

# A Hierarchical Model Predictive Control Approach for Handling Demand Charges Using Battery Systems

Ranjeet KUMAR<sup>1\*</sup>, Michael J. WENZEL<sup>2</sup>, Matthew J. ELLIS<sup>2</sup>, Mohammad N. ELBSAT<sup>2</sup>, Kirk H. DREES<sup>2</sup>, Victor M. ZAVALA<sup>1</sup>

<sup>1</sup> University of Wisconsin–Madison, Department of Chemical and Biological Engineering,  
Madison, Wisconsin, USA

Email: rkumar32@wisc.edu, victor.zavala@wisc.edu

<sup>2</sup> Johnson Controls International, Building Efficiency,  
Milwaukee, Wisconsin, USA

Email: mike.wenzel@jci.com, matthew.j.ellis@jci.com, mohammad.elbsat@jci.com, kirk.h.drees@jci.com

\* Corresponding Author

## ABSTRACT

Applications in energy systems often require to simultaneously mitigate long-term and short-term electricity costs. Demand charges, in particular, constitute an important component of the electricity bills for large consumption units such as buildings and manufacturing plants. Mitigating long-term and short-term costs poses a challenging multiscale planning problem that should make decisions at fine timescales and over long time horizons. This work presents a hierarchical model predictive control (MPC) approach to tackle this problem in the context of stationary battery systems. The goal is to determine the optimal charge-discharge policy for the battery to minimize hourly costs and a monthly demand charge. In the proposed hierarchical MPC approach, the state of charge (SOC) policy is assumed to be periodic, which allows to cast the long-term planning problem as a tractable stochastic programming problem. Here, every period (e.g., a day or week) represents an operational scenario and the targets for the periodic SOC levels and the peak cost are to be determined. The long-term planner MPC communicates the periodic SOC targets and maximum peak level to a short-term MPC controller. The short-term MPC controller determines the intra-period charge/discharge policies (at high resolution) while meeting the targets of the long-term planning. A simulation case study for a university campus is presented to demonstrate that the hierarchical MPC scheme yields optimal demand charge and charge-discharge policy under nominal (perfect forecast) conditions. Comparative studies of the proposed hierarchical MPC scheme and standard MPC schemes that use ad-hoc approaches to handle demand charges are also presented. Under imperfect forecasts, the simulations show that the hierarchical MPC scheme results in significant improvements in demand charge reduction over a standard MPC scheme that uses a discounting factor to capture long-term effects.

## 1. INTRODUCTION

Peak electricity demands or the demand charges remain a serious concern for utilities since they pose capacity challenges to the power grid. This situation has provided opportunities to energy storage systems to create savings by reducing the peak electricity demands of the buildings and campuses (de Salis *et al.*, 2014; Johnson *et al.*, 2011; Oudalov *et al.*, 2007; Rahimi *et al.*, 2013; Lu *et al.*, 2014; Dong *et al.*, 2011; Joshi and Pindoriya, 2015). In this context, MPC is used in Braun (1990); Ma *et al.* (2012) to mitigate demand charges of a building HVAC system. Demand charges pose a challenging multiscale planning problem that should make decisions at fine timescales while mitigating long-term costs. In particular, handling MPC planning formulations over long horizons can be intractable. To overcome this issue, the authors in Braun (1990); Ma *et al.* (2012) penalize the peak electricity demand over the short-term receding horizon. This approach is practical but can yield overly conservative policies and deteriorate economic performance. Long-term discounting cost factors are used in Risbeck *et al.* (2017); Patel *et al.* (2016) to reduce the conservatism of short-term MPC formulations. This approach is intuitive but does not provide optimality guarantees. The work in Zavala (2016) proposes a hierarchical MPC scheme, with the adjoint (dual) information obtained

from a long-term and coarse MPC controller used to guide the control policy of a short-term MPC controller. It is demonstrated that this approach can achieve optimality. Unfortunately, continuity of the adjoint profiles is necessary for this approach, which is not guaranteed in general. Alternative hierarchical MPC schemes (Scattolini and Colaneri, 2007; Picasso *et al.*, 2010) available in the literature provide feasibility but not optimality guarantees. Moreover, such approaches cannot handle peak costs.

In this work, the demand charges for buildings are handled by battery systems by using a recently developed approach for hierarchical model predictive control (MPC). Here, a long-term planner MPC provides guiding targets to the short-term MPC controller. In the proposed hierarchical MPC approach, the state of charge (SOC) policy is assumed to be periodic, which is a reasonable assumption in the context of energy systems because loads and price profiles have strong periodic components (Huang *et al.*, 2011; Subramanian *et al.*, 2014; Risbeck *et al.*, 2015). This assumption makes it possible to cast the long-term planning problem as a tractable stochastic programming problem. Here, the period (e.g., a day or week) represents an operational scenario and we seek to determine targets for the periodic SOC levels and the peak cost. The periodic SOC targets and peak cost are communicated to a short-term MPC controller. The intra-period charge/discharge policies (at high resolution) are determined by the short-term MPC controller while meeting the targets obtained from the long-term planning.

The performance of the hierarchical MPC scheme is demonstrated using an application in buildings with electricity storage through simulation case studies. Here, the goal is to determine the optimal short-term (hourly) charge-discharge policy while mitigating long-term (monthly) demand charges from utilities. Using the simulation case studies, it is shown that the proposed hierarchical MPC scheme yields optimal demand charge and charge-discharge policy under nominal (perfect forecast) conditions. Comparative studies of the proposed hierarchical MPC scheme and standard MPC schemes that use ad-hoc approaches to handle the multiple timescales are also presented. The solution of the hierarchical MPC scheme is compared with that from a standard MPC scheme that uses a discounting (weighting) factor to account for the inability of solving the long horizon problem. Under imperfect forecasts, it is observed that the cost from the hierarchical MPC scheme provides superior performance over standard MPC because it can capture long-term variability in a more systematic manner.

## 2. PROBLEM FORMULATION

We begin by considering the following MPC problem:

$$\min_{\mathbf{x}_{\mathcal{N}}, \mathbf{u}_{\mathcal{N}}} \sum_{t=0}^{N-1} a_t^T x_t + b_t^T u_t + c_t^T d_t + \max_{t \in \mathcal{T}} (p_t^T x_t + q_t^T u_t + r_t^T d_t) \quad (1a)$$

$$\text{s.t. } x_{t+1} = Ax_t + Bu_t + Cd_t, \quad t = 0, \dots, N-1 \quad (1b)$$

$$u_t \in \mathcal{U}, \quad t = 0, \dots, N-1 \quad (1c)$$

$$x_t \in \mathcal{X}, \quad t = 0, \dots, N \quad (1d)$$

Here,  $a_t \in \mathbb{R}^{n_x}$ ,  $b_t \in \mathbb{R}^{n_u}$  and  $c_t \in \mathbb{R}^{n_d}$  are time-additive stage costs associated with the states  $x_t \in \mathbb{R}^{n_x}$ , controls  $u_t \in \mathbb{R}^{n_u}$ , and  $d_t \in \mathbb{R}^{n_d}$ , respectively.  $p_t \in \mathbb{R}^{n_x}$ ,  $q_t \in \mathbb{R}^{n_u}$  and  $r_t \in \mathbb{R}^{n_d}$  are the costs associated with the states  $x_t \in \mathbb{R}^{n_x}$ , controls  $u_t \in \mathbb{R}^{n_u}$ , and  $d_t \in \mathbb{R}^{n_d}$ , respectively, of which only the peak cost (time-max cost) is considered. The horizon length is denoted as  $N$ . Trajectories for control actions and states over the horizon are denoted as  $\mathbf{u}_{\mathcal{N}} := (u_0, u_1, \dots, u_{N-1})$ , and  $\mathbf{x}_{\mathcal{N}} := (x_1, x_2, \dots, x_N)$ . The dynamics of the linear system are described by the matrices  $A \in \mathbb{R}^{n_x \times n_x}$ ,  $B \in \mathbb{R}^{n_x \times n_u}$ , and  $C \in \mathbb{R}^{n_x \times n_d}$ . The state  $x_0$  is provided as the initial condition. The states  $x_t$  and controls  $u_t$  are bounded by the polyhedral sets  $\mathcal{X}$  and  $\mathcal{U}$ , respectively.

The time set is represented by  $\mathcal{T} := \{0, 1, \dots, N\}$  and it is also considered that the set  $\mathcal{T}$  is partitioned (in lexicographic order) into a set of short time *periods*  $\Xi := \{0, \dots, M\}$  with each period  $\xi \in \Xi$  comprising of equal number of time steps  $N_T$  satisfying  $M \times N_T = N$ . Further, each period is defined as  $\mathcal{T}_{\xi} := \{0, \dots, N_T\}$ . For convenience, the sets  $\bar{\Xi} := \Xi \setminus \{M\}$  and  $\bar{\mathcal{T}}_{\xi} := \mathcal{T}_{\xi} \setminus \{N_T\}$  are also defined. We partition states, controls, and disturbance policies into stages and denote the stage policies as  $u_{\xi,t}$ ,  $x_{\xi,t}$ , and  $d_{\xi,t}$  for  $\xi \in \Xi$  and  $t \in \mathcal{T}_{\xi}$ . For compactness in notation,  $u_{\xi, N_T} = 0$  and  $d_{\xi, N_T} = 0$  are defined for all periods  $\xi$ . These partitions are used to reformulate the MPC problem in the following

equivalent form:

$$\min_{u_{\xi,t}} \sum_{\xi \in \Xi} \sum_{t \in \mathcal{T}_{\xi}} a_{\xi,t}^T x_{\xi,t} + b_{\xi,t}^T u_{\xi,t} + c_{\xi,t}^T d_{\xi,t} + \max_{\xi \in \Xi} \max_{t \in \mathcal{T}_{\xi}} (p_{\xi,t}^T x_{\xi,t} + q_{\xi,t}^T u_{\xi,t} + r_{\xi,t}^T d_{\xi,t}) \quad (2a)$$

$$\text{s.t. } x_{\xi,t+1} = Ax_{\xi,t} + Bu_{\xi,t} + Cd_{\xi,t}, \xi \in \Xi, t \in \mathcal{T}_{\xi} \quad (2b)$$

$$x_{\xi+1,0} = x_{\xi,N_T}, \xi \in \bar{\Xi} \quad (2c)$$

$$x_{0,0} = \bar{x}_0 \quad (2d)$$

$$x_{\xi,t} \in \mathcal{X}, u_{\xi,t} \in \mathcal{U}. \quad (2e)$$

Here, the constraint (2c) enforces continuity between stages.

By enforcing periodicity of the state at the end of every stage, the following modified problem is obtained:

$$\min_{u_{\xi,t}} \sum_{\xi \in \Xi} \sum_{t \in \mathcal{T}_{\xi}} a_{\xi,t}^T x_{\xi,t} + b_{\xi,t}^T u_{\xi,t} + c_{\xi,t}^T d_{\xi,t} + \max_{\xi \in \Xi} \max_{t \in \mathcal{T}_{\xi}} (p_{\xi,t}^T x_{\xi,t} + q_{\xi,t}^T u_{\xi,t} + r_{\xi,t}^T d_{\xi,t}) \quad (3a)$$

$$\text{s.t. } x_{\xi,t+1} = Ax_{\xi,t} + Bu_{\xi,t} + Cd_{\xi,t}, \xi \in \Xi, t \in \mathcal{T}_{\xi} \quad (3b)$$

$$x_{\xi+1,0} = x_{\xi,N_T}, \xi \in \bar{\Xi} \quad (3c)$$

$$x_{\xi,N_T} = x_{\xi,0}, \xi \in \Xi \quad (3d)$$

$$x_{\xi,t} \in \mathcal{X}, u_{\xi,t} \in \mathcal{U}. \quad (3e)$$

The optimization formulation (3) represents the long-term MPC planning problem with the enforced periodicity constraints. Here, the variable  $x_{0,0}$  is a free variable that is sought to be optimized. By combining the periodicity constraint (3d) and the stage continuity constraints (3c), a reformulated stage continuity constraints can be obtained in the form of  $x_{\xi+1,0} = x_{\xi,0}$ ,  $\xi \in \bar{\Xi}$ . A *lifting* variable  $x_0$  is further introduced to reformulate  $x_{\xi+1,0} = x_{\xi,0}$ ,  $\xi \in \bar{\Xi}$  as  $x_{\xi,0} = x_0$ ,  $\xi \in \bar{\Xi}$ . Consequently, the goal of the long-term MPC formulation (3) is to find the optimal periodic state  $x_0$  and control policies  $u_{\xi,t}$ ,  $\xi \in \Xi, t \in \mathcal{T}_{\xi}$  that minimize the time-additive and peak costs. We also reformulate the peak cost function to obtain the following final equivalent form of (3):

$$\min_{u_{\xi,t}} \sum_{\xi \in \Xi} \sum_{t \in \mathcal{T}_{\xi}} a_{\xi,t}^T x_{\xi,t} + b_{\xi,t}^T u_{\xi,t} + c_{\xi,t}^T d_{\xi,t} + \eta \quad (4a)$$

$$\text{s.t. } p_{\xi,t}^T x_{\xi,t} + q_{\xi,t}^T u_{\xi,t} + r_{\xi,t}^T d_{\xi,t} \leq \eta, \xi \in \Xi, t \in \mathcal{T}_{\xi} \quad (4b)$$

$$x_{\xi,t+1} = Ax_{\xi,t} + Bu_{\xi,t} + Cd_{\xi,t}, \xi \in \Xi, t \in \mathcal{T}_{\xi} \quad (4c)$$

$$x_{\xi+1,0} = x_0, \xi \in \bar{\Xi} \quad (4d)$$

$$x_{\xi,N_T} = x_0, \xi \in \bar{\Xi} \quad (4e)$$

$$x_{\xi,t} \in \mathcal{X}, u_{\xi,t} \in \mathcal{U}. \quad (4f)$$

The solution of the optimization problem (4) is denoted as  $x_{\xi,t}^*, u_{\xi,t}^*, \eta^*$ , where  $\eta^*$  is the peak cost over the entire planning horizon. It is also noted that  $x_{\xi+1,0}^* = x_{\xi,0}^* = x_0^*$ .

The structure of (4) reveals that the only coupling variables between stages are  $x_0$  and  $\eta$ . Therefore, (4) can be seen as a *stochastic programming problem* in which periods are operational scenarios,  $x_0$  and  $\eta$  are *design variables* or *first-stage variables*, and  $x_{\xi,t}, u_{\xi,t}$  are *recourse policies* for scenarios. The problem (4) is decomposed into  $M$  subproblems by fixing the design variables to their optimal values  $x_0^*$  and  $\eta^*$ :

$$\min_{u_{\xi,t}} \sum_{\xi \in \Xi} \sum_{t \in \mathcal{T}_{\xi}} a_{\xi,t}^T x_{\xi,t} + b_{\xi,t}^T u_{\xi,t} + c_{\xi,t}^T d_{\xi,t} + \eta^* \quad (5a)$$

$$\text{s.t. } p_{\xi,t}^T x_{\xi,t} + q_{\xi,t}^T u_{\xi,t} + r_{\xi,t}^T d_{\xi,t} \leq \eta^*, \xi \in \Xi, t \in \mathcal{T}_{\xi} \quad (5b)$$

$$x_{\xi,t+1} = Ax_{\xi,t} + Bu_{\xi,t} + Cd_{\xi,t}, \xi \in \Xi, t \in \mathcal{T}_{\xi} \quad (5c)$$

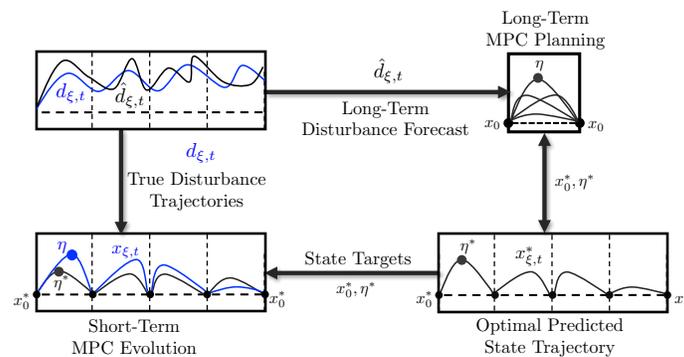
$$x_{\xi+1,0} = x_0^*, \xi \in \bar{\Xi} \quad (5d)$$

$$x_{\xi,N_T} = x_0^*, \xi \in \bar{\Xi} \quad (5e)$$

$$x_{\xi,t} \in \mathcal{X}, u_{\xi,t} \in \mathcal{U}. \quad (5f)$$

It is noted that the subproblem (5) has the structure of a standard MPC problem with periodicity constraints. The SP formulation (4) provides an opportunity to implement a *hierarchical MPC scheme*, in which the long-term MPC problem of the form (4) (equivalently (3)) can guide a short-term MPC controller of the form (4), with the targets for the design variables obtained from the long-term MPC. The targets for the periodic state  $x_0^*$  and the peak cost  $\eta^*$  provide a form of communication between the hierarchical levels. Figure 1 provides a schematic representation of the hierarchical MPC scheme.

From the SP setting it is also revealed that when the *disturbance forecasts are perfect*, the solution of the short-term MPC controller will yield an optimal stage trajectory  $u_{\xi,t}^*$  and  $x_{\xi,t}^*$  since the targets  $x_{\xi,0}^*$  and  $\eta^*$  are optimal, and these targets also correspond to the minimum cost for the entire horizon (as obtained from the long-term MPC problem). The SP setting also indicates that, when the forecasts are imperfect, the targets  $x_0^*, \eta^*$  may not be optimal and it may not be feasible for the subproblem (5) to achieve the provided design targets by the long-term MPC planner. This situation can be mitigated by penalizing deviations from the target (which will find the closest feasible point) or by re-optimizing the design targets using the actual realized disturbances when they become available in real-time. The SP setting also reveals that it is possible to find targets that remain optimal and feasible for all realizations (or many realizations) by considering a larger number of scenarios of the disturbance in the planning problem. Consequently, the proposed approach provides a framework to easily construct robust formulations. Another important feature of the hierarchical MPC approach is that there is no need to weight or discount the long-term costs in the short-horizon MPC subproblem because the long-term effects in the costs are already accounted for by the long-term MPC. Moreover, there already exist advanced techniques to solve the SP problem efficiently by using decomposition schemes based on parallel linear algebra and Benders/Lagrangian decomposition (Zavala *et al.*, 2008; CarøE and Schultz, 1999; Geoffrion, 1972a).



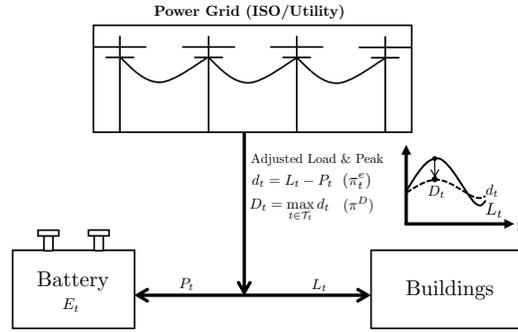
**Figure 1:** Hierarchical MPC scheme.

### 3. STATIONARY BATTERY CASE STUDY

Batteries are flexible assets that can be used to provide energy and can aid utility companies by providing demand-side management capabilities for buildings or manufacturing facilities (Rastler, 2010; Oudalov *et al.*, 2006). The use of batteries for demand charge mitigation has been studied in Kumar *et al.* (2018); Sigrist *et al.* (2013); White and Zhang (2011); Lucas and Chondrogiannis (2016); Sebastián (2016); Oudalov *et al.* (2006); Shi *et al.* (2017). In such settings, the objective function of the MPC scheme takes the form of the formulation in (1), where the additive costs represent the total time-of-use energy cost and peak costs represent demand charges. The setting considered in this work is sketched in Figure 2.

#### 3.1 Long-Term MPC Formulation

The elements of the long-term MPC formulation for the battery planning problem include the model parameters, data, and variables, which are listed in Nomenclature section.



**Figure 2:** Interactions between battery, buildings, ISO, and utility.

**Objective Function** The objective is to minimize total cost, which is given by the demand charge and the revenues collected from power and regulation:

$$\sum_{\xi \in \Xi} \sum_{t \in \mathcal{T}_\xi} \pi_{\xi,t}^e (L_{\xi,t} - P_{\xi,t}) + \pi^D D. \quad (6)$$

Here, the energy cost  $\pi_{\xi,t}^e (L_{\xi,t} - P_{\xi,t})$  represents the time-additive cost and the demand charge is the time-max cost. The component  $\pi_{\xi,t}^e L_{\xi,t}$  in the cost function is just a constant with respect to the optimization, and therefore we can drop this component from the cost function. The component  $-\pi_{\xi,t}^e P_{\xi,t}$  provides the cost saving by using the battery energy instead of buying energy directly from the utility. Therefore, the following cost function is considered for the further analysis:

$$\sum_{\xi \in \Xi} \sum_{t \in \mathcal{T}_\xi} -\pi_{\xi,t}^e P_{\xi,t} + \pi^D D. \quad (7)$$

**Constraints** The constraints on the system are the physical charging/discharging limits of the battery, the battery state of charge (SOC) dynamics, and the peak demand computation. The constraints of the SP are replicated for every scenario (or period)  $\xi \in \Xi$ . The storage dynamics are given by the difference equation:

$$E_{\xi,t+1} = E_{\xi,t} - P_{\xi,t}, \quad t \in \tilde{\mathcal{T}}_\xi, \xi \in \Xi \quad (8)$$

The battery ramp discharge rate is constrained as:

$$-\overline{\Delta P} \leq P_{\xi,t+1} - P_{\xi,t} \leq \overline{\Delta P}, \quad t \in \tilde{\mathcal{T}}_\xi, \xi \in \Xi \quad (9)$$

The residual demand  $d_k$  requested from the utility is:

$$d_{\xi,t} = L_{\xi,t} - P_{\xi,t}, \quad t \in \mathcal{T}_\xi, \xi \in \Xi \quad (10)$$

The peak demand must satisfy:

$$d_{\xi,t} \leq D, \quad t \in \mathcal{T}_\xi, \xi \in \Xi \quad (11)$$

It is assumed that the ISO does not allow the battery to sell back electricity. This is modeled by using the constraint:

$$P_{\xi,t} \leq L_{\xi,t}, \quad t \in \mathcal{T}_\xi, \xi \in \Xi \quad (12)$$

The initial SOC is a design variable which is enforced by using the following non-anticipativity constraint:

$$E_{\xi,0} = E_0, \quad \xi \in \Xi \quad (13)$$

Finally, the periodicity constraints are enforced, i.e. the final state of charge in each scenario is the same as the initial state:

$$E_{\xi, N_T} = E_0, \xi \in \Xi \quad (14)$$

The bounds on the variables are given by:

$$0 \leq E_{\xi, t} \leq \bar{E}, t \in \mathcal{T}_{\xi}, \xi \in \Xi \quad (15a)$$

$$-\underline{P} \leq P_{\xi, t} \leq \bar{P}, t \in \mathcal{T}_{\xi}, \xi \in \Xi \quad (15b)$$

The SP is solved to obtain the targets for the periodic battery SOC  $E_0^*$  and for the peak demand  $D^*$ . These targets are then used to guide a short-term MPC controller that obtains the battery operating policy at every stage.

### 3.2 Short-Term MPC Formulation

For simplicity in the presentation, it is assumed that the short-term MPC controller only updates its control policies at the beginning of every stage  $t = t_{\xi}$  (where  $t_{\xi} = \xi N_T$ ,  $\xi \in \Xi$ ) over horizon  $\mathcal{T}_{\xi} := \{t, t+1, \dots, t+N_T\}$ . The short-term problem at time  $t_{\xi}$  uses forecasts for prices and loads over the prediction horizon  $\tilde{\mathcal{T}}_{\xi}$  (in the perfect information case this matches the scenarios of the long-term MPC formulation). The solution of the problem at time  $t_{\xi}$  is implemented for a block of  $N_T$  hours. This approach is different from the traditional approach in which the control policies are updated at every time step *within* the stage  $\xi$ . The short-term MPC formulation in stage  $\xi$  is given by:

$$\min_{P_{\xi, t}, F_{\xi, t}} \sum_{t \in \mathcal{T}_{\xi}} \pi_{\xi, t}^e (L_{\xi, t} - P_{\xi, t}) + \pi^D D^* \quad (16a)$$

$$s.t. \quad E_{\xi, t+1} = E_{\xi, t} - P_{\xi, t}, t \in \tilde{\mathcal{T}}_{\xi} \quad (16b)$$

$$-\bar{\Delta P} \leq P_{\xi, t+1} - P_{\xi, t} \leq \bar{\Delta P}, t \in \tilde{\mathcal{T}}_{\xi} \quad (16c)$$

$$d_{\xi, t} = L_{\xi, t} - P_{\xi, t}, t \in \mathcal{T}_{\xi} \quad (16d)$$

$$P_{\xi, t} \leq L_{\xi, t}, t \in \mathcal{T}_{\xi} \quad (16e)$$

$$E_{\xi, N} = E_0^* \quad (16f)$$

$$E_{\xi, 0} = E_0^* \quad (16g)$$

$$d_{\xi, t} \leq D^* \quad (16h)$$

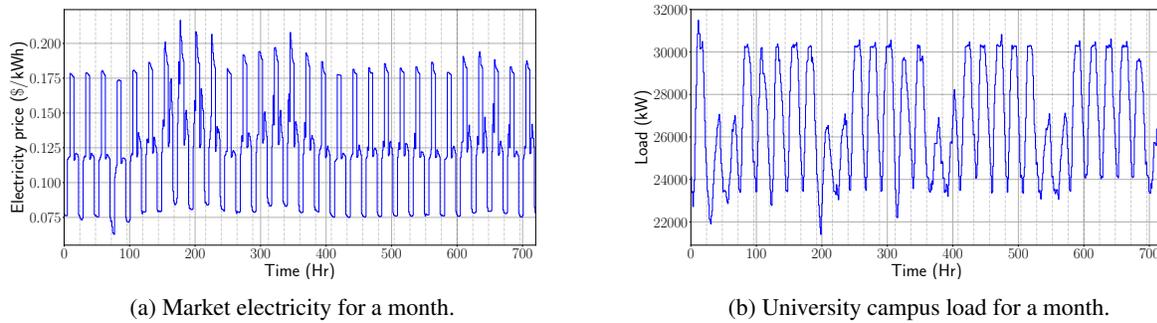
$$0 \leq E_{\xi, t} \leq \bar{E}, t \in \mathcal{T}_{\xi} \quad (16i)$$

$$-\underline{P} \leq P_{\xi, t} \leq \bar{P}, t \in \mathcal{T}_{\xi} \quad (16j)$$

## 4. RESULTS

In this section, the results from the simulation case studies based on the MPC formulation described in Section 3 are presented. For the simulation case studies, a utility-scale stationary battery that has a capacity 0.5 MWh and rated power of 1 MW for both charge and discharge is considered, and a ramping limit of 0.5 MW/hr is assumed. Historical data for one month for energy prices from PJM Interconnection, shown in Figures 3a are used (PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia in the United States). Historical load data from a typical university campus for a month is used as the disturbance profile shown in Figure 3b. From the Figures 3 it can be clearly observed the disturbance profiles have strong periodic components and therefore, the proposed hierarchical MPC scheme based on enforcing periodicity is an appropriate approach for planning of such systems. A planning horizon of one month (i.e.,  $N = 720$ ) is considered and stages of 24 hours are used to create the SP formulation (i.e.,  $N_T = 24$  and  $M = 30$ ).

Perfect forecasts are assumed in the first case study considered. In these experiments, the cost of the hierarchical MPC scheme are compared with the cost of a long-term MPC formulation *with and without periodicity constraints*. This comparison seeks to evaluate the impact of assuming an optimal periodic policy. In the second study, the performance of the hierarchical MPC scheme is evaluated under imperfect forecasts. To do so, its performance is compared against a standard MPC scheme that performs hourly updates of the control policy and that uses a prediction horizon of 24

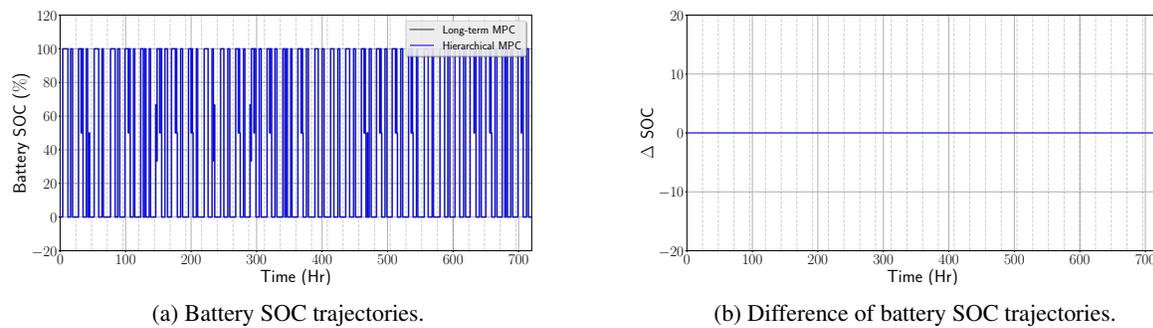


**Figure 3:** Market and load data used for the case studies.

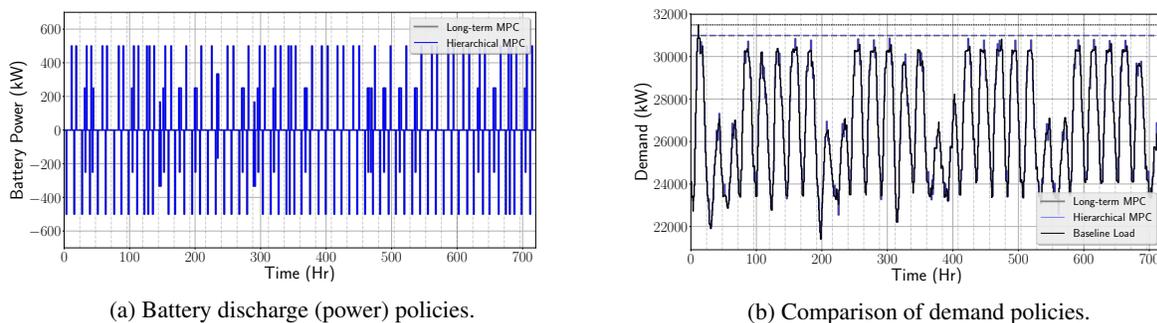
hours. For the standard MPC approach, periodicity constraints are not imposed. Instead, a discounting (weighting) factor is used for the demand charges based on the length of horizon. In this case study, a discounting factor of  $\frac{1}{30}$  is used.

#### 4.1 Perfect Forecasts

Figures 4-5b compare the policies obtained with the long-term MPC planning problem and the hierarchical MPC scheme. The grey vertical lines denote 24-hour periods (scenarios). It can be seen that the policies are identical; the equivalence indicates that the solutions of the period subproblems are unique (for fixed targets  $D^*$  and  $E_0^*$ ).



**Figure 4:** Comparison of SOC policies.

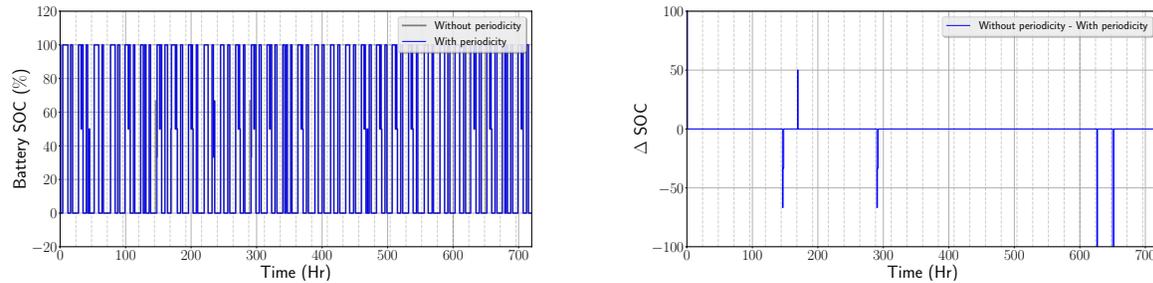


**Figure 5:** Comparison of battery power and building demand policies.

Figure 6 shows the SOC policy obtained from the long-term MPC problem (2) without the periodicity constraints. It can be observed that the SOC is quasi-periodic. The cost items obtained with the different formulations are summarized in Table 1. It is also found that the total cost obtained with no periodicity constraints is only 0.04% lower than that obtained with periodicity constraints (3). It can thus be concluded that assuming a periodic policy does not limit performance.

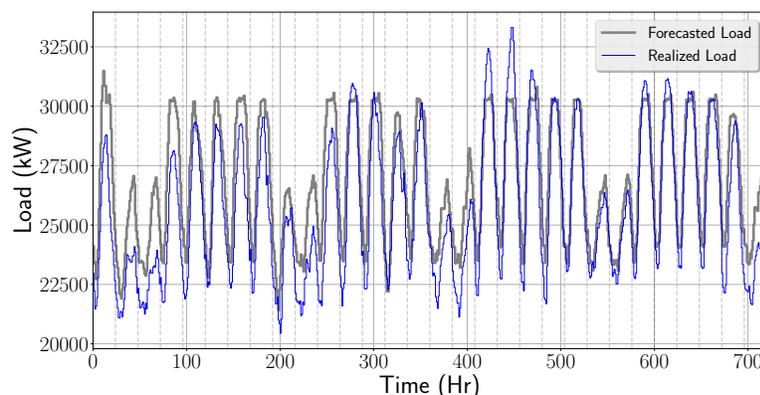
**Table 1:** Comparison of cost items under perfect forecasts.

Cost Item (\$/month)	Long-Term MPC (with periodicity)	Hierarchical MPC	Long-Term MPC (without periodicity)
<b>Total cost</b>	126,690.05	126,690.05	126,637.27
<b>Demand charge</b>	128,594.86	128,594.86	128,594.86
<b>Energy</b>	-1,904.81	-1,904.81	-1,957.59

**Figure 6:** SOC policy without periodicity (left). Comparison of SOC policies with and without periodicity (right).

#### 4.2 Imperfect Forecasts

Figure 7 shows the forecasted load and the realized load used in the case studies with imperfect forecasts. It can be observed that the peak in the realized load (33,315.55 kW) is more than 1800 kW higher than the peak in the forecasted load (31,486.71 kW). The design peak demand ( $D^*$ ) obtained for the hierarchical MPC scheme using the forecasted load profile is 31,186.71 kW. This target value  $D^*$  leads to infeasibility of the short-term MPC controller when using the realized load profile because the size and power rating of the battery is not able to achieve this provided target for peak demand.

**Figure 7:** Forecasted and realized load profiles.

In Table 2, the cost items obtained with the different MPC schemes are compared. It is observed that the total cost obtained from the hierarchical MPC is only 0.02% higher than that obtained with the long-term MPC formulation that uses the advance knowledge of the realized load to compute policies (perfect information). It is found that hierarchical MPC is able to identify the optimal demand charge of long-term MPC even under imperfect forecast. This is important because the demand charge is a significant component of the total cost. The higher total cost of hierarchical MPC is thus attributed to the suboptimal periodic SOC levels obtained from the long-term MPC with the forecasted load profiles.

The performance of standard MPC schemes, one that uses the realized load (perfect information) and another that uses

the forecasted load (imperfect information) to compute policies are also evaluated. By comparing long-term MPC and standard MPC with realized loads (perfect forecasts), it can be immediately noted that standard MPC yields a suboptimal policy and a higher total cost. This highlights that the use of the discount factor only provides an ad-hoc approximation. Under imperfect forecasts, standard MPC also results in 2.24% higher total cost compared to hierarchical MPC. These results highlight the lack of robustness of the standard MPC approach. This also highlights that even under the imperfect forecast case, the hierarchical MPC provides a more effective approach to handle long-term demand charges because it systematically captures the load variability observed throughout the month and handles the long-term cost effects.

**Table 2:** Comparison of cost items under imperfect forecasts.

Cost Item (\$/month)	Long-Term MPC (Forecasted Load)	Long-Term MPC (Realized Load)	Hierarchical MPC (Imperfect Forecast)	Standard MPC (Perfect Forecast)	Standard MPC (Imperfect Forecast)
<b>Total cost</b>	126,690.05	135,334.06	135,374.74	136,230.18	138,411.67
<b>Demand charge</b>	128,594.86	137,220.12	137,220.12	138,057.22	140,330.69
<b>Energy</b>	-1,904.81	-1,886.06	-1,845.38	-1,827.04	-1,919.01

## 5. CONCLUSIONS AND FUTURE WORK

In this work, an approach to handle long horizons in MPC was proposed in the context of energy systems arising due to the need to capture long-term peak costs. In this approach, if periodicity constraints are enforced over short-term periods, the long horizon MPC problem can be posed as a stochastic programming problem with each period representing a scenario, the periodic state and peak cost targets representing the design variables and the intra-stage operational policies representing the recourse variables. The SP setting reveals a mechanism to construct a hierarchical MPC scheme under which a long-term MPC planner provides state and peak cost targets to guide a short-term MPC controller. Through simulation case studies of a typical university campus with stationary battery storage, where the goal is to use the battery to decrease peak demand charges, it is shown that this hierarchical MPC scheme provides optimal operational policies under nominal (perfect forecast) conditions and can be extended to handle imperfect forecasts by correcting the short-term policies. It is also demonstrated through the simulation case study that the hierarchical MPC scheme yields improved performance over standard MPC schemes that use short-time horizons and long-term discounting factors. Extensions to this work include updates (re-optimization) of the stochastic programming formulation to correct the periodic initial/terminal states. The use of a stochastic programming setting also enables the use of algorithms such as Benders decomposition (Geoffrion, 1972b; Rahmani *et al.*, 2016), which can be used to progressively update the high-level MPC layer by adding feasibility and optimality cuts.

## NOMENCLATURE

### Model Parameters and Data

- $L_{\xi,t} \in \mathbb{R}$ : Buildings load [kW].
- $\pi_{\xi,t}^e \in \mathbb{R}$ : Market price for electricity [\$/kWh].
- $\pi^D \in \mathbb{R}_+$ : Demand charge (monthly) [\$/kW].
- $\bar{E} \in \mathbb{R}$ : Battery storage capacity [kWh].
- $\bar{P} \in \mathbb{R}$ : Maximum discharging rate (power) [kW].
- $\underline{P} \in \mathbb{R}$ : Maximum charging rate (power) [kW].
- $\overline{\Delta P} \in \mathbb{R}$ : Maximum ramping limit [kW/h].

### Model Variables

- $P_{\xi,t} \in \mathbb{R}$ : Net battery discharge rate (power) [kW]. If  $P_{\xi,t} > 0$ , the battery is being discharged and if  $P_{\xi,t} < 0$  the battery is being charged.
- $E_{\xi,t} \in \mathbb{R}_+$ : State of charge (SOC) of the battery [kWh].
- $d_{\xi,t} \in \mathbb{R}_+$ : Load requested from utility [kW].
- $D = \max_{\xi \in \Xi} \max_{t \in \mathcal{T}_\xi} d_{\xi,t}$ : Peak load over horizon  $\mathcal{T}$  [kW]

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