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Enhanced Robust Index Model for Load Scheduling of a Home Energy Local Network With a Load Shifting Strategy

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ABSTRACT In this paper, an enhanced robust index model is proposed to optimize the robust level of home energy local network (HELN) due to the uncertainty of customer behavior. Numerous household appliances are considered, which are divided into three categories: 1) essential loads; 2) shiftable loads; and 3) throttleable loads. The proposed robust optimization is formulated to minimize the total energy cost and maximize the robust level and satisfaction level of end users. An enhanced robust index (RI) with the upper and lower limits of the robust level is integrated into load scheduling in the form of a cost function as well as additional constraints, to avoid excessive robust levels for some of the appliances and obtain a reasonable energy dispatch strategy. Moreover, a load shifting strategy is proposed based on a quick sort algorithm to improve the robust level and further reduce the energy cost of HELN. This paper investigates how the robust optimization strategy behaves in different demand response scenarios. Finally, the case studies and numerical results are presented to discuss the effectiveness of the proposed model through an integrative simulation approach.

INDEX TERMS Load scheduling, enhanced robust Index model, home energy local network (HELN), load shifting, robust optimization.

NOMENCLATURE

T_t^{h}	Temperature of electric water heater (EWH) (°C)
T_{set}^{h}	Thermostat setpoint of EWH (°C)
D_h	The deadband of the EWH (°C)
T_t^{AC}	Room temperature of air conditioner (AC) (°C)
D_{AC}	The deadband of the AC(°C)
T_{set}^{AC}	Thermostat setpoint of AC (°C)
P_t^{DG}	Power of DG at time t(kW)
$P_{\mathrm{PV}}^{\max}$	Maximum power from photovoltaic (kW)
$P_{\mathrm{W}}^{\max}$	Maximum power from wind power (kW)
P_t^{grid}	Power interaction at time t(kW)
L_t	Total load of household at time t (kW)
$\eta_{\mathrm{ch}}^{\mathrm{ev}}$	Charging efficiencies of EV
$\eta_{\mathrm{disch}}^{\mathrm{ev}}$	Discharging efficiencies of EV
$E_{\mathrm{oc},t}^{\mathrm{ev}}$	SOE of EV at period t
$P_t^{\mathrm{ev,ch}}$	Charging power of EV (kW)
$P_t^{\mathrm{ev,disch}}$	Discharging power of EV (kW)
$E_{\mathrm{oc,min}}^{\mathrm{ev}}$	Minimal SOE for EV
$E_{\mathrm{oc,max}}^{\mathrm{ev}}$	Maximal SOE for EV
$\varepsilon_{\mathrm{ev}}$, C_{ev}	Energy loss efficiencies and rated capacity
Δt	The duration of the time interval (h)
$\eta_{\mathrm{ch}}^{\mathrm{ess}}$	Charging efficiencies of ESS
$\eta_{\mathrm{disch}}^{\mathrm{ess}}$	Discharging efficiencies of ESS
$E_{\mathrm{oc},t}^{\mathrm{ess}}$	SOE of ESS at period t
$P_t^{\mathrm{ess,ch}}$	Charging power of ESS (kW)
$P_t^{\mathrm{ess,disch}}$	Discharging power of ESS (kW)
$E_{\mathrm{oc,min}}^{\mathrm{ess}}$	Minimal SOE for ESS
$E_{\mathrm{oc,max}}^{\mathrm{ess}}$	Maximal SOE for ESS
$\varepsilon_{\mathrm{ess}}$, C_{ess}	Energy loss efficiencies and rated capacity
$P_{v,t}^{in}$	Sum of power flow into the EV (kW)
$P_{v,t}^{com}$	Sum of power flow out the EV (kW)
$P_{es,t}^{in}$	Sum of power flow into the ESS (kW)
$P_{es,t}^{com}$	Sum of power flow out the ESS (kW)
$P_{gd,t}^{in}$	Sum of power flow into grid (kW)
$P_{gd,t}^{com}$	Sum of power flow out from grid (kW)

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N_{v1}, N_{v2}	Device number of flow into/from of EV
N_{es1}, N_{es2}	Device Number of flow into/from of ESS
$P_{\max}^{\text{ev,ch}}$	Maximal charging power of EV (kW)
$P_{\max}^{\text{ev,disch}}$	Maximal discharging power of EV (kW)
$P_{\max}^{\text{ess,ch}}$	Maximal charging power of ESS (kW)
$P_{\max}^{\text{ess,disch}}$	Maximal discharging power of ESS (kW)
$P_{l,t}^{in}$	Sum of power output to all appliances (kW)
$P_{d,t}^{com}$	Sum of power output from all DGs (kW)
$P_{\max}^{\text{DG}}$	Upper limit of power for micro generator (kW)
$P_{\min}^{\text{DG}}$	Lower limit of power for micro generator (kW)
$P_{Grid}^{\max}$	Limit on power interaction with grid (kW)

I. INTRODUCTION

SMART grids, which combine information technologies, control methodologies and electrical power grids [1], are currently being studied around the world. A smart grid aims to enable more active end-user participation, rather than passive consumption points, and the number of smart households has increased recently [2], [3]. Currently, the electricity demands requested from downstream sectors of a smart grid are constantly increasing. One effective way to meet these electricity energy demands is by using home energy management systems (HEMS) to monitor and manage major household appliances [4]. Because HEMS can receive different information flows (such as load data, electricity price data and the power interaction), they can play an important role in energy management and demand response (DR) [5]. It is expected that the economic and societal benefits of using a smart grid outweigh the costs of installing the communication network and smart meters, so many studies have been conducted in the area of smart buildings, particularly on effective structure and optimal strategies of a home energy local network (HELN) with the integration of renewable energy.

In terms of demand-side management, there are two main techniques: one is a direct load control, and the other is a DR based on time variations [6]. If power grid adopts the direct load control strategy, the utility company first contracts with the consumers, because a noncritical load can be cut off during peak hours to relieve overload or congestion on the main grid. On the other hand, DR strategy based on a time varying price often encourages customers to shift energy consumption away from peak hours in return for some benefits. Most current research is mainly focused on how to optimize the users' energy consumption given their predefined energy demand. In particular, Tsui and Chan [7] proposed a load management method of various household appliances for supporting the DR through an energy management system in a smart home. Load schedules are executed under the premise that forecast data is accurate. However, uncertainties in forecasting data, i.e., the price of electricity and the renewable energy power, make accurate forecasting difficult, which can lead to significant economic losses and dissatisfied end users.

To solve the load scheduling problem of uncertainty, many stochastic optimization methods have been proposed. For stochastic models, the load scheduling problem is typically modeled as a random process or as proper probability distribution functions (PDFs), which are integrated into the energy optimization problem in the form of constraints or added into the objective function as the expected function. References [8]–[11] depicted the uncertainties of renewable energy, and the stochastic optimization method was proposed to solve an energy consumption problem. Specifically, wind power generation was forecasted using the statistical information of historical data in [9], and Atia and Yamada [11] introduced the energy optimization problem using the scenario generation techniques. However, sufficient historical data are difficult to obtain in real situations, and the computational burden of a scenario- based method will grow with an increase of scenarios. In [12]–[14], the uncertainty in the price of electricity was investigated in load scheduling, and the impact of price uncertainty on energy management was analyzed. Deng *et al.* [13] formulated an optimization problem with the expectation and temporally coupled constraints. Dual decomposition and a stochastic gradient were utilized to solve the energy consumption problem instead of resorting to the stochastic dynamic programming. Moreover, to cope with uncertainty of load forecasting, [15], [16], and [11] proposed an energy consumption scheduling model to minimize the energy cost for customers. Different from the methods used in [17], Gong *et al.* [18] converted stochastic constraints to linear constraints using Gaussian approximations to reduce optimization complexity. If there are many uncertainties to be considered, the model, and especially their relationships, are rather complex.

As another effective method for addressing the stochastic optimization problem, robust optimization has been applied in power systems recently, since it does not require accurate PDFs of uncertainties. Melhem *et al.* [19] proposed a robust optimization algorithm of energy management, which aims to reduce the electricity expenses of residential consumers. Chen *et al.* [20] proposed a robust optimization approach of the DR management, where price uncertainty is simulated using uncertainty intervals. The results of [20] indicated that the stochastic optimization introduces a higher computational burden than that of a robust approach, although the latter method obtains a more conservative scheme. In [21], robust optimization, with the objective of reducing the electricity payment of all home appliances, takes the worst case into account, based on the real-time electricity pricing. To reduce the conservative level of the robust solution, the authors of [22] proposed a parameter allowing a trade-off between the price of robustness and protection against uncertainty to be achieved. The novelty in that work was coping with uncertainty in customer behavior to schedule noninterruptible controllable appliances. It can be seen from most of the above studies that the robustness of a single appliance is not described in detail, so Wang *et al.* [23] presented a robust index (RI) method to cope with the uncertainties caused by the customer behavior in order to minimize comfort violation. The proposed method is independent of the historical data and can improve the robustness of appliance scheduling with only a slight increase in computational time. Above reference is mainly focusing on improving the robustness of different appliances, but excessive strong robust levels can make some of the appliances concentrate on the same period, and increase the energy cost because of the advancing or delaying some time during which the electricity price is much higher. Therefore, in this paper, based on [23], to enhance the robust level of different appliances while considering the uncertainty of user behavior, a new enhanced robust optimization with the upper and lower limits of robust level is proposed to optimize the robust level and reduce the energy cost of entire household. The main constructions can be stated as follows:

1) Based on [23], a new robust optimization method is proposed, and the RIs with lower and upper limit of all appliances are integrated into the cost function of load scheduling as well as in the form of constraints, to avoid excessive robust levels for some of the appliances.

2) To describe the satisfaction level accurately under robust optimization with the randomness of customer behavior, a new satisfaction function considering the RIs of different appliances, is established in the multiobjective optimization problem of load schedule. Some advantages can be achieved by comparing to other existing satisfaction function method.

3) The load shifting algorithm is added into the load schedule. The operating order/priority of different types of loads are adjusted based on a quick sort algorithm (QSA), The proposed strategy can improve the robust level of household appliances and also reduce the energy cost of the household.

The rest of paper is organized as follows. The framework of the HELN is introduced in section II. Section III models the optimization model of the energy management problem. Section IV proposes a multiobjective optimization model considering load shifting strategy. Illustrative case studies are presented in section V, and the paper is concluded in section VI.

II. THE FRAMEWORK OF HOME ENERGY LOCAL NETWORK

A. FRAMEWORK OF HOUSEHOLD LOAD SCHEDULING

We consider a home energy local network (HELN), in which the energy storage system (ESS) and electric vehicle (EV) are equipped and the energy from/to power grid is shared through the power line, and the microgenerator and renewable energy generation are integrated into the HELN, as shown in Fig. 1. The appliance loads of the HELN are categorized into three types: the essential, shiftable and throttleable appliances. The essential appliances are interactive and have minimal scheduling flexibilities, e.g., electric stoves, lamps and TVs, which are modeled by fixed power curves over the scheduling horizon. The shiftable appliances have specified energy consumption profiles and flexible delays, e.g., washing machines (WM), clothes dryers (CD), etc.

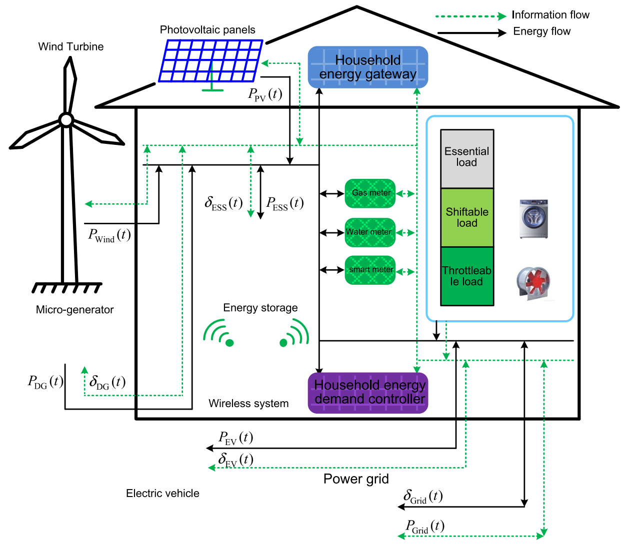

FIGURE 1. System structure of home energy local network.

Throttleable appliances are adjusted within a range during their operational period, e.g., plug-in EVs (when they are charging). In addition, thermostatically controlled loads (TCL) are interruptible but with the unique characteristics that belong to throttleable appliances. The typical appliances with TCL in this paper mainly include an electric water heater (EWH) and air conditioner (AC).

The proposed robust optimization method in this paper is to maximize the robust operation level of appliances by assessing the uncertainty influences of user behavior. The energy consumption scheduling vector for above three types of household appliances could be described as in (1)

$$\begin{aligned} e_u &= [e_u^1, \cdots, e_u^t, \cdots, e_u^T] \\ e_v &= [e_v^1, \cdots, e_v^t, \cdots, e_v^T] \\ e_w &= [e_w^1, \cdots, e_w^t, \cdots, e_w^T] \end{aligned} \tag{1}$$

where scalar e_u^t, e_v^t, and e_w^t represent the power consumption that is scheduled for essential appliance $u \epsilon U$, shiftable appliance $v \epsilon V$, and throttleable appliances $w \epsilon W$ at time interval t, respectively. Where, U, V and W are the set of essential, shiftable and throttleable appliances. Moreover, the total load of the entire household is obtained as

$$L_t = \sum_{u \in U, v \in V, w \in W} (e_u^t + e_v^t + e_w^t) \tag{2}$$

According to the above definitions, the peak load and minimum load of the HELN, respectively, are

$$L_{\max}/L_{\min} = \max_{t \in T} L_t / \min_{t \in T} L_t \tag{3}$$

where T is the total number of all unit time intervals.

B. HOUSEHOLD APPLIANCES MODEL

In this paper, the DR has no impact on the optimization of energy consumption for the essential appliances. The reason is that power consumption of the essential load is a constant value in the objective function of energy optimization.

1) SHIFTABLE APPLIANCES

In this case, each consumer should preset a start time and end time where the appliances can be scheduled. The energy consumption strategy is designed to shift the operational period of appliances based on optimization objective and DR strategy. The constraints of shiftable appliances are described in (4)

$$\begin{cases} \sum\limits_{t \in T_v} e_v^t = E_v \\ e_v^t = 0, \quad \forall t \in T \backslash T_v \end{cases} \tag{4}$$

where T_v is the number of time slots within the appliance's time window, and E_v is the sum of total energy consumption for v shiftable load, respectively.

2) THROTTLEABLE APPLIANCES

In terms of the throttleable appliances, the energy consumption scheduler of HELN does not aim to change the appliance's operational period, but instead mainly focuses on adjusting the operational power demand of each throttleable appliance within the predetermined operation time interval t. We denote the total energy consumption as E_w. The constraints of throttleable appliances are described as

$$\begin{cases} \sum\limits_{t \in T_w} e_w^t \leq E_w \\ e_w^t = 0, \quad \forall t \in T \backslash T_w \end{cases} \tag{5}$$

where T_w and E_w are the sum of the operational time and the total energy consumption for w throttleable appliances.

3) THERMOSTATICALLY CONTROLLED APPLIANCES

TCLs are throttleable but with unique characteristics. In this study, EWH and AC are typical TCLs, which share many similarities despite many specific differences. In terms of the EWH, the thermal dynamic model is stated from both the heat exchanged with the environment and the heat provided by the EWH resistance, which is shown in [24]. The EWH has a thermostat setpoint and a deadband. The EWH must be maintained within the range of the thermostat setpoint, so we have

$$T_{set}^h - D_h \leq T_t^h \leq T_{set}^h \tag{6}$$

The temperature of hot water inside of the EWH tank could be described as a function of time in [24]

$$T_t^h = T_t^\tau e^{-\frac{1}{R'C}(t-\tau)} + R'(GT_{out} + B(t)T_{in} + Q) \times (1 - e^{-\frac{1}{R'C}(t-\tau)}) \tag{7}$$

where, τ is the previous sample (t-1, hours), G is the ratio of the surface area to thermal resistance of the tank. The calculation method of other parameters in (6) are given in [24].

Moreover, the AC is also operated in a throttleable manner to reduce its electricity consumption cost. Then, room temperature can be modeled from the thermal properties of air and the heating/cooling exchange between the house and ambient air, which is shown in [25]. Then, the constraint of room temperature is described in (8)

$$T_{set}^{AC} - D_{AC} \leq T_t^{AC} \leq T_{set}^{AC} \tag{8}$$

Note that the dynamic models of the TCLs are rather complex, but energy-balance constraints for them are used in this paper.

C. MODEL OF EV AND ESS

In this paper, the performance of V2G is considered. During operation, the storage capacity level of an EV at period $t+1$ is determined by that of its previous period as well as its charging or discharging operation [26], the state-of-energy (SOE) of the EV are described in (9) and (10), which is given by

$$E_{oc,t+1}^{ev} = E_{oc,t}^{ev} + P_t^{ev,ch} \Delta t \eta_{ch}^{ev} / C_{ev} - \varepsilon_{ev} \Delta t \tag{9}$$

$$E_{oc,t+1}^{ev} = E_{oc,t}^{ev} - P_t^{ev,disch} \Delta t / (\eta_{disch}^{ev} C_{ev}) - \varepsilon_{ev} \Delta t \tag{10}$$

$$E_{oc,min}^{ev} \leq E_{oc,t}^{ev} \leq E_{oc,max}^{ev} \tag{11}$$

The EV model employed in this study is described by (9) – (11). Equations (9) and (10) define the SOE of EV, and constraint (11) represents the minimal and maximal SOE of EV.

The ESS is connected with the power grid, and its model is similar to that of EV; the basic difference is that the ESS is available at the household all day. More importantly, the ESS could provide electricity energy to resident appliances, and the EV could be supported by the ESS. The priority of supporting electricity to a household appliance from the ESS is higher than that of the EV. Then, dynamic model of the ESS [26] is described

$$E_{oc,t+1}^{ess} = E_{oc,t}^{ess} + P_t^{ess,ch} \Delta t \eta_{ch}^{ess} / C_{ess} - \varepsilon_{ess} \Delta t \tag{12}$$

$$E_{oc,t+1}^{ess} = E_{oc,t}^{ess} - P_t^{ess,disch} \Delta t / (\eta_{disch}^{ess} C_{ess}) - \varepsilon_{ess} \Delta t \tag{13}$$

$$E_{oc,min}^{ess} \leq E_{oc,t}^{ess} \leq E_{oc,max}^{ess} \tag{14}$$

D. MODEL OF MULTIPLE ENERGY INTERACTION OF HELN

The energy flow diagram of the HELN is shown in Fig. 2.

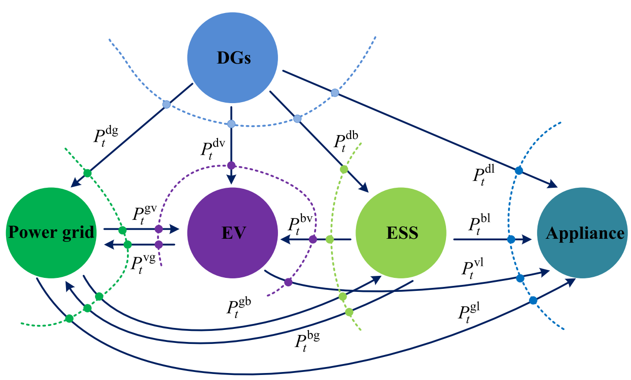

FIGURE 2. Energy flow diagram of a home energy local network.

It can be seen from Fig. 2 that the dynamic flows of energy are complex. P_t^{dg}, P_t^{dv}, P_t^{db} and P_t^{dl} are the powers from the distributed generations (DGs) to the grid/ EV/ ESS/load at time t, respectively. P_t^{gv}, P_t^{gb} and P_t^{gl} are the power from the grid to EV/ ESS/ load at time t, respectively. P_t^{bv}, P_t^{bg} and P_t^{bl} are the power from the ESS to EV/ grid/ load at time t, respectively. P_t^{vg} and P_t^{vl} are the power from the EV to grid/ load at time t, respectively (kW).

It should be noted that if $P_t^{\mathrm{gv}} \neq 0$, $P_t^{\mathrm{vg}} = 0$, and vice versa. If $P_t^{\mathrm{gb}} \neq 0$, $P_t^{\mathrm{bg}} = 0$, and vice versa. In addition, the energy flow model employed in this study is described by (15) ~ (18).

$$P_t^{\mathrm{ev,ch}} = \sum\nolimits_{n\in N_{v1}} P_{v,n,t}^{in} \leq P_{\max}^{\mathrm{ev,ch}} \tag{15}$$

$$P_t^{\mathrm{ev,disch}} = \sum\nolimits_{n\in N_{v2}} P_{v,n,t}^{com} \leq P_{\max}^{\mathrm{ev,disch}} \tag{16}$$

$$P_t^{\mathrm{ess,ch}} = \sum\nolimits_{n\in N_{es1}} P_{es,n,t}^{in} \leq P_{\max}^{\mathrm{ess,ch}} \tag{17}$$

$$P_t^{\mathrm{ess,disch}} = \sum\nolimits_{n\in N_{es2}} P_{es,n,t}^{com} \leq P_{\max}^{\mathrm{ess,disch}} \tag{18}$$

Constraints (15) and (16) depict the upper limit of charging and discharging of the EV, and (17) and (18) limit the charging and discharging power of the ESS, respectively.

III. OPTIMIZATION MODEL OF HOME ENERGY MANAGEMENT

A. MODEL OF DISTRIBUTED GENERATION

In this paper, DGs such as a diesel generator are considered. The relation between the generation cost and the power generation is stated in (19)

$$C_p(P_t^{\mathrm{DG}}) = a\left(P_t^{\mathrm{DG}}\right)^2 + bP_t^{\mathrm{DG}} + c \tag{19}$$

where a, b, and c are the cost coefficients.

In addition, each house has distributed renewable generators, such as a rooftop PV panel or a wind turbine. Renewable energy generation is usually uncertain, which is modeled in [19] for wind power and PV. The bounds of the amount of power generated by the PV system and wind system are shown

$$0 \leq P_t^{\mathrm{pv}} \leq P_{\mathrm{PV}}^{\max}, \quad \forall t \tag{20}$$

$$0 \leq P_t^{\mathrm{wind}} \leq P_{\mathrm{W}}^{\max}, \quad \forall t \tag{21}$$

In this paper, renewable energy generation should be utilized as much as possible, and excess renewable energy generation can be stored in the ESS/EV. Since the uncertainty of wind power and PV are described in [19], a battery ESS is integrated into the HELN because an energy storage device with a fast response is necessary to cover the shortfall or overflow of generation due to sudden variations in wind or solar output. The WT generation system is modeled on a 2 kW wind turbine, and the PV power generation is modeled on 15 m^2 of photovoltaic cells in the household.

B. OPTIMIZATION MODEL OF HOME ENERGY MANAGEMENT

The electricity energy demand may not be fully supported by all DGs, so the household must be connected to a power grid for additional power support. Therefore, the power interaction cost with the main grid is given by (22)

$$C_g(P_{gd,t}^{in}, P_{gd,t}^{com}) = \kappa_t^{grid}\left(\sum\nolimits_{n\in N_{gd2}} P_{gd,n,t}^{com} - \sum\nolimits_{n\in N_{gd1}} P_{gd,n,t}^{in}\right) \tag{22}$$

and

$$\kappa_t^{\mathrm{grid}} = \frac{1+Sgn(P_t^{\mathrm{grid}})}{2}\kappa_t^{buy} + \frac{1-Sgn(P_t^{\mathrm{grid}})}{2}\kappa_t^{sell} \tag{23}$$

where κ_t^{buy} and κ_t^{sell} are prices of buying and selling electricity, respectively, $Sgn()$ is the symbolic function.

The operation costs of the ESS and EV are introduced because they could smooth the power fluctuation of wind power and PV and improve the stability of the power grid. The cost functions are described by (24)-(25)

$$C_s(P_{es,t}^{in}, P_{es,t}^{com}) = \kappa_{\mathrm{ess}}\left(\sum\nolimits_{n\in N_{es1}} P_{es,n,t}^{in} + \sum\nolimits_{n\in N_{es2}} P_{es,n,t}^{com}\right) \tag{24}$$

$$C_v(P_{v,t}^{in}, P_{v,t}^{com}) = \kappa_{\mathrm{ev}}\left(\sum\nolimits_{n\in N_{v1}} P_{v,n,t}^{in} + \sum\nolimits_{n\in N_{v2}} P_{v,n,t}^{com}\right) \tag{25}$$

where κ_{ess} and κ_{ev} are the operation coefficients of cost for the ESS and EV, respectively.

Therefore, the total cost of the HELN is minimized in this paper, and the objective function of the optimization problem regarding the energy cost is described in (26)

$$\begin{aligned}\text{Min: } C_{energy}(t) = C_p(P_t^{\mathrm{DG}}) + C_s(P_{es,t}^{in}, P_{es,t}^{com}) \\ + C_v(P_{v,t}^{in}, P_{v,t}^{com}) + C_g(P_{gd,t}^{in}, P_{gd,t}^{com})\end{aligned} \tag{26}$$

$$\text{Subject to: } P_{l,t}^{in} = e_u^t + e_v^t + e_w^t \tag{27}$$

$$P_{d,t}^{com} = P_t^{\mathrm{wind}} + P_t^{\mathrm{pv}} + P_t^{\mathrm{DG}} \tag{28}$$

$$P_{\min}^{\mathrm{DG}} \leq P_{n,t}^{\mathrm{DG}} \leq P_{\max}^{\mathrm{DG}} \tag{29}$$

$$-P_{Grid}^{\max} \leq P_{Grid}(t) \leq P_{Grid}^{\max} \tag{30}$$

Note that (27) and (28) are the power balance constraints of the HELN. Constraint (29) determines the upper and lower limit of power for the microgenerator at period t, and (30) depicts the upper limit of power interaction with the main grid. Additionally, constraints also includes (5) ~ (18), (20) and (21) in household load optimization scheduling.

IV. ROBUST OPTIMIZATION WITH LOAD SHIFTING STRATEGY

In this section, we present a robust optimization method that considers the load shifting strategy. User behavior uncertainty refers to the advance or postpone of time deadlines, which can cause the satisfaction violation. In this scheme, a multiobjective optimization model is formulated in terms of total energy cost of the HELN and the satisfaction level of end users.

A. ROBUST OPTIMIZATION WITH LOAD SHIFTING STRATEGY

In this paper, based on the [23], a new robust optimization method is proposed to improve the robust level of appliances. First, the robust index (RI) is only integrated into appliance scheduling in the form of additional constraints in [23], but in this method, the RI is added into objective function and also RI is considered in the constraints of load optimization problems. Moreover, the load shifting strategy is adjusted based on the QSA to improve the RI of appliances and reduce the energy cost of the entire household.

The RI is developed to utilize in the load schedule of the HELN by considering the uncertainty of end user behavior in [23]; i.e., the time deadlines may be advanced or postponed in practice. The larger the RI is, the more robust the schedule optimization will be. Take the shiftable appliance as an example, which is illustrated in Fig. 3.

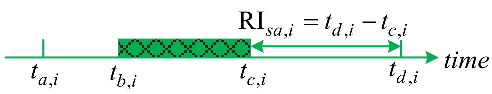

FIGURE 3. Robust indexes of shiftable appliances.

The shiftable appliance is permitted to work during $[t_{ai}, t_{di}]$ and is scheduled to work during $[t_{ai}, t_{ci}]$. The deadline of the shiftable appliance is preset at/near t_{ci}. The time margin is

$$\mathrm{RI}_{sa,i} = t_{d,i} - t_{c,i} \tag{31}$$

where $\mathrm{RI}_{sa,i}$ represents the RI of the shiftable appliance, and t_{ci} is the planned finish time of the task. Additionally, the RI of the throttleable appliance RI_{ta} and the RI of the TCL RI_{TCL} are defined in [23].

However, the RIs of all kinds of household appliances are only integrated into the load scheduling as an additional constraint. To maximize the robust level of all appliances, the RIs will be added into the objective function of the optimization problem based on [23], the cost function of RI for all household appliances is given by

$$C(\mathrm{RI}_{sa}, \mathrm{RI}_{ta}) = \sum\nolimits_{Nsa} \mathrm{RI}_{sa,i} + \sum\nolimits_{Nta} \mathrm{RI}_{ta,j} \tag{32}$$

where N_{sa} and N_{ta} represent the number of the shiftable appliance and throttleable appliance.

Generally, a much stronger RI level does not mean that a more reasonable result can be obtained, especially in extreme cases. The considered upper bound and lower bound of RI can avoid excessive robust levels for partial loads and obtain a reasonable dispatch strategy, the RI constraints are given by

$$\mathrm{RI}_{sa,\min} \le \mathrm{RI}_{sa} \le \mathrm{RI}_{sa,\max} \tag{33}$$

$$\mathrm{RI}_{ta,\min} \le \mathrm{RI}_{ta} \le \mathrm{RI}_{ta,\max} \tag{34}$$

where, $\mathrm{RI}_{sa,\min}$ and $\mathrm{RI}_{sa,\max}$ are the lower limit and upper limit of RI for shiftable appliances, $\mathrm{RI}_{ta,\min}$ and $\mathrm{RI}_{ta,\max}$ are the lower limit and upper limit of RI for throttleable appliances.

Moreover, the operation order of appliances will be changed to obtain the load schedule with an expected robust level. Let S[.] be an array of RIs for household appliances. First, two pointers that are referred to as first and last are set up to operate the partition program. The initial values of two pointers are the lower and upper limits of the RIs. If there are n elements in the list, then first $= 0$ and last $= n - 1$. The partition program is introduced in [27], and the operational order of appliances based on the QSA is illustrated in algorithm 1. Algorithm 1 summarizes the iterative process to find the maximum RI of for the entire HELN.

Algorithm 1 Quick Sort Algorithm for the Order of Loads

1: **Set** the desired objective function
2: **Initialize** the importance and deadline of appliances
3: **Quick Sort** (int S[], int i = first, j = last){
    If ($i < j$){
        Int split = part(S, i, j)
        Quicksort(S, i, split-1)
        Quicksort(S, split + 1, j)
    }
}
4:**Return** results

After ensuring the operational order of appliances by QSA, the constraints reflecting load operational order are described

$$\begin{cases} \varphi_{L1}^{init}(t) = \begin{cases} 1, & \delta_t^{L1} = 1 \quad and \ \delta_{t-1}^{L1} = 0 \\ 0, & else \end{cases} \\ \varphi_{L2}^{end}(t) = \begin{cases} 1, & \delta_t^{L2} = 1 \quad and \ \delta_{t+1}^{L2} = 0 \\ 0, & else \end{cases} \end{cases} \tag{35}$$

$$\varphi_{L1}^{init}(t) \times k_{L1}^{init} \ge \varphi_{L2}^{end}(t) \times k_{L2}^{end} \tag{36}$$

where k_{L1}^{init} is the start time of the appliance L_1, and k_{L2}^{end} is the ending time of appliance L_2.

B. MAXIMIZATION OF USER SATISFACTION

As mentioned before, the sudden advance of time deadlines may lead to a satisfaction violation because the tasks may not be finished in time under new deadlines. Therefore, the satisfaction level will be modeled reasonably. At present, the satisfaction level would be 100% when the schedule time is in the required time interval; otherwise, the satisfaction level decreases to 0 nonlinearly [28]. To reflect the satisfaction level, a new satisfaction function is modeled in (37)

$$C_{csi}(t) = \sum\nolimits_{N} \omega_i CSI_i(t) \tag{37}$$

Then, $N = N_{sa} + N_{ta}$, and $CSI_i(t)$ is given

$$CSI_i(t) = \begin{cases} 1, & [t_{b,i}, t_{c,i}] = [t_{a,i}, t_{d,i}] \\ 0.8 + \kappa \dfrac{t_{d,i} - t_{c,i}}{t_{d,i} - t_{a,i}}, & t \in [t_{a,i}, t_{d,i}] \\ 0, & t \notin [t_{a,i}, t_{d,i}] \end{cases} \tag{38}$$

where κ is a positive constant, and $\kappa = 0.2$.

TABLE 1. The shiftable appliance demands.

Appliance	Power /kW	Operation Periods/h	RI ≥	RI ≤
Induction cooker (IC)	2.1	12:00~13:30 18:00~20:00	0.25	0.5
Microwave oven (MO)	0.7	06:00~07:30	0.25	0.5
Smoke machine (SM)	0.225	12:00~13:30 18:00~20:00	0.25	0.5
Water Boiler (WB)	1.8	06:00~07:30 12:00~13:30 18:00~21:00	0.25	0.5
Hang ironing machine (HIM)	1.5	20:00~23:30	0.25	0.5
Rice Cooker (RC)	0.9	12:00~13:30 18:00~20:00	0.25	0.5
Washing Machine (WM)	0.5	20:00~23:00	0.25	0.5
Hair Dryer(HD)	2.0	06:15~07:30 22:30~00:00	0/0.25	0.25/0 .5
Water Dispenser (WD)	1.2	12:00~13:30 18:00~23:30	0/0.5	0.25/0 .75
Disinfection cabinet (DC)	0.52	21:00~23:00	0.25	0.5

It can be seen from (38) that the larger time margin (t_{di}-t_{ai}), the more robust the load scheduling will be, and the higher satisfaction will be obtained, with the maximum satisfaction being 100%.

C. OPTIMIZATION MODEL OF LOAD APPLIANCES

Based on the discussion of Part III, a new optimization model for load scheduling is formulated to minimize the total energy cost and maximize the satisfaction level of end users, which is described in (39)

$$(P) \quad \min \frac{f_1(x)}{\xi_1 f_2(x) + \xi_2 f_3(x)}$$
$$\Rightarrow \min \frac{\sum_{t\in T} C_{energy}(t)}{\xi_1 \sum_{t\in T} C(\mathrm{RI}_{sa}, \mathrm{RI}_{ta}) + \xi_2 \sum_{t\in T} C_{csi}(t)} \tag{39}$$

where, $\xi_1 + \xi_2 = 1$, ξ_1, $\xi_2 \epsilon [0,1]$, are the weighting coefficients determined by the significance of individual objective. We can therefore incorporate the operation order of (35) and (36) into the constraints, along with the sum of the RIs (32) and satisfaction level (37) into the objective function of the optimization problem, to find an optimal scheduling scheme. The constraints in Part III of load scheduling are also included in the optimization problem (39). The normalized process of objective function is given in [29]. In addition, Particle Swarm Optimization (PSO) is utilized to calculate the energy optimization model due to a highlight when solving a nonlinear optimization problem.

V. CASE STUDY

In this paper, a load consumption over the scheduling horizon is presented for a four-member family house, $a = 0.00637$, $b = 0.168$, and $c = 0$. The horizon of load scheduling is assumed to be one day (from 0:00 to 23:59). Different load demands are shown in the Tables 1 and 2. In our considered residential HELN, we assume that the essential appliances consume approximately 2.5 kW, and the self-adaptive PSO [30] is utilized to solve optimization model, where the inertia weight factor $\omega_{min} = 0.4$ and $\omega_{max} = 0.9$, the maximal iteration number $N_{max} = 300$, and the other parameters are shown in [30]. A complete flow chart of proposed load schedule is illustrated in the algorithm 2, and the load shift strategy based on QSA is described in the algorithm 3, where $C_{\mathrm{energy}}(\ new)$ and $C_{\mathrm{energy}}(\ old)$ are energy cost before and after load shift. The simulation is tested using an dual-core computer, each core has a dominant frequency of 2.6 GHz, and the RAM capacity of PC is 8 GB. To solve this load schedule, it requires not only household energy management system information (household appliances, and the integrated main grid), but also the system data of the wind power and PV generation. In proposed load schedule scheme, it is assumed that there is no power interaction between grid and EV during day time from 4:00 A.M. to 7:00 P.M., because the SOC of EV can be full before departure, and EV could arrive at home at 7:00 P.M. Initially, the HELN sets the initial demand schedule for each appliance according to preferable

TABLE 2. The throttleable appliance demands.

Appliance	Power /kW	Periods/h	RI ≥	RI ≤
EWH	4.0	19:00~23:00	0	0
AC	2.5	00:00~06:00 12:00~13:30, 21:30~23:59	0.0/0.0/0.0	1.5/0.0/1.5

Algorithm 2 Optimization Algorithm for Load Scheduling

Initialization:

1:Collect an array of system data for the HELN.

2:Input: $\boldsymbol{x}_{1,i} \sim \boldsymbol{x}_{11,i}$ are power varibales, $\boldsymbol{x}_{12,i} \sim \boldsymbol{x}_{23,i}$ are loads, $\boldsymbol{x}_{24,i} \sim \boldsymbol{x}_{27,i}$ are temperatures and state of charge, $\boldsymbol{i} = 1,2,\ldots,96$.

3:Input the parameters of Particle Swarm Optimization.

4:Give maximum iterations $\boldsymbol{N}_{\mathbf{max}}$ and computation precision.

Iteration:

5:Calculate objective function and obtain decision variables:

$$(P) \min \frac{\sum_{t\in T} C_{energy}(t)}{\xi_1 \sum_{t\in T} C(RI_{sa}, RI_{ta}) + \xi_2 \sum_{t\in T} C_{csi}(t)}$$
$$\text{Subject to}: \ (4) \sim (18),\ (20) \sim (21),\ (27) \sim (30)$$
$$\text{and } (33) \sim (36)$$

6:Update the position and velocity of each particle.

7:Obtain the optimal value based on penalty function.

8:Update the operational state of EWH, AC, EV and ESS for next time slot, which are T^h_{t+1}, T^{AC}_{t+1}, $E^{\mathrm{ev}}_{\mathrm{oc},t+1}$, $E^{\mathrm{ess}}_{\mathrm{oc},t+1}$

Algorithm 3 Load Shifting Based on QSA

Iteration:
While $i <= Num$
if RI $>=$ RI i,max,
  Sort appliances according to priority using QSA
  RI←RI+1
  Update the equality constraints in (27) and (28)
  if cost function $C_{energy}(new) < C_{energy}(old)$
    RI←RI+1
  else
    RI←RI
  endif
endif
$i \leftarrow i + 1$
Endwhile

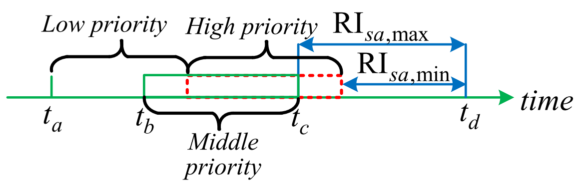

FIGURE 4. Priority of household appliances.

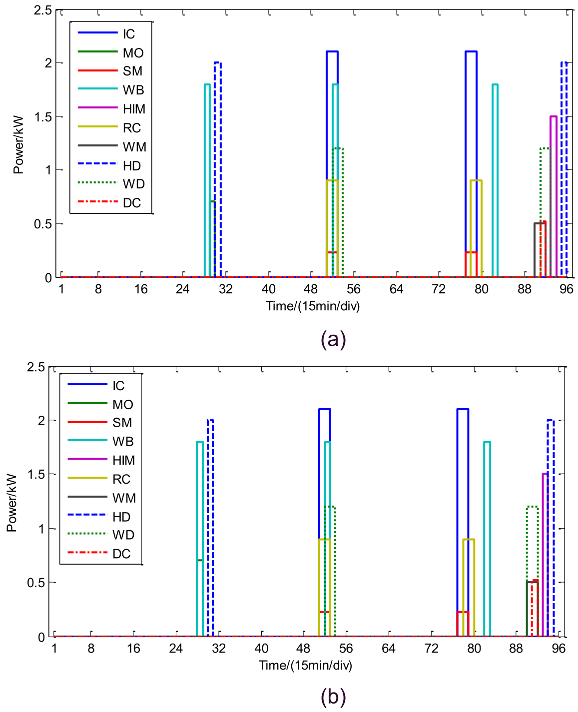

FIGURE 5. Results of the load schedules for two cases. (a) Case 1. (b) Case 2.

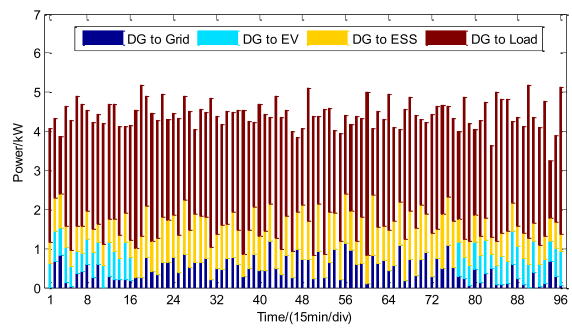

FIGURE 6. Power output from the DG.

demand schedule, then scheduling problem (39) is optimized using system information, including the demand constraints (4)~(18), power constraints (20)~(21), (27)~(30), and robust constraints (33)~(34) and operating order (35)~(36).

A. PERFORMANCE FOR DIFFERENT SCHEDULING SCHEMES

To evaluate the performance of the proposed energy consumption scheme, two different scheduling schemes are compared in this section, and both of them do not considered load shifting strategy in this section. A baseline scheme (case 1), where no RI in the cost function is performed as the scheme proposed in [23], and an enhanced robust load schedule (case 2) are compared, in which the objective function is (39), $\xi_1 = 0.5$, $\xi_2 = 0.5$, and (4)~(18), (20)~(21), (27)~(30) are taken as the constraints of proposed optimization scheme. The upper and lower limits of the RI constraints are shown in Table 1.

TABLE 3. Cost results for different cases.

Case	Energy cost (￥)	RI level	Satisfaction level
1	100.8290	6.25	23.21
2	108.6464	7.0	23.33

The above two subcases are compared to the energy cost, RI level and satisfaction level of the load scheduling, which are shown in Table 3. It is obvious from Table 3 that the RI level achieved by the proposed schemes are larger than that of the baseline schemes in [23], but energy cost of case 2 is higher than that of Case 1. The reason for this is that the MO, HD and WD are advanced by approximately 0.25 h to finish earlier during 06:00~ 07:30, 22:30~00:00, and 18:00~23:30, respectively. The robust levels of EWH and AC remain unchanged for two cases, which are the upper limits of RI, so Fig.5 shows the results of other appliances scheduling of two cases. In addition, the power from DG to grid, EV, ESS and load are given in Fig.6. It can be seen from Fig.6, the amount of electricity from DG to load is much more than the other power flow from DG, such as "DG to grid", "DG to EV", "DG to ESS". The reason is that DG located in HELN mainly aims at supplying electricity to all kinds of appliances, other power exchanges from the DG are to achieve maximal economic profit for entire HELN.

Compared with Case 1, the RIs of different appliances are added into the energy consumption model in the cost function for Case 2. The RIs of household appliances are maximized and satisfy the RI constraints (RI_{sa-set}, RI_{ta-set}). According to calculation results, in terms of the Case 2, the number of loads achieved the maximal robust level is much more than that of the Case 1, i.e., MO(06:00∼07:30), HD (22:30∼00:00), and the WD (18:00∼23:30), which maximizes the robust level of the entire household to resist a much greater uncertainty, Therefore, the results indicate that the proposed scheme can further maximize and reflect the robustness of the load schedule.

B. PERFORMANCE ANALYSIS WITH LOAD SHIFTING

In this subsection, we seek to compare the performances of the load scheduling schemes at different periods, so three cases (06:00 ∼07:30, 12:00∼13:30 and 18:00∼20:00) are designed to verify the validity of proposed energy consumption scheme. The model of the load schedule mainly includes the objective function (39), $\xi_1 = 0.5$, $\xi_2 = 0.5$, the energy constraints (4)∼(18), (20)∼(21), (27) ∼ (30), the RI constraints in [23], and the operating order constraints (35)∼(36) of the appliances. To assess the robustness of load schedules, the "robust rates" of shiftable appliances and throttleable appliances are defined in the (40) and (41), respectively:

$$RBI_{sa,i} = \frac{RI_{sa,i}}{RD_{sa,i}} \times 100\% \tag{40}$$

$$RBI_{ta,k} = \frac{\sum_{j\in[t_a,t_e]} RI_{ta1,kj} + \sum_{j\in[t_e,t_d]} RI_{ta2,kj}}{\sum_{j\in[t_a,t_e]} RD_{ta1,kj} + \sum_{j\in[t_e,t_d]} RD_{ta2,kj}} \times 100\% \tag{41}$$

where $RD_{sa,i} = t_{d,i}$-$t_{a,i}$, i is the number of shiftable load. $RD_{ta1,kj} = t_{e,k}$-$t_{a,k}$ and $RD_{ta2,kj} = t_{d,k}$-$t_{e,k}$, k is the number of throttleable appliances.

TABLE 4. Cost and RI for shiftable loads.

Number	Energy cost (￥)	Order of shifted appliance
A	107.0609	HD
B	107.0609	HD
C	98.8566	HD→RC

In this simulation, Case A acts as a base case, where the load shifting strategy is implemented only during 06:00∼07:30 for the household appliances. In Case B and Case C, the load shifting strategies are integrated in energy optimization problem during two periods (06:00∼07:30 and 12:00∼13:30), and all three periods (06:00∼07:30, 12:00∼13:30 and 18:00∼ 20:00) are assessed separately. According to the simulation results in Table 4, for the 06:00∼07:30 period, the energy cost of HELN can be obtained through load shifting, and has reduced from 108.6464￥ to 107.0609￥, and HD is shifted and advanced 0.25h in this period, and the load shifting results are shown in Fig.7 (a). The robust level of appliance has increased from 7.0 to 7.25. Based on the numerical results of Case A, Case B also considers load shifting strategy during two time

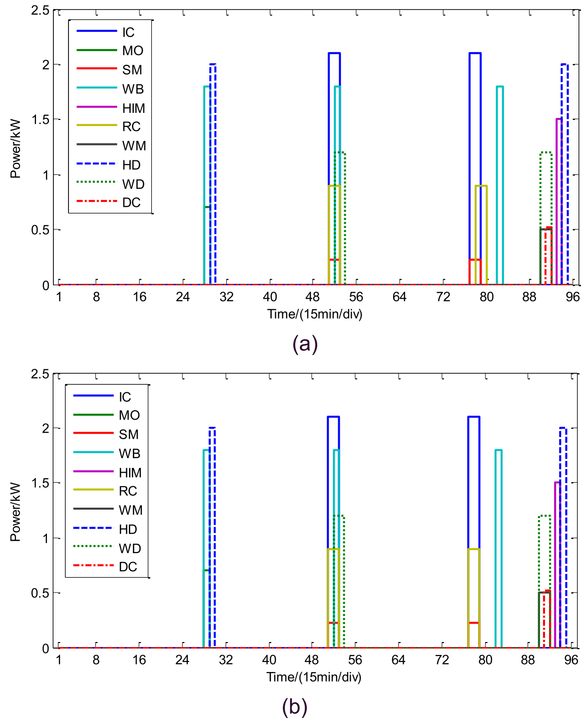

FIGURE 7. **Results of load shifting of different time periods. (a) Results of load shift at 06:00∼07:30 and 12:00∼13:30. (b) Results of load shift at 18:00∼20:00.**

periods (06:00∼07:30, 12:00∼13:30), where energy cost has kept as the same as the ones of Case A, in addition to the HD, no new appliance is shifted in this period. In terms of Case C, energy cost has reduced from 107.060￥ to 98.8566￥ based on the cost of Case B, after the load shifting of HD, the RC (18:00∼20:00) is also advanced 0.25h, and the robust level of the appliance has increased to 7.50, and the load scheduling results for different periods are shown in Fig.7 (b). According to the proposed load shifting strategy, the robust rates for a few appliances, i.e., HD (06:15∼07:30) and RC (18:00∼20:00), have increased from 0.0% to 20.0%, and from 12.5% to 25.0%, respectively. So the validity of the proposed load shift strategy in the optimization problem is demonstrated.

C. PERFORMANCE ANALYSIS WITH SATISFACTION LEVEL

When considering the load scheduling that account for user satisfaction, the performance of load scheduling is influenced by different defined satisfaction functions. The effect of two satisfaction levels on the optimized results are compared: one is the proposed satisfaction function, the other is the function in [28]. The weighted coefficients of (39) are set as $\xi_1 = 0.5$, $\xi_2 = 0.5$, and the constraints (4)∼(18), (20)∼(21), (27)∼(30), the RI constraints and the load shifting of household appliances are considered. The satisfaction levels at period 12:00∼13:30 are as an example to illustrate the effectiveness of proposed function, whose results are shown in Fig.8, while the satisfaction levels is 100% according to [28]. It can be observed that the results achieved

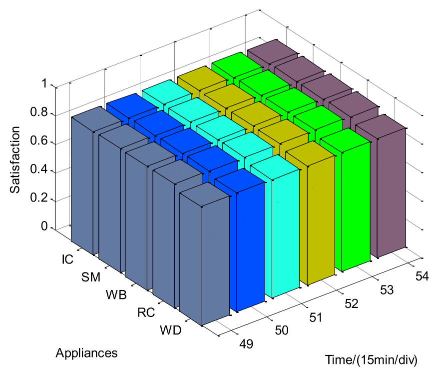

FIGURE 8. Satisfaction level of the proposed function.

by proposed schemes, the satisfaction levels of most appliances, i.e., IC, SM, WB and RC, are 86.667%, while the ones of WD is 83.333%, are less than those of [28] due to the RI message in the objective function.

Comparing with the conventional satisfaction function, the RI level based on proposed satisfaction function has increased from 6.75 to 7.5. Specially, the operation ending time of loads i.e., IC (18:00∼20:00), SM (18:00∼20:00), RC (12:00∼13:30) and WD (12:00∼ 13:30) are advanced 0.25 *h*, but the ones of HIM (20:00∼ 23:00) is delayed 0.25 *h*, and the ones of other appliances remain unchanged, so the robust level of all appliances has increased 0.75 *h*. Therefore, the proposed function can reflect the operation level of each appliance in detail, and obtain reasonable dispatch results and an enhanced robust level for the energy consumption problem.

VI. CONCLUSIONS

This paper proposes a new robust optimization method for the load scheduling of household appliances with the uncertainty of customer behavior, in which robust index (RI) with the upper and lower limits of robust level is integrated into load scheduling in the form of a cost function as well as additional constraints. The proposed load shifting strategy not only aims to improve the robust level of end users, but also decrease the energy cost of household. A numerical study for multiobjective optimization problem is investigated for assessing the impacts of the DR on the energy cost, robust level and the satisfaction level. Simulation results indicate that the proposed robust scheduling algorithm can improve the robust level of the entire household and reduce the energy cost by shifting the operating order for some of appliances. In addition, it has been shown that the proposed satisfaction function with the RIs of appliances can reflect satisfaction level of appliances in detail and achieve more reasonable results for energy scheduling.

REFERENCES

[1] A. Ouammi, "Optimal power scheduling for a cooperative network of smart residential buildings," *EEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 1317–1326, Jul. 2016.

[2] K. H. S. V. S. Nunna and S. Doolla, "Responsive end-user-based demand side management in multimicrogrid environment," *IEEE Trans. Ind. Informat.*, vol. 10, no. 2, pp. 1262–1272, May 2014.

[3] O. Kilkki, A. Alahäivälä, and I. Seilonen, "Optimized control of price-based demand response with electric storage space heating," *IEEE Trans. Ind. Informat.*, vol. 11, no. 1, pp. 281–288, Feb. 2015.

[4] Y. H. Lin and M. S. Tsai, "An advanced home energy management system facilitated by nonintrusive load monitoring with automated multiobjective power scheduling," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1839–1851, Jul. 2015.

[5] G. Graditi, M. L. Di Silvestre, R. Gallea, and E. R. Sanseverino, "Heuristic-based shiftable loads optimal management in smart micro-grids," *IEEE Trans. Ind. Informat.*, vol. 11, no. 1, pp. 271–280, Feb. 2015.

[6] M. H. Albadi and E. F. El-Saadany, "A summary of demand response in electricity markets," *Electr. Power Syst. Res.*, vol. 78, no. 11, pp. 1989–1996, 2008.

[7] K. M. Tsui and S. C. Chan, "Demand response optimization for smart home scheduling under real-time pricing," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1812–1821, Dec. 2012.

[8] H. Gangammanavar, S. Sen, and V. M. Zavala, "Stochastic optimization of sub-hourly economic dispatch with wind energy," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 949–959, Mar. 2016.

[9] L. Yang, M. He, V. Vittal, and J. Zhang, "Stochastic optimization-based economic dispatch and interruptible load management with increased wind penetration," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 730–739, Mar. 2016.

[10] M. Shafie-khah and P. Siano, "A stochastic home energy management system considering satisfaction cost and response fatigue," *IEEE Trans. Ind. Informat.*, vol. 14, no. 2, pp. 629–638, Feb. 2018.

[11] R. Atia and N. Yamada, "Sizing and analysis of renewable energy and battery systems in residential microgrids," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1204–1213, May 2016.

[12] R. de Sa Ferreira, L. A. Barroso, P. Rochinha Lino, M. M. Carvalho, and P. Valenzuela, "Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach," *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2285–2295, Dec. 2013.

[13] R. Deng, Z. Yang, J. Chen, and M.-Y. Chow, "Load scheduling with price uncertainty and temporally-coupled constraints in smart grids," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2823–2834, Nov. 2014.

[14] H. T. Nguyen, D. T. Nguyen, and L. B. Le, "Energy management for households with solar assisted thermal load considering renewable energy and price uncertainty," *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 301–314, Jan. 2015.

[15] P. Samadi, H. Mohsenian-Rad, V. W. S. Wong, and R. Schober, "Tackling the load uncertainty challenges for energy consumption scheduling in smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 1007–1016, Jun. 2013.

[16] C. A. Correa-Florez, A. Gerossier, A. Michiorri, R. Girard, and G. Kariniotakis, "Residential electrical and thermal storage optimisation in a market environment," *CIRED-Open Access Proc. J.*, vol. 2017, no. 1, pp. 1967–1970, Oct. 2017.

[17] M. Parvania and M. Fotuhi-Firuzabad, "Demand response scheduling by stochastic SCUC," *IEEE Trans. Smart Grid*, vol. 1, no. 1, pp. 89–98, Jun. 2010.

[18] C. Gong, X. Wang, W. Xu, and A. Tajer, "Distributed real-time energy scheduling in smart grid: Stochastic model and fast optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1476–1489, Sep. 2013.

[19] F. Y. Melhem, O. Grunder, Z. Hammoudan, and N. Moubayed, "Energy management in electrical smart grid environment using robust optimization algorithm," *IEEE Trans. Ind. Appl.*, vol. 54, no. 3, pp. 2714–2726, May/Jun. 2018.

[20] Z. Chen, L. Wu, and Y. Fu, "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1822–1831, Dec. 2012.

[21] Y. F. Du, L. Jiang, Y. Li, and Q. Wu, "A robust optimization approach for demand side scheduling considering uncertainty of manually operated appliances," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 743–755, Mar. 2018.

[22] K. Paridari, A. Parisio, H. Sandberg, and K. H. Johansson, "Robust scheduling of smart appliances in active apartments with user behavior uncertainty," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 1, pp. 247–259, Jan. 2016.

[23] C. Wang, Y. Zhou, J. Wu, J. Wang, Y. Zhang, and D. Wang, "Robust-index method for household load scheduling considering uncertainties of customer behavior," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1806–1818, Jul. 2015.

[24] S. A. Pourmousavi, S. N. Patrick, and M. H. Nehrir, ''Real-time demand response through aggregate electric water heaters for load shifting and balancing wind generation,'' *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 769–778, Mar. 2014.
[25] N. G. Paterakis, O. Erdinç, A. G. Bakirtzis, and J. P. S. Catalão, ''Optimal household appliances scheduling under day-ahead pricing and load-shaping demand response strategies,'' *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1509–1519, Dec. 2015.
[26] Y. Zhang, R. Wang, T. Zhang, Y. Liu, and B. Guo, ''Model predictive control-based operation management for a residential microgrid with considering forecast uncertainties and demand response strategies,'' *IET Gener., Transmiss. Distrib.*, vol. 10, no. 10, pp. 2367–2378, Jul. 2016.
[27] W. Xiang, ''Analysis of the time complexity of quick sort algorithm,'' in *Proc. Int. Conf. Inf. Manage., Innov. Manage. Ind. Eng.*, Nov. 2011, pp. 408–410.
[28] A. Anvari-Moghaddam, H. Monsef, and A. Rahimi-Kian, ''Optimal smart home energy management considering energy saving and a comfortable lifestyle,'' *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 324–332, Jan. 2015.
[29] F. S. Gazijahani and J. Salehi, ''Stochastic multi-objective framework for optimal dynamic planning of interconnected microgrids,'' *IET Renew. Power Gener.*, vol. 11, no. 14, pp. 1749–1759, Dec. 2017.
[30] M. Hu, T. Wu, and J. D. Weir, ''An adaptive particle swarm optimization with multiple adaptive methods,'' *IEEE Trans. Evol. Comput.*, vol. 17, no. 5, pp. 705–720, Oct. 2013.

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