of the clear-sky direct and diffuse horizontal irradiance. When \( c_i = 3 \), the direct horizontal irradiance is 0. Thus, the global horizontal irradiance is only a fraction of the clear-sky diffuse horizontal irradiance. \( I_A(\cdot) \) is the characteristic function of a set \( A \) \( (I_A(x) = 1 \) if \( x \in A \) and 0 otherwise), and the indicator function \( I(\cdot) = \{I_1(\cdot), I_2(\cdot)\} \) is defined by \( I(1) = (1,1) \), \( I(2) = (0,0) \), and \( I(3) = (1,0) \).

For a certain value of the sky-cover \( SC_t \), any of the three conditions, \( c_i = 1, 2, \) or 3, are possible as the sky-cover value is a spatial average of the fraction of the sky covered by clouds. To model this uncertainty, we assume that the probability of the sky condition \( c_i \) depends only on the sky-cover \( SC_t \) via a logistic regression expression:

\[
p(c_i = i|SC_t) = \frac{e^{r_i SC_t}}{1 + e^{r_i SC_t}}, \quad i = 1, 2, 3,
\]

where the parameters \( r_1 = -7, r_2 = 0 \) and \( r_3 = 7 \) are from local typical meteorological year (TMY3) data.

We model the cloud variability by a 2-D autoregressive process, in which, the future state is expressed as a linear function of the current state plus a Gaussian error term. Thus, the error can accumulate as the time step increases, and the autoregressive process captures the increase in solar irradiance uncertainty within a prediction horizon. The latent 2-D autoregressive process (\( a_t \)) is given by:

\[
a_{1,t+1} = \alpha_1 a_{1,t} + \sigma_1 z_{1,t},
\]

\[
a_{2,t+1} = \alpha_2 a_{2,t} + \sigma_2 z_{2,t},
\]

where \( z_t = (z_{1,t}, z_{2,t}) \) is a 2-D Gaussian noise, and the parameters \( \alpha_1 = 0.1, \alpha_2 = 0.1, \sigma_1 = 0.6 \) and \( \sigma_2 = 0.1 \) are inferred from TMY3 data. Details on the model training and validation are presented in Liu et al., (2018).

### 2.3 Predictive Controller

We implement stochastic model predictive control for the solar system operation as it accounts for the uncertain solar forecast, while satisfying the constraints on equipment capacity and room conditions affecting occupant thermal comfort. Figure 2 shows the flow chart of the optimal control algorithm for each prediction horizon. At the beginning of a prediction horizon (\( K = 24 \) hours), the predictive controller reads the initial temperature states (\( x_0 \)) from TRNSYS and it also receives weather forecast information (sky-cover, outdoor dry bulb temperature, etc.) for the prediction horizon. The solar forecast model in Section 2.2 is used to quantify the uncertainty in solar irradiance. Optimal control decisions are made every 1 hour (control horizon) between 6:00 am and 20:00 pm.

**Figure 2:** Optimal control algorithm.

The objective function is the expected value of the accumulated electric energy consumption over the prediction horizon \( K \):
\[
\min_{u_0:K-1} \mathbb{E} \left[ \sum_{t=0}^{K-1} J_t(x_t, u_t, I_{g,t}) \right],
\]
where the cost at a time \( t \) is:
\[
J_t(x_t, u_t, I_{g,t}) = \begin{cases} 
\frac{HC_{\text{max}}(x_t, v_t, I_{g,t}) + \eta_h}{\text{COP}_t(x_t, v_t, I_{g,t})}, & \text{if } HC_{\text{max}}(x_t, v_t, I_{g,t}) < u_t \leq u_{\text{max}}(x_t, v_t, I_{g,t}) \\
u_t, & \text{if } 0 \leq u_t \leq HC_{\text{max}}(x_t, v_t, I_{g,t}).
\end{cases}
\]

(5)

The control variable \( (u_t) \) is the total heating power provided by the air-to-water heat pump and the backup heater (installed in the TES tank in case of insufficient heating from the heat pump). Equation (6) represents the sum of the electricity consumption from the heat pump and the backup heater at a time step. The COP and maximum heating capacity \( (HC_{\text{max},t}) \) of the heat pump at time \( t \) are functions of the solar irradiance \( (I_{g,t}) \) and outdoor dry bulb temperature (through the outlet air temperature of the UTC, \( T_{\text{bipvt},t} \)) and the tank temperature \( (T_{\text{tank},t}) \), which is one of the system states \( (x_t) \). The backup heater has a maximum capacity \( (P_{\text{max}}) \) of 5000 watts and efficiency of 90% \( (\eta_h) \). A UTC model \((\text{Li et al., 2014})\) incorporated in the controller receives information on the predicted solar irradiance from the forecast model, along with the outdoor dry bulb temperature forecast \((\text{which is part of the exogenous inputs}) v_t\). and calculates \( T_{\text{bipvt}} (T_{\text{bipvt},t} = q (v_t, I_{g,t})) \) during the prediction horizon. Therefore, the COP and \( HC_{\text{max}} \) are both functions of the system states, exogenous inputs, and solar irradiance:
\[
\text{COP}_t(x_t, v_t, I_{g,t}) = 6.2504 + 0.13387 T_{\text{bipvt},t} - 0.09867 T_{\text{tank},t} + 0.005864 T_{\text{bipvt},t}^2
\]
\[+ 0.0004 T_{\text{tank},t}^2 - 0.0015 T_{\text{bipvt},t} T_{\text{tank},t},
\]
\[HC_{\text{max}}(x_t, v_t, I_{g,t}) = 25.3537 + 0.73377 T_{\text{bipvt},t} - 0.06237 T_{\text{tank},t} + 0.0056 T_{\text{bipvt},t}^2
\]
\[+ 0.0017 T_{\text{tank},t}^2 - 0.0047 T_{\text{bipvt},t} T_{\text{tank},t}.
\]

(7)

Equations (7) and (8) show that the efficiency and capacity of the heat pump increase as \( T_{\text{bipvt}} \) increases. The low-order system model used in the controller is shown in Figure 3 while additional details are provided in \( \text{Li et al., 2015} \). The system dynamics is given by:
\[
x_{t+1} = Ax_t + Bu_t + B_v v_t + B_w w_t,
\]

(10)

where
\[
x_t = \begin{bmatrix} T_{\text{room},t} \\
T_{\text{floor},t} \\
T_{\text{tank},t} \\
T_{\text{enve},t} \\
a_{1,t} \\
a_{2,t}
\end{bmatrix},
\]
\[
v_t = \begin{bmatrix} T_{a,t} \\
T_{a2} \\
T_{a3} \\
IG(t) \end{bmatrix},
\]
\[
w_t = \begin{bmatrix} h_1 (I_{g,t}(a_t, c_t)) \\
h_2 (I_{g,t}(a_t, c_t)) \end{bmatrix},
\]\n\[
a_t = \begin{bmatrix} a_{1,t} \\
a_{2,t}
\end{bmatrix}.
\]

\( x_t \) is the system state vector, in which \( T_{\text{enve}} \) is the average envelope temperature of the room, \( T_{\text{room}} \) is the room air temperature, \( T_{\text{floor}} \) is the average floor slab temperature, \( T_{\text{tank}} \) is the average tank temperature, \( a_t = (a_{1,t}, a_{2,t}) \) is the state of the solar irradiance model. \( v_t \) is the external input vector, in which \( T_a \) is the outdoor dry bulb temperature from the NOAA weather forecast. We do not consider the forecast uncertainty on \( T_a \) as it is typically small and would have negligible impact on this heavy thermal mass system. \( IG \) is the internal heat gain, which is considered known based on the building operation schedule. The variables \( T_{a2} \) and \( T_{a3} \) represent the ambient temperature of the TES tank and air temperature of the adjacent zone, respectively, and are assumed to be constant. The stochastic disturbance
$w_t$ corresponds to the 2-D Gaussian noise $z_t$, perturbing $a_t$ as well as to the random sky condition $c_t$. The function $l_{g,t}(a_t, c_t)$ is the global horizontal irradiance (see Section 2.2), while,

$$h(l_{g,t}) = \begin{bmatrix} h_1(l_{g,t}) \\ h_2(l_{g,t}) \end{bmatrix} = \begin{bmatrix} q_{SG1,t} \\ q_{SG2,t} \end{bmatrix},$$

gives the solar heat gain on the floor ($q_{SG2}$) as well as other building interior surfaces ($q_{SG1}$). $A \in \mathbb{R}^{6 \times 6}$, $B_u \in \mathbb{R}^{6 \times 1}$, $B_v \in \mathbb{R}^{6 \times 4}$ and $B_w \in \mathbb{R}^{6 \times 4}$ are time invariant matrices.

![Figure 3: The thermal network for the state-space model (Li et al., 2015).](image)

We use chance constraints on the temperature states and feasible sets of control inputs. The following constraints impose minimum bounds on the expected room, floor and tank temperatures,

$$E[x_{i,t+1}] - T_{\text{min},i,t+1} \geq 0,$$

for the first 3 states $i = 1, \ldots, 3$. Similarly, the constraints below impose maximum bounds on the expected building temperatures,

$$T_{\text{max},i,t+1} - E[x_{i,t+1}] \geq 0,$$

where $T_{t,\text{max}}$ and $T_{t,\text{min}}$ are known based on the values and schedules given in Liu et al., (2018). Finally, we enforce with high probability the control bounds with the following constraint. A small value of $\alpha = 1\%$ is used to ensure that, with 99\% of the probability, the control input $u_t$ does not exceed the equipment capacity,

$$\mathbb{P} \left[ 0 \leq u_t \leq u_{\text{max},i} \left( x_t, v_t, l_{g,t}(a_t, c_t) \right) \right] \geq 1 - \alpha.$$

To solve the optimal control problem at each prediction horizon in the SMPC, we use a new approximate dynamic programming (ADP) methodology (Bertsekas, 1995) that represents the optimal cost-to-go functions using Gaussian process regression (Rasmussen & Williams, 2006), and achieves good solution quality (Liu et al., 2018). Our implementation is based on the Python package developed by Paritosh et al., (2017). A complete ADP solution for a 24-hour prediction horizon takes about 30-40 minutes in average considering the system operation schedule using 100 nodes at Rice supercomputing cluster at Purdue University.

## 3. RESULTS ANALYSIS

In this section, we present emulation results to compare the performance of SMPC with two other control approaches. A benchmark control strategy is the theoretical performance bound (PB), in which we assume that the future actual weather condition is perfectly known in advance. Therefore, both the controller and TRNSYS receive measured weather data in PB. A well-tuned rule-based control (RBC) is also used as baseline. The RBC considers weather forecast information including outdoor dry bulb air temperature ($T_a$) and sky-cover (sc). It predicts heat pump power ($Q_{hp}$) aiming at utilizing solar energy to improve the system efficiency. Therefore, the schedule strictly follows solar availability considering some thresholds of outdoor dry bulb temperature. The details of the RBC are presented in Appendix A. A 24-hour prediction horizon is implemented for the SMPC and PB. The same initial temperature states are used for all cases. To eliminate the effect of initial states, we use a pre-simulation period of five days. The occupied-hour temperature exceedance (in °C-hr, ASHRAE Standard 55, 2013) and electricity consumption (in kWh), are used as performance metrics.
\[
\Delta T_{\text{op}} = \sum_{\text{occupied}} (|T_{\text{op}}^t - T_{\text{set}}| \Delta t).
\]

where \( T_{\text{op}} \) is the operative temperature in °C; \( T_{\text{set}} \) is the setpoint temperature in °C; \( \Delta t \) is the time step in hour. The occupied hours we considered in this study are from 8:00 am to 18:30 pm.

Emulations were performed for a winter month (Jan. 16th to Feb. 16th, 2017) for the three control strategies and the results are shown in Table 1. During this period, the outdoor dry bulb temperature varies from -15°C to 18°C. Overall, SMPC results in slightly less temperature exceedance (3.22°C-hr in occupied hours) but higher electricity consumption (57.28 kWh, 34.7%) over a month compared to PB. Compared to RBC, SMPC saves around 44.0% (177.09 kWh) electricity consumption. Also, SMPC improves room thermal comfort, reducing the temperature exceedance during occupied hours to 25.1% of RBC.

### Table 1: Performance metrics comparison for the winter month emulation (Jan. 16th – Feb. 16th, 2017).

<table>
<thead>
<tr>
<th>Metrics</th>
<th>SMPC</th>
<th>PB</th>
<th>RBC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature exceedance (occupied hours) (°C-hr)</td>
<td>Lower-setpoint: 77.86 Upper-setpoint: 104.50 Total: 182.36</td>
<td>Lower-setpoint: 84.85 Upper-setpoint: 100.73 Total: 185.58</td>
<td>Lower-setpoint: 0 Upper-setpoint: 727.54 Total: 727.54</td>
</tr>
<tr>
<td>Total heating energy (kWh)</td>
<td>664.80</td>
<td>566.80</td>
<td>1574.00</td>
</tr>
<tr>
<td>Total electricity (kWh)</td>
<td>222.41</td>
<td>165.13</td>
<td>399.50</td>
</tr>
</tbody>
</table>

### 4. CONCLUSIONS

In this paper we presented an emulation framework to demonstrate the closed-loop operation of a building-integrated solar system with a stochastic model predictive controller that optimizes solar energy utilization under uncertain solar forecast. The results show that SMPC outperforms rule-based control (RBC) in terms of both energy savings and temperature control. For the integrated system and climate considered in this work, it reduces the electricity consumption by 44% in a winter month and reduces thermal comfort violations by 75%. In summary, the developed SMPC approach has shown promising results for the operation of building-integrated solar systems as it achieves similar performance on comfort control and results in more realistic energy savings compared to the performance bound (PB), which assumes perfect knowledge of the future disturbances. It should be noted that its performance in actual implementation also depends on the accuracy of the process model and input data.

### NOMENCLATURE

- \( sc \): sky-cover, %
- \( I_{\text{dir}} \): direct horizontal irradiance, W/m²
- \( c \): sky condition
- \( K \): prediction horizon
- \( u_t \): control input at time \( t \)
- \( v_t \): the vector of exogenous inputs at time \( t \)
- \( B \): input matrix
- \( z_t \): the Gaussian noise at time \( t \)
- \( T_o \): outdoor dry bulb temperature, °C
- SMPC: stochastic model predictive control
- GPR: Gaussian process regression
- COP: Coefficient of Performance
- RFH: radiant floor heating
- UTC: unglazed transpired solar collector
- \( I_g \): global horizontal irradiance, W/m²
- \( I_{\text{dir}} \): diffuse horizontal irradiance, W/m²
- \( t \): time step index
- \( x_t \): the vector of system states at time \( t \)
- \( w_t \): the vector of stochastic disturbances at time \( t \)
- \( A \): state matrix
- \( a \): the vector of autoregressive process
- \( Q_{\text{hp}} \): heat pump heating power, kW
- MPC: model predictive control
- ADP: approximate dynamic programming
- BIPV/T: building-integrated photovoltaic-thermal
- HVAC: Heating, Ventilation and Air-Conditioning
- TES: thermal energy storage

### REFERENCES


**APPENDIX A. RULE-BASED CONTROL**

<table>
<thead>
<tr>
<th>Time of the day</th>
<th>Heat pump operations</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>0-6 am</strong></td>
<td>• $Q_{hp} = 0$ kW.</td>
</tr>
<tr>
<td><strong>6-8 am</strong></td>
<td>• $Q_{hp} = 5$ kW, if $T_a \leq 8°C$ for the following period (8-10 am) in average.</td>
</tr>
<tr>
<td></td>
<td>• $Q_{hp} = 0$ kW, otherwise.</td>
</tr>
<tr>
<td><strong>8-10 am</strong></td>
<td>• Find $Q_{hp}$ values from Table C2, if $T_a \leq -8°C$ for the following period (10 am-12 pm) in average.</td>
</tr>
<tr>
<td></td>
<td>• Find $Q_{hp}$ values from Table C3, if $-8°C &lt; T_a \leq 0°C$ for the following period (10 am-12 pm) in average.</td>
</tr>
<tr>
<td></td>
<td>• Find $Q_{hp}$ values from Table C4, if $0°C &lt; T_a \leq 8°C$ for the following period (10 am-12 pm) in average.</td>
</tr>
<tr>
<td></td>
<td>• $Q_{hp} = 0$ kW, otherwise.</td>
</tr>
<tr>
<td><strong>10 am -12 pm</strong></td>
<td>• Find $Q_{hp}$ values from Table C2, if $T_a \leq -8°C$ for the following period (12-14 pm) in average.</td>
</tr>
<tr>
<td></td>
<td>• Find $Q_{hp}$ values from Table C3, if $-8°C &lt; T_a \leq 0°C$ for the following period (12-14 pm) in average.</td>
</tr>
</tbody>
</table>
Find \( Q_{hp} \) values from Table C4, if \( 0 ^\circ C < T_a \leq 8 ^\circ C \) for the following period (12-14 pm) in average.

\[ Q_{hp} = 0 \text{ kW, otherwise.} \]

12-14 pm

- Find \( Q_{hp} \) values from Table C2, if \( T_a \leq -8 ^\circ C \) for the following period (14-16 pm) in average.
- Find \( Q_{hp} \) values from Table C3, if \(-8 ^\circ C < T_a \leq 0 ^\circ C \) for the following period (14-16 pm) in average.
- Find \( Q_{hp} \) values from Table C4, if \( 0 ^\circ C < T_a \leq 8 ^\circ C \) for the following period (14-16 pm) in average.
- \( Q_{hp} = 0 \text{ kW, otherwise.} \)

14-16 pm and 16-20 pm

- Find \( Q_{hp} \) values from Table C2.

- Find \( Q_{hp} \) values from Table C3, if \( T_a \leq -8 ^\circ C \) for the following period (14-16 pm) in average.
- Find \( Q_{hp} \) values from Table C4, if \( 0 ^\circ C < T_a \leq 8 ^\circ C \) for the following period (14-16 pm) in average.
- \( Q_{hp} = 0 \text{ kW, otherwise.} \)

Table A2: Heat pump power input look-up table (8am, 10am and 12pm, \( T_a \leq -8 ^\circ C \))

<table>
<thead>
<tr>
<th>( Q_{hp} ) in kW</th>
<th>Average sc at the following period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&gt;0.8</td>
</tr>
<tr>
<td>Average sc at the current period</td>
<td></td>
</tr>
<tr>
<td>&gt;0.8</td>
<td>10</td>
</tr>
<tr>
<td>0.5-0.8</td>
<td>8</td>
</tr>
<tr>
<td>0.2-0.5</td>
<td>6</td>
</tr>
<tr>
<td>&lt;0.2</td>
<td>6</td>
</tr>
</tbody>
</table>

Table A3: Heat pump power input look-up table (8 am, 10 am and 12 pm, \(-8 ^\circ C < T_a \leq 0 ^\circ C \))

<table>
<thead>
<tr>
<th>( Q_{hp} ) in kW</th>
<th>Average sc at the following period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&gt;0.8</td>
</tr>
<tr>
<td>Average sc at the current period</td>
<td></td>
</tr>
<tr>
<td>&gt;0.8</td>
<td>5</td>
</tr>
<tr>
<td>0.5-0.8</td>
<td>5</td>
</tr>
<tr>
<td>0.2-0.5</td>
<td>4</td>
</tr>
<tr>
<td>&lt;0.2</td>
<td>4</td>
</tr>
</tbody>
</table>

Table A4: Heat pump power input look-up table (8 am, 10 am and 12 pm, \( 0 ^\circ C < T_a \leq 8 ^\circ C \))

<table>
<thead>
<tr>
<th>( Q_{hp} ) in kW</th>
<th>Average sc at the following period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&gt;0.8</td>
</tr>
<tr>
<td>Average sc at the current period</td>
<td></td>
</tr>
<tr>
<td>&gt;0.8</td>
<td>2</td>
</tr>
<tr>
<td>0.5-0.8</td>
<td>2</td>
</tr>
<tr>
<td>0.2-0.5</td>
<td>2</td>
</tr>
<tr>
<td>&lt;0.2</td>
<td>2</td>
</tr>
</tbody>
</table>

Table A5: Heat pump power input look-up table for 14-16 pm and 16-20 pm

<table>
<thead>
<tr>
<th>( Q_{hp} ) in kW</th>
<th>14-16 pm</th>
<th>16-20 pm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average ( T_a ) for the next 28 hours</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( T_a &gt; 8 ^\circ C )</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>( 0 ^\circ C &lt; T_a \leq 8 ^\circ C )</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>(-8 ^\circ C &lt; T_a \leq 0 ^\circ C )</td>
<td>6</td>
<td>4</td>
</tr>
<tr>
<td>( T_a \leq -8 ^\circ C )</td>
<td>8</td>
<td>6</td>
</tr>
</tbody>
</table>