Model Predictive Control Framework for Operation of Smart Sustainable Buildings

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Abstract
Buildings are a major contributor to global primary energy consumption and total greenhouse gas emissions. However, buildings have immense potential to improve the efficiency of the global energy sector. This paper investigates the use of model predictive control (MPC) for the operation of a large variety of energy devices in a building. The optimization problem is formulated as a mixed-integer-linear-program (MILP). Apart from cost minimization, an original feature of this work is that a novel sustainability criterion is implemented to maintain the net-zero-energy (nZE) target of the building. The proposed framework is simulated with two different electricity price tariff structures. The simulation results showed a 12\% reduction in energy cost for the proposed approach in comparison to the benchmark model when simulated for one month period.

Key Innovations

The overall contribution of the present work to the scientific literature can be summarized as follows –

- \textit{Modelling framework for energy devices} – The presented framework incorporates accurate modelling of the internal dynamics of energy devices that can provide demand response flexibility in a generic domestic building. These include heating ventilation and air condition system, hot water system, battery storage system, photovoltaic panel, electric vehicle and other shiftable loads (washing machine, dryer and dishwasher).

- \textit{Introduction of sustainability criterion} – In addition to the operating cost minimization, the building energy management system (BEMS) aims to maintain the building’s sustainability by enforcing a novel adaptive sustainability criterion that monitors and regulates the building’s nZE status. This is generally a less explored idea in the literature.

Practical Implications

The proposed framework would be suitable for implementation in BEMS of real-buildings. An important application of the proposed BEMS would be in energy retrofitting of existing structures. An important point that must be considered during the real-life implementation of the proposed approach is the uncertainty in the external disturbances forecast.

Introduction
Buildings are seen as key entities in the energy infrastructure, which has immense potential to reduce greenhouse gas emissions (GHG) and improve the global energy sector’s efficiency. To tap into this enormous potential, a shift towards smart-sustainable buildings (SSBs) is needed. In SSBs, the fundamental aim is to not only improve the energy efficiency through intelligent control (\textit{smart}) but also to reduce the overall GHG emissions during the operational phase of the building via local renewable energy production (\textit{sustainable}). The sustainability of an SSB at its operation stage can be ensured if its on-site renewable energy production nearly compensates its yearly energy consumption, thus designating the term \textit{nearly zero-energy buildings (nZEB)} (Annunziata et al., 2013). However, transitioning towards SSBs includes technical challenges such as implementing smart infrastructures like a BEMS that can automatically and optimally steer renewable energy sources, energy storage, and buildings’ energy load (Shareef et al., 2018).

BEMS operates the energy devices of building with the help of smart sensors, smart meters, bi-directional communication with the grid and advanced control techniques. One such technique is MPC, in which the optimization problem is solved at each time step with updated information about the system and external disturbances. MPC has been widely used in the power system community on various topics ranging from microgrid operation (Bordons et al., 2020), voltage and frequency control (Ersdal et al., 2015), flexibility optimization on district levels (Diekerhof et al., 2018), etc.

In the context of individual buildings, MPC is mostly used for optimal operation of heating-ventilation-air-conditioning (HVAC) systems, which are the major drivers for shaping the energy demand in buildings. Many studies have also investigated the inclusion of photovoltaics (PVs) (Kuboth et al., 2019), electric vehicles (EVs), battery storage systems (BSS) and thermal energy storage within MPC energy management.
The vast majority of the research works have refrained from modelling a fully comprehensive set of the available elements (RES, energy storage, shiftable loads, HVACs, EV) into a single study, leaving one or the other. For example—many studies opt to use simplistic continuous models for shiftable appliances or cluster the load in the baseline load, unlike the present work, where the intrinsic operation of shiftable load is modelled using sequential operation models through binary variables. While some researchers have made valiant efforts to close this literature gap (Killian et al., 2018), relevant research remains sparse. Another crucial aspect to consider is the building’s environmental impact at the operational stage. Studies have reported that BMES with the sole objective of cost minimization can actually lead to increases in a building’s GHG emissions (Knudsen and Petersen, 2016). Some researchers have addressed this issue by considering CO₂ emission costs in the objective function, formulating the problem as a multi-objective problem (Paridari et al., 2014). In this work, we employ a novel sustainability criterion to monitor and regulate the energy consumption of the building. While minimizing the operational cost remains the driving force of the optimization, the added sustainability criterion effectively upgrades the smart building to a smart-sustainable building by maintaining the nZΕ mandate of the building.

The contribution of this paper is two-fold: 1) to present a BEMS framework with detailed intrinsic modelling of a comprehensive set of energy devices; 2) introduction of a novel sustainability criterion into the optimization problem. The optimization problem is formulated as an MILP program and solved within the MPC scheme. (Camacho and Alba, 2013). MILP programs are mostly solved with branch-and-bound methods. The main advantage of it is that the solution (if reached) is guaranteed to be optimal. With the state-of-the-art optimization solvers, it is possible to set the desired level of optimality also. Other methods like meta-heuristics can take a longer time to reach the optimal solution and may not always guarantee convergence to the optimal solution (Pickering et al., 2016).

**Modeling and Problem Formulation**

In this work, SSB is considered to host the following energy devices (see Fig. 1): PV panel, BSS, HVAC system, domestic hot water (DHW) system, time-shiftable appliances (e.g., washing machine, dishwasher, and clothes dryer) and an EV. SS is assumed to be fully electrified, i.e., complete load demand of the building, including the thermal load, is supplied by electricity. The BEMS have bi-directional communication with all the energy devices, i.e., it can send activation signals to them and receive information about their current states.

The following subsections will present the optimization problem formulation. Let \( \mathcal{H} = \{1, 2, \ldots, H\} \) be the set of time instants with \( H \) as time horizon, and \( \Delta k \) as the sample time.

**Space Heating and Cooling Demand**

The indoor air temperature of the SSB is mainly influenced by the ambient air temperature \((T_a)\), the solar irradiance \((\phi_s)\), and the heating/cooling power \((\phi_h)\) supplied by the HVAC system. The building’s overall thermal dynamics are modeled using a lumped-capacitance method with the indoor air temperature \((T_i)\) and the temperature of the internal heat-accumulating medium \((T_m)\) as states. Internal mass such as furniture, floor, ceiling, etc., are lumped into the internal heat-accumulating medium. The following first-order differential equations represent the thermal dynamics of the building:

\[
C_i \dot{T}_i = \frac{(T_i - T_m)}{R_{im}} + A_w \cdot \eta \cdot \phi_s
\]

\[
C_m \dot{T}_m = \frac{(T_m - T_i)}{R_{im}} + \frac{(T_a - T_i)}{R_{ia}} + \eta_h \phi_h + A_w \cdot (1 - \eta) \cdot \phi_s
\]

where \( C_i \) and \( C_m \) are the heat capacities of indoor air and heat-accumulating medium, \( R_{im} \) is the thermal resistance against heat transfer between indoor air and heat-accumulating medium, and \( R_{ia} \) is the thermal resistance against heat transfer between indoor and external air. \( A_w \) is the building’s effective window area, and \( \eta \) is the fraction of solar irradiance, which directly affects \( T_m \). \( \eta_h \) denotes the efficiency of the HVAC system.

Eq. (2) ensure that the temperature of the indoor air must be maintained between a specified temperature range of \( T_{i, \text{min}} \) and \( T_{i, \text{max}} \) (thermal comfort).

\[
T_{i, \text{min}} - v_{1,k} \leq T_{i,k} \leq T_{i, \text{max}} + v_{2,k} \quad \forall k \in \mathcal{H}
\]

\[
v_{1,k}, v_{2,k} \geq 0 \quad \forall k \in \mathcal{H}
\]

where \( v_1 \) and \( v_2 \) are non-negative slack variables. The slack variables are introduced to avoid numerical infeasibility issues of the optimization problem if the
constraints can not be satisfied. There is usually a large penalty cost associated with these variables, which is included in the optimization problem’s objective function, this is to ensure that the constraints are not compromised unnecessarily. These types of constraints are referred to as soft constraints.

In addition to the constraints on the indoor temperature, the maximum and minimum allowed power consumption of the HVAC system at any given time instant \( k \) is restricted between \( \phi_{h}^{\text{min}} \) and \( \phi_{h}^{\text{max}} \).

\[
\phi_{h}^{\text{min}} \leq \phi_{h,k} \leq \phi_{h}^{\text{max}} \quad \forall k \in \mathcal{H} \quad (3)
\]

### DHW Demand

Domestic hot water is considered to be supplied by a hot water storage tank (HWST). The HWST temperature (\( T_{\text{HWST}} \)) is affected by the heat loss to the ambient, power supplied by the heating element (\( \phi_{\text{htnk}} \)) and the power consumption \( \phi_{c} \) occurred during hot water draw. The overall model is given in eq. (4) which governs the energy balance in the tank.

\[
C_{t} \hat{T}_{\text{tank}} = U_{\text{tank}} A_{\text{tank}} (T_{a} - T_{\text{tank}}) - \phi_{c} + \phi_{\text{htnk}} \quad (4)
\]

where \( U_{\text{tank}} \) represents the heat loss coefficient of HWST to the ambient, \( C_{t} \) is the heat capacity of water in HWST and \( A_{\text{tank}} \) is the surface area of the tank.

The temperature of water in the HWST needs to be maintained between a certain temperature range as follows

\[
T_{\text{tank}}^{\text{min}} - v_{3,k} \leq T_{\text{tank},k} \leq T_{\text{tank}}^{\text{max}} + v_{4,k} \quad \forall k \in \mathcal{H} \\
v_{3,k}, v_{4,k} \geq 0 \quad \forall k \in \mathcal{H} \quad (5)
\]

\( T_{\text{tank}}^{\text{min}} \) and \( T_{\text{tank}}^{\text{max}} \) is the minimum and maximum allowable temperature of water in the HWST. \( v_{3} \) and \( v_{4} \) are slack variables.

The constraint on power consumption of the heating element is given in eq. (6) with \( \phi_{\text{htnk}}^{\text{max}} \) as the maximum allowable power.

\[
0 \leq \phi_{\text{htnk},k} \leq \phi_{\text{htnk}}^{\text{max}} \quad \forall k \in \mathcal{H} \quad (6)
\]

### Battery Storage System

The BSS is modelled using the energy balance approach as follows:

\[
E_{k+1} = E_{k} + \eta_{c} P_{c,k} \Delta k - \frac{P_{d,k}}{\eta_{d}} \Delta k \quad \forall k \in \mathcal{H} \quad (7)
\]

where \( E_{k} \) denotes the energy stored in the battery at time instant \( t \). \( P_{c} \) and \( P_{d} \) are the charging and discharging power of the BSS with \( \eta_{c} \) and \( \eta_{d} \) as the charging and discharging efficiencies respectively.

Eqs. (7) can be rewritten in terms of the state-of-charge (SOC) of the BSS using following relation:

\[
S_{k} = \frac{E_{k}}{E_{\text{max}}} \quad \forall k \in \mathcal{H} \quad (8)
\]

where \( S_{k} \) denotes the SOC of the BSS at time instant \( k \), \( E_{\text{max}} \) is the maximum energy storage capacity of the BSS.

For efficient operation of the BSS, SOC is constrained between a specified range \( S_{\text{min}} \) and \( S_{\text{max}} \) as follows

\[
S_{\text{min}} \leq S_{k} \leq S_{\text{max}} \quad \forall k \in \mathcal{H} \quad (9)
\]

The power input and output of the BSS is restricted by a maximum charging (\( P_{c,\text{max}}^{\text{max}} \)) and discharging power \( P_{d,\text{max}}^{\text{max}} \).

\[
0 \leq P_{c,k} \leq P_{c,\text{max}}^{\text{max}} \quad \forall k \in \mathcal{H} \quad (10a) \]

\[
0 \leq P_{d,k} \leq P_{d,\text{max}}^{\text{max}} \quad \forall k \in \mathcal{H} \quad (10b)
\]

\[
\zeta_{1} + \zeta_{2} \leq 1 \quad \forall k \in \mathcal{H} \quad (10c)
\]

where \( \zeta_{1} \) and \( \zeta_{2} \) are binary variables representing the charging and discharging status of the BSS. Eq. (10c) ensures that the BSS does not charge and discharge simultaneously. Notice that when \( \zeta_{1} \) or \( \zeta_{2} \) are 0, eqs. (10a) and (10b) collapses to keep the charging and discharging power at zero.

### Shiftable Appliances

Shiftable appliances provide further flexibility to the SSB by shifting their power consumption to different time periods depending upon the BEMS objective. The shiftable appliances’ operation can be modelled using various methods; we adopt the sequential operation with binary variables approach in this work (Sou et al., 2011). The appliances are considered to operate in different energy phases. For instance, the first phase of the dishwasher is pre-washing the dishes and then wash, rinse, and drain phases, etc.

### Decision Variables

To model the intricate operation of the shiftable appliances, some decision variables are declared first. Let \( \mathcal{N} = \{1, 2, \ldots, N\} \) denote the set of appliances and \( \mathcal{M}_{i} = \{1, 2, \ldots, M_{i}\} \) denote the set of energy phases associated with the appliance \( i \in \mathcal{N} \). The first decision variable is a binary variable \( \alpha_{i,j}^{k} \) representing the ON/OFF status of the appliance \( i \) in \( \mathcal{N} \) in the energy phase \( j \) at the time step \( k \in \mathcal{H} \), i.e., the value of 1 corresponds to ON status and 0 to the OFF status of the appliance. The power consumption of the appliance \( i \) during the energy phase \( j \) at the time instant \( k \) is denoted by \( P_{i,j}^{k} \). An auxiliary binary variable \( \beta_{i,j}^{k} \) is defined, if an energy phase \( j \) of appliance \( i \) has finished its operation at time instant \( k \), \( \beta_{i,j}^{k} \) assumes the value of 1 and remains unchanged after. Finally, another auxiliary binary variable \( \gamma_{i,j}^{k} \) is defined, which helps keep track of waiting time between different energy phases or appliances.
Operational Time Constraint: This constraint ensures that each energy phase $j$ of an appliance $i$ run for a specified duration $\Omega_{i,j}$.

$$\sum_{k \in \mathcal{H}} \alpha_{i,j}^k = \Omega_{i,j} \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{M}_i$$ (11)

$$\alpha_{i,j}^k = 0 \quad \forall k \in \mathcal{F}_{i,j}$$ (12)

where $\mathcal{F}_{i,j}$ denotes the set of time instants when the energy phase $j$ of appliance $i$ is not allowed to operate.

Continuous Operation Constraint: The following constraint is to guarantee that energy phase remains uninterrupted once started.

$$\alpha_{i,j}^k + \beta_{i,j}^k \leq 1 \quad \forall i \in \mathcal{N}, j \in \mathcal{M}_i, k \in \mathcal{H}$$ (13a)

$$\alpha_{i,j}^{k-1} - \alpha_{i,j}^k \leq \beta_{i,j}^k \quad \forall i \in \mathcal{N}, j \in \mathcal{M}_i, k = 2, 3 \ldots H$$ (13b)

$$\beta_{i,j}^{k-1} \leq \beta_{i,j}^k \quad \forall i \in \mathcal{N}, j \in \mathcal{M}_i, k = 2, 3 \ldots H$$ (13c)

In the above set of constraints, constraint (13a) describes that when energy phase $j$ of the appliance $i$ is in operation at the time instant $k$, $\alpha_{i,j}^k$ is 1 and consequently $\beta_{i,j}^k$ is 0 indicating that the energy phase is not finished yet. As the energy phase is over, eq. (13b) forces $\beta_{i,j}^k$ to switch from 0 to 1 suggesting that the energy phase has finished. Eq. (13c) ensures that once the energy phase is finished $\beta_{i,j}^k$ remains 1 for the rest of the time horizon.

Sequential Operation Constraint: This constraint is to enforce the ordering of the energy phases and appliances. Eq. (14) ensures that the energy phase $j$ is only activated once the energy phase $j - 1$ is finished.

$$\alpha_{i,j}^k \leq \beta_{i,j}^{k-1} \quad \forall i \in \mathcal{N}, k \in \mathcal{H}, j = 2, 3, \ldots M_i$$ (14)

Delay Constraint: This constraint is to model delay between the consecutive energy phases and the appliances by using another auxiliary variable $\gamma_{i,j}^k$.

$$\gamma_{i,j}^k = \beta_{i,j}^k - (\alpha_{i,j}^k + \beta_{i,j}^k) \quad \forall i \in \mathcal{N}, k \in \mathcal{H}, j = 2, 3, \ldots M_i$$ (15)

As per eq. (15), $\gamma_{i,j}^k$ assumes value of 1 only when the energy phase $j - 1$ of appliance $i$ has finished at the time slot $k$ and the energy phase $j$ is yet to start. Once energy phase $j$ is started at time step $k$, $\gamma_{i,j}^k$ switches its value back to 0. So the delay constraint can be formulated as follows

$$D^\text{min}_{i,j} \leq \sum_{k \in \mathcal{H}} \gamma_{i,j}^k \leq D^\text{max}_{i,j} \quad \forall i \in \mathcal{N}, j = 2, 3, \ldots M_i$$ (16)

where $D^\text{min}_{i,j}$ and $D^\text{max}_{i,j}$ denote the minimum and maximum time delay allowed between the energy phase $j$ and $j - 1$ for appliance $i$. Eqs. (14)-(16) can be modified to model sequential operation of different appliances and delay between them.

EV Battery Model

Apart from driving, the EV can also provide additional flexibility for energy management to the SSB. For the EV battery, the SOC $(S_{EV,k})$ at any time instant $k$ is dependent upon the charging power $(P_{EV,ck})$ power, discharging $(P_{EV,dk})$ power and the power demand of the vehicle while driving $(\pi_k)$.

$$S_{EV,k+1} = S_{EV,k} + \Delta k \frac{E_{\text{max, EV}}}{\eta_{EV,c}} (\eta_{EV,c} P_{EV,ck} - \eta_{EV,d} P_{EV,dk} - \pi_k)$$ (17)

where $\eta_{EV,c}$ and $\eta_{EV,d}$ are the charging and discharging efficiencies, and $E_{\text{max, EV}}$ is the maximum energy storage capacity of the EV battery.

The SOC of the EV battery is restricted to stay between some minimum $(S_{EV}^{\text{min}})$ and maximum $(S_{EV}^{\text{max}})$ values (eq. (18)).

$$S_{EV}^{\text{min}} \leq S_k \leq S_{EV}^{\text{max}} \quad \forall k \in \mathcal{H}$$ (18)

The charging and discharging rate of the EV battery need to be lower than their respective maximum values of $P_{EV,c}^{\text{max}}$ and $P_{EV,d}^{\text{max}}$. Similar to the BSS, simultaneous charging/discharging of the EV battery is not allowed. Further, it is assumed that the EV battery only charge/discharge while the vehicle is parked at the SSB. The following constraints formulate these conditions as:

$$0 \leq P_{EV,ck} \leq P_{EV,c}^{\text{max}} \mu_{1,k} \quad \forall k \in \mathcal{H}$$ (19a)

$$0 \leq P_{EV,dk} \leq P_{EV,d}^{\text{max}} \mu_{2,k} \quad \forall k \in \mathcal{H}$$ (19b)

$$\mu_{1,k} + \mu_{2,k} \leq 1 \quad \forall k \in \mathcal{H}$$ (19c)

$$\mu_{1,k}, \mu_{2,k} = 0 \quad \forall k \in \mathcal{G} \subset \mathcal{H}$$ (19d)

where $\mu_1$ and $\mu_2$ are binary variables representing the status of charging and discharging of the EV battery. $\mathcal{G}$ denotes the set of time instants when the vehicle is not parked at the SSB.

Power Exchange with the Power Grid

A bi-directional power exchange with the power grid is considered, i.e. power can be both bought and fed back to the grid. To prevent simultaneous buying/selling of power, the following constraint is imposed using two binary variables $\psi_1$ and $\psi_2$.

$$0 \leq P_{\text{buy},k} \leq P_{\text{buy}}^{\text{max}} \psi_1 \quad \forall k \in \mathcal{H}$$ (20a)

$$0 \leq P_{\text{sell},k} \leq P_{\text{sell}}^{\text{max}} \psi_2 \quad \forall k \in \mathcal{H}$$ (20b)

$$\psi_1 k + \psi_2 k \leq 1 \quad \forall k \in \mathcal{H}$$ (20c)

where $P_{\text{buy}}^{\text{max}}$ and $P_{\text{sell}}^{\text{max}}$ are the maximum power values that can be bought from and sold to the grid respectively.
PV Power Generation

The PV power profile is obtained from the PV performance tool, a part of the photovoltaic geographical information system (PVGIS) available from the European Commission (PVGIS).

Power Balance Constraint

This constraint ensures the power balance in the building, i.e., at any time instant $k$, the total power generation and consumption need to be equal.

$$P_{sell,k} + P_{c,k} + P_{EV,c,k} + |\phi_{h,k}| + \sum_{i \in N} \sum_{j \in M_i} P_{i,j} \Delta t_{i,j}$$

$$+ \phi_{tnk,k} = P_{PV,k} + P_{buy,k} + P_{d,k} + P_{EV,d,k} \quad \forall k \in H$$

Sustainability Criterion

As mentioned previously, the BEMS intends to achieve the building’s sustainability target, i.e., the nZE mandate. At the design stage, it is assumed that the building has the capability to produce as much energy as it consumes by PV power generation on a yearly basis (nZEB). Due to the cost minimization objective and mismatch between real PV power (operational stage) and forecasted PV power (design stage), it is possible that the SSB’s energy consumption exceeds the energy consumption target and jeopardize the nZE status. So to ensure the SSB’s sustainability, the following constraint is imposed at each time instant

$$\sum_{k \in H} (P_{buy,k} - P_{sell,k}) \Delta k + \sum_{j=1}^{k-1} (P_{buy,j} - P_{sell,j}) \Delta k \leq v_5$$

The constraint in eq. (22) is imposed at each time step in an adaptive manner as follows

- At the first time step, the constraint is imposed on the system as $\sum_{k \in H} (P_{buy,k} - P_{sell,k}) \Delta k \leq v_5$
- If the net power consumption is negative ($P_{sell} \geq P_{buy}$) by $\Delta E_1$ amount at the previous time step, then the constraint at next time step will be formulated as $\sum_{k \in H} (P_{buy,k} - P_{sell,k}) \Delta k \leq v_5 + \Delta E_1$, i.e., a relaxed constraint.
- If the net power consumption is positive ($P_{sell} \leq P_{buy}$) at previous time step by $\Delta E_1$ amount, then the constraint at the next time step will be formulated as $\sum_{k \in H} (P_{buy,k} - P_{sell,k}) \Delta k \leq -v_5 - \Delta E_1$, i.e., a tightened constraint.

The constraint is applied adaptively so that the cumulative net power consumption is zero at the end of the year, thus maintaining the building’s sustainability.

Overall Problem Formulation

The objective $J$ of the controller is to minimize the operational cost of the SSB.

$$J = \sum_{k \in H} \left( C_k (P_{buy,k} - P_{sell,k}) + \frac{4}{n} \rho_n v_{u,k} + \rho_5 v_5 \right)$$

where $C_k$ is the electricity prices at the time instant $k$. $\rho$ is a large number, used to penalize the objective function for constraint violations in eq. (2) and (5).

The overall optimization problem is formulated as follows

$$\min \{ \phi_{h,k}, \phi_{tnk,k}, \alpha_{i,j}^k, P_{buy,k}, P_{sell,k}, P_{c,k}, P_{d,k}, P_{EV,c,k}, P_{EV,d,k} \}$$

subject to  equations (1) – (22)

(24)

Numerical Case Study

Simulation Setup

To demonstrate the advantage of the proposed framework, a simulation case study is carried out. The parameter values for the building are adopted from (Madsen and Holst, 1995). Although these values correspond to a smaller space than a typical building, the proposed framework applies to any general building. Since the heating system’s modelling is out of the present work scope, it is assumed that space heating and hot water demand are satisfied using a heat pump with a constant coefficient of performance of 3. For the HWST, a tank of effective volume 0.2 m³ is considered with the overall heat loss coefficient ($U_{tnk}A_{tnk}$) of 1.63 W/K (Becker et al., 2015). The power consumption during hot water draw is derived from the typical domestic hot water usage profiles (Hendron and Engebrecht, 2010). The weather data is obtained from the typical meteorological year generator tool of PVGIS (TMY). For energy storage, a Lithium-ion BSS with 3.6 kWh energy storage capacity with a rated power of 2 kW is utilized (SAMSUNG). An electric vehicle with a battery capacity of 16 kWh and rated power of 3.6 kW is considered (MITSUBISHI).
For shiftable appliances, the parameters used in the study are adopted from (Sou et al., 2011). They are presented in Table 1, where \( i = 1, 2 \) and 3 refer to the washing machine, clothes dryer, and dishwasher, respectively. A maximum delay of 15 minutes (1-time step) is considered between the consecutive energy phases. The clothes dryer is allowed to delay its operation for 30 minutes after the washing machine finishes its operation. The time instants during which the appliances are allowed to run are based on general assumptions; for example, the user would not prefer to run washing machine and clothes dryer during the night period, or dishwasher runs once per day after the dinner. For electricity cost, historical market data for wholesale energy price provided by Nord Pool is employed (NORDPOOL). The wholesale electricity prices have been scaled up to represent retail electricity prices for residential customers.

The optimization problem is formulated in Matlab with YALMIP interface (Löfberg, 2004) and is solved using CPLEX optimizer (IBM, 2017). The simulation is performed with a \( \Delta k = 15 \) minute sample time and a prediction horizon of \( H = 24 \) hours.

### Table 1: Shiftable appliances parameters

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<th>Parameter</th>
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### Results and Discussion

**Real-Time-Price Tariff:** First, the overall system is simulated with a real-time-price (RTP) tariff structure for electricity prices. Figure 2 shows the power exchange of the building with the grid during the simulation period. Figure 2(a) presents the power bought from the grid, and Fig. 2(b) shows the power fed back into the grid. The localized peaks for power import from the grid are seen during low energy price periods. On the other hand, the peaks for power export to the grid are observed during high energy price periods, thus minimizing the building’s overall operating cost.

BEMS manages to exploit the demand-response flexibility provided by the energy devices to achieve the objective of cost minimization; one example that demonstrates this is shown in Fig. 3. For example, at time step 58, the heat pump starts preheating the building until time step 61 since the energy prices are low during this period. This heat is released to the indoor air during time step 61 to 66, avoiding the need for heating during this period since the energy cost is higher. Towards the end of the day, when the electricity prices drop significantly, the heat pump runs at full power and preheats the building again.

Figure 4 demonstrates the demand response flexibility utilized by the BEMS through the shiftable appliances. Figure 4 shows the intrinsic operation of different energy phases of the washing machine. It can be seen that after the third energy phase has finished its operation, the fourth energy phase does not start immediately; instead, it uses the allowed delay flexibility of one timestep since the energy prices drop by then, thus leading to cost-savings. Similar behaviour was observed for the dishwasher as well.

**Time-of-Use Tariff:** Next, the overall system is simulated with a Time-of-Use (TOU) electricity price structure, i.e., electricity usage is charged at different rates during peak hours and off-peak hours. In this work, the considered electricity prices are 0.1247 €/kWh between 12:00 am to 6:00 am and 12:00 pm.
to 2:00 pm (off-peak hours); and for the rest of the day (peak hours), the price is 0.1656 €/kWh.

Figure 5 shows the power exchange with the grid in this case for a 1-day simulation period. It can be seen that BEMS tries to buy power from the grid during low-price periods (off-peak hours) and sell back to the grid during high-price periods (peak hours).

Further in Figure 7(a) and (b), the cumulative net power consumption for a ten days period in January and June, respectively, is shown. In Figure 7(a), the net power consumption stays positive most of the time. The downward spikes represent the time instants during which the power generation is higher than the power consumption. Figure 7(b) shows that the cumulative net power consumption is negative due to the high PV power generation. The upward spikes are the time periods during which the power consumption is higher than the power generation. At the end of the year, BEMS is expected to maintain the cumulative net power below 0 as per equation (22).

Table 2: Energy consumption and electricity cost for 1-day simulation period

<table>
<thead>
<tr>
<th>Case</th>
<th>Energy-use (kWh)</th>
<th>Cost (€)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deterministic MPC with SC</td>
<td>43.23</td>
<td>1.1492</td>
</tr>
<tr>
<td>Deterministic MPC wout SC</td>
<td>47.72</td>
<td>1.1444</td>
</tr>
</tbody>
</table>

It is also evident from the SOC pattern of the BSS in Figure 6. BSS becomes fully charged (90%) at time instant 24 and 58, i.e., just before the beginning of high-price periods, so that it can discharge during that time interval and meet the power demand.

Figure 6: SOC pattern of BSS

Accounting for the sustainability criterion: To ensure the nZE mandate of the SSB, a sustainability criterion was imposed in equation (22). Table 2 shows the comparison of energy cost and consumption for deterministic MPC with and without the sustainability criterion over a 1-day simulation period. The energy consumption is lower with the sustainability criterion since BEMS tries to operate the appliances with minimal energy usage. Even with the lower energy consumption, the energy cost increases slightly due to the sustainability criterion’s emphasis, which makes BEMS use minimal energy at the expense of increased cost. However, such situations may exist when the energy cost is the same with or without the SC.

Finally, to demonstrate the cost-saving, the building is simulated with a baseline scenario for one month. The results are compared with the proposed approach under the RTP pricing scheme. For the baseline case, the BEMS does not aim to minimize the operating cost; the objective of the BEMS is only to maintain the temperature of indoor air and water in HWST between the assigned values. The shiftable loads are operated without any shifting and/or delay and start operating as soon as the activation request is received. The BEMS managed to achieve a 12% reduction in energy cost in comparison to the benchmark approach.

Conclusions and Future Work

The paper presented a comprehensive framework for energy management in a smart-sustainable building. It was shown that the MPC-based BEMS could steer these devices effectively and optimally according to different modern electricity tariff schemes. Based on the proposed approach, not only the operation cost of energy devices can be reduced significantly, but buildings’ sustainability can be maintained as well. The proposed approach achieved a 12% reduction in the energy cost compared to a baseline approach.

The part of the work is based upon the premise that a smart grid infrastructure exists, allowing grid operators to send a real-time price signal to the SSB,
which is not realistic at present. Further, the proposed energy management framework is comprehensive and scalable to generic residential SSBs; however, it is not straightforward to acquire suitable dynamical models of thermal behaviour of SSBs and require extensive work such as data gathering.

Another important challenge is the intrinsic uncertainties in the weather forecast that can affect the indoor air temperature; consequently, the occupants’ thermal comfort can be jeopardized. To avoid this, BEMS needs to consider these uncertainties when making optimal decisions. Future work will take this into account, and a chance-constraint MPC will be employed instead of the deterministic MPC as presented.

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