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ENENGY MANAGEMENT OF SMART COMMUNITY WITH EV CHARGING USING DISTRIBUTED MODEL PREDICTIVE CONTROL

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ABSTRACT

Human activities in buildings are connected by various transportation measures. For the emerging Smart and Connected Communities (S&CC), it is possible to synergize the energy management of smart buildings with the vehicle operation/travel information available from transportation infrastructure, e.g. the intelligent transportation systems (ITS). Such information enables the prediction of upcoming building occupancy and upcoming charging load of electrified vehicles. This paper presents a predictive energy management strategy for smart community with a distributed model predictive control framework, in which the upcoming building occupancy and charging load are assumed to be predictable to certain extent based on the ITS information. An illustrative example of smart community is used for simulation study based on a Modelica simulation model, in which a chilled-water plant sustains the ventilation and air conditioning of three buildings, and each building is assumed to host a number of charging stations. Simulation study is performed to validate the proposed strategy.

INTRODUCTION

Buildings and transportation are two pillars for industrialized societies: buildings provide the place for human's habitat and various activities, while transportation facilitates the commutation among buildings. Buildings is a primary sector of energy consumption, e.g. in the U.S., accounting for about 76% of electricity use and 40% of all primary energy use [1]. Reducing building energy consumption is essential to energy and environmental sustainability and cost reduction for building operation. In addition to the plug loads, a primary portion of energy consumption in buildings is attributed to the heating, ventilation, and air conditioning (HVAC) systems. Development of smart buildings technology enables advanced building energy management through integration with grid operation, distributed energy resources (DER), electric vehicles (EV), smart metering and demand response. At a larger scale, smart community extends the smart building operation to a cluster of buildings with coherent connections of power, water, transportation and information.

Building occupancy is a primary aspect for energy management. Building occupancy affects the set point for thermal environment control as well as the thermal load. In this study, we consider the energy management of smart community in the context of synergy with the Intelligent Transportation Systems (ITS) and ramification of electrified transportation. The contemporary ITS technology has enabled onboard real-time prediction of travel time and driving cycle for a specific trip, as well as onboard battery state-of-charge consumption for EV operation. Such capability can thus bring forth the following benefit for predictive energy management for smart building and/or smart community operation: predictive information on building occupancy and EV charging load and duration.

Figure 1 illustrates a scenario of smart community that consists of a number of buildings whose ventilation and air conditioning is sustained by a central chilled-water plant. Each building is attached with a parking lot with EV charging stations. The power demands by the chilled-water plant, buildings and associated EV charging are assumed to be sustained by the distribution grid local to the community, subject to a distribution transformer. The associated equipment operation are regulated by mechanisms of daily-ahead dynamic electricity pricing such as time-of-use (TOU) and demand charge.

Advancements in information, communication and sensing technologies have laid the backbones for smart community [2-4]. Demand response (DR) has been well received for peak load shifting operation for both residential and commercial building operations [5][6]. Handling of distributed energy resources (DERs) has resorted to various distributed optimization methods, e.g. game theoretical approaches [7]. Model predictive control (MPC) has been well investigated for building energy management due to its capability in handling constraints and incorporating future information [8]. Integrated scheduling of the building HVAC and EV charging has been studied in a relatively simple fashion [9]. Notice that smart community operation, distributed MPC has been the suitable solution over the centralized MPC due to the curse of dimensionality and the need for scalability and reconfigurability of implementation.

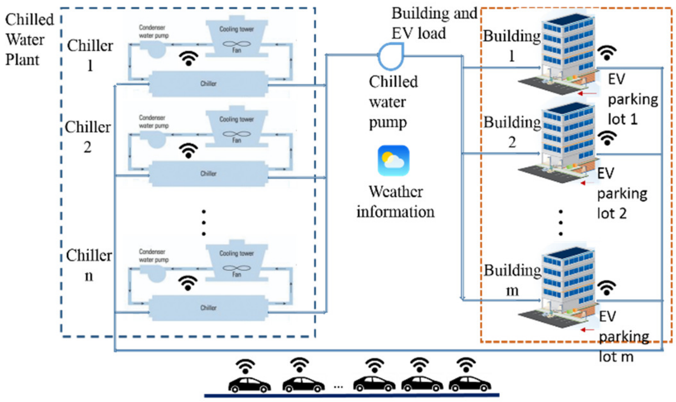

Figure 1. Schematic for smart community energy management

In this study, we approach the optimize energy management of smart community with three major features: 1) a distributed model predictive control framework is considered, which treats the central plant of heating/cooling source and individual buildings as agents; 2) predictive information on upcoming building occupancy and EV charging load is assumed to be available through the synergy with ITS information; and 3) simulation based evaluation is based on the development of multi-physical dynamic simulation model using the Modelica platform [10].

The remainder of this paper is organized as follows. The system description will be provided in next section, followed by the formulation of the distributed dynamic optimization problem. The simulation model and control oriented models will then be described. The active-set primal-dual algorithm adopted for the distributed MPC framework will be briefly reviewed, and then the simulation results will be presented. The final section concludes the paper.

NOMENCLATURE

n: number of chillers
m: number of buildings
x_i: state vector for the ith building
T_{bi}: space temperature of the ith building
T_{sai}:supply air temperature of the ith building
T_{ri}: return water temperature of the ith building
L_i: aggregated SOC for EVs at the ith building
x_{m+1}: states of the chiller water plant
T_{lmix}: supply water temperature from chilled water plant
T_{rmix}: return water temperature to chilled water plant
u_i: inputs for the ith building
$\dot{m}_{bi}$: chilled water mass flow rate to Building i
M_i: the EV charging power at the i^{th} building
u_{m+1}: vector of inputs for the chilled-water plant
$\dot{m}_{wj}$: condensing water flow rate of chiller j
$\dot{m}_{aj}$: fan flow rate of cooling tower j
T_{lj}: leaving water temperature out of chiller j
$\dot{m}_{cj}$: leaving water mass flow rate of chiller j
p : dynamic electricity price
ϕ_i: AHU power consumption of the i-th building
Q: weighting matrix
R: weighting matrix
P_j: power consumption of chiller j
$\overline{SOC}$: upper bound of SOC
DC: demand charge
dc: demand charge rate
T_s: sampling time
c: capacity of onboard battery
υ: charging power supplied for charging the device
ω: disturbance vector
occ_i: number of occupants in the i-th building
T_{amb}: ambient temperature
Rad: solar radiation
RH: relative humidity
A_i: state matrix
B_i: input matrix
C_i: output matrix
D_i: feedthrough matrix
E_i: disturbance matrix
$T_{bi,set}$: temperature setpoint of the i-th building

Problem Formulation

The smart community considered in this study is simplified as a number of buildings sustained by central plant cooling. The distributed MPC is anchored on a multi-agent system framework. The chilled-water plant is deemed as one agent that incorporates n chillers. Each building is treated as an agent that includes the chilled-water based air handling unit (AHU) for thermal comfort regulation, as well as its own EV parking lot. As simple treatment, each building is simplified as a single zone regulated by one AHU. The state-space model for each agent follows:

$$x_i(k+1) = A_i x_i(k) + B_i u(k) + E_i \omega(k) \quad (1)$$

$$y_i(k) = C_i x_i(k) + D_i u(k) \quad (2)$$

where i= $1,2,\dots,m+1$. For $i = 1, \dots, m$, $x_i = [T_{bi}, T_{ri}, T_{sai}, L_i]^T$, $u = [u_1, u_2, \dots, u_m, u_{m+1}]^T$, with $u_i = [\dot{m}_{bi}, T_{lmix}, M_i]^T$. For the chilled-water plant, $x_{m+1} = [T_{lmix}, T_{rmix}]^T$, $u_{m+1} = [\dot{m}_{w1},, \dots \dot{m}_{wn,} \dot{m}_{a1}, \dots, \dot{m}_{an}, T_{l1}, \dots T_{ln}, \dot{m}_{c1}, \dots \dot{m}_{cn}]$, with $j = 1, 2, \dots, n$. The disturbance vector is $\omega = [occ_1, occ_2, \dots occ_m, T_{amb}, Rad, RH]^T$, A_i, B_i, C_i, D_i, E_i are matrices with compatible dimensions. For the j-th chiller, the power consumption is $P_j = Power_j(T_{lj}, \dot{m}_{aj}, \dot{m}_{wj}, \dot{m}_{cj}, T_{wb}, T_{rmix})$, which is evaluated with a 6D look-up table (LUT).

To achieve the optimal energy management for smart community, the goal is to minimize the cost for energy consumption of thermal regulation and EV charging which includes both TOU and demand charges, while meeting the requirement of thermal comfort regulation and charging demand. The associated optimization problem can be framed as:

$$\min_{u_1,\ldots,\, u_{m+1}} J = \sum_{k=1}^{N}\Big\{p(k)\Big[\sum_{j=1}^{n} P_j(k) + \sum_{i=1}^{m}(\phi_i(k) + M_i(k))\Big] + \sum_{i=1}^{m}\Big(T_{bi}(k) - T_{bi,set}(k)\Big)' * Q * \Big(T_{bi}(k) - T_{bi,\,set}(k)\Big) + DC\Big\} + (L(T) - \overline{SOC})' * R * (L(T) - \overline{SOC}) \quad (3)$$

s.t.

$$x_i(k+1) = A_i x_i(k) + B_i u(k) + E_i \omega(k) \quad (3a)$$

$$y_i(k) = C_i x_i(k) + D_i u(k) \quad (3b)$$

$$\dot{m}_{w,min} \le \dot{m}_{wj} \le \dot{m}_{w,max} \quad (3c)$$

$$\dot{m}_{a,min} \le \dot{m}_{aj} \le \dot{m}_{a,max} \quad (3d)$$

$$\dot{m}_{c,min} \le \dot{m}_{cj} \le \dot{m}_{c,max} \quad (3e)$$

$$T_{l,min} \le T_{lj} \le T_{l,max} \quad (3f)$$

$$SOC_{min} \le L(k) \le SOC_{max} \quad (3g)$$

$$0 \le v(k) \le v_{max} \quad (3h)$$

$$\sum_{j=1}^{n} \dot{m}_{cj} = \sum_{i=1}^{m} \dot{m}_{bi} \quad (3i)$$

where $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$. DC is the demand charge, which is determined by

$$DC = dc * \max_{1 \le k \le N}\{\sum_{j=1}^{3} P_j(k) + \sum_{i=1}^{3}[\phi_i(k) + M_i(k)]\} \quad (3j)$$

Simulation Model and Control Oriented Models

There are two efforts of model development in this study. First, a Modelica based dydnamic simulation model is developed for the smart community system using Dymola and TIL Library. Modelica enables an equation based multi-physical simulation platform, which is suitable choice for smart community systems which is a mixture of building HVAC, electrical, mechanical and control systems. The illustrative system consists of three chillers and three buildings, i.e. n = 3 and m = 3. Figure 2 shows the entire system layout in Dymola. The chiller plant is shown in the left blue dash box to the left, in which there are three chillers are configured in parallel.

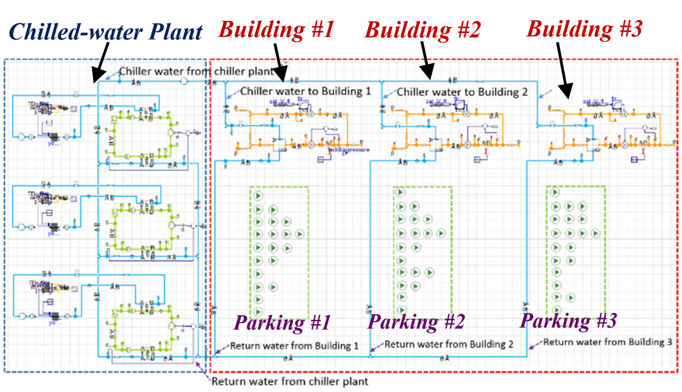

Figure 2 Dymola layout of simulation model of the illustrative smart community system.

In the dash box to the right, three buildings of the community are shown, each contains an AHU and zone model. Each building is attached with a parking lot of 20 charging stations, and each charging station is modeled with a battery pack representing the EV. The charging mode and charging power can be set by the control algorithms. The charging power and duration for each charging station can be programmed. The length of water pipe between buildings is 40m, and the length of water pipe between Building 1 and the chiller plant is 20m.

Then the control oriented models as described in the previous section are obtained via system identification algorithms. Open-loop tests are performed using Pseudo Random Binary Sequence (PRBS) inputs in order to meet the requirement of persistent excitation considering the number of model parameters involved. The MATLAB System Identification Toolbox [11] is used to estimate the model parameters.

Distributed MPC for Predictive Energy Management of Smart Community System

For the large-scale dynamic optimization problem for energy management of smart community, DMPC is an appropriate solution due to the computational loads involved for the large number of buildings and charging stations. Several DMPC methods have been investigated, such as dual decomposition (DD) [12][13], interior point decomposition (IPD) [14], Nash equilibrium (NE) [15], and alternating direction method of multipliers (ADMM) [16]. The advantages of DD is that the algorithm is simple to implement; however, its convergence is known to be very slow and it cannot guarantee primal feasibility until convergence. IPD has faster convergence, but may lose accuracy in the presence of ill conditioning. NE may obtain an undesirable optimal point of the controlled system. ADMM has better convergence rates than DD, but requires many more iterations to converge and high communication cost. In particular, the primal-dual active-set (PDAS) method has recently been shown to be suited for distributed control with high communication cost. Although the communication cost of PDAS is higher than DP and ADMM in each iteration, the number of iterations to convergence is much less. Overall, the communication cost of PDAS is much less than other DMPC methods. Therefore, in this study, the PDAS method is selected to solve the associated DMPC problem.

A PDAS method for strictly convex quadratic programs that was initially proposed by Hintermüller [17] and expand upon by Curtis [18]. In this algorithm, multiple constraints are added to or removed from the active set during each iteration of the algorithm. As a result, the algorithm often converges in very few iterations and it exhibits local superlinear convergence [19].

The PDAS algorithm is described as follows. Assume that a large-scale system can be decomposed into n subsystems which are sparsely coupled. Each subsystem i is connected to its neighbors $\mathcal{N}(i)$ via state and/or input coupling. Each subsystem has own local performance for state x_i and input u_i . The associated DMPC problem can be framed as:

$$\min_{X,U} \sum_{k=0}^{N}\sum_{i=1}^{n} p_i(x_i(k), u_i(k)) \quad (4a)$$

$$s.t.\ x_i(k+1) = A_i x_i(k) + B_i u(k) + E_i \omega(k) \tag{4b}$$

$$x_i(k) \in X_i, i = 1, \dots, n, and\ k = 0, \dots, N-1 \tag{4c}$$

$$u_i(k) \in u_i, i = 1, \dots, n, and\ k = 0, \dots, N-1 \tag{4d}$$

where N is the prediction horizon. $A = \begin{bmatrix} A_1 & 0 & \dots \\ 0 & \ddots & \vdots \\ \vdots & \dots & A_r \end{bmatrix}, B = [B_1, \dots, B_r]^T$. $x(k) \in \mathcal{R}^n$ is the predicted state under the control action $u(k) \in \mathcal{R}^m$ and forecasted disturbance $\omega(k) \in \mathcal{R}^n$ over horizon N, $x(k) = [x_1(k), \dots x_r(k)]^T$ and $u(k) = [u_1(k), \dots u_s(k)]^T$. For subsystem i, the vector of states and inputs within the prediction horizon is denoted as $z_i \triangleq [x_i^T(0) \dots x_i^T(N)\ u_i^T(0) \dots u_i^T(N-1)]^T$. Then, the DMPC design problem becomes

$$\min_{z_1, z_2, \dots, z_n} \sum_{i=1}^{n} p_i(z_i) \tag{5a}$$

$$s.t.\ A_i z_i \le b_i\ \forall i \in \{1, \dots, N\} \tag{5b}$$

$$C_i z_i = d_i\ \forall i \in \{1, \dots, N\} \tag{5c}$$

For $N = 1$, the DMPC program is defined with a quadratic objective function [18][19], i.e.

$$\min_z \frac{1}{2} z^T P\, z + c^T z \tag{6a}$$

$$s.t. Cz = d \tag{6b}$$

$$\underline{z} \le z \le \overline{z} \tag{6c}$$

where $z \epsilon \mathcal{R}^p$, $c \in \mathcal{R}^p$, $C \in \mathcal{R}^q$, $d \in \mathcal{R}^q$, and $P = P^T \succ 0$.

Let $\upsilon \epsilon \mathcal{R}^p$ be the dual variables corresponding to the equality constraints (6b), and $\bar{\lambda} \epsilon \mathcal{R}^p$ and $\underline{\lambda} \epsilon \mathcal{R}^p$ be the dual variables for the upper and lower bound constraints (6c). The Karush-Kuhn-Tucker (KKT) necessary and sufficient conditions for optimality for the quadratic program (6) are:

$$Pz + c + C^T \upsilon + \bar{\lambda} - \underline{\lambda} = 0 \tag{7a}$$

$$Cz - d = 0 \tag{7b}$$

$$\min(\bar{z} - z, \bar{\lambda}) = 0 \tag{7c}$$

$$\min(z - \underline{z}, \underline{\lambda}) = 0 \tag{7d}$$

Let $\mathcal{J} = \{1, \dots, p\}$ be the index set for the elements of z. For a primal variable z, we define the following disjoint subsets of $\mathcal{J}$:

$$\bar{A} = \{j \in \mathcal{J}: z_j = \bar{z}_j\} \tag{8a}$$

$$\underline{A} = \{j \in \mathcal{J}: z_j = \underline{z_j}\} \tag{8b}$$

where $\overline{\mathrm{A}}$ is the set of components of z that are active at their upper bound $\bar{\mathrm{z}}$, and $\underline{\mathrm{A}}$ is the set of elements of z that are active at their lower bound $\underline{\mathrm{z}}$. By defining $\mathcal{A} = \underline{\mathcal{A}} \cup \bar{\mathcal{A}}$, $\mathrm{I} = \mathcal{J} \backslash \mathcal{A}$ is the set of element of z that are not active. We denote by $\mathrm{z}_{\mathcal{A}}$ the elements $\mathrm{z_j}$ of z for $\mathrm{j} \in \mathcal{A}$. Similarly, z_I is the element $\mathrm{z_j}$ of z for $\mathrm{j} \in \mathcal{J}$. The algorithm is initialized with an active-set partition $\overline{\mathrm{A}}$, $\underline{\mathrm{A}}$ and I. There must exist some $\mathrm{z_I}$ such that set $\mathrm{Z_I}$ is not empty, where $\mathrm{Z_I}$ is defined as follows;

$$\mathrm{Z_I} \coloneqq \{\mathrm{z_I} | \mathrm{Cz} = \mathrm{C_A z_A} + \mathrm{C_I z_I} = \mathrm{d}\} \tag{9}$$

The first step of the algorithm is to find primal variables $\mathrm{z_I}$ and equality dual variables υ that satisfy (7a) and (7b).

$$\begin{bmatrix} \mathrm{P_{I,I}} & \mathrm{C_I^T} \\ \mathrm{C_I} & 0 \end{bmatrix} \begin{bmatrix} \mathrm{z_I} \\ \upsilon \end{bmatrix} = \begin{bmatrix} -\mathrm{P_{I,A} z_A} - \mathrm{C_I} \\ -\mathrm{C_a z_a} + \mathrm{d} \end{bmatrix} \tag{10}$$

where $\bar{\lambda}_\mathrm{I} = \underline{\lambda_\mathrm{I}} = 0$.

Next is to update the inequality dual variables $\underline{\lambda}$ and $\bar{\lambda}$ to satisfy (7a), i.e.

$$\bar{\lambda}_\mathrm{j} = \begin{cases} \mathrm{P_j z} + \mathrm{c_j} + (\mathrm{C^T}\upsilon)_\mathrm{j} & \text{if } \mathrm{j} \in \bar{\mathcal{A}} \\ 0 & \text{if } \mathrm{j} \notin \bar{\mathcal{A}} \end{cases} \tag{11a}$$

$$\underline{\lambda}_\mathrm{j} = \begin{cases} \mathrm{P_j z} + \mathrm{c_j} + (\mathrm{C^T}\upsilon)_\mathrm{j} & \text{if } \mathrm{j} \epsilon \underline{\mathcal{A}} \\ 0 & \text{if } \mathrm{j} \notin \underline{\mathcal{A}} \end{cases} \tag{11b}$$

where P_j is the j-th row of P. The active sets are updated as

$$\bar{A}^+ \leftarrow \{(j | (z_j > \bar{z}_j\ and\ j \in I))\} \tag{12a}$$

$$\underline{A}^+ \leftarrow \{(j | (z_j < \underline{z}_j\ and\ j \in I))\} \tag{12b}$$

$$I^+ \leftarrow \{(j | j \notin \bar{A}^+ \cup \underline{A}^+)\} \tag{12c}$$

where superscript '+' indicates the update of the active set at the next iteration.

Algorithm 1 Primal Dual Active-Set Method

1: Find feasible initial active-set partition $\bar{A}_0, \underline{A}_0, I_0$
2: **while** $\underline{\boldsymbol{A}}^+ \neq \underline{\boldsymbol{A}}$ $\boldsymbol{or}$ $\bar{\boldsymbol{A}}^+ \neq \bar{\boldsymbol{A}}$ **do**
3: Solve minimization problem (10)
4: Update duals using (11a) (11b)
5: Update active-sets $\bar{A}$ and $\underline{A}$ using (12a) (12b) (12c)
6: **end while**

For $N \ge 1$, the PDAS based DMPC design problem becomes [20]:

$$\min_{X,U} x(N)^T P x(N) + \sum_{k=0}^{N-1} (x(k)^T Q x(k) + u(k)^T R u(k)) \tag{13a}$$

$$s.t. x_i(k+1) = A_i x_i(k) + B_i u(k) + E_i \omega(k) \tag{13b}$$

$$\underline{x} \le x_i((k) \le \bar{x}, k = 1, \dots N \tag{13c}$$

$$\underline{u} \le u(k) \le \bar{u}, k = 0, \dots, N-1 \tag{13d}$$

$$x(0) = x_t \tag{13e}$$

Symmetric matrices $Q, R, P \succ 0$ are defined as

$$P = \begin{bmatrix} P_1 & & \\ & \ddots & \\ & & P_r \end{bmatrix}, Q = \begin{bmatrix} Q_1 & & \\ & \ddots & \\ & & Q_r \end{bmatrix}, R = \begin{bmatrix} R_1 & & \\ & \ddots & \\ & & R_s \end{bmatrix}.$$

Algorithm 1 is repeated at every computational step.

Simulation results

The proposed DMPC based smart community energy management strategy is simulated for the plant model described in the second section. Figure 3 shows the disturbance and electricity price used in the simulation. The sampling period is 300 seconds. The prediction horizon is 30 time steps. The zone temperature setpoints are 23, 24 and 25°C for Buildings 1, 2 and 3, respectively. The day-ahead electricity price profile for Dallas on April 7, 2017 was obtained from the database of the Electric Reliability Council of Texas (ERCOT) [21].

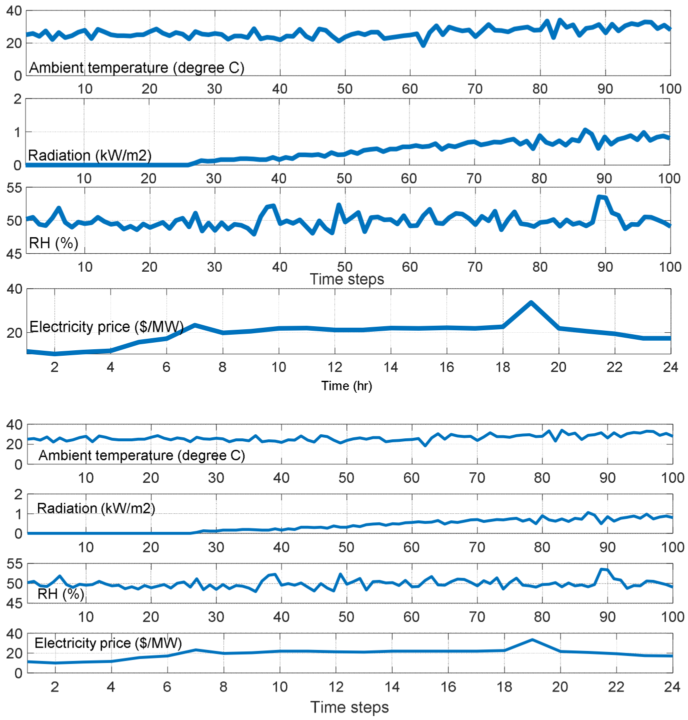

Figure 3. Ambient condition and electricity price for the simulated period

For three buildings, we expect 20 EV (each carries 25 people) coming to each building. The EV arrival rate is assumed to follow a Poisson distribution as shown in Figure 4. Each vehicle will stay for at least five steps. The onboard battery capacity is 16kWh. The nominal charging rate is 6.4kW. The battery charging takes 2.5 hours to fully charge the vehicle batteries.

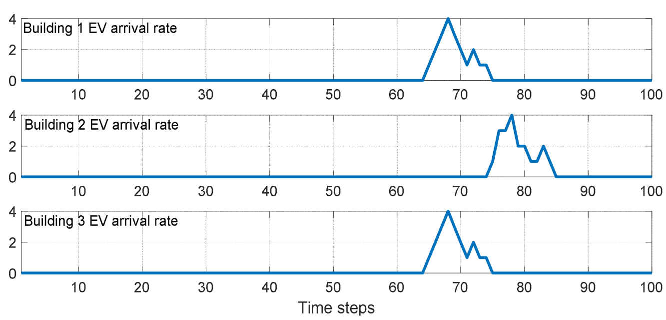

Figure 4. EV arrival rates at Buildings 1, 2 and 3.

First, a centralized MPC scheme is applied to solve the scenario of system operation. Figure 5 shows the results of building temperature tracking along with profiles of key process variables for chiller plant operation. Figure 6 shows the profiles of power consumption and electricity bills.

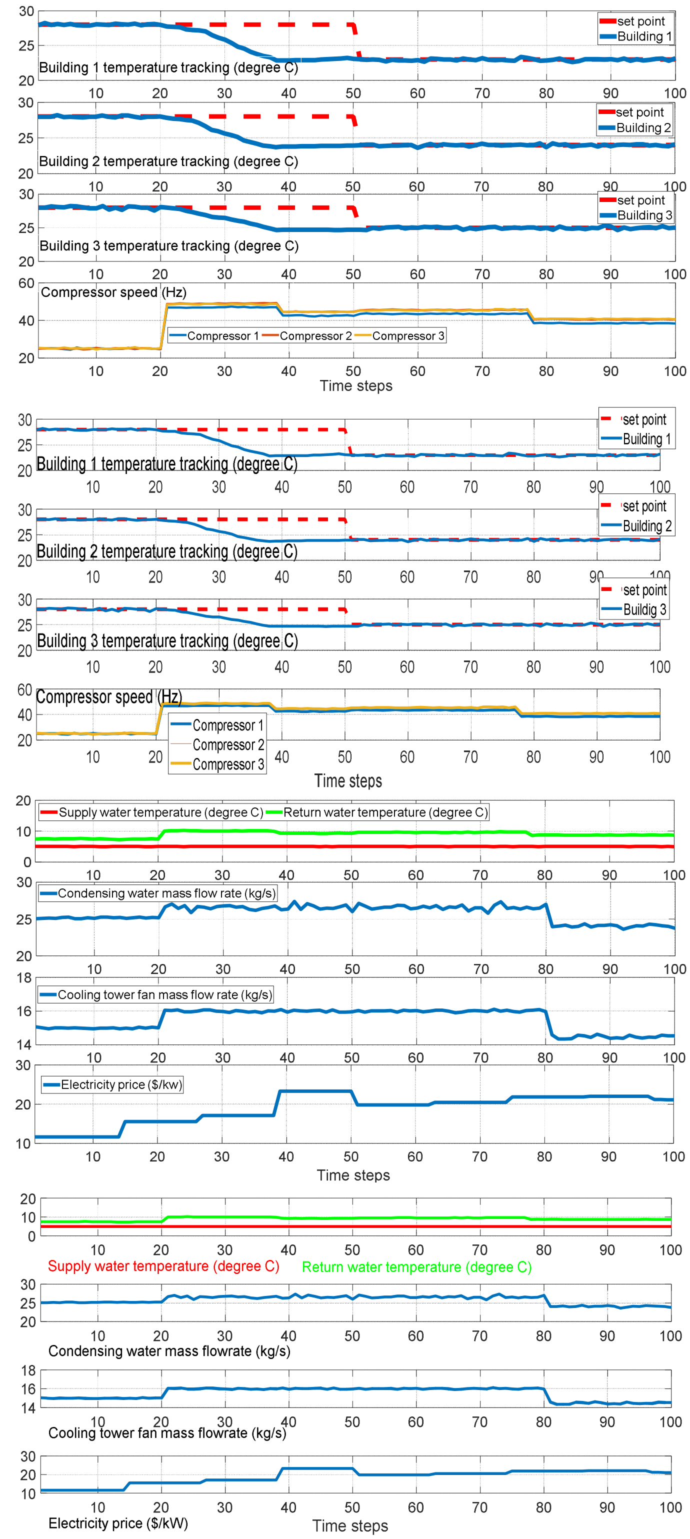

Figure 5. Simulation results of centralized MPC: building temperature tracking and chiller plant operation.

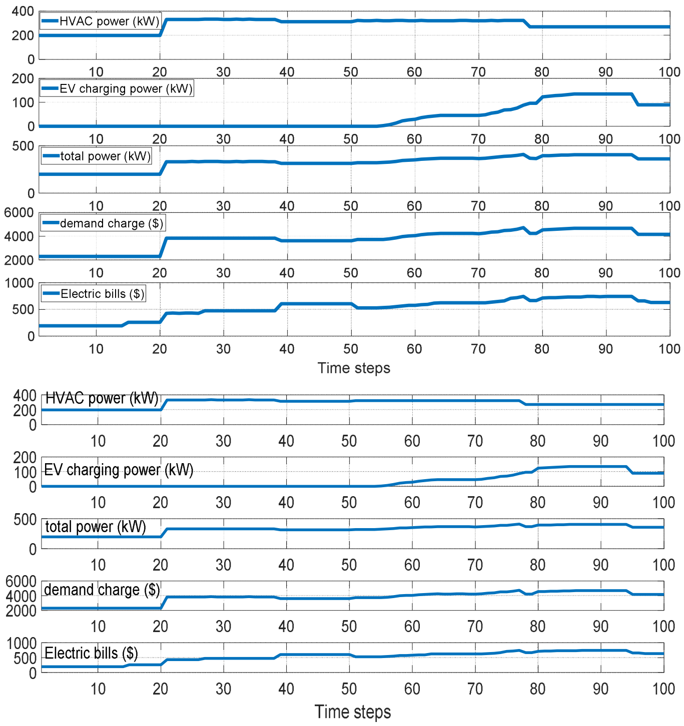

Figure 6. Simulation results of centralized MPC: Power consumption of HVAC and EV charging and electricity bills

Then, the distributed MPC algorithm described above is applied. Figures 7, 8 and 9 show the simulation results of thermal comfort regulation and EV charging for Buildings 1, 2 and 3, respectively. Figure 10 shows the profiles of the key process variables for the chiller plant operation. Figure 11 shows the trajectories of power consumption and electricity charges from the distributed MPC.

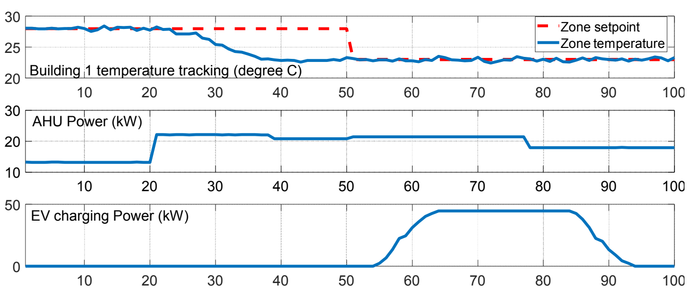

Figure 7. DMPC simulation results for Building-1 energy management.

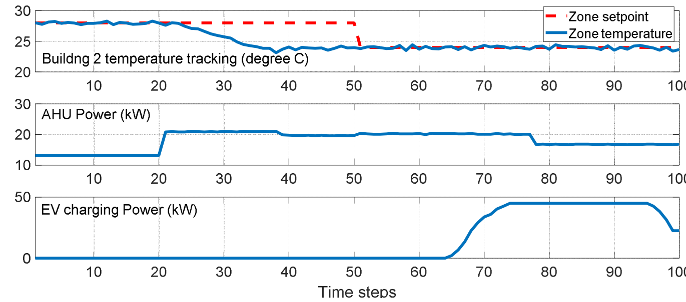

Figure 8. DMPC simulation results for Building-2 energy management.

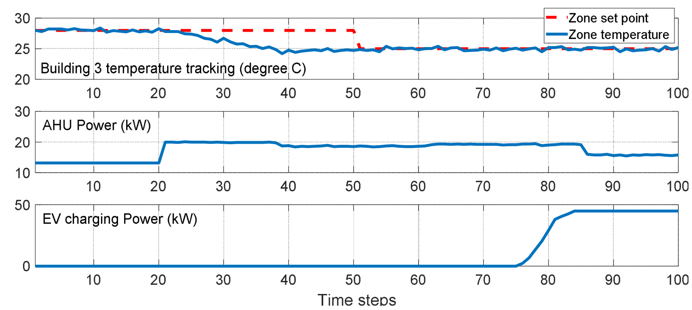

Figure 9. DMPC simulation results for Building-3 energy management.

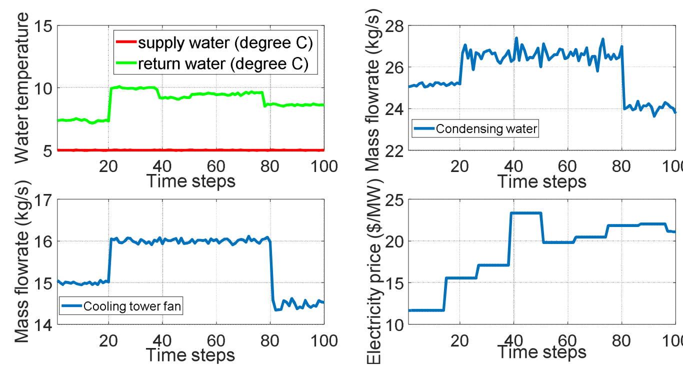

Figure 10. Chiller plant operation during DMPC simulation.

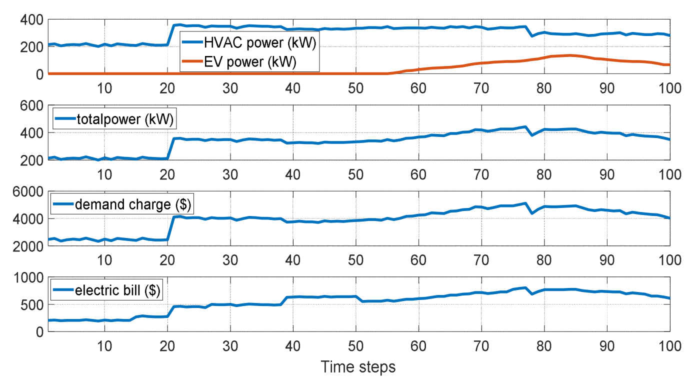

Figure 11. Trajectories of power consumption and electricity charges

For the simulated period, the combined cost of TOU charge and demand charge of DMPC are higher than corresponding values obtained from centralize MPC. Within the simulated period, the total power consumption of the centralized MPC is 2,685.2 kWh, while in comparison DMPC yields 2,825.5kWh, 5.15% increase. The TOU charge of the centralized MPC is $52.33, while that for the DMPC is $54.98, 5.06% increase. The demand charges are $4,725.1 and $5,111.0 for the centralized MPC and the distributed MPC, respectively. Demand charge of DMPC is 8.17% higher than that of centralized MPC. Further work is under way to improve the performance of the DMPC.

Conclusion

A DMPC based predictive energy management strategy is proposed for smart community with chilled water plant and EV charging load, enabled by ITS driven prediction for occupancy-vehicle arrival information. A Modelica based dynamic simulation model is developed for the smart community, including chiller plant, building HVAC and EV battery charging. DMPC is benchmarked against a centralized MPC. The simulation shows that the distributed MPC has performed reasonably but further improvement of DMPC is needed. There is no significant fluctuation in the power consumption profile with the predictive control policy due to the introduction of predictive occupancy and vehicle charging information reinforced by ITS information exchange. Notice that in this study, the peak EV charging power takes up to 25-30% of total power consumption. If more EVs are present to parking lot charging, this share will certainly increase. Further work is conducted under way to improve the DMPC performance reducing the discrepancy from the centralized MPC results. Also, the uncertainty quantification and propagation issues will be study in near future.

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