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A modeling framework for optimal energy management of a residential building

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ABSTRACT

Residential buildings are currently equipped with energy production facilities, e.g., solar rooftops and batteries, which in conjunction with smart meters, can function as smart energy hubs coordinating the loads and the resources in an optimal manner. This paper presents a mathematical model for the optimal energy management of a residential building and proposes a centralized energy management system (CEMS) framework for off-grid operation. The model of each component of the hub is integrated within the CEMS. The optimal decisions are determined in real-time by considering these models with realistic parameter settings and customer preferences. Model predictive control (MPC) is used to adapt the optimal decisions on a receding horizon to account for the deviations in the system inputs. Simulation results are presented to demonstrate the feasibility and effectiveness of the proposed CEMS framework. Results show that the proposed CEMS can reduce the energy cost and energy consumption of the customers by approximately 17% and 8%, respectively, over a day. Using the proposed CEMS, the total charging cycles of the ESS were reduced by more than 50% in a day.

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1. Introduction

The U.S. Department of Energy Microgrid Exchange Group defines microgrid as a group of interconnected loads and distributed energy resources (DERs) within clearly identified electrical boundaries that act as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid and operate in both grid-connected or island-modes, respectively. While grid-connected microgrids have the advantage that the grid acts as a supply reservoir to balance the demand when needed, such a facility is not available for an isolated microgrid. The isolated microgrids are constrained by the generation capacity available within the microgrid only, and are expected to rely on various controllable and intermittent resources to match and balance the demand supply gap. Therefore, energy management in isolated microgrids is a much more challenging problem [1]. A residential building with typical loads, and DERs such as distributed generators (DGs), storage devices, controllable loads, etc., can be considered a microgrid that can be operated in a controlled and coordinated manner either connected to the grid or in an islanded mode.

Significant efforts are being made by researchers to develop intelligent control algorithms integrated with information technology to manage energy consumption and thereby regulate load growth. Demand response (DR) programs are being implemented by utilities and Local Distribution Companies (LDCs) to alter the load shape in response to price signals or operator requests during critical conditions. DR is defined by the Federal Energy Regulatory Commission (FERC) in [2] as: “Changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at time of high wholesale market price or when system reliability is jeopardized.” These programs help the LDC to maintain a fairly uniform load level, thereby reducing its need for new supply resources or feeders.

Although DR has taken center-stage in the context of smart grids, demand-side management (DSM) programs have been in existence and practice for several decades now [3]. For example, the authors in [4] state that one way to reduce costs is to use direct utility-consumer communications to implement a “load follow supply” concept. In such a system, the customer’s demand

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Nomenclature

Indices

k	time sample (every 15 min), k =1,2,. . .,96

Parameters

η_{chg}, η_{dchg}	charging and discharging efficiency, respectively [p.u.]
η_{MPPT}	efficiency of PV's DC/DC converter
τ	time interval [h]
φ	self discharge rate [p.u.]
C	equivalent heat capacity [J/°C]
C_1, C_2	cost of the ESS related to discharging power [$/W] and charging cycles [$/CYC], respectively
$\overline{E}$	rated energy capacity of ESS [kWh]
G	irradiation on the device surface, G = 1000 W/m^2
L_m, L_h	energy loss associated with medium and high charging/discharging rate [p.u.]
$\overline{P}_{chg}$, $\overline{P}_{dchg}$	maximum power drawn and supplied by the ESS, respectively [W]
P_{Dem}	base load profile of a building [W]
$\underline{P}_{gen}$, $\overline{P}_{gen}$	minimum and maximum power output of diesel generator, respectively [W]
$\overline{P}_{grid}$	maximum power that can be purchase from the grid [W]
P_{hvac}	rated power of HVAC unit [W]
P_{pv}, P_{pv}^{rated}	output power and rated power of solar PV, respectively [W]
Q, R	equivalent heat rate [W] and thermal resistance [°C/W], respectively
R_l, R_m, R_h	charging/discharging of the ESS at low, medium, and high rate, respectively [W]
RUP, RDN	ramp-up and ramp-down limit of diesel generator, respectively [W]
$\underline{SOC}$, $\overline{SOC}$	initial and final state of charge of the ESS, respectively [p.u.]
T^{out}	outside temperature [Celsius]
$\underline{T}$, $\overline{T}$	upper and lower bounds of temperature [Celsius]

Variables

C_{ess}, C_{gen}	operating cost of ESS and diesel generator, respectively [$]
C_l, C_m, C_h	binary variable to check charging level status of ESS: low/medium/high, respectively
CYC	total number of charging cycles [p.u.]
D_l, D_m, D_h	binary variable to check discharging level status of ESS: low/medium/high, respectively
E_{bat}	energy of the ESS [Wh]
J	objective function value [$]
P_{chg}, P_{dchg}	power drawn and supplied by the ESS, respectively [W]
P_{grid}	power purchased from grid [W]
P_{gen}	output power of a diesel generator [W]
S_k, S^{ht}	status [ON/OFF] of diesel generator and HVAC unit, respectively
SOC	state of charge of the ESS [p.u.]
T	inside temperature of the building [Celsius]
u	binary variable to check when new charging cycle starts
u_1, u_2	binary variable associated with charging and discharging of ESS, respectively

would be controlled through interruption of power for specific uses. DSM programs encourage customers to be more energy efficient which can be achieved by shifting the demand from peak hours to mid-peak or off-peak hours; reducing energy consumption; and consuming locally produced energy [5–7].

It has been shown in [8] that up to 30% energy savings can be brought about in a residential building by optimizing the operation and management of the building's energy system without changing the building structure or hardware configuration of its energy supply system. There is a potential for improving the building's energy efficiency by optimal operation of the various energy sources and controllable loads. Rooftop solar photo-voltaic (PV) generation, energy storage system (ESS), DG and controllable loads can be considered as a part of a residential building in a smart grid. However, in order to achieve the desired objective, all microgrid assets, local generation resources, storage devices and controllable loads, need be integrated into a proper control and management system.

The optimal energy management problem in microgrids has been extensively investigated in the literature [8–13]. To solve a dispatch problem for microgrids, meta-heuristic and heuristic techniques, such as genetic algorithms, evolutionary algorithms, particle swarm optimization, and Tabu search have been proposed by researchers [14]. In [10], a coordinated control approach for microgrid energy management was proposed that comprised a scheduling and a dispatch layer. The optimal integrated scheduling and control of building energy supply resources was considered in [8] with the objective to minimize the overall cost of electricity and natural gas consumption and significant energy cost savings were obtained.

In [11], a model for optimal operation of a microgrid is proposed; the problem is decomposed into a grid-connected operation master problem and an islanded operation subproblem. The scheduling decisions are revised based on islanding cuts that ensured sufficient generation was available to guarantee a feasible island, which were further revised to dispatch the generating units, ESS and controllable loads. In [15], a generalized formulation smart energy management of a microgrid was proposed with a multi-objective function that sought to minimize the operating cost and the environmental impacts taking into account the uncertainty of the exogenous variables and forecasted inputs.

A probabilistic approach was proposed in [12] to analyze a microgrid's operational performance considering uncertainties in solar PV, ESS and conventional generators. A microgrid operations model was proposed in [13] where load curtailment was minimized by efficiently scheduling the available resources when power from the main grid was interrupted for an extended period of time. All the above studies discussed, are from the perspective of the grid, while behavior of an individual customer has not been considered. In the context of smart grids where customers are equipped with local energy production resources and controllable loads, it is important to study their load behavior as it may affect the operating decisions of a microgrid/grid. Thus, in this paper, the proposed centralized energy management system (CEMS) focuses on determining the load profile of a building which can help utilities/microgrids operate in a reliable, safe, and cost effective manner.

Lot of work has been reported on energy management in buildings, cost optimal strategies, and energy consumption forecast [16–23]. In [23], the thermal behavior of a building equipped with energy production and storage facility is modeled. Two strategies are considered i.e., managing solar PV and wind; and managing solar PV, wind and ESS; results show that by shifting the loads from peak hours to off-peak hours can bring about a reduction in energy costs. However, uncertainty due to weather and energy demand is not considered in this work. In [24], a control algorithm is proposed that uses hot water storage tanks to simultaneously dispatch the heating and electrical devices. In another work on energy management [25], a predictive controller is implemented with centralized supervisory control and data acquisition (SCADA) to optimize the comfort of users while energy waste is minimized. In [26], various DR strategies are tested on HVAC schedules to reduce the peak power consumption and obtain a flexible load shape. In [27], energy management is carried out with storage systems and solar PV, with the objective of reducing the peak demand and maximizing the use of solar PV generation. In [28], an energy management strategy is proposed for a commercial buildings using solar PV and ESS to reduce the energy cost and CO_2 emissions. In [29], an energy management system for a home is proposed that includes optimal scheduling of electric vehicle charging and home appliances to reduce the energy cost.

The model predictive control (MPC) technique, an advanced control technique, has found recent applications because of its various advantages. It determines the future behavior of the system considering uncertainties in demand forecast, weather forecast, and renewable energy generation forecast [30]. Lot of work can be found in the literature where MPC is applied to dispatch problems in power systems [14,31–38]. In [32], a smart distribution power flow framework was proposed to determine the smart charging schedules of plug-in electric vehicles using MPC. A modeling framework for analyzing the impact and scheduling of price-responsive and controllable loads in a three-phase distribution system was presented in [33] using MPC. In [34], MPC was used for a dynamic dispatch problem; the convergence and robustness of the MPC algorithm was also demonstrated. In [34], the centralized supervisory MPC controller was replaced with two distributed supervisory MPC controllers, each responsible for providing the optimal reference trajectories to the local controller of the corresponding subsystem.

From the aforementioned discussions, it is clear that there is a need to manage energy for the end user that will not only help customers reduce their energy costs but also help the electrical grid by improving energy efficiency and alleviate the cost of recurring system upgrades. This will also help the electrical grid to operate in a secure, resilient, and reliable manner. These energy management systems can help customers participate in DR programs while their comfort is not compromised. Thus, the objective of this paper is to develop an optimization framework for a CEMS of a residential building, operating as an isolated microgrid, that can optimally dispatch the generation sources in real time to satisfy the demand. The MPC technique is used to monitor the evolution of the system over a finite time horizon while implementing the solution from the current time step only. System conditions and parameters are updated at each time step using feedback mechanisms to inform the optimization model for the next step. The main contributions of this paper are as follows:

- The development of a CEMS mathematical model that is a comprehensive representation of a building's energy management system in the context of smart grids.
- The presentation of detailed operational models of various components such as DG, HVAC, solar PV and battery storage system to accurately capture their characteristics and physical constraints.
- The integration of the controllable loads, such as HVAC, into the decision-making process of the CEMS over the operating horizon.
- The consideration of the interactions with the grid that can be controlled by an LDC, or a microgrid operator, to alter the customers' load profiles in real-time.
- The consideration of uncertainties associated with weather and demand forecast; for example, every 15 min inputs are checked so that dispatch values are meaningful in real-time.

The remainder of the paper is organized as follows: in Section (2) the detailed models of various components in a residential building are presented. The modeling approach and the overall framework for residential buildings are discussed in Section (3) and the optimization problem is presented in Section (4). Section (5) discusses results of various case studies carried out to demonstrate the effectiveness of the proposed framework. Finally, the main findings are summarized and the concluding remarks are outlined in Section (6).

2. EMS models of a residential building

2.1. Loads

Loads can typically be classified as fixed loads that should always be met, and controllable loads that may be curtailed or shifted to another time. In this paper, both fixed and controllable loads are considered. A 24-h load profile is used to represent the building's power demand. In order to estimate the thermal load of the building, an approximation of its internal load is required. Internal loads of the building comprise those from the electric cooking range, external lighting, internal lighting, refrigerator and miscellaneous loads. The method proposed in [39] is used here to calculate the base load profile of the building.

An equivalent thermal model of an HVAC unit, suited to residential buildings, proposed in [40], is used. When the HVAC unit is turned ON/OFF, the dynamic behavior of the inside temperature of the residential building can be expressed as follows [40]:

$$T(k)=T^{out}(k)-(T^{out}(k)-T(k-1))e^{-(\tau/RC)}+S^{ht}(k)QR(1+e^{-(\tau/RC)}), \tag{1}$$

$$\underline{T}(k) \le T(k) \le \overline{T}(k), \quad \forall k \in [1,m], \quad m \in \mathbb{N}, \tag{2}$$

where parameters R, C, and Q are obtained from curve fitting, either from the performance curve produced by the precise model presented in [40] or by practical measurements. The inside temperature variation is controlled within a narrow temperature band of $\pm 2\,^{\circ}$C. Thus, this model captures the normal temperature and the maximum temperature deviation that the customer is willing to accept.

2.2. Energy storage system

The charging/discharging of the ESS in a microgrid needs to be coordinated to ensure the supply-demand balance. The residential building is considered to be equipped with batteries for energy storage. The generic dynamic model of the ESS is given as follows:

$$\begin{aligned} E_{bat}(k) = (1-\varphi)E_{bat}(k-1) + \tau \cdot \left(\eta_{chg}P_{chg}(k) - \frac{P_{dchg}(k)}{\eta_{dchg}}\right) \\ + \overline{E}(-L_mC_m(k) - L_hC_h(k) - L_mD_m(k) - L_hD_h(k)), \end{aligned} \tag{3}$$

$$0 \le P_{chg}(k) \le \overline{P}_{chg}u_1(k), \tag{4}$$

$$0 \le P_{dchg}(k) \le \overline{P}_{dchg}u_2(k), \tag{5}$$

$$u_1(k) + u_2(k) \le 1, \tag{6}$$

$$SOC(k) = \frac{E_{bat}(k)}{\overline{E}}, \tag{7}$$

$$\underline{SOC} \le SOC(k) \le \overline{SOC}, \quad \forall k \in [1,m], m \in \mathbb{N} \tag{8}$$

and

$$SOC(k) = 0.3 \quad \text{at} \quad k = N. \tag{9}$$

Eq. (3) relates the energy state of the ESS at time k to that at time $k-1$, and the charging and discharging energies at time k. Eqs. (4) and (5) ensure that the charging and discharging power levels are within specified values. Eq. (6) ensures that the ESS is either in charging, discharging, or in idle mode. The state-of-charge (SOC) of the ESS can be computed using (7), and the upper and lower limits on the energy level of the ESS is given by (8). Finally, Eq. (9) ensures that by the end of the day the energy level of the ESS is not fully depleted and can compensate for any error in weather forecast.

$$P_{chg}(k) \leq R_1 C_l(k) + R_2 C_m(k) + R_3 C_h(k), \tag{10}$$

$$P_{dchg}(k) \leq R_1 D_l(k) + R_2 D_m(k) + R_3 D_h(k), \tag{11}$$

$$C_l(k) + C_m(k) + C_h(k) \leq 1, \tag{12}$$

$$D_l(k) + D_m(k) + D_h(k) \leq 1, \quad \forall k \in [1, m], m \in \mathbb{N}. \tag{13}$$

Furthermore, one of the features of this paper is linearizing the charging/discharging capacity, which is discussed next. In Eqs. (10) and (11) the upper limits on charging and discharging, $P_{chg}(k)$ and $P_{dchg}(k)$ respectively, are split into three levels: low, medium, and high. As the charging/discharging rate of the ESS increases, the energy loss increases as depicted in Eq. (3). L_m and L_h are the loss coefficients associated with medium and high charging/discharging rates, respectively. Constraints (12) and (13) ensure that the ESS is either operating at low, medium, or high levels of charging/discharging at any given time k. The following equations present a formulation for calculating the charging cycles of ESS:

$$u(k) - v(k) = u_1(k) - u_1(k-1), \tag{14}$$

$$u(k) + v(k) \leq 1, \tag{15}$$

$$CYC = \sum_k u(k), \tag{16}$$

$$C_{ess}(k) = \tau C_1 P_{dchg}(k) + C_2 CYC, \quad \forall k \in [1, m], m \in \mathbb{N}. \tag{17}$$

Eqs. (14)-(16) are used to calculate net charging cycles. Eq. (14) ensures that $u(k) = 1$ when a new charging cycle starts by comparing the charging status of the ESS at current and previous time. For example, if at $k = 2$: $u_1(1) = 0$ and $u_1(2) = 1$, this will enforce $u(2) = 1$ to denote a new charging cycle has started; similarly if $u_1(1) = 1$ and $u_1(2) = 1$, this will enforce $u(2) = 0$ denoting battery is in the same charging cycle. Finally, Eq. (16) computes the total number of charging cycles which will impact the operating cost of the battery, as indicated in the second term of Eq. (17). The cost function of the ESS (17) comprises two parts: cost associated with discharging power and cost of the charging cycles.

2.3. Interaction with the power grid

Connection with the external grid can be used to compensate for the uncertainties related to weather and demand forecast. The power driven from the grid is considered by the transformer capacity, as follows:

$$0 \leq P_{grid}(k) \leq \overline{P}_{grid}(k), \quad \forall k \in [1, m], m \in \mathbb{N}. \tag{18}$$

2.4. Solar PV model

The power output of a solar PV module is modeled as a function of the solar radiation, given as follows: [41]:

$$P_{pv}(k) = \frac{G(k)}{1000} P_{pv}^{rated} \eta_{MPPT}, \quad \forall k \in [1, m], m \in \mathbb{N}, \tag{19}$$

2.5. Distributed generator

The operating constraints at each time k on DG are given as follows:

$$\underline{P}_{gen} S(k) \leq P_{gen}(k) \leq \overline{P}_{gen} S(k), \tag{20}$$

$$P_{gen}(k) \leq P_{gen}(k-1) + RUP(k), \tag{21}$$

$$P_{gen}(k-1) - P_{gen}(k) \leq RDN(k), \tag{22}$$

$$\forall k \in [1, m], m \in \mathbb{N}. \tag{23}$$

The dispatchable DG is subject to minimum and maximum generation capacity limits (20), ramp up (21) and ramp down (22) rate limits. The unit commitment state $S(k)$ is one when unit is committed and is zero otherwise.

The fuel consumption of a DG can be represented as a quadratic and convex function which can be approximated by piecewise linear segments (d). Each piecewise segment introduces the binary variables and continuous variables analytically:

$$C_{gen}(k) = \sum_d (\alpha_d P_d(k) + \beta_d B_d(k)) \quad , \forall k \in [1, m], \quad m \in \mathbb{N}. \tag{24}$$

where α is the slope of the line and β_d is the Y-intercept of segment d. To ensure only one segment is considered i.e., only one variable $B_d(k)$ takes the value 1 at any given time k, is given as follows:

$$\sum_d B_d(k) \leq 1, \quad \forall k \in [1, m], \quad m \in \mathbb{N}. \tag{25}$$

This ensures that at any given time k when $\sum_d B_d(k) = 1$, the DG is turned on otherwise the unit is in off state. Based on this, the output of DG is given as:

$$P_{gen}(k) = \sum_d P_d(k), \tag{26}$$

$$\underline{P}_d(k) B_d(k) \leq P_d(k) \leq \overline{P}_d(k) B_d(k), \tag{27}$$

$$\forall k \in [1, m], m \in \mathbb{N}. \tag{28}$$

3. Overall framework

Fig. 1 presents an overview of a residential building which includes various appliances, ESSs, energy production systems, a smart meter and two-way communication links between these components. The proposed mathematical model and the associated optimization solver resides in the central hub controller (CEMS). This controller uses the mathematical model of each component in the building, parameter settings, external information, and user preferences, to generate the optimal operating decisions for all components over the scheduling horizon. The device database includes all technical characteristics of components such as rated power/energy, storage/production level, and external information includes weather and forecast, solar radiation and demand forecasts.

3.1. Modeling approach

A smart microgrid operations framework is proposed that optimally accommodates load variations of the building. It is important to obtain accurate information on future load and/or availability of renewable energy resources for dispatch signals to be meaningful. The proposed framework is depicted in Fig. 2, where inputs such as the building load profile, weather forecast, outside temperature for the next day are available. An update rate of 15 min is used, which is consistent with the fastest available solar power forecasting systems and suitable for capturing load variations. Thus, every 15 min the CEMS is executed within an MPC framework to revise its operating decisions by updating the inputs from their forecast values.

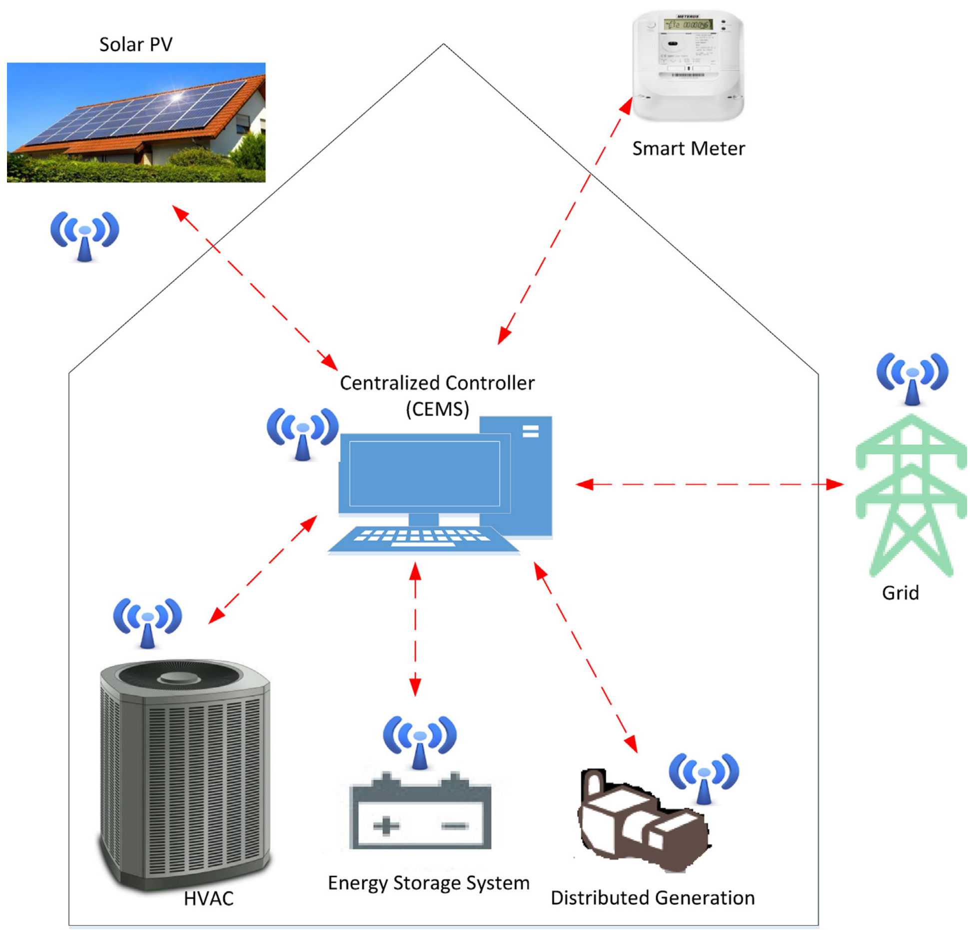

Fig. 1. Residential building energy hub architecture.

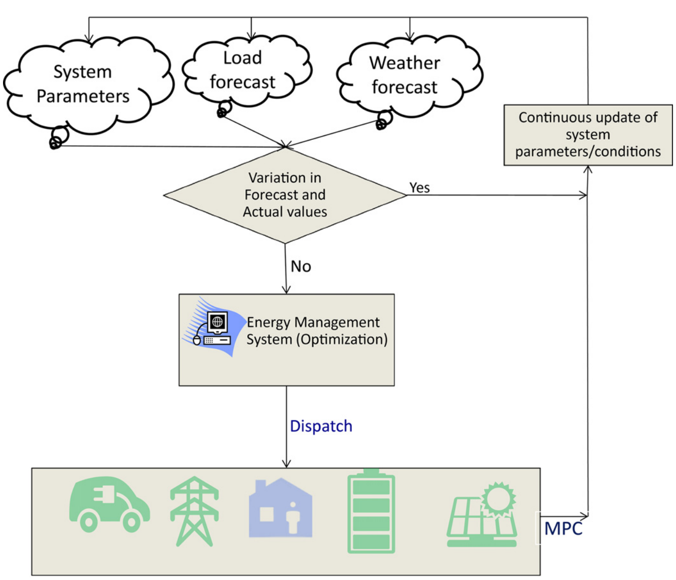

Fig. 2. Framework of the proposed CEMS for the residential microgrid.

4. Optimization problem

4.1. Mathematical model

The objective of grid-connected operation is to minimize the residential building's operation cost

$$J = \sum_{k=1}^{m} (C_{gen}(k) + C_{ess}(k) + C^{grid} Pgrid(k)). \tag{29}$$

When the microgrid operates in isolated mode, the variable P_{grid} will be fixed to zero. At any given time k, the power balance equation ensures that the sum of the power generated by DERs (i.e., dispatchable and non-dispatchable units), the ESS, and the power from the main grid matches the load

$$\begin{aligned} P_{Dem}(k) &= P_{pv}(k) + P_{grid}(k) + P_{dchg}(k) - P_{chg}(k) \\ &\quad + P_{gen}(k) - P_{hvac} S^{ht}(k), \quad \forall k \in [1, m], m \in \mathbb{N}. \end{aligned} \tag{30}$$

Thus, the overall mathematical model comprises the objective function (29), constraint (30) and components constraints discussed earlier (1)–(27). The proposed model is an MILP problem and is implemented in GAMS [42] using the CPLEX solver. The computational time is fraction of seconds which makes it easy to implement this in real-time.

4.2. MPC implementation

The MPC-based control approach works as follows: at any time k, the CEMS receives the current weather and load data, and forecast data from $k+1$ to $k+N-1$. The CEMS then solves the optimization problem (1)–(30) over this N-interval time horizon. The actual operation at time k will implement the optimization result for that time only. Then, at time $k+1$, the CEMS obtains updated information for the next N time intervals (from $k+1$ to $k+N$) and solves this finite horizon optimization problem again, and determines

Table 1
Summary of case studies.

Case	Description
Base Case	*Business as Usual*: Maximize the customer comfort such that the temperature deviation from the set points is minimized while all other constraints on the devices are met
Case 1	*Perfect Forecast*: Minimize operating cost assuming that the weather and demand forecasts are perfect
Case 2	*Impact of Imperfect Forecast*: Error due to not considering actual forecast is studied
Case 3	*MPC Approach*: Errors in forecasting parameters is considered

the optimal decisions for time $k+1$. The time horizon moves forward by one time slot for the new optimization. As this finite time horizon optimization procedure schedules the building operation considering the current and the forecast information. Such an algorithm requires communication between the central controller and all components in the residential building to collect information and a powerful central controller to process large amount of data.

5. Case studies and simulation results

The residential building considered is grid-connected however, the cost of power is significantly increased to minimize the power purchased from the grid. Solar PV panels with maximum rated power of 1.5 kW and one DG unit rated at 1 kW are assumed. An energy storage unit is included with storage capacity of 12 kWh with maximum charging and discharging power of 6 kW. The charging and discharging efficiencies are assumed to be 86%. For the simulation study, time interval of 15 min is assumed with an overall horizon of 24 h. The HVAC unit with a maximum power of 2.5 kW is used as a controllable load. Table 1 presents a summary of case studies considered, and are discussed next to illustrate the effectiveness of the proposed model.

5.1. Base Case

This case assumes that customers do not care about the energy price and are interested in maximizing their comfort level. In this case, customers set a desired temperature on the thermostat, and the deviation from the set point is minimized, as defined in Eq. (31).This scenario considers constraints on the operation of the devices, and upper and lower limits on temperature. This case study demonstrates how majority of the homes and residential buildings normally operate.

$$J = \sum_{k} (T_k - T_{set})^2. \tag{31}$$

5.2. Case 1: Perfect forecast

In this case, it is assumed that the weather and demand forecasts are perfect and there is no error. Fig. 3 compares the optimal charging/discharging decisions of the ESS in Base Case and Case 1; note that negative power represents charging and positive power implies discharging. We see that the ESS is used more in Base Case as compared to Case 1, the number of charging cycles reduce by 54.5% in Case 1 as seen in Table 2. In Case 1, all charging/discharging occurs at low level (less than 2000 W) to avoid energy losses at

Table 2
Summary results of Base Case and Case 1.

	Base Case	Case 1
Energy cost [$/day]	2.35	1.96
Energy consumption /day [kWh]	40.01	36.94
Number of ESS charging cycles	11	5

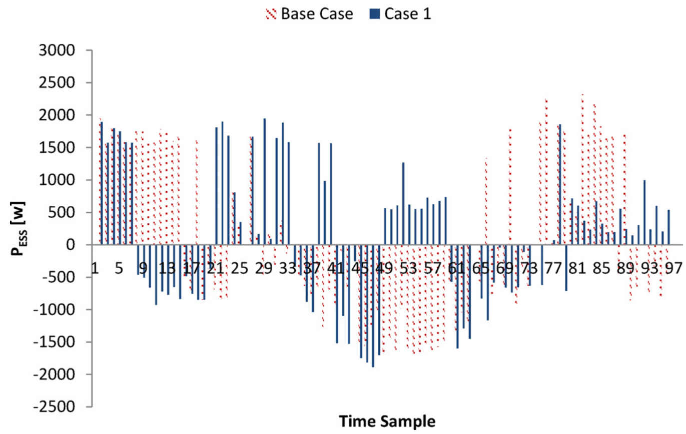

Fig. 3. Comparison of charging and discharging power levels for the ESS in Base Case and Case 1.

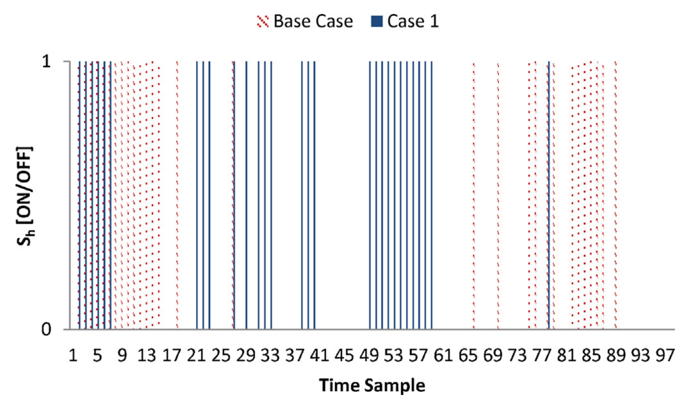

Fig. 4. ON/OFF decisions of HVAC for Base Case and Case 1.

higher charging/discharging levels unlike the Base Case. Fig. 4 illustrates the optimal operation schedule of the HVAC unit in Base Case and Case 1; 1 represents HVAC is ON while 0 means OFF state. We observe that the HVAC is ON a lot more in the Base Case as compared to Case 1. Also, in Case 1, the HVAC is ON when solar PV is available (pre-heating the building), thereby reducing the energy cost. The resulting indoor temperature for a typical winter day is presented in Fig. 5 for Base Case and Case 1. Since the T_{set} in Base Case is fixed at 22 °C, the inside temperature is always maintained close to T_{set}. In Case 1, as expected, the inside temperature of the residential building is maintained close to 20 °C (lower limit of temperature) since the objective here is to minimize the operating cost of the

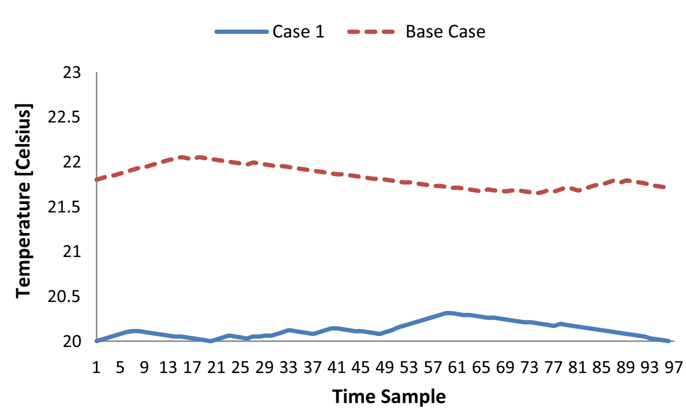

Fig. 5. Comparison of optimal indoor temperature of the building on a typical winter day.

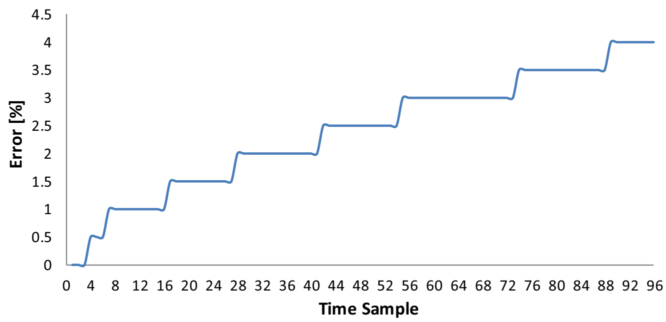

Fig. 6. Case 2: Forecast error increasing with time.

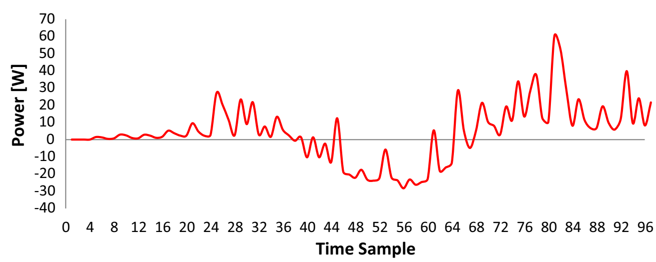

Fig. 7. Case 2: Mismatch between demand and generation.

building. To summarize these two cases, it is possible to reduce the energy cost by optimally managing various sources and loads in a building. In this case, on a given day, the proposed CEMS can benefit customers reduce their energy cost by 16.6% (Table 2). By controlling the load and not compromising on the comfort of the customers, it is possible to reduce the energy consumption, as seen in Table 2.

5.3. *Case 2: Impact of imperfect forecast*

In this case, it is assumed that the 24 h ahead forecast inputs, considered in Case 1, are not accurate. A piece-wise linear forecast error is assumed, which increases with time, as shown in Fig. 6. The objective of this case study is to get an idea of the magnitude of mismatch because of forecast error when the optimal dispatch solution from Case 1 is applied. Using 24 h ahead imperfect forecast and the optimal dispatch solution from Case 1, results in mismatch between the demand and generation as shown in Fig. 7 where positive axis represents excess generation while the negative axis is unmet load. From this solution excess energy that is wasted or the demand that is not met fully at specific hours is noted. The inside temperature of the building is also affected as the temperature goes below the lower acceptable limit at k = 96 as shown in Fig. 8. Thus, it is evident that it is important to update the dispatch solution in real-time because of forecast errors.

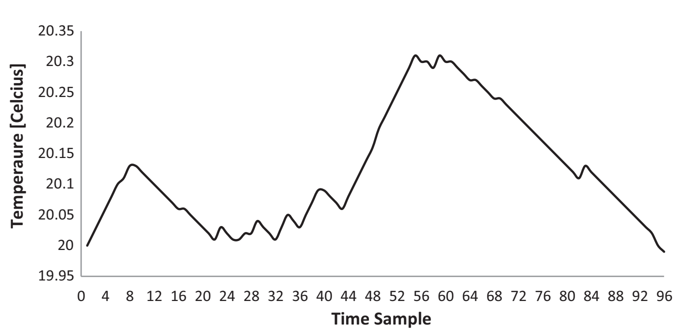

Fig. 8. Case 2: Indoor temperature of the building with imperfect forecast.

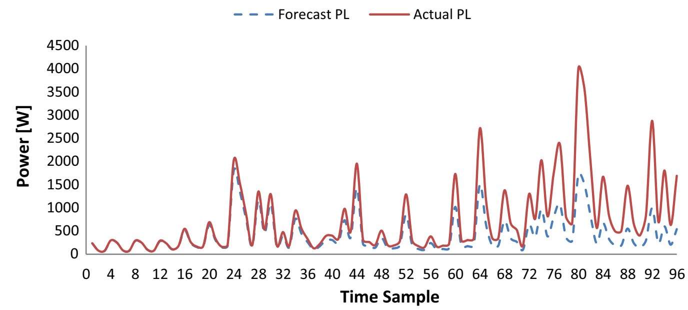

Fig. 9. Case 3: Forecast and actual values of base load.

5.4. *Case 3: MPC approach*

In the previous case study it is evident that there is a need to consistently check if any input or system data has changed. If there is a difference between the forecast and actual inputs, the CEMS will revise its inputs and system parameters to obtain a new set of optimal decisions for the remaining time period. The MPC approach allows for errors in the forecasting methods to be identified and updates the response in real-time. In this case study, simulations are carried out a day before to determine the optimal dispatch for the next day based on forecast of demand and weather inputs. Every 15 minutes, the CEMS revises the system parameters and inputs based on the error in forecast values. For example, at k = 0, the CEMS determines the optimal dispatch values from k=1 to 96, but implements the values obtained for k = 1 only; similarly, at k = 3, CEMS determines the optimal dispatch taking into account new inputs and system conditions from k= 4 to 96 and implements the solution for k = 4 only, and so on.

A linear forecast error is assumed for demand and weather uncertainties; as time increases, the error increases. The inputs are revised every 15 min based on the forecast error and inputs at previous time interval. Fig. 9 presents a comparison of the forecast versus the actual demand over a 24 h period. It is noted that the forecast is very close to the actual at closer intervals while the forecast error increases for latter intervals. For example, at k = 20 the forecast load is 632.5 W while the actual load is 641 W and at another hour k = 60 i.e., 3 PM the forecast load is 1020 W while the actual load is 1732 W. This figure shows the importance of updating/checking inputs at regular intervals in order to have meaningful dispatch results. The error between the forecast and actual values close to the current time step is very small, however, for forecasts of latter intervals, the error increases.

Figs. 10 and 11 present the optimal dispatch of the ESS and the inside temperature profile of the building using the MPC approach, respectively. Fig. 10 shows that most of the charging occurs when

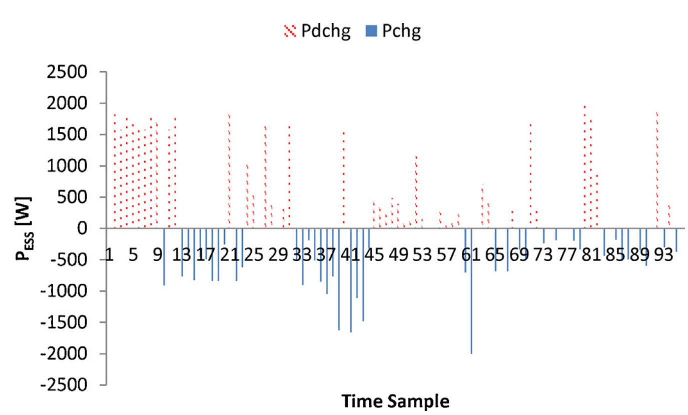

Fig. 10. Case 3: Optimal dispatch of the ESS using MPC.

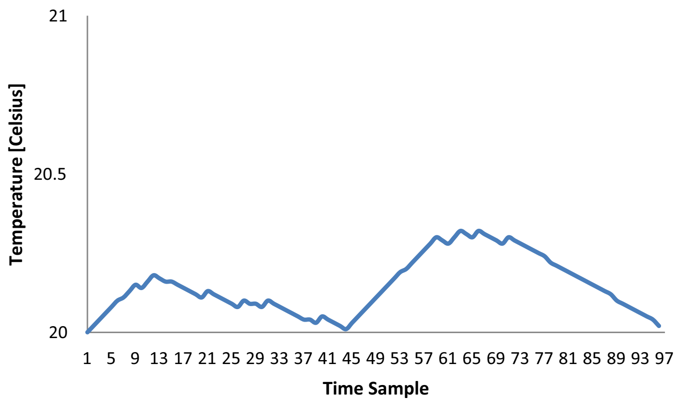

Fig. 11. Case 3: Indoor temperature of the building using MPC.

solar PV is available and the discharging of the ESS occurs in the early morning hours. In Fig. 11, it is noted that the building preheats when solar PV is available (k = 45–70) in order to maximize the use of solar PV generation.

6. Conclusions

This paper proposed a framework using MPC to determine the optimal dispatch of various energy resources to meet the demand of a residential building. The proposed CEMS uses the mathematical models of the components, the parameter settings, external information, and user preferences to generate the optimal operating decisions for all components over the scheduling horizon. In particular, the CEMS considers HVAC as a controllable load and optimally schedules its operations to meet the desired objectives.

Various case studies were carried out to demonstrate the effectiveness of the proposed framework in real-time applications. MPC was applied in the presence of uncertainties in the demand and weather forecast to derive the optimal solution in real-time. The main features of the proposed CEMS are (1) the capability to optimize the use of energy resources and controllable loads, and (2) promotes the use of renewable energy while meeting the comfort level of customers. The inclusion of an ESS to the building results in greater flexibility in energy management as it overcomes the issues associated with intermittent nature of renewables and physical constraints of DG. It also contributes to matching the energy demand with local production in a cost effective way.

The controllable loads such as HVAC systems also provide flexibility in balancing the intermittent electricity generation from renewables, such load following services can help reduce the operating costs. It was demonstrated through a case study that during the day when solar energy was available, the HVAC pre-heated the building, resulting in reducing energy costs and energy consumption.

The simulation results showed that using the proposed CEMS in a building, it was possible to reduce the energy bill by optimally managing all the resources. For example, the case study presented here shows reduction in energy bill and energy consumption of the customers by 17% and 8%, respectively, over a day. Furthermore, it is important to have a flexible generation source that can take care of mismatch between supply and demand. The CEMS also helps in improving the life cycle of subsystems. For example, total charging cycles of the ESS were reduced from 11 to 5 in the case study presented. The overall framework shows the advantages of using MPC approach that aims at minimizing the error in the forecasting tools in order to obtain a meaningful dispatch. Another strength of this framework lies in the low computational costs, it takes fraction of seconds to run the proposed model which makes it easy to implement this in real-time.

Further developments will include two-way interaction with the grid, which is important in the context of smart grids. The controlled load profiles obtained from the CEMS can be communicated to the LDC. The latter can use this information to determine the optimal operating decisions for the feeder. Furthermore, the LDC or microgrid controller can send control signals to each CEMS in the form of a peak cap signal or price signal to ensure safe, reliable and cost-effective operation of the grid.

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