A Real-Time Electricity Scheduling for Residential Home Energy Management

Shenglin Li, Junjie Yang, *Member,* WenZhan Song, *Senior Member, IEEE,* An Chen

***Abstract*—The effect of home energy management system (HEMS) is even more pronounced at the edge of smart grid infrastructure. However, the isolated scheduling horizons and the uncertainty about scheduling inputs are the major challenges for HEMS. In this paper, a novel demand-side management system, namely, a real-time electricity scheduling (RTES) for residential home energy management, is presented to operate the smart home. The proposed management system attempts to achieve minimizing the cost payment by optimally scheduling smart appliances and improving the utilization of renewable energy. Most importantly, it considers the uncertainty in the renewable generation and the subjectivity in electricity consumption. Our RTES adopts a 24-hours rolling horizon, and the optimization problem be solved by an effective genetic algorithm at regular intervals. Moreover, to reduce the impact caused by the discrepancy between the predictive information and the actual information, we design an effective real-time prediction method for the renewable generation, and update the inputs of scheduling system before each optimization calculation. Simulation results confirm that the proposed approach can improve the performance of the home electricity scheduling, reduce the impact of uncertainty on the system, and reduce the total energy costs.**

***Index Terms*—Demand-side management, distributed generation, genetic algorithm, home energy management, real-time optimization, information prediction, smart grid.**

I. Introduction

A. Motivation and Background

An important and rapidly growing application of Internet of Things (IoT) is the smart grid. IoT devices and technologies are the key drivers contributing to the growth of smart grid, smart homes, electric transportation and distributed energy storage systems [1]. The smart grid aims to improve efficiency, reliability and security through automation and modern communication technologies [2]. A key element of the smart grid is home energy management system (HEMS), the goals of HEMS are to save energy, reduce users' energy costs, improve consumers' comfort level, and maintain grid stability [3]. Moreover, under the support of advanced metering infrastructure (AMI) technology, physical quantities detected by HEMS have wider range, higher frequency and better grain size than before [4]. Wireless sensor networks (WSNs) play a key role in energy management applications, and they enable the smart grid to extend to dwelling houses. In some instances, wireless communication has some advantages over wired communication, such as low-cost infrastructure, and convenient connection to difficult or unreachable areas [5]. Currently, there are several mainstream smart home wireless communication technologies: HomeRF, infrared, ZigBee, Wi-Fi, Z-wave, Bluetooth, etc. [5], [6].

Electricity cannot be stored on a large scale, and electricity consumption varies over different periods. These features have led to new peak levels in electricity demand and created additional pressure to balance demand and generation for utility [7]. As a remedy to these problems, various time-varying electricity pricing (EP) models have been proposed: real-time pricing (RTP), critical peak pricing (CPP), and time of use pricing (TOUP) [8]. Real-time electricity pricing, which encourages users to shift deferrable household appliances to off-peak hours, can not only minimize the cost, but also play an important role in the peak clipping and valley filling. The recent theoretical studies in [9] have focused on researching the economic benefits of RTP between utility and user. Chavali and Yang *et al.* [10] adopted day-ahead pricing scheme, where the EP for the day is determined on the previous day.

More and more houses integrate with renewable energy (RE) which includes photovoltaic (PV) arrays and wind turbine (WT). Therefore, when we design the HEMS for residential microgrid, the intermittency of renewable energy, and the subjectivity in electricity consumption must also be considered.

B. Literature Overview

Currently, according to whether the input information of the HEMS is known, we can divide it into two main research categories. They both deal with demand response (DR) for the optimum operation of smart appliances.

The first category focuses on the day-ahead electricity scheduling (DAES). The biggest feature of this strategy is to treat scheduling information as known. For example, Chen *et al.* [11] employed DR based on day-ahead price signals for reducing energy cost. Erdinc and Paterakis *et al.* [12], [13] developed a detailed HEMS structure for determining the optimal day-ahead appliance scheduling of a smart household based on hourly pricing and peak power-limiting strategy. In [14], considering the RTP and uncertainties of operation time and RE power generation, the authors proposed a new demand-side management technique and energy-efficient scheduling algorithm to reduce the monetary expenditures.

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S. Li is with the College of Electronics and Information Engineering, Shanghai University of Electric Power, Shanghai 200090, China (e-mail: iamlshl@126.com).

J. Yang is with Shanghai Dianji University, Shanghai 201306, China, and with the College of Electronics and Information Engineering, Shanghai University of Electric Power, Shanghai 200090, China (e-mail: yangjunjie@shiep.edu.cn).

W.Z. Song is with the College of Engineering at University of Georgia, Athens, GA 30602 USA (e-mail: wsong@uga.edu).

A. Chen is with the Department of Computer Science at University of Georgia, Athens, GA 30602 USA (e-mail: an.chen25@uga.edu).

However, there are three major problems for DAES. Firstly, it is impracticable to acquire perfect prediction. To achieve the optimal electricity scheduling, most papers with DAES usually assumed that the actual information among RTP, RE power generation, and the user's power consumption are the same as the prediction. Secondly, this DAES method does not consider the real-time nature of RTP. Lots of users with similar DAES strategies will generate new peak in electricity, and then the utility will adjust RTP for maintaining the power system stability. Thirdly, the DAES system will release all the energy before the end of the day without considering the needs of the next day.

The second category is real-time electricity scheduling (RTES) of the HEMS. This category has taken more into account the impact of scheduling information deviation. To the best of our knowledge, there was little research on RTES. Paterakis *et al.* [15] provided a novel real-time rolling horizon optimization framework for the optimal operation of a smart home. However, [15] has considered the intermittent behavior of RE generation with rolling optimization, but the range of rolling horizon was from the current moment to the end of the day. The model only has been evaluated for maximizing one day's economic benefits without considering the impact on the next day. Liu *et al.* [16] presented a real-time household load priority scheduling algorithm based on renewable sources availability prediction. However, in [16], the authors just considered the dynamic priority scheduling for appliances, and their algorithm may be more reasonable if they had considered the cost of computing time. Moreover, the authors did not investigate that the installation of battery can greatly improve the economic efficiency.

HEMS which manages electrical devices and smart appliances can be summed up as a complex optimization problem with multiple constrains. Solving this problem requires detailed information about user specifications and preferences, which is difficult to achieve in practice [10]. When the mathematical model is relatively simple, the traditional methods can find the optimal solution very well. For example, [7], [12], and [13] applied mixed-integer linear programming (MILP) problem, [9] investigated a linear programming problem, and [17] developed an integer linear programming problem. However, most of the optimization problems are non-linear or non-convex [18]. There are some limitations in the traditional programming methods. Firstly, these methods handle only a limited number of controllable loads [19]. Then, when the problem entails non-convex programming or MILP, traditional methods may not be found to be feasible or the calculated times may be too high [20].

Furthermore, the commercial solvers (such as CPLEX, MOSEK, CVX and LINGO *et al.*) that would cost amount of expense are not suitable to be implemented in embedded devices such as smart meters [20]. The solvers also do not have the flexibility in constructing and developing the algorithm, and the solving process of solvers cannot be changed for improving the performance [21].

Meta-heuristic approaches were extensively used by researchers considered the limitation of computational effort [22]. Compared to other meta-heuristic approaches, the genetic algorithm (GA) can solve linear or non-linear, discrete or continuous optimization problems which cannot be afforded by any other conventional approaches. [23] chose GA to solve the optimization problem due to it can find near-optimal solutions in an acceptable computing time, and the flexibility of the algorithm for various problems. In [21], the scheduling problem has been solved by GA which not only reduces the cost and peak-to-average ratio (PAR), but also schedules different types of large number of appliances.

In this paper, the optimization model is formulated as a multi-constrained mixed integer problem (MCMIP), and the model is non-convex. Moreover, the number of controlled appliances and the scheduling accuracy can be adjusted according to the user's preference, and the scale of optimization variable is variable. Furthermore, if the other optimization goals such as comfort are added, the current model will become non-linear. For the above reasons, we prefer to use GA as the optimization method of this paper.

C. Contributions

The uncertainty of scheduling information is the major challenge of HEMS. If the prediction information has a great error, it will not be able to achieve scheduling goals in actual environment. The main contributions of this paper are summarized as follows.

1) To the authors' best knowledge, this real-time scheduling system is the first one been proposed to reduce the error of PV power generation prediction, adjust the electricity consumption behaver, and minimize the cost payment. The decision is always optimized, and the economic performance of which is improved by 8.4% compared with the state of the art.
2) For maximizing the economic benefit of electricity scheduling, the existing HEMS will always release all the energy of the battery before the end of the day. In other words, no matter how high the EP and how low the PV power generation is in the next day, the battery will not store energy for the next day. However, in this paper, this problem is solved by the real-time electricity scheduling. Battery operation at each period is optimally adjusted based on changes in scheduling information to further reduce the cost payment.
3) The scheduling system is provided to investigate a collaborative scheduling which includes peak power-limiting strategies, energy storage system (ESS), and bi-directional power flows of ESS (ESS-to-home and ESS-to-grid) and RE (RE-to-home and RE-to-grid).
4) To meet the requirement of time efficiency in the real-time scheduling, an efficient GA based ESS management strategy is proposed for solving the problem.

D. Organization

The rest of the paper is organized as follows. In Section II, We introduce system architecture and models of HEMS. Section III introduces the problem formulation. We propose RTES algorithm for smart appliances, which is introduced in Section IV. Afterwards, to validate the proposed approach, several case studies are introduced in Section V. Finally, Section VI concludes the paper.

II. System Architecture And Model

A. System Architecture

HEMS comprises smart appliances, RE system (photovoltaic arrays and wind turbine), energy storage system (e.g. battery packs), home energy management controller (HEMC), smart controllers, smart meters, etc. The entire architecture of HEMS is shown in Fig. 1.

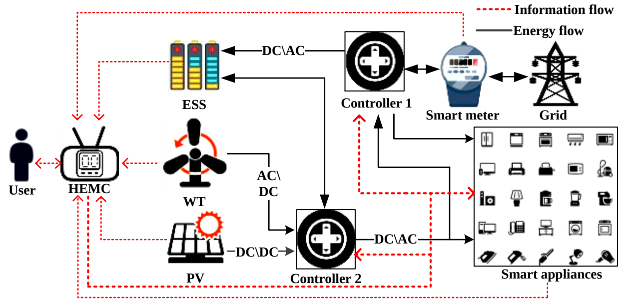

Fig. 1. A block diagram of typical HEMS

ESS plays the role of energy transfer. User will purchase energy from the grid at low prices period and store it in the ESS. Then ESS will power the appliances when the EP is high. The ESS can also be used to store excessive renewable energy (RE) generation. Users can sell the excessive electricity generated by RE to the grid, i.e., the ability of bi-directional power flows. However, to limit user's peak electricity consumption, HEMS should consider the peak power limiting strategy imposed by utility [24].

B. *Household Smart Appliances Model*

The smart appliances are generally divided into two categories: non-deferrable loads (refrigerator, lighting, computer, etc.) and deferrable loads (dish washer, washing machine, water pump, etc.) [25]. The electricity tasks (ETs) of appliances within rolling horizon (RH) are shown in Fig. 2.

For the deferrable loads, HEMC can shift their electricity usage from the higher EP periods to the lower EP periods, but they must satisfy some requirements. Whereas, for the non-deferrable loads, the HEMC must unconditionally power it when the user needs. Therefore, the non-deferrable loads do not participate in the optimization scheduling. But they need to be overlapped on total electricity demand as part of household electricity consumption.

The length of rolling horizon (LRH) is the scheduling scope. We use the interval of optimization to define the scheduling interval between two adjacent optimization executions. The RH moves on the time axis at regular interval (e.g., half an hour), and HEMC optimizes the operation of electrical appliances in the RH. We divide the RH into H periods and the length of period (LTP) $\Delta h = 24/H$ hour (e.g. the LTP is half an hour when $H = 48$ in Fig. 2). The variable $a = 1,2,\ldots,A$ represents the number of deferrable loads. A binary variable $s_a(h)$ is presented to denote the operation state of appliance a in period h, $h \in \{1, 2, \ldots, H\}$. $s_a(h) = 1$ represents that the appliance is at working state and $s_a(h) = 0$ is at idle state [23]. $[\alpha_a, \beta_a]$ indicates the operation time range of appliance a and d_a represents the length of time to complete the task. Then appliance a should satisfy the time constraints shown as:

$$\sum_{h=\alpha_a}^{\beta_a} s_a(h) = d_a, \ \forall a \tag{1}$$

$$s_a(h) = 0, \ \ if \ h \in [1, H] \ and \ h \notin [\alpha_a, \beta_a], \ \ \forall a. \tag{2}$$

Based on whether the appliances need to keep working until the completion of the task, we can further divide the deferrable loads into two types: interruptible loads (e.g., washing machine, water pump, etc.) and non-interruptible loads (e.g., rice cooker, microwave oven, etc.).

The deferrable loads need to satisfy that the total number of 1 within variable s_a equals d_a in the operation range.

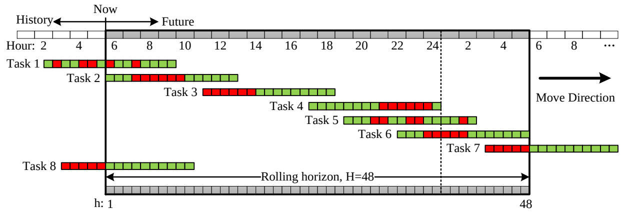

Fig. 2. Real-time electricity tasks scheduling within rolling horizon

$$s_a(h) = 0 \ or \ 1, \ \ if \ h \in [\alpha_a, \beta_a] \ \ \forall a. \tag{3}$$

However, the non-interruptible loads (NILs) require that there must have d_a consecutive values 1. The constraint is described below.

$$\sum_{\xi=h+1}^{h+d_a} s_a(\xi) \geq d_a[s_a(h+1) - s_a(h)], \ \ \forall a \in \text{NILs}, \forall h. \tag{4}$$

To simplify the calculation, we assume that the appliance a run at the average power P_a. The total power consumption $P_{def}(h)$ during period h for the deferrable loads can be calculated by

$$P_{def}(h) = \sum_{a=1}^{A} s_a(h) P_a \ , \ \ \forall h. \tag{5}$$

Furthermore, to satisfy the consumption of electrical appliances, there are three power supplies: ESS discharging $P_{ESS,app}^{dch}(h)$, RE source $P_{RE,app}(h)$, or power purchased from grid $P_{grid,app}^{dch}(h)$. Therefore, the power consumption $P_{app}(h)$ of all smart appliances can be calculated by (6) and (7).

$$P_{app}(h) = P_{def}(h) + P_{ndef}(h), \ \ \forall h \tag{6}$$

$$P_{app}(h) = P_{ESS,app}^{dch}(h) + P_{RE,app}(h) + P_{grid,app}(h), \ \ \forall h. \tag{7}$$

C. *Energy Storage System Model*

The state of charging (SOC) $SOC(h)$ reflects the ratio of remaining ESS capacity $E_{rem}(h)$ to its maximum capacity E_{ESS} at end of period h, and to avoid energy storage system (ESS) over-discharge and overcharge, we need to add constraints for the SOC, showed in (8) and (9). The SOC of ESS is limited by imposing a less than its capacity SOC_{max} and a least SOC limit SOC_{min}.

$$SOC(h) = E_{rem}(h) / E_{ESS} \ , \ \ \forall h \tag{8}$$

$$SOC_{min} \leq SOC(h) \leq SOC_{max}, \ \ \forall h. \tag{9}$$

Considering the ESS charging and discharging efficiency, the λ_{ESS}^{ch} and λ_{ESS}^{dch} respectively represent the charging and discharging efficiency [13]. The two different efficiencies correspond to two different power indicators, respectively. Therefore, the dynamic energy conservation between charging power $P_{ESS}^{ch}(h)$ and discharging power $P_{ESS}^{dch}(h)$ of ESS is shown by (10) - (13).

$$\begin{aligned} SOC(h) = {} & SOC(h\text{-}1) \\ & + (P_{ESS}^{ch}(h)\lambda_{ESS}^{ch} - P_{ESS}^{dch}(h) / \lambda_{ESS}^{dch}) \Delta h / E_{ESS} \ , \ \ \forall h \end{aligned} \tag{10}$$

$$SOC(h) = SOC^{ini}, \ \ if \ \ h = 0 \tag{11}$$

$$0 \leq P_{ESS}^{ch}(h) \leq P_{ESS}^{ch,max} u_{ESS}(h), \ \ \forall h \tag{12}$$

$$0 \leq P_{ESS}^{dch}(h) \leq P_{ESS}^{dch,max} (1 - u_{ESS}(h)), \ \ \forall h. \tag{13}$$

Where $P_{ESS}^{ch,max}$ and $P_{ESS}^{dch,max}$ respectively represent the value of maximum charging power and the maximum discharging power. Because the ESS can be either charge or discharge in a period, we introduce a binary variable $u_{ESS}(h)$ to indicate charging state ($u_{ESS}(h) = 1$) or discharging state ($u_{ESS}(h) = 0$).

In addition, there is also a power balance between charge and discharge:

$$P_{ESS}^{ch}(h)=P_{RE,ESS}^{ch}(h)+P_{grid,ESS}^{ch}(h),\ \ \forall h \tag{14}$$

$$P_{ESS}^{dch}(h)=P_{ESS,app}^{dch}(h)+P_{ESS,grid}^{dch}(h),\ \ \forall h. \tag{15}$$

Where $P_{RE,ESS}^{ch}$, $P_{grid,ESS}^{ch}$, $P_{ESS,app}^{dch}$, and $P_{ESS,grid}^{dch}$ respectively indicate the power flow from RE to ESS, grid to ESS, ESS to appliances, and ESS to grid.

Moreover, $P_{ESS}(h)$, the output power of the ESS (positive value for charging and negative value for discharging), is calculated by (16) for simplifying the calculation.

$$P_{ESS}(h)=P_{ESS}^{ch}(h)-P_{ESS}^{dch}(h),\ \ \forall h. \tag{16}$$

As the RH moving forward, we need to update the appliance's variables (e.g. α_a , β_a and d_a) in real time.

Furthermore, the horizon edge may be within the allowed working range of the ETs (e.g. Task 1 and Task 8 in Fig. 2). In this paper, the working status of appliances be update in real time by HEMC. For the appliances which on the left edge of the horizon, we substitute the remaining workload for d_a and the number 1 for α_a. Whereas for the right edge of the horizon, we assume that the scheduling system give priority to competing electricity tasks (ETs), i.e., when the allowable working time range of the appliance a in the horizon is less than d_a, we make the appliance a to work in this range, otherwise we replace the value H with β_a.

D. Renewable Energy Model

The power balance of RE can be modeled by (17) and (18).

$$P_{RE,gen}(h)=P_{RE,use}(h)+P_{RE,discard}(h),\ \ \forall h \tag{17}$$

$$P_{RE,use}(h)=P_{RE,grid}(h)+P_{RE,app}(h)+P_{RE,ESS}^{ch}(h),\ \ \forall h. \tag{18}$$

Where $P_{RE,gen}$ is the power generated by RE, $P_{RE,use}$ is the power consumed by household, and $P_{RE,discard}$ is the discarded energy when it is not available.

E. Information Prediction and Adjustment

The RTES system includes real-time information prediction and adjustment. In the real-time electricity scheduling, the system's inputs are predicted and updated at each period. We only need to accurately predict the information in the upcoming period and the remaining time periods of the RH do not need to be as accurate as the first period.

The prediction not only depends on a large amount of historical data, but also has a higher correlation with the past few periods. In this paper, the designed information prediction model of RE generation consists of two parts for the future 24 hours: the long-term trend forecast and the short-term accurate fit. The long-term trend forecasting is based on prior knowledge, and we use the data fitting strategy for short-term accurate prediction.

1) The power prediction of RE: Base on the power generation characteristics, we design a prediction model for power generation. According to weather forecast, we select the average generation of different weather types (e.g. sunny, cloudy, rainy, snowy, etc.) in each season, and see it as the forecasting trend of RE power; Then, we fit the data in the upcoming period by adopting the past 5 hours data and the future trend data from 2th to 3th hour; Last, we replace the first period of the future 24-hour power trend with the fitting data. In this method, we select a fitting method of polynomial function with 5 fitting orders.

2) The ETs adjustment: In general, the loads participating in the electricity scheduling are deferrable. However, the user's consumption habits are variegated. Sometimes, for meeting the user's comfort, the user will additionally increase, change, or delete some ETs. Therefore, the subjectivity of the user makes it difficult to predict the user's consumption. This also is one of the main reasons why DAES strategy is sensitive to information prediction errors. There are some literatures on dynamically inferring users' demands for electricity. For example, a human-centric smart home energy management system integrates ubiquitous sensing data to discover the patterns of power usage and cognitively understand the behaviors of human beings [26].

In the real-time electricity scheduling system, the strategy we have adopted is the online registration of ETs. In other words, we divide all ETs into regular tasks and changeable tasks. In this paper, we assume that the daily regular tasks are known. For changeable tasks, user can increase, change, or delete these changeable tasks at any time.

F. Power Balance of Grid

Power balance between supply and consumption must be maintained, it can be defined as:

$$P_{grid}(h)=P_{ESS}(h)+P_{app}(h)-P_{RE,use}(h),\ \ \forall h. \tag{19}$$

However, the EPs of purchasing and selling are usually different. $P_{grid,buy}$ represents the power purchased from the utility and $P_{grid,sell}$ denotes the power sold to grid. They can be calculated and constrained by (20) – (24).

$$P_{grid}(h)=P_{grid,buy}(h)-P_{grid,sell}(h),\ \ \forall h \tag{20}$$

$$P_{grid,buy}(h)=P_{grid,app}(h)+P_{grid,ESS}(h),\ \ \forall h \tag{21}$$

$$P_{grid,sell}(h)=P_{ESS,grid}(h)+P_{RE,grid}(h),\ \ \forall h \tag{22}$$

$$0\le P_{grid,buy}(h)\le P_{grid,buy,max}(h),\ \ \forall h \tag{23}$$

$$0\le P_{grid,sell}(h)\le P_{grid,sell,max}(h),\ \ \forall h. \tag{24}$$

III. Problem Formulation

In this section, we propose a mathematical representation about the residential scheduling goal: electricity cost payment minimization. Most of the related literatures regard the cost payment minimization as the basic scheduling objective, and the basic objective equation can be expressed as:

$$\begin{aligned} \min Cost_{pay} &= \left\{ \begin{aligned} &\Delta h\sum_{h=1}^{H}[P_{grid,buy}(h)RTP_{buy}(h) \\ &-P_{grid,sell}(h)RTP_{sell}(h)] \end{aligned} \right\} \\ s.t.\quad & \text{constraints } (1)-(4),(6),(9)-(13), \\ & (16),(18),(19),(23),(24). \end{aligned} \tag{25}$$

In the problem (25), if we divide 24 hours into 48 periods, we can find that there are 48 continuous variables in the ESS and lots of 0-1 integer variables for deferrable loads. The optimization model also is formulated as a multi-constrained mixed integer problem (MCMIP).

IV. Electricity Scheduling Algorithm

Due to the facts that the RTES system updates the input information and solves the optimization problem (25) within a limited time interval, the optimization algorithm is required with better time efficiency. In this section, a RTES algorithm based on GA and ESS management strategy is proposed.

A. ESS management strategy

From the ESS constraints (8) – (13), we can find that the

Algorithm 1 ESS Management Strategy

Collect SOC^{ini}, RTP_{buy}, RTP_{sell}, $P_{grid,buy,max}$, $P_{grid,sell,max}$, $P_{RE,gen}$, and P_{ndef} within rolling horizon.
Initial P_{app} by using GA and (6), $P_{ESS} := \mathbf{0}$.
Update $P_{grid} = P_{ESS} + P_{app} - P_{RE,gen}$, and find discarded RE by comparing lower limit of peak power.
Repeat (for each period existed discarded RE)
  Find one charging period in discarded RE periods and one discharging period by sorted EP in descending order.
  Find the biggest transferred power.
  Update P_{ESS}, P_{grid}.
Until there is no period for discarding PV.
Repeat (for each allowed discharge period by sorted EP in descending order)
  Discharge the initial capacity of the ESS.
  Update P_{ESS}, P_{grid}.
Until the end of the period or $SOC(H)$ is equal to SOC_{min}.
Repeat (for each allowed charge period by sorting EP in ascending order)
  Find discharging period by sorting EP in descending order.
  Find the biggest transferred power.
  Compare the electricity costs before and after this operation.
  If the electricity bill becomes smaller **Then**
    Update P_{ESS}, P_{grid}.
  End
Until there are no periods that can be operated or the total cost cannot be reduced.

each ESS variable interacts with each other. As an adaptive global optimization probability search algorithm, genetic algorithm is widely used to solve complex optimization problems, but the local search ability is not strong. The new generation of feasible solution is accomplished by random crossovers and mutations, and it will cost a lot to reach the optimal solution itself. If the continuous ESS variables are used as the optimization variables of GA, it can not only greatly increase the algorithm complexity, but also may take a lot of time to converge to the optimal solution.

It should be noted that when the EP, RE power generation, consumption power and peak power limiting are collected, it will correspond to the unique optimal solution of ESS. Therefore, we can design an ESS management strategy based on the collected data. In this paper, the more detail about the ESS management strategy for finding the optimal P_{ESS} is summarized in Algorithm 1. The designed strategy consists of following four steps:

Firstly, a set feasible solution of smart appliances is initialized by GA, and the power consumption $P_{app}(h)$ is calculated by (6); Then, considering the gap between $P_{app}(h)$ and $P_{RE,gen}(h)$, we store PV energy that should have been discarded and releasing it at high EP periods; Next, the initial power of ESS is discharged at high EP periods; Last, ESS charges during the low-price periods and discharges during the high price periods. Noted that if there is one charging power for a certain period, there must be a discharge operation with the same power in another period. It is also worth noting that the above four-cycle steps need to not only meet the constraints of problem (25), but also reduce the total cost before execution. Once the total cost cannot be reduced, the cycle will stop.

B. *Efficient GA Based ESS Management Strategy*

The MCMIP (25) is non-convex, if we use the traditional solution method; it is easy to be trapped at a local optimal

Algorithm 2 Genetic Algorithm

Initialize the first-generation population of deferrable loads.
gen: = 1.
While *gen* ≤ *Maxgen*
  $n_{cross} := 1$, $n_{mutate} := 1$.
  Finding the optimal P_{ESS} by **Algorithm 1**.
  Calculate *fitness* by using (25) – (26).
  Choose the M*P_{dng} individuals in descending fitness order as the best individuals.
  Select the individuals by using the roulette wheel.
  Repeat
    Select randomly two chromosomes, if $p_c > rand$, cross they by single point crossover.
    $n_{cross} := n_{cross}+1$.
  Until $n_{cross} := M/2$.
  Repeat
    Select randomly one chromosome, if $p_m > rand$, mutate it by binary mutation.
    $n_{mutate} := n_{mutate}+1$.
  Until $n_{mutate} := M$.
  After 3 basic operations of the individuals plus the best individuals together for the next iteration.
End while

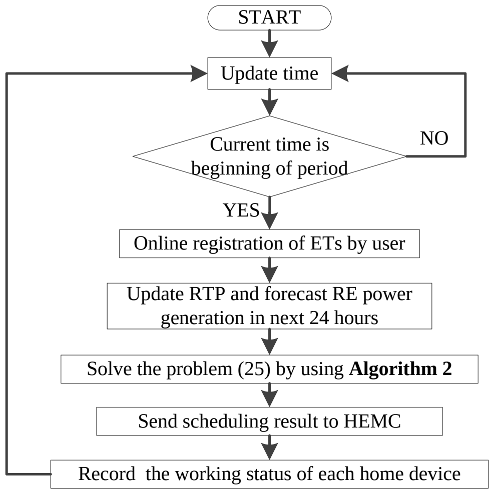

Fig. 3. Real-time electricity scheduling algorithm

point and insensitive to initial solutions. In addition, the calculation time may be too high. However, the real-time system requires that the optimization result be obtained within the period. The meta-heuristic algorithms can remedy these issues. Among the meta-heuristic algorithms, the GA and the particle swarm optimization (PSO) are often applied to the optimization problem. Adopting GA for solving scheduling problems has also been approved to be a suitable solution [17], [19]. In this paper, we also use GA to optimize the variables of the appliances. For improving the convergence speed of the algorithm, the effective GA based ESS management strategy is summarized in Algorithm 2. The more explanations about GA are described in the previous study [27]. Furthermore, considering the cost payment of HEMS may be negative, we introduce a coefficient c for defining the fitness function, as given by

$$fitness = 1/(Cost_{pay} + c). \tag{26}$$

C. *Real-time Electricity Scheduling Algorithm*

The real-time electricity scheduling (RTES) system needs to update the future 24-hour system inputs included ETs, EP and RE power generation at the beginning of each period. The system also needs to record the working data of ESS and the working status of other devices in real time.

TABLE I
BASIC PARAMETERS OF ESS

Variable	Value	Variable	Value
SOC_{min}	0.2	E_{ESS}	20 kWh
SOC_{max}	0.9	λ_{ESS}^{ch}	0.99
$P_{ESS}^{ch,max}$	5 kW	λ_{ESS}^{dch}	0.99
$P_{ESS}^{dch,max}$	5 kW	-	-

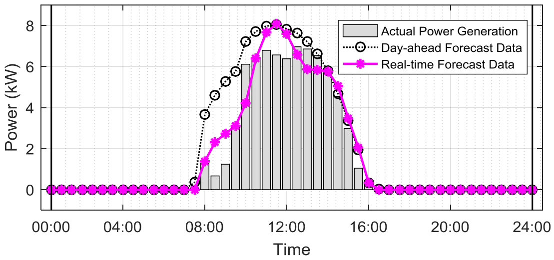

Fig. 4. Real-time power prediction of RE.

In this paper, the designed RTES algorithm is summarized in Fig. 3. The RTES algorithm runs at regular interval. Once current time is the beginning of each period, the home electricity scheduling optimization will be performed once. Before solving the optimization problem (25), the HEMC will collect the data of RE, EP, ETs and working status of each home device. After that, the HEMC controls the operation and records the working status of each device in real time.

The HEMS adopted real-time electricity scheduling (RTES) algorithm mainly has two advantages. Firstly, it can reduce the impact of consumption uncertainty, and quickly response the change of RE generation. Secondly, it also allows user to change, add, or delete ETs at any time.

V. SIMULATION RESULTS AND DISCUSSIONS

In this paper, two types of information uncertainty are considered to evaluate the system performances between day-ahead electricity scheduling (DAES) and RTES. These uncertainties are RE generation and user's electricity consumption. When the electricity cost payment is calculated by actual information, we need to design an error handling mechanism for ensuring that current scheduling does not affect the scheduling of subsequent periods. We assume that user buy electricity from the utility if the error is larger than 0 (power shortage). However, when the error is less than 0 (power surplus), the priorities of processing should be: first saving electric energy to ESS, second selling electric energy to utility, last discarding.

We divide 24 hours into H = 48 periods. Non-deferrable load consumption during each period was recorded, and the average power consumption curve of the non-deferrable load consumption is given. The initial SOC is 0.5, and the other parameters of ESS are summarized in Table I.

The GA basic parameters obtained after many experiments include population size M = 40, the selected rate P_{dng} = 0.9, the crossover rate p_c = 0.7, the mutation rate p_m = 0.1, and the roulette wheel is used to select excellent individuals.

Integrating the bi-directional power flows between the end-user and the utility, we assume that the next 24-hour RTP signal of each period available for the consumer via the smart meter is given, and user subscribe the RTP program issued by Illinois Power Company [28]. Moreover, we assume that the selling price is half of the purchasing price, and the exchange power limit between the user and the grid is given.

All simulations were implemented using a personal computer using MATLAB R2016a.

TABLE II
TWO NEW ELECTRICITY TASKS ON DECEMBER 1, 2017

Period	Power (kW)
10, 11, 12, 13, 14, 15, 16, 17, 18	4, 4, 4, 4, 4, 5.5, 4, 4, 4
33, 34, 35, 36, 37, 38, 39, 40	4.5, 4.5, 4.5, 4.5, 5.5, 5, 4, 4

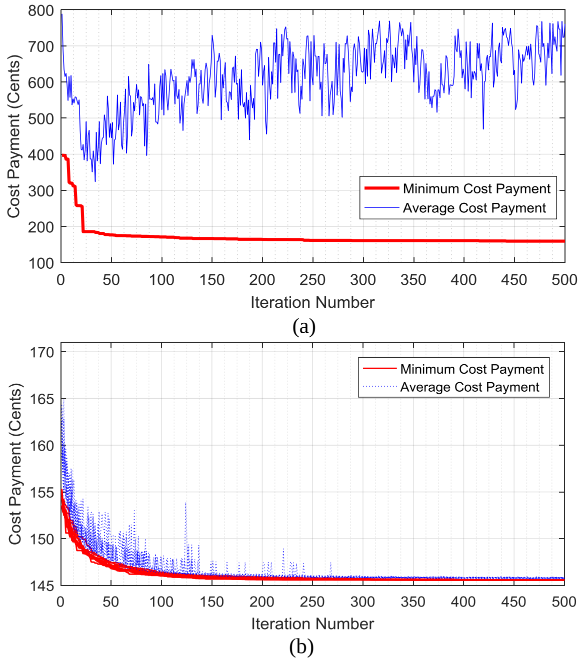

Fig. 5. Performance comparison of GA. (a) Optimization result of traditional GA. (b) Trend of resulting along the GA based ESS management strategy performing 10 times.

A. HEMS Information Prediction

The RE system consists of three PV arrays, the power information of each PV array adopted by California solar initiative 15-minute interval data [29], and the California weather type information adopted by National Oceanic & Atmospheric Administration are used to test [30]. An example for predicting the power generation of RE on December 1, 2017 is shown in Fig. 4. We observed that the mean absolute deviation (MAD) of real-time prediction during 24 hours can reduce from 0.467 kW (day-ahead forecast) to 0.273 kW.

We assume that the regular deferrable tasks included m = 6 non-interruptible ETs and n = 24 interruptible ETs are given [27], and user has the same regular deferrable tasks every day. For the change tasks, user can increase, change, or delete tasks at any time. In this paper, we assume that the user will register two new ETs to HEMC at 4:30 on December 1, 2017, as can be seen from Table II. It should be noted that these two new ETs cannot be detected by the DAES system and will be detected by RTES system at 4:30.

B. Performance of GA based ESS Management Strategy

As shown in Fig. 5, we adopted the actual information as DAES system's inputs for analyzing the performances of GA based ESS management strategy and traditional GA. From the result in Fig. 5(a), we found that the average cost payment of the population during the evolution process has large fluctuations. Moreover, the traditional algorithm converges to 159, which indicates that it falls into a local optimal point due to complex constrains of ESS. However, the cost payment with actual information of GA based ESS on December 1, 2017 along the 500 iterations of GA is performed 10 times, as can be shown in Fig. 5(b). We can see that the worst average cost payment of unoptimized electricity scheduling is

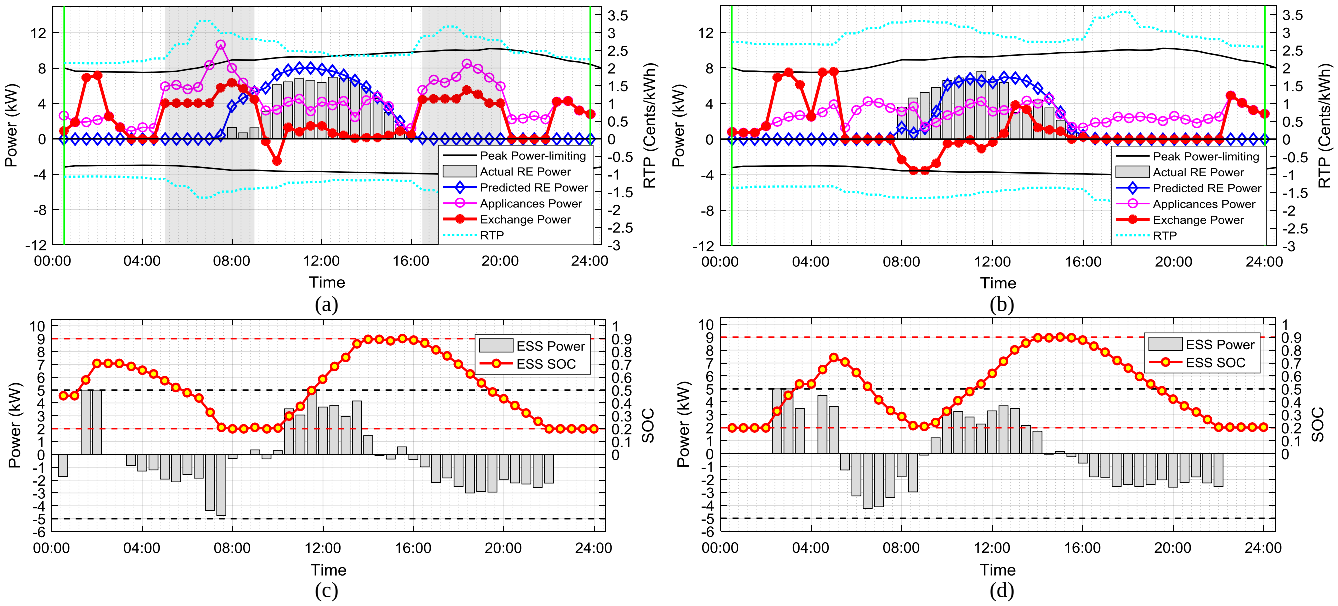

Fig. 6. Scheduling results of DAES with prediction error. (a) Day-ahead scheduling result on December 1, 2017. (b) Day-ahead scheduling result on December 2, 2017. (c) The ESS output power and SOC on December 1, 2017. (d) The ESS output power and SOC on December 2, 2017.

about 165 cents, the minimum cost payment is rapidly declining at 146.2 cents after 100 iterations, and the cost almost tends to stabilize at about 146 cents (reduced by 11.52% compared to no optimization) after 120 iterations with 42.12 seconds. We can also find that the 10 curves of minimum cost payment are similarly decreasing during the iterations.

In addition, we also use the solver LINGO to solve the same optimization problem, and the optimal cost payment is 145.545 cents. This shows that the designed algorithm can obtain a solution that is very close to the global optimal. However, the solver cannot adapt to the possible variation of the optimization model according to user needs. This is also one of the main reasons why we choose GA.

Therefore, the GA based ESS management strategy with the maximum number of iterations *Maxgen* = 120 not only steadily optimize the electricity payment, but also meet the requirements of the real-time system with 30 minutes interval. It should be noted that the solutions of two adjacent periods have certain similarities, and the RTES system can use the optimal solution of the previous period as a reference for the current initial solution of GA, which will further reduce the optimization time.

In the same simulated environment without information prediction errors in RE generation and ETs, we respectively perform DAES (Case 1) and RTES (Case 2) from December 1, 2017 to December 2, 2017. Compared to these two case studies, both cases can fully utilize renewable energy, but Case 2 provides a cost reduction of 12.754 cents. We can find that the end SOC of ESS on December 1, 2017 is 0.9 in Case 2 rather than 0.2 in Case 1. This is because the optimal solution of DAES is only obtained within 24 hours. However, the decision of RTES on each period is always optimal solution within the next 24 hours. The reason why the ESS is charged during the last few periods is because the EP during the several periods in future is higher.

However, it should be noted that this DAES result is difficult to achieve in real life because error-free prediction of RE generation and consumption cannot be achieved. In addition, user will not completely sacrifice their electrical comfort for saving cost payment. Therefore, we should evaluate the system performance in the real environment with information prediction error.

C. *Impact of Information with Prediction Error*

To respectively demonstrate the impact of prediction error on DAES and RTES, we assume there are errors in information prediction. The ETs prediction error (the user will register two new ETs to HEMC at 4:30) only exists on the first day.

To be able to make a comparative analysis for presenting the merits of the proposed methodology, such cost payment, SOC, and utilization rate of RE will be necessary. With the same prediction errors, we respectively perform the DAES (Case 3) and the RTES (Case 4) from December 1, 2017 to December 2, 2017. The total electricity scheduling profiles of two cases are shown in Fig. 6 and Fig.7, respectively. We analyze the performance comparison between DAES and the RTES from three aspects: cost payment, SOC of ESS, and utilization rate of RE respectively.

For meeting the electricity demand of the registered two new ETs and not to affect the subsequent scheduling of ESS, DAES system will buy electricity from 4:30 to 9:00 and from 16:00 to 20:00, and the total cost payment during two days is 240.38 cents, as can be seen from Fig. 6(a). However, when the user need to adjust their ETs, the RTES system immediately responds to the adjustment after it is identified, and calculates the new optimal scheduling strategy with 220.19 cents of the total cost payment. This strategy saves electricity bills by avoiding buying electricity at high rates and the relevant results are presented in Fig. 7(a).

The ESS plays an important role in saving costs. Not only can ESS save excess renewable energy, ESS can also charge at low-rate periods and discharge at high-rate periods. The comparison of charging/discharging between Case 3 and Case 4 are shown in Fig. 6(c)(d) and Fig. 7(c)(d), respectively. The end SOC of DAES system within one day always reduces to 0.2 for saving cost, but the RTES system maybe not (the end SOC is 0.9 on the first day). The RTES system will find the optimal strategy within the rolling horizon rather than in a certain day. Therefore, the battery will store energy for the next day if necessary, and the saving potential of the ESS can be further utilized by RTES system.

Increasing the utilization of RE can further save cost

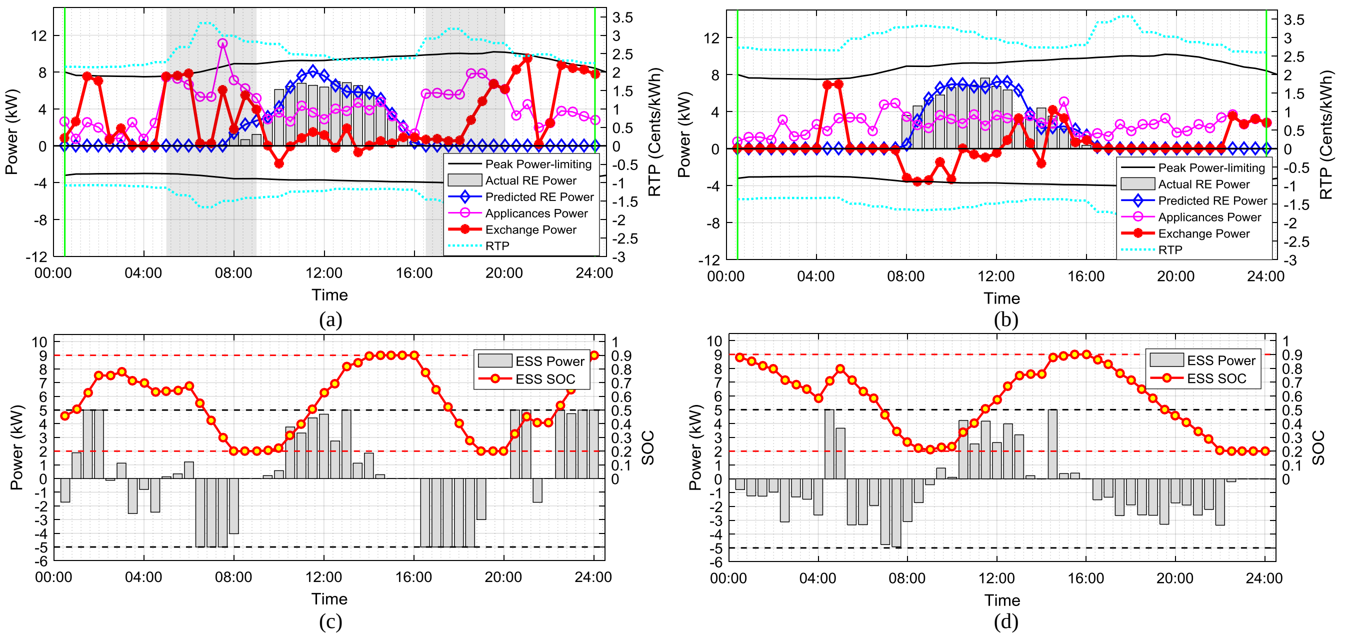

Fig. 7. Scheduling results of RTES with prediction error. (a) Real-time scheduling result on December 1, 2017. (b) Real-time scheduling result on December 2, 2017. (c) The ESS output power and SOC on December 1, 2017. (d) The ESS output power and SOC on December 2, 2017.

TABLE III
PERFORMANCE COMPARISON BETWEEN 4 CASES

			December 1, 2017				December 2, 2017				
Case	Error	Strategy	SOC^{ini}	SOC^{end}	RE Rate	Bill (cents)	SOC^{ini}	SOC^{end}	RE Rate	Bill (cents)	Total Bill (cents)
1	No	DAES	0.5	0.2	100%	146.212	0.2	0.2	100%	69.796	216.008
2	No	RTES	0.5	0.9	100%	174.001	0.9	0.2	100%	29.253	203.254
3	Yes	DAES	0.5	0.2	100%	161.159	0.2	0.2	98.87%	79.221	240.380
4	Yes	RTES	0.5	0.9	100%	181.189	0.9	0.2	**99.70%**	39.001	**220.190**

payment. In the HEMS, RE can supply energy for home loads, store excess energy in ESS, and sell unused energy to the utility. Under the limited ESS capacity and the peak power-limiting strategies, HEMS needs to schedule RE generation based on predicted generation. However, the prediction error may lead to the incomplete use of renewable energy. Due to the prediction error of DAES, there is a discarding of RE at period 17 and 18 on December 2, 2017 because the selling power exceed the selling limit, and the utilization is 98.87% as can be seen from Fig. 6(b). However, the utilization be increased to 99.70% in RTES system by real-time prediction of RE generation as can be seen from Fig. 7(b).

The comparison of the 4 different case studies in this paper is summarized in Table III. We can find that the economic benefit of RTES is better than that of RTES regardless of whether there are errors in information prediction.

In addition, the prediction error still exists. If we subdivide 24 hours into more periods, it will further reduce the prediction error and get closer to the actual information.

VI. Conclusions And Future Work

This paper, as the major contribution to the literature on smart home operation, proposes a RTES for HEMS, which considers the errors of information prediction. Moreover, this scheduling system is provided to investigate a collaborative scheduling which includes peak power limit, ESS, and bi-directional power flows of ESS and RE. Unlike most of the previous HEMS strategies that focus on DAES, we design the real-time scheduling which ensures that the scheduling of each period is the best decision based on prediction information within the future 24 hours. We have designed a GA based on ESS management strategy to meet the time efficiency. The real-time prediction approach of RE generation and the online registration of ETs are proposed for reducing information error. This paper makes two basic assumptions: The RTP signal and the daily regular tasks in future 24 hours are known before performing each scheduling optimization. Four test cases were examined. Simulation results show that RTES system has better performance of total electricity cost payment than DAES system, and HEMS with RTES algorithm can quickly respond to the sudden change of system inputs. Moreover, the battery will store energy for the next day if necessary by the RTES.

Some limitations of this study are as follows. To improve the scheduling flexibility and reality, the temperature appliance and the electric vehicle should be modeled separately to participate in the scheduling. Moreover, we should consider the cost of electricity storage, and the prediction of user energy usage behaver rather than online registration. The RTES also needs to be deployed on the embedded device for detection. These are the future works need to investigate.

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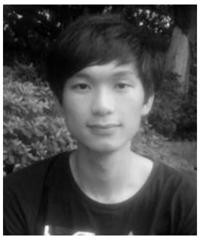

Shenglin Li received the B.S. degree in optoelectronic information engineering from Shanghai University of Electric Power, China, in 2016. He is currently working toward the M.S. degree in smart grid information and communication engineering at Shanghai University of Electric Power, China. His research interest includes smart grid and wireless sensor networks.

Junjie Yang received his B.E. and M.S. degrees both from Changchun University of Science and Technology, in 1998 and 2001, respectively, and the Ph.D. degree from Shanghai Jiao Tong University in 2005. He is a full professor of Shanghai Dianji University. His research interest includes smart grid, wireless sensor networks, and optical networks.

WenZhan Song received Ph.D. in Computer Science from Illinois Institute of Technology (2005), B.S. and M.S. degree from Nanjing University of Science and Technology (1997 and 1999). He is a Chair Professor of Electrical and Computer Engineering in the University of Georgia. Dr. Song’s research focuses on cyber-physical systems and security and their applications in energy, environment, food and health sectors. He is a NSF CAREER awardee (2010).

An Chen received the B.Sc. degree in computer science from Macau University of Science and Technology, Macau, in 2011 and the M.Sc. degree in computer science from New Jersey Institute of Technology, NJ, USA, in 2015. Currently, He is working towards the Ph.D. degree with department of computer science at University of Georgia, GA, USA, under the guidance of Dr. Wenzhan Song. His research interests are mainly in the areas of distributed algorithm, sensor network, optimization theory, and smart grid.