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Economic MPC-Based Smart Home Scheduling With Comprehensive Load Types, Real-Time Tariffs, and Intermittent DERs

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ABSTRACT Smart home scheduling, facilitated by advanced metering, monitoring, and manipulation technology, plays an important role in the energy transition in terms of accommodating intermittent renewable energy and improving energy consumption efficiency. The key functionalities of home energy scheduling are usually implemented by leveraging the flexibility of household appliances, such as thermostatically controlled loads (TCLs) and energy storage units, to improve the peak-to-average ratio for utilities and reduce energy bills for customers. However, the consumption patterns of appliances are greatly influenced by a variety of factors, including real-time tariffs, ambient temperature profiles, indoor activities, and solar irradiance. Hence, smart home energy scheduling is a challenging task because most of these impacting factors are stochastic and difficult to predict. To properly model and manage the uncertainty factors associated with smart home appliance scheduling, an economic model predictive control (MPC)-based bilevel smart scheduling scheme is proposed in this paper. The comprehensive modeling of distributed generation and household appliances is performed at the single-household level. The home energy scheduling problem is formulated on two levels, with the upper level emphasizing the economic impact and the lower level focusing on capturing TCL responses. The correlations among different TCLs and their performance under the influence of various uncertainty factors, such as environmental impacts and user behaviors, are considered. The efficiency of the proposed MPC-based bilevel optimization model and the effectiveness of the home energy scheduling strategy in managing uncertainties are validated and illustrated in numerical studies.

INDEX TERMS Smart homes, scheduling, thermostats, intermittent renewable energy, bilevel optimization, economic model predictive control.

I. INTRODUCTION

The integration of renewable energy sources is increasing quickly around the world to address the goal of developing a more sustainable energy structure. Meanwhile, the intermittency and uncertainty of renewable energy sources have brought significant challenges to the power industry in terms of accommodating renewable power generation. Demand-side management, as a promising solution to absorb fluctuating renewable generation, has drawn much attention in recent years, especially at the household level. Benefiting from the development of advanced metering infrastructure (AMI) and information and communication technologies, including Wi-Fi and ZigBee, smart household appliances that were once considered autonomous are becoming a great source of flexibility with the help of home energy management techniques [1]. Smart devices and the digital twins they are built upon are changing almost all aspects of everyday life, increasing convenience, efficiency, and resilience [2]. Regarding energy utilization, it has been verified that smart home scheduling can effectively reduce the electricity bill for customers and significantly improve the peak-to-average ratio (PAR) [3].

Smart home scheduling, implemented either by tariffs or by incentives, is widely considered an effective measure of active demand-side management. Many studies have been

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done on this topic. For example, smart home scheduling is usually implemented at the individual and community levels [4]. At the individual household level, appliances are sorted into three categories, namely, uncontrollable, shiftable, and thermostatically controlled [5]. In [6], the application of schedulable loads in smart homes is integrated with solar thermal energy, micro combined heat and power (micro-CHP), heat pumps and batteries to maintain room temperature within a comfortable range. Thermostatically controlled loads (TCLs) are believed to be capable of providing ancillary services such as regulation and reserve, and their aggregated flexibility capacity is evaluated using different virtual battery models, which are derived from geometric tractable approximation [7], modification of an equivalent energy storage model [8], etc. In [9], the stochastic operation of a solar-powered smart home is implemented with stochastic mixed-integer linear programming (MILP) and Monte Carlo simulation to capture uncertainties in the thermal load. In addition, transactive hierarchical scheduling for TCLs is studied in [10] to regulate TCLs in a distributed fashion via coordination between the system and devices. Meanwhile, behind-the-meter household appliances and distributed energy resources (DERs) also fall under the category of smart home scheduling, which has been discussed extensively in studies such as [11] and [12]. At the community level, game theory is a common measure to address the interplay between different end-users and aggregators to consider their mutual benefits [13] by adopting new technologies such as multi-agents [14], clustering [15], and inference [16] from the artificial intelligence field. Treating the community as a whole, which is another perspective of community-level energy scheduling, falls into the area of distribution system operations. Many proposals have been made under this topic in areas such as demand-side management [17], microgrid operation [18], DER integration [19], and distributional locational marginal pricing (DLMP) [20]. Nonetheless, current community-level energy scheduling studies do not typically have detailed models of individual household demands and DERs. Thus, more work needs to be done to integrate energy scheduling at both the individual and community levels to properly handle uncertainty.

Among the various techniques to address uncertainty, model predictive control (MPC) is a combination of optimization and control that has been widely implemented because of its capability of handling multi-input multi-output (MIMO) problems and its consideration of future trends. The capability of economic MPC to absorb time-varying costs and peak demand charges for electricity consumers is verified in [21], and the asymptotic stability of the economic MPC algorithm for economic load dispatch and load frequency control is derived in [22]. To date, the MPC-based optimization method has already been applied to the energy sector in a number of fields, such as electric vehicle charging [23], microgrid operation [24], and energy scheduling [25]. Economic MPC, as its name suggests, usually optimizes the operating cost of the system under control, and it is used extensively in power industries [26], [27]. Implementations of economic MPC in controller design for dual-model power-split electric vehicles (EVs) [28], voltage regulation in distribution networks [29], and the operation and control of modern thermal power plants [30] have been investigated, among other applications. In terms of solving energy scheduling problems, economic MPC-based models have been employed to solve economic dispatch problems at the bulk system level in addition to some adaptations such as distributed organization [31], backwards square completion [32], and virtual power plants [33]. At the micro level, MPC-based solutions to smart residential, community, and home scheduling have also been obtained, though they are limited. In [34], residential community load management considering standalone hybrid renewable energy systems was optimized via an MPC-based method. In [35], a home energy management system (HEMS) employed an MPC-based method to manage battery usage and solar power production based on weather and market forecasts. Compared with works in the traditional smart home scheduling area, the existing works are quite limited and coarse, although the characteristics of the economic MPC-based method make it an ideal candidate for smart home scheduling.

In this paper, the operation model of a single household with intermittent DERs and comprehensive load types is studied. The proposed model takes real-time tariffs into account to determine the most profitable and feasible strategy for the corresponding customers. Casual customer behavior is also taken into account, along with other uncertainties embedded in real-time tariffs and external environmental factors such as the solar irradiance and ambient temperature. To effectively solve this MIMO problem, a bilevel economic MPC model is proposed. The upper level addresses the economic dispatch of smart appliances and handles discrete decision-making variables associated with the switching operation of loads over a longtime span. The lower level focuses on the detailed control performances of continuous household appliances. The upper level optimizes the monetized cost based on the feedback from the lower level, and the lower level optimizes and updates the energy consumption according to the external environment and market situation, considering both the energy cost and the user's comfort level. It should also be mentioned that the proposed method is designated for active prosumers, but it is still generalizable to different sorts of smart home individuals, such as traditional passive loads.

The remainder of this paper is organized as follows: In Section II, the smart home scheduling problem considering comprehensive load types, real-time tariffs, and intermittent DERs is formulated. In Section III, a bilevel economic MPC model is developed to solve the home scheduling problem. In Section IV, the efficiency of the proposed model and the bilevel economic MPC-based method are verified and demonstrated through numerical results and comparisons. Finally, Section V concludes the paper.

II. PROBLEM FORMULATION

A smart home system includes measurement and control units, distribution system interfaces, small DERs, and various household appliances. Proper modeling of energy generation, distribution and utilization is a prerequisite for optimal household energy management. Referring to the categorization proposed in [5], household appliances are divided into non-schedulable, schedulable, and TCL clusters in this paper. Here, different types of energy supply, along with comprehensive load types, are studied in a categorized way. The diagram of a smart home is illustrated in Figure 1.

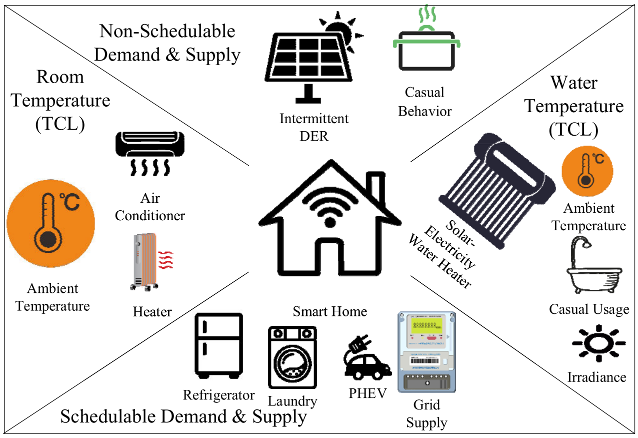

FIGURE 1. Composition of a smart home.

A. NON-SCHEDULABLE SUPPLY AND DEMAND

In this paper, the non-schedulable household supply is produced by self-owned small DERs such as solar panels and biomass. The generation of small DERs, denoted as $S_{DER}(h)$, shows potential intermittence, which is determined by many circumstantial factors. Meanwhile, the non-schedulable household demand includes two types of loads. One is the background load, which is constantly consuming power while neither the customer nor the HEMS can control it. Refrigerators are considered an example of background household appliances in this paper. Another type of load is at-will demands, such as televisions and lighting loads, because they are generally controlled by the user. The aggregated non-schedulable demand, denoted as $L_{NS}(h)$, can be imitated with white noise of a certain value.

B. SCHEDULABLE SUPPLY AND DEMAND

Schedulable household appliances account for a large share of the total energy consumption in smart homes. The time requirements of most schedulable appliances, e.g., laundry machines, dishwashers, and EVs, are not too strict, meaning that they have significant potential to shift their consumption. Another unique schedulable device is energy storage, which can flexibly switch between consuming and generating power depending on the needs of the customer.

1) SCHEDULABLE LOADS

For a schedulable appliance m with a rating power of ξ_m and a required operating duration of d_m (number of time slots), its operation is mainly governed by temporal constraints (i.e., the starting time slot α_m and ending time slot β_m) and energy constraints (denoted as d_m). We denote the remaining required duration at the beginning of slot h as $x_m(h)$, and the operational requirements of appliance m can be specified by (1)-(4). The aggregated schedulable load at time slot h, denoted as $L_S(h)$, can be calculated by adding the consumption of every schedulable appliance at the corresponding hour together, as shown in (5). The set of schedulable appliances working in the home is denoted as Ω_M. The scheduling interval (i.e., the length of the time slot) is denoted as Δ.

$$x_m(h+1) = x_m(h) - u_m(h) \tag{1}$$
$$x_m(h) = d_m, \quad \forall h \leq \alpha_m \tag{2}$$
$$x_m(h) = 0, \quad \forall h > \beta_m \tag{3}$$
$$l_m(h) = \xi_m u_m(h) \tag{4}$$
$$L_S(h) = \sum_{\Omega_M} l_m(h) \tag{5}$$

where the binary variable $u_m(h)$ and the continuous variable $l_m(h)$ describe the on/off status and the energy consumption of appliance m at slot h, respectively.

In addition to the schedulable load model discussed above, certain demand such as washing machine generally performs tasks in consecutive manner. These consecutive tasks can also be incorporated into the proposed framework using the following two solutions. One way is to treat consecutive tasks as one task that can be suspended in the middle. Another way is to modify the transition relationship to cover the constraints that guarantee the consecutive relationship. Suppose the set of loads that is established prior to load m is Ω_m; the modifications will be to substitute (1) and (2) with (6) and (7) and to add one more constraint indicating the consecutive relationship expressed in (8). Several of the modified expressions are compatible with the rest; that is, the other expressions do not need to be modified.

$$x_m(h+1) = x_m(h) - \sum_{n \in \Omega_m} u_n(h) - u_m(h) \tag{6}$$
$$x_m(h) = d_m + \sum_{n \in \Omega_m} d_n, \quad \forall h \leq \alpha_m \tag{7}$$
$$x_m(h) \geq \sum_{n \in \Omega_m} x_n(h), \quad \forall h \tag{8}$$

where load n is an element inside Ω_m.

2) SCHEDULABLE SUPPLY

In this paper, both self-generation and external acquisition are considered types of schedule power supply for the household concerned. In other words, household demand can obtain energy from either self-owned DERs or the connected distribution power system. It should be mentioned that although the energy supply from the distribution power system can be accessed at will, the electricity price fluctuation needs to be considered by household owners. We denote the electricity acquired from the external power system as $S_{grid}(h)$ and the real-time tariff as $p_{grid}(h)$. The energy cost C_h can be calculated by (9). Note that $p_{grid}(h)$ is an uncertain factor.

$$C_h = S_{grid}(h)p_{grid}(h) \tag{9}$$

3) BATTERY

For household management, the output of the battery $S_B(h)$ can be positive, negative, or 0, as defined in (10). The state-of-charge (SOC) level of the battery is denoted as χ and is constrained by (11) and (12).

$$S_B(h) = \mu(h)q_B \tag{10}$$

$$\chi(h+1) = \chi(h) - \frac{S_B(h)}{Q_B} \tag{11}$$

$$0 \leq \chi(h) \leq 1, \quad \forall h \tag{12}$$

where $\mu(h)$ is the operation decision for the battery at time slot h and varies continuously within $[-1, 1]$. The variables q_B and Q_B are the rated battery charging/discharging power and the capacity of the battery, respectively.

Note that the battery model (10)-(12) does not have a set of complementary constraints to avoid simultaneous charging/discharging behaviors. As discussed in [36], if the simultaneous charging/discharging cannot bring arbitrage to the energy storage, the complementary constraints can be relaxed. In this paper, the simultaneous charging and discharging will not bring arbitrage to the smart homes. Thus, the complementary constraints can be relaxed and the energy storage model remains exact. This is also observed in the simulation results where no batteries demonstrate simultaneous charging/discharging behavior.

C. TCLs

Although TCLs can be regarded as schedulable demands, they have some unique features. Generally, the operation of a TCL is a closed-loop control focusing on a continuous state variable. For household TCL demand, such as indoor heating and cooling, room temperature is usually the sole state variable, and an air conditioner or electric heater is normally employed for thermostat control.

We denote the state variable of TCL k at time step t as $y_k(t)$, and the corresponding appliance can be scheduled to meet the users' requirements, namely, a desired temperature T_k and tolerable variation threshold γ_k. The temperature requirements can be modeled by (13). The sampling time of the measurement equipment servicing the TCL is Δ_k. Note that Δ_k is determined only by the property of the TCL and may be different from the time interval of home energy scheduling.

$$|y_k(t) - T_k| \leq \gamma_k \tag{13}$$

In this paper, a modified TCL model is developed to consider the coordination and interaction among different appliances. In other words, a certain TCL k such as the indoor temperature can be served by multiple appliances. The set of appliances serving the same TCL k is denoted as Λ_k, and the set of TCLs is denoted as Ω_{TCL}. The state transition of a TCL is jointly determined by its appliances and by other influencing factors, such as the ambient temperature, as described in (14). The energy consumption for TCL k by equipment e at step t, denoted as $Q_e^k(t)$, can be expressed as the product of its nominal consumption (converted to a step size) ζ_e^k and the on/off decision variable $v_e^k(t)$, as shown in (15).

$$C_a^k \frac{dy_k(t)}{dt} = \frac{\phi_t^k - y_k(t)}{R^k} - \sum_{e\in\Lambda_k} COP_e^k Q_e^k(t) - \varepsilon(t), \quad \forall k \in \Omega_{TCL} \tag{14}$$

$$Q_e^k(t) = \zeta_e^k v_e^k(t) \tag{15}$$

where C_a^k and R^k are the equivalent thermal capacity (kJ/^{o}C) and the equivalent thermal resistance (^{o}C/kW) of TCL k, respectively. COP_e^k is the coefficient of performance of equipment e for TCL k, and ϕ_t^k is the ambient temperature measured at time step t. $\varepsilon(t)$ stands for potential casual behavior, to be discussed in later sections.

In addition, the TCL consumption is derived from its sampling step Δ_k. Suppose there are S steps in one energy scheduling slot Δ; then, the aggregated energy consumption from the TCLs in time step t and the consumption in slot h, l_{TCL} and L_{TCL}, can be calculated as in (16) and (17), respectively.

$$l_{TCL}(t) = \sum_{\Omega_{TCL}} \sum_{\Lambda_k} Q_e^k(t) \tag{16}$$

$$L_{TCL}(h) = \sum_{t=1}^{S} l_{TCL}(t) \tag{17}$$

The developed models (13)-(17) generalize the household TCL demands to accommodate different situations. Two examples are described below:

- Bidirectional control: The indoor temperature can be maintained within an acceptable range by an air conditioner for cooling and an electric heater for heating. In this case, the coefficient of performance (COP) of the air conditioner is positive, whereas that of the heater is negative, according to (14).
- Multiple supply appliances: TCL scheduling is a cross-section scheduling problem in which both the heat and electricity sections are involved. In a household with intermittent energy-based equipment such as a solar-electricity water heater, there may be two, three, or more involved sections. Referring to (14), the physical meaning of the COP can be extended to the rate of conversion to heat or cold from other energy carriers, such as solar irradiance, natural gas, and a direct heat supply. In the case of a solar-electricity water heater, the heater will prioritize the solar energy for heating purposes.

Another important issue to address in TCL modeling is uncertainty. The intermittence and randomness of multiple energy supplies and customer behaviors, along with environmental factors such as the ambient temperature, all contribute to the uncertainty of TCLs. In addition to the ambient temperature and fluctuating energy prices, this paper considers uncertainty factors associated with intermittent heat/cold supply and casual heat mass loss.

Taking a solar-electricity water heater as an example, the nominal consumption from solar section $\zeta_{\text{Solar}}^{\text{Tank}}$ is intermittent. Casual heat mass loss, denoted as $\varepsilon(t)$, represents all potential casual behaviors. In the water heater case, $\varepsilon(t)$ stands for heat mass loss from the casual usage of hot water. It should be noted that the water tank will be refilled to its original capacity with input water of ambient temperature. The heat loss will be the thermal energy of the temperature difference of the consumption quantity θ_t, as expressed in (18).

$$\varepsilon(t) = C_a^k \theta_t(\phi_t - y_k(t)) \tag{18}$$

D. OBJECTIVE AND CONSTRAINTS

The aggregate supply and demand should be kept in balance for each household, as expressed in (19). The objective of smart home scheduling is to minimize the electricity procurement cost over the observation duration, denoted as C_D. In summary, the home energy scheduling model can be described by the objective function (20) with (1)-(19) as constraints.

$$\begin{aligned} L_{NS}(h) + L_S(h) + L_{TCL}(h) \\ = S_{grid}(h) + S_{DER}(h) + S_B(h) \end{aligned} \tag{19}$$

$$\min C_D = \sum_{h=1}^{H} C_h = f([X, Y], [U, V], [\Theta, \Phi]) \tag{20}$$

where $X = \{x_m, \chi\}, Y = \{y_k\}, U = \{u_m, \mu\}, V = \{v_e^k\}$. Θ, Φ are the parameters of the slot and step, respectively, that are monitored or set in the unit.

III. ECONOMIC MPC-BASED SCHEDULING APPROACH

A bilevel economic MPC-based smart home scheduling model with schedulable loads, non-schedulable loads, and TCLs is discussed in detail in this section. The discrete schedulable loads operated based on the MPC slot are formulated in the upper-level model, and the continuous TCLs are controlled in the lower level.

A. ECONOMIC MPC

An economic MPC is primarily implemented via three fundamental steps, namely, sampling (for a discrete time-varying model), estimation, and control (strategic decision-making) [37], [38]. In the case of smart home scheduling considering multiple TCLs, continuous and discrete variables coexist and affect each other. We denote the state variable and control variable at step κ as $x(\kappa)$, $u(\kappa)$, respectively. The prediction model for estimation and control can be described by the state function and output function shown in (21) and (22), respectively. It should be mentioned that if the numbers of the states and the outputs of the prediction model are the same, the output function can be omitted. The elements in the output function (control variables) $\theta(\kappa)$ can be controlled to within a predefined range. The cost function of the economic MPC controller $\Gamma(\kappa)$ is shown in (23). The second interpretation of the cost function reveals that the cost function at the current moment is composed of the actual cost/quantity at the current moment $C(\kappa)$ and the expected cost/quantity of the subsequent moments under the current strategy, which is the core of MPC.

$$x(\kappa + 1) = f(x(\kappa), u(\kappa)) \tag{21}$$

$$\theta(\kappa) = f(x(\kappa), u(\kappa)) \tag{22}$$

$$\Gamma(\kappa) = f(u(\kappa), \theta(\kappa)) = C(\kappa) + \mathrm{E}[\sum_{\delta=\kappa+1}^{K} C(\delta)] \tag{23}$$

where κ is the current step of an observation duration with K steps.

B. BILEVEL ECONOMIC MPC FORMULATION OF SMART HOME SCHEDULING WITH COMPREHENSIVE LOAD TYPES, REAL-TIME TARIFFS AND INTERMITTENT DERS

The smart home scheduling problem with comprehensive load types, real-time tariffs and intermittent DERs can be described as a daily cost minimization problem that is scheduled for each time slot. Moreover, the TCLs can be controlled to within each scheduling time slot because they generally have different sampling windows. Hence, the smart home energy scheduling problem can be split into two stages: energy scheduling and real-time control. In the bilevel economic MPC model, the upper level focuses on the former (discrete MPC loads with a time length of Δ), and the lower level focuses on the latter (continuous MPC loads with a time length of Δ_k). For simplicity, we define the interval of the upper-level model (i.e., Δ) as a *slot* and the interval of the lower-level model (i.e., Δ_k) as a *step*, unless otherwise specified.

A short-time scheduling strategy is made at the beginning of each time slot, while a real-time control strategy is made at the beginning of each time step. In this paper, a two-level economic MPC is considered—that is, economic MPC is applied to both stages—to track the uncertainties at different time scales. The upper level minimizes the energy cost while balancing the supply and demand, addressing the needs of different schedulable loads, and taking all measured disturbances (including the estimated TCL consumption on the lower level) into account. The lower level minimizes the energy consumption without violating the user comfort level requirement. The approximations and corrections in the lower level are clarified in the previous section. The interaction and optimization of the two-level model can be expressed with the flowchart shown in Figure 2.

1) UPPER-LEVEL: DISCRETE MPC LOADS

Generally, smart home energy scheduling mainly aims at minimizing the energy procurement cost through the manipulation of schedulable loads over a period of time. The typical energy scheduling time horizon and time interval are one day (i.e., 24 hours) and one hour, respectively. Clearly, decisions on this sort of arrangement can be represented with a series of discrete decision variables.

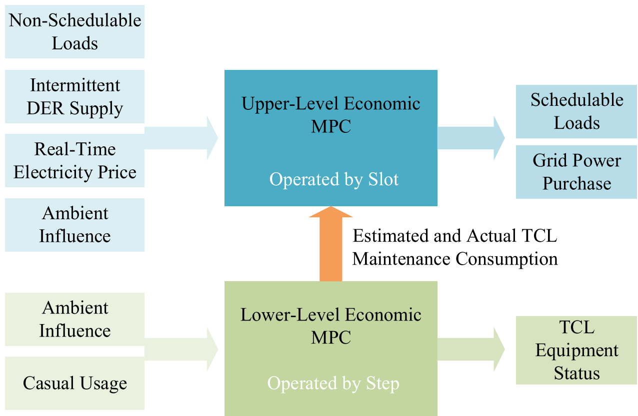

FIGURE 2. Interaction and optimization of the two-level economic MPC model.

When real-time tariffs and intermittent DERs are considered, traditional dynamic programming methods are no longer feasible in solving the smart home scheduling problem. The reason is that dynamic programming methods allocate the appliance consumption schedules into different hours one by one based on a certain parameter setting assumption, which contradicts the real-time tariffs and the intermittency of DERs. In this paper, each schedulable appliance is described with a state variable and a control variable for each slot (Δ). For a normal schedulable appliance m, the binary control variable u_m denotes its working mode for the slot, and x_m denotes the remaining required working hours. Then, the transition relationship for slot h can be described according to (1)-(5). For the batteries, the continuous control variable μ and the state variable (SOC) function χ are as stated in (10)-(12). The upper-level model may also include other inputs, such as measurement data and lower level feedback.

Schedulable loads are controlled at the slot scale. The short-time scheduling problem at time slot h can be optimized by minimizing the cost function as expressed in (24). It should be mentioned that the cost function minimizes the cost of the current time slot h and all the other slots in the duration.

$$\Pi_h(X, U, \Theta) = C_h + \mathrm{E}[\sum_{h+1}^{D} C_\eta] \tag{24}$$

where Π_h is the cost function for the energy scheduling problem at time slot h; the second item on the right is stochastic and represents the expected cost for the remaining time slots, which is determined by the optimized energy scheduling results and external dynamics. D is the number of slots in the MPC observation duration.

According to the definition of C_h in (9) and the energy balance constraints in (19), it can be inferred that the cost function of the upper level is jointly determined by the external environment (including DER generation, real-time tariffs, etc.), discrete schedulable load scheduling, and feedback from the lower level (TCL consumption). The expected cost term C_η can be described as:

$$C_\eta = (L_{NS}(\eta) + L_S(\eta) + L_{TCL}(\eta) - S_{DER}(\eta) - S_B(\eta))p_{grid}(\eta) \tag{25}$$

The optimization model of the upper level can be given as

$$obj \text{ minimize } (24)$$
$$s.t.\ (1-5), (10-12), (19), (25)$$

2) LOWER LEVEL: CONTINUOUS MPC LOADS

In the lower level, the real-time TCL load control is modeled to absorb the fluctuations in generation or consumption introduced by intermittent DER generation or arbitrary energy consumption behaviors. TCLs (such as indoor temperature) may be measured on a minute or even second basis, and the appliances for maintaining their desired intervals, such as air conditioners and heating facilities, are also recommended to be controlled every few minutes (e.g., in step units) to maintain the thermostat requirements. At the same time, frequent on/off switching should be restricted to protect the lifespan of appliances. Therefore, the states of TCLs are modeled as continuous variables and further discretized according to the TCL sampling step Δ_k, as described in (14). The discretization of the state variable y_k of TCL k can be described by (26).

$$\mathrm{d}y_k(t+1)/\mathrm{d}t = \lambda_k y_k(t) - \sum_{e \in \Lambda_k} \lambda'_{k,e} v_e^k(t) + \sum_{\phi_t^{k,j} \in \Phi} \lambda''_{k,j} \phi_t^{k,j} \tag{26}$$

where $\lambda_k, \lambda'_{k,e}, \lambda''_{k,j}$ are the coefficients in the discretized transition equation and the corresponding unit conversions are based on the length of time step Δ_k. $\phi_t^{k,j}$ is the measured disturbance related to the state transition of TCL k.

The real-time control problem at time step t can be optimized by minimizing the cost function expressed in (27). The external energy consumption of step t, denoted as q_t, can be calculated with (28), utilizing (14), (15), and (26). It should also be noted that the cost function minimizes the energy consumption of all the other time steps in the same time slot rather than that of the current step.

$$\pi_t(Y, V, \Phi) = q_t + f_{pe}(t) + \sum_{t+1}^{S} (q_\tau + f_{pe}(\tau)) \tag{27}$$

$$q_t = \sum_{e \in \Lambda'_k} \zeta_e^k v_e^k(t) \tag{28}$$

where Λ'_k is the subset of Λ_k that consumes electricity (including DER-generated electricity). $f_{pe}(t)$ is the penalty function of comfort level loss, which is a function of $|y_k(t) - T_k|$ and increases suddenly when the value exceeds γ_k, as suggested in (13).

It should be mentioned that the cost function of the lower-level model optimizes the energy consumption rather than the energy cost, as does its output to the upper level. As there might be many steps in a single slot h, the upper level only requires the results of two steps: the first step z_1 and last step z_S in the slot. z_1 and z_S are the electricity consumption of the entire time slot h (the sum of each step's consumption); the upper level adopts z_1 for the current slot h decision and z_S for revising the data of slot h.

$$z_1 = q_1 + \sum_{2}^{S} q_\tau \tag{29}$$

$$z_S = \sum_{1}^{S} q_t \tag{30}$$

The calculation of $\sum_{1}^{S} Eq_\tau$ in (30) for the current slot h is obtained from the real-time control model, whereas those for the other slots are estimated by the predicted on/off states based on the outdoor temperature and previous working states, in units of the length of each time slot.

The optimization model of the lower level can be given as

$$\begin{aligned} &obj \text{ minimize } (27) \\ &s.t. (13-18), (26), (28) \end{aligned}$$

C. CASE SETUP: AN EXAMPLE

In this section, a simple example of the proposed bilevel optimization framework will be discussed to demonstrate the short-term scheduling (upper level) of the example smart home, which has three control variables: the plugin hybrid EV (PHEV) charging/idle indicator u_1, laundry working/idle indicator u_2, and battery charging/discharging/idle indicator u_3. It also has three state variables: the PHEV remaining demand x_1, laundry remaining demand x_2, and SOC of battery x_3. The real-time tariff θ_1, casual consumption behavior θ_2, and photovoltaic (PV) array generation θ_3 are the three inputs (measured disturbances). Additionally, the upper level takes the lower-level output, i.e., the consumption of the TCLs, as another input.

Based on the above settings, the upper-level model consists of the state transition equations (31)-(33). The purchase cost C_h is calculated as in (34), and the cost function of the MPC model, which covers the whole observation duration, is the same as in (24).

$$x_1(h+1) = x_1(h) - u_1 \tag{31}$$

$$x_2(h+1) = x_2(h) - u_2 \tag{32}$$

$$x_3(h+1) = x_3(h) + u_3 \tag{33}$$

$$\begin{aligned} C_h = \theta_1(&u_1 q_{PHEV} + u_2 q_{Laundry} \\ &+ u_3 q_B + \theta_2 - \theta_3 + z_1) \end{aligned} \tag{34}$$

$$\min \Pi_h(X, U, \Theta) = C_h + \mathrm{E}[\sum_{h+1}^{D} C_\eta] \tag{24}$$

where q_B is the charging rate (per time slot) of the battery and q_{PHEV} and $q_{Laundry}$ are the rated power of the PHEV and laundry machine at work, respectively.

In this example, we assume the smart home has two TCLs that are subject to real-time control: the room temperature control, maintained by an air conditioner and an electric heater, and the water temperature in the solar-electricity water heater, maintained by an electric heater. The lower-level model has three control variables: the air conditioner on/off indicator v_1, heater on/off indicator v_2, and water heater on/off indicator v_3; it also has two state variables: the indoor temperature $y_1$and tank water temperature y_2. In this case, three disturbances, namely, the ambient temperature ϕ_1, the heat radiation ϕ_2, and the casual usage ϕ_3, are taken into account.

The lower-level model includes the state transition equations (35) and (36). The energy consumption for time step t, denoted as q_t, is calculated as in (37). The cost function of the MPC model, which covers the whole observation duration (slot length), is the same as in (27).

$$\begin{aligned} \mathrm{d}y_1(t+1)/\mathrm{d}t = \;&\lambda_1 y_1(t) - \lambda_2 v_1(t) - \lambda_3 v_2(t) \\ &+ \lambda_4 \phi_1(t) \end{aligned} \tag{35}$$

$$\begin{aligned} \mathrm{d}y_2(t+1)/\mathrm{d}t = \;&\lambda_5 y_2(t) - \lambda_6 v_3(t) + \lambda_7 \phi_1(t) \\ &+ \lambda_8 \phi_2(t) + \lambda_9 \phi_3(t) \end{aligned} \tag{36}$$

$$q_t = \zeta_{AC} v_1(t) + \zeta_H v_2(t) + \zeta_{WH} v_3(t) \tag{37}$$

$$\min \pi_t(Y, V, \Phi) = q_t + f_{pe}(t) + \sum_{t+1}^{S} (q_\tau + f_{pe}(\tau)) \tag{27}$$

where $\lambda_i, i = 1, \ldots, 9$ are the coefficients in the discretized transition equation as defined in (26); $\zeta_{AC}, \zeta_H, \zeta_{WH}$ are the nominal consumption (converted to the step size) of the air conditioner, heater and electricity section of the water heater, respectively; and $f_{pe}(t) = (y_1(t) - T_1)^2 + (y_2(t) - T_2)^2$.

TABLE 1. Home appliances.

Appliance	Type	Total Required Energy (kWh)/Power Level (kW)	Earliest Starting Time	Latest Ending Time
Refrigerator	Background	-/0.1	-	-
PHEV	Schedulable	12/2	18:00	6:00
Laundry	Schedulable	5/1	9:00	18:00
Air Conditioner	TCL	-/1.3	-	-
Air Heater	TCL	-/1	-	-
Auxiliary Water Heater	TCL	-/1.5	-	-

IV. NUMERICAL RESULTS AND DISCUSSION

A. CASE DESCRIPTION

The parameters of the equipment considered in the example smart home are listed in Tables 1 and 2. To evaluate a full EV charging cycle, the observation duration is set to two days, and the time slot and step are set to 1 hour and 5 minutes, respectively. In addition to the household appliances, a normal 1Soltech 1STH-250-WH distributed PV array (detailed in the NREL System Advisor Model) is equipped on the roof of the home to support the household along with the power grid with a real-time tariff. In this case, solar energy is also

TABLE 2. TCL and its parameters.

TCL	Room	Water Tank
C_a (kJ/°C)	1.788×10^6	585.2
R (°C/kW)	4.2698×10^{-7}	0.61×10^{-3}
Target temperature (°C)	21 °C	70°C
Tolerable temperature (°C)	18-24	50-100

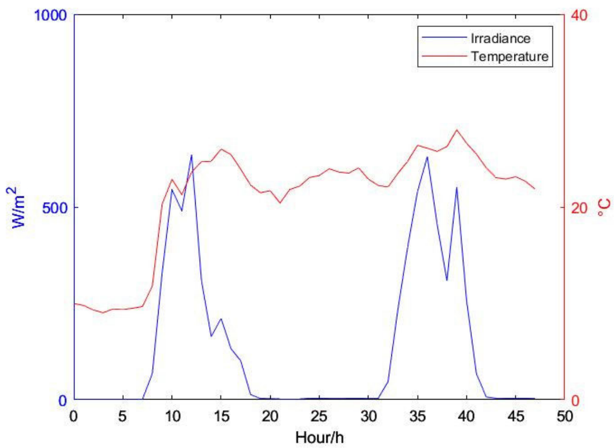

FIGURE 3. Sunlight irradiance and outdoor temperature over a typical 48-hour period.

exploited by a solar-electricity water heater, which provides hot water for the users. Its installed capacity is 140 L, the radiant area is 2.24 m^2, and the inclination angle is 60°. The available consumption value ζ of solar irradiance in units of steps can be calculated by the product of the radiant area and irradiance intensity. The utilization rate of the auxiliary heat is 80%. The COP values of the solar and electricity sections are 2.7778×10^{-4} and 1, and those of the air conditioner and heater are also equal to 1, as they are assumed to consume electricity. Suppose there are three casual hot water usages over the 48 hours, which occur randomly in three-hour increments. It is assumed that these casual usages occur at 23:00 (1st day), 7:00 (2nd day), and 22:00 (2nd day). The consumption each time is 25 L, and the tank is instantly refilled with water at 20 °. The actual sunlight irradiance and outdoor temperature over a typical 48-hour period are shown in Figure 3 [39]. The real-time electricity price over a typical 48-hour period is shown in Figure 4 [40].

B. RESULTS AND DISCUSSION

To maintain the required indoor temperature and water tank temperature, the optimized working states of the heater, air conditioner, and water heater are as depicted in Figures 5 and 6. It can be inferred from the profiles of the indoor temperature and water temperature in the tank, as shown in Figures 7 and 8, that the optimized household energy consumption strategy meets the TCL requirements perfectly. The aggregated consumption of the TCLs (z_{S1} for the room temperature and z_{S2} for the water temperature in the tank) is also shown in Figures 9 and 10.

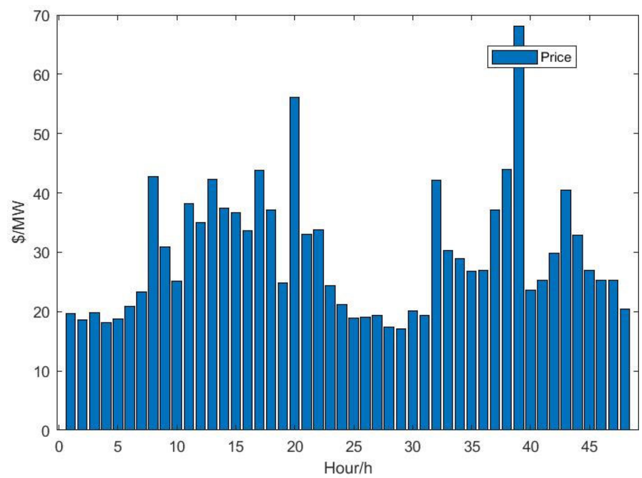

FIGURE 4. Electricity price of the real-time market over a typical 48-hour period.

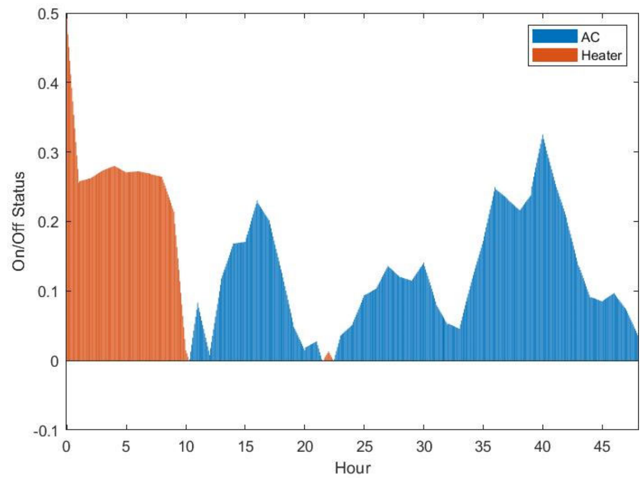

FIGURE 5. Working status of the heater and air conditioner.

As shown in Figures 5, 7, and 9, explicit switching between heating and cooling can be achieved via MPC models while simultaneously taking the price fluctuation and ambient influence into account. It can also be inferred from Figures 6, 8, and 10 that the solar-electricity water heater can completely rely on solar irradiation for the TCL during the daytime. The casual usage induces a limited increase in the energy consumption, which can be seen in Figures 6 and 10 as spikes. Compared with traditional proportional-integral-derivative (PID) control, which focuses only on one appliance or one trajectory, the advantage of the proposed MPC method is self-evident in solving this MIMO problem with uncertainties. The adoption of MPC in both levels also facilitates the full coverage of the model-based methodology over the whole operation, ensuring smooth interaction between the two levels.

The optimal household energy scheduling is given in Table 3. The strategy developed by the proposed method is compared with that developed by traditional dynamic programming, which can also be found in Table 2. The aggregated cost, computation time and TCL comfort interval

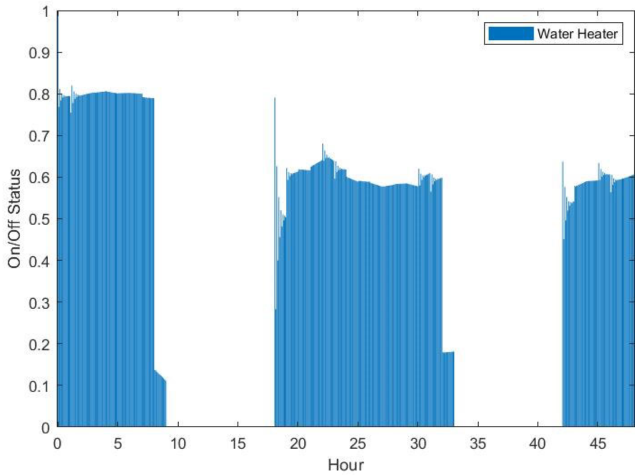

FIGURE 6. Working status of the water heater.

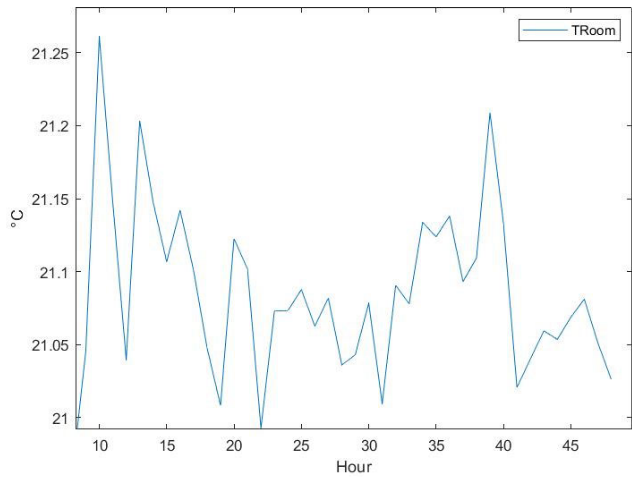

FIGURE 7. The indoor temperature over a typical 48-hour period.

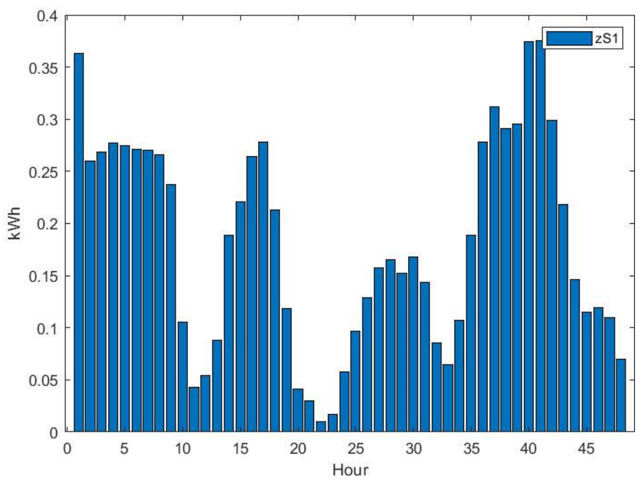

FIGURE 8. The temperature of the water in the tank over a typical 48-hour period.

deviations of traditional dynamic programming and PID are compared with the MPC method on an Intel® Core ™ i7-10710U CPU @1.10 GHz 1.60 GHz, as shown in Table 4. The computation time is the sum of the required decision time

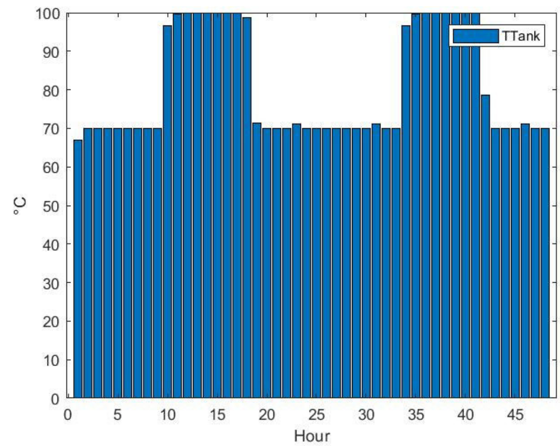

FIGURE 9. The aggregate consumption for TCL 1 maintenance (room temperature).

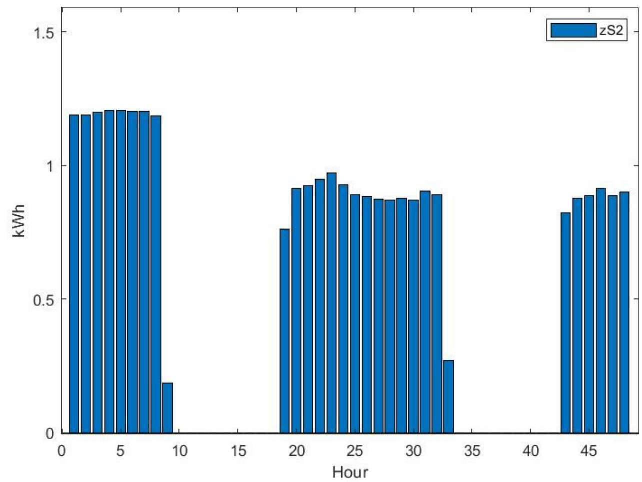

FIGURE 10. The aggregate consumption for TCL 2 maintenance (water temperature in the tank).

for each hour. It should be emphasized that the advantage of the proposed method is its absorption capability for different kinds of uncertainties and its MIMO character, which are not available in traditional dynamic programming or PID control. The comparison aims to verify that, with these new advantages, the demand for computing power and computing speed in new methods has not increased significantly and has possibly decreased.

According to Tables 3 and 4, the scheduling plan of the MPC-based method can cut the energy cost from \$1.952 to \$1.683 compared with those of dynamic programming and PID control. In particular, the savings for appliances belonging to the upper level are \$0.183, and the savings of TCL control are \$0.086 (approximately). It is demonstrated that the increase in the computational cost is trivial for the aforementioned improvements brought by the proposed bilevel MPC house energy scheduling. It should also be mentioned that due to the MIMO incompatibility of PID, the bench case employs relays to trigger the air conditioner and heater. The sample time of the step in PID is assumed to be the same as that employed in the lower-level MPC model.

TABLE 3. Scheduling plans.

Comparisons	Appliance		Energy Cost ($)	Aggregated Computation Time (s)
	PHEV	Laundry		
Working hours by proposed MPC method (two levels)	1 2 3 4 5 6 25 26 27 28 29 30	9 10 11 12 16 34 35 36 40 41	1.693	289.034
Working hours by proposed MPC method (upper level)	1 2 3 4 5 6 25 26 27 28 29 30	9 10 12 15 16 34 35 36 40 41	0.777	0.532
Working hours by dynamic programming	1 2 3 4 5 21 22 23 24 28 29 48	9 10 12 15 16 34 35 36 40 41	0.960	0.002

TABLE 4. Comparisons.

Methodology	Energy Cost ($)	Computation Time for TCL Strategies (s)	Variance Sum of Room Temperature
The proposed MPC method (total)	1.6932	288.5	0.4931
Dynamic programming	0.96	-	-
PID for TCL1	0.277	146.9	2.0874
PID for TCL 2	0.715	125.8	-
Dynamic programming+PID	1.952	272.7	2.0874

V. CONCLUSION

In this paper, smart home energy scheduling is modeled as a MIMO problem and is solved by a new bilevel economic MPC-based method. A complete set of home appliances (non-schedulable, schedulable, TCLs, etc.) and possible DER and storage integration are described and studied in this paper. The simulation results confirm that the proposed method can effectively address the real-time operation and control of household appliances, handle various uncertainty factors, and maintain a satisfactory comfort performance with a marginal increase in the computational burden. The method proposed in this paper involves the real-time detection and update of the components involved—in particular, TCL-related detection—i.e., full monitoring and control, which may be somewhat extravagant for a home environment. Future research will consider the home intelligent scheduling problem in the case of uneven digital levels; that is, there will be some missing measurements and decision-making information. The finer characterization of the modeling and energy access conditions will also be investigated in future studies.

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