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A Home Energy Management System With Renewable Energy and Energy Storage Utilizing Main Grid and Electricity Selling

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ABSTRACT With the development of new technologies in the field of renewable energy and batteries, increasing number of houses have been equipped with renewable energy sources (RES) and energy storage systems (ESS) to reduce home energy cost. These houses usually have home energy management systems (HEMS) to control and schedule every electrical device. Various studies have been conducted on HEMS and optimization algorithms for energy cost and peak-to-average ratio (PAR) reduction. However, none of papers give a sufficient study on the utilization of main grid's electricity and selling electricity. In this paper, firstly, we propose a new HEMS architecture with RES and ESS where we take utilization of the electricity of the main grid and electricity selling into account. With the proposed HEMS, we build general mathematical formulas for energy cost and PAR during a day. We then optimize these formulas using both the particle swarm optimization (PSO) and the binary particle swarm optimization (BPSO). Results clearly show that, with our HEMS system, RES and ESS can help to drop home energy cost significantly to 19.7%, compared with the results of previous works. By increasing charge/discharge rate of ESS, energy cost can be decreased by 4.3% for 0.6 kW and 8.5% for 0.9 kW. Moreover, by using multi-objective optimization, our system can achieve better PAR with an acceptable energy cost.

INDEX TERMS Home energy management systems, electricity selling, renewable energy sources, energy storage systems, day-ahead price, meta-heuristic algorithms.

I. INTRODUCTION

In recent decades, the rate of global warming and climate change have been more severe, causing world extreme events such as hemispherical sea ice melting, serious flood, strong hurricane, and so on. One of main causes of global warming is carbon dioxide emissions from the consumption of fossil fuel to meet daily energy demand. To mitigate this problem, researches have been conducted in two different ways: finding more renewable energy resources (RES) to replace fossil fuel and utilizing energy in a most efficient way with the integration of RES and energy storage systems (ESS). For the purpose of utilization, smart grid (SG) has been introduced as a replacement of the existing power grid which does not support consumer's new requirements. The SG utilizes the latest communication technologies to improve the traditional electrical power system. With integration of RES and ESS, SG helps decrease the emission of carbon particulate and greenhouse gases as well as climate change mitigation (CCM) [1]. Two key integral parts of SG which make it better than traditional grids are advanced metering infrastructure (AMI) and demand side management (DSM).

The main functions of AMI are energy measurement and information collection. It comprises of smart meters and Information and Communication Technology (ICT). The ICT enables SG to keep the consumers updated about varying

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electricity prices, or events/failures due to devices or disasters. It also sends information of energy consumption measured by smart meter to electricity operators to enable the operators to monitor and analyze real-time data and make real-time decisions about activities of power networks.

DSM is an important part in the energy management of SG. DSM provides a diversity of functionalities in various areas such as electricity market control, energy management, infrastructure construction and management of decentralized energy resources [2]. DSM, which includes demand response (DR) and energy optimization, encompasses a broader range of energy demand management concepts. DSM seeks a balance between energy supply and demand on the both side of utilities and consumers whereas DR focuses on the consumer side only. The DR is used for the programs designed to help end-users to reduce short-term energy demand in response to a price signal from the electricity hourly market, or a trigger initiated by the electricity grid operator [3]. DR seeks to adjust the demand for power, rather than the supply. However, it is examined in the literature that researchers considered the DSM and DR are interchangeable [4].

Usually, the main objective of DSM and DR functions in SG is to encourage the consumers to utilize their RES (local generators) for their load, especially at peak hours, whereby decreasing the dependence on electricity providers. The second objective is to encourage consumers to shift home load: moving the time of energy use from peak hours to off-peak hours [2], [5]. These objectives also help the consumers to reduce their electricity cost and energy consumption in peak hours. Moreover, with amazing development of electric mobile devices such as electric vehicles (EV) and revolution of the technologies in RES, consumers are encouraged to participate in electricity market by selling surplus energy. The buyers can be electric cars, other houses and even electricity providers. To achieve the above objectives, a home energy management system (HEMS) is required at the consumer side. HEMS controls and optimizes RES, ESS and home appliances in a most efficient way and also helps consumers to incorporate other DSM activities.

Various studies have proposed algorithms to optimize the operation of home appliances such as linear programming (LP) [6], mixed integer linear programming (MILP) [7], [8], mixed integer nonlinear programming (MINLP) [9], [10], dynamic programming (DP) [11], or convex programming (CP) [12]. However, these techniques have very slow convergence rate with a large number of variables, and in some cases, they are unable to handle a lot of appliances [3], [13]. Meta-heuristic algorithms are employed in HEMS to deal with such shortcomings. The most widely used meta-heuristic algorithms are particle swarm optimization (PSO), binary particle swarm optimization (BPSO), genetic algorithm (GA), wind-driven optimization (WDO), bacterial foraging optimization (BFO) and Jaya algorithm [3], [13], [14], [15].

Based on the above background, we propose a new HEMS with integration of RES and ESS. Our HEMS is connected with electricity operator through AMI. Electricity operator sends useful forecast information to our HEMS by using AMI such as pricing information and solar irradiance. The proposed HEMS makes the following contributions.

- With the integration of RES and ESS, we propose a novel HEMS architecture to reduce energy cost and PAR. In our HEMS, utilizing main grid and electricity selling are emphasized and described as follows: Our ESS can be used to store electricity from main grid at low price time as well as electricity from RES. This electricity is reused for home load at high price time. Moreover, our HEMS allows prosumers to sell surplus electricity at appropriate time slots.
- With the proposed HEMS architecture, we build general mathematical formulas where we consider utilization of main grid and electricity selling as well as the selling price. Based on these formulas, our HEMS gives detailed schedules for each electrical device during a day. Furthermore, the amount of electricity utilized from main grid and the amount of electricity sold to the outside are also determined at each time slot.
- In proposed HEMS, we combine two algorithms, PSO and BPSO, for optimization because of the complexity of the HEMS architecture: BPSO is used for binary variables and PSO is used for continuous variables.
- We evaluate the proposed HEMS by performing extensive simulations. Firstly, we focus on the minimization of energy cost using single-objective optimization. Secondly, we apply multi-objective optimization to the HEMS to minimize both energy cost and PAR.
- We further analyze our proposed HEMS with the effects of changing the selling price. In addition, the effect of different ESS charge/discharge rate and ESS capacity for reducing the energy cost are also evaluated.

The rest of this paper is organized as follows. Section II reviews the related works to our system and our paper's contributions. In Section III, we describe our HEMS architecture in detail. Problem formulation of total energy cost and PAR during a day is built in Section IV. PSO and BPSO algorithms are presented in Section V. In Section VI, simulations and the results are discussed. Finally, Section VII draws the conclusion of our paper after which some future works are also highlighted.

II. RELATED WORK AND MOTIVATION

Recently, various studies have been conducted on HEMS with various optimization algorithms. The common targets of these studies were to minimize energy cost and PAR. Beside the two objectives, some papers also consider user comfort (UC) such as waiting time, thermal comfort, air quality and so on.

In [9], a home automation/energy management system (HAEMS) with integrated ESS was presented.

The objective of this paper was to optimize a mixed objective function which includes energy cost, user's convenience and thermal comfort. The tariff used in their system was RTP pricing. In this paper, they used General Algebraic Modeling System (GAMS) software with Cplex/Dicopt solvers as the main optimization engine. They considered their HAEMS in three scenarios: naive, normal, and smart. The simulation results showed that in smart scenario, their HAEMS has improved the mixed objective function up to 55% and 25% with respect to the naive and normal scenarios in a hot weather condition and up to 63% and 38% in a cold weather condition. However, in this paper, RES was not included and PAR was not considered. In [10], authors proposed a residential smart energy management system (RSEMS) with integrated ESS and RES. A hybrid objective function was built to optimize the energy cost, user's satisfaction and thermal comfort simultaneously. They used MATLAB and GAMS for optimization tasks. Their RSEMS was compared with conventional EMS in two scenarios: hot summer day and cold winter day. Their RSEMS helped to improve hybrid objective function up to 29% and 33% in hot and cold weather conditions respectively. However, PAR was not considered in this paper. In both [9] and [10], utilizing main grid's electricity at low price time and electricity selling activities were mentioned but they were not emphasized. Authors did not give a detailed schedule for selling operation at each time slot. Moreover, selling price was not considered. Their works can not be applied in case selling price is smaller than the price of main grid.

In [16], an ontology-driven multi-agent based energy management system (MAS) was proposed. This system was used to monitor and optimally control a micro-grid system with integrated homes or buildings (residential micro-grid) with various RES. At homes, different agents including EMS were implemented to cooperate with each other to reach an optimal operating strategy. Moreover, this system also had useful agents such as central coordinator agent (CCA) which is responsible for collecting and sharing useful information, and battery bank agent (BBA) to compensate any real-time power imbalances within the residential micro-grid economically. The BBA was also a device which stores the surplus of energy and provides energy back to micro-grid. The BBA was able to sell or buy energy from utility. Authors tested their system in three scenarios: naive, normal, and smart with different time frames (weekdays and weekend), different climate (hot and cold), pricing schemes (RTP, TOU, and flat rate). Through a number of simulations, they demonstrated that the proposed MAS had the capability to reduce system's operation cost and to ensure user's needs under different weather conditions, time frames, and pricing schemes. However, MAS focused on the whole residential micro-grid, not for a single home.

In [11], authors proposed an energy management system for a group of homes with integrated ESS and RES to optimize the energy cost. At each home, an energy consumption controller (ECC) with dynamic programming was suggested for load scheduling and a game theoretic approach was adopted to model power trading between these users. At each time slot, ECC was re-run to turn on or off home appliances and users could re-choose selling price and amount of trading energy based on Nash equilibrium. Their simulation results showed that with the support of their system, energy consumption was decreased from 1360.9 kWh to 820.2 kWh. Hence, energy cost of their system was reduced from $62.91 to $40.37. However, the utilization of main grid and PAR were not considered.

In [3], an optimized home energy management system (OHEMS) with integrated RES and storage resource to optimize the energy cost and PAR was proposed. The tariff in their system was a day-ahead pricing. They applied many heuristic algorithms into OHEMS and compared results of these algorithms. These heuristic algorithms are genetic algorithm (GA), binary particle swarm optimization (BPSO), wind driven optimization (WDO), bacterial foraging optimization (BFO) and hybrid GA-PSO (HGPO). Their study shows that HGPO gives the lowest total energy cost and BFO gives the lowest PAR among these algorithms. However, the user comfort (UC) was not discussed. In this work, authors gave a fixed plan for the operation of RES and ESS. ESS is only used to store 30% of RES energy at day time and discharged at high price time slot at night time. 70% of RES energy is used for home load. With this fixed plan, their OHEMS cannot utilize the electricity of the main grid at time which has low price. Moreover, their OHEMS does not support consumers to sell electricity.

In [13], HEMS with different heuristic algorithms and different tariffs was studied. Their objectives were to minimize energy cost, PAR and maximize user comfort. The user comfort in their papers is waiting time of user. The tariffs applied in their system were real-time electricity pricing (RTEP) and critical peak pricing (CPP). Four heuristic algorithms applied in their system were wind driven optimization (WDO), harmony search algorithm (HSA), genetic algorithm (GA) and GHSA which combines the attributes of GA and HSA. They also considered their HEMS in two cases single home (SH) and multiple homes (MH). Their simulation results showed that GHSA outperformed the other algorithms in terms of objectives. However, in their HEMS, the integration of RES and ESS into residential side was ignored.

Muhammad Awais in [17] presented home energy management (HEM) with three heuristic algorithms: bacterial foraging optimization algorithm (BFOA), flower pollination algorithm (FPA) and hybrid bacterial flower pollination algorithm (HBFPA). They test the proposed scheme in a single home and in smart community involving multiple households. Their targets were to minimize energy cost and PAR with affordable users' waiting time. The proposed HBFPA shows efficacy for energy cost and for reduction of PAR with reasonable user waiting time. However, they did not consider RES and ESS in their HEM.

In [8], an optimization and energy management in the smart home was proposed. Energy consumption was optimized with the integration of ESS, electric vehicle, and two kinds of RES: solar energy and wind energy. The selling energy was also considered. The system was simulated in three scenarios: 1 day, 4 days and 7 days. MILP and heuristic algorithms were compared in the three scenarios. However, their system does not have AMI, hence they did not receive information from electricity operators. In their system, they forecast daily load in general and home appliances were not described. They did not give a detailed schedule for each device at home. Hence, this system cannot be applied to DSM. In addition, authors only consider minimizing energy cost without taking PAR into account.

In [18] and [19], straightforward solution of HEMS was proposed with direct current (DC) power management. In their HEMS, smart DC sockets with load shedding algorithm were used to control home devices with priority. However, home devices were turned on or off by smart sockets only according to the threshold of energy consumption at each sampling period, and time constraints of home devices were not considered.

In [6], an OEMS for reduction of energy cost was studied. In this work, plug-in hybrid electric vehicle (PREV) batteries and ESS were used to collect electricity and determine the optimization values. The PREV provides electricity for ESS when demand is low and ESS is discharged for home when demand is high. They used linear programming to solve the optimization problem. However, RES was not considered in this model.

In [20], an energy management system with load forecasting based on Kalman Filter was demonstrated. In their system, a PV system, ESS and critical peak pricing (CPP) were used. ESS was used to store excess PV power and provide the charged power as needed. Kalman Filter was used to forecast the home load for the next day. Their system need to be trained to construct load forecasting model. However, their system did not have AMI to receive information from electricity operators. The DSM and DR activities were also not considered. In addition, their system did not give a detailed schedule for each home appliance.

The brief comparison of research works on HEMS is listed in Table 1 where a HEMS supporting selling operation allows prosumers to change selling price and give a detailed amount of energy sold to the outside. On the other hand, selling capability means that a HEMS is considered to sell electricity to the outside but it does not support to change selling price and does not give a schedule for selling. Motivated by the above literature works, we suggest a novel HEMS with integration of RES and ESS utilizing main grid and electricity selling whose objective is to minimize both energy cost and PAR.

III. HEMS ARCHITECTURE

Fig. 1 shows the main elements of the proposed HEMS. We assume that every consumer is equipped with AMI, a main controller (MC), ESS and a PV system as RES.

In general, AMI refers to collection of systems that include smart meter (SM), advanced communications and data management systems [13]. AMI works as a backbone from electricity providers to consumers. SM works as a communication gateway between our house and providers. SM is responsible for reading, processing and sending energy usage data from our house to the providers via AMI. Moreover, AMI is also used to transmit useful grid information from electricity providers to consumers. These kinds of information may be the price information, forecast temperature, solar irradiance, and wind speed.

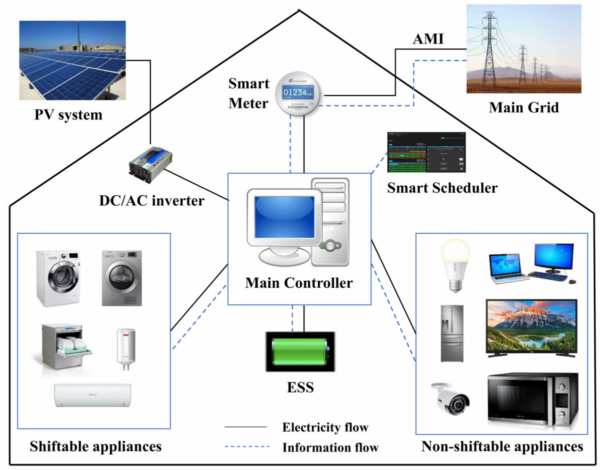

FIGURE 1. HEMS architecture.

The MC is the heart of our HEMS. Main task of MC is to control all home appliances including a PV system and ESS. MC is able to turn on or off every device in our system based on schedule calculated through our optimization algorithms. A smart scheduler (SS) that performs optimization algorithms is installed inside MC. At the beginning of the day, the useful information is received from electricity provider via AMI. SS is then run to create an optimized schedule for every device during a day. MC can control all appliances following this schedule to achieve the minimization of energy cost and PAR.

There are many kinds of RES such as wind turbines, PV systems, fuel cells. In our system, we use a PV system because of its easy installation and cheap price. A DC/AC inverter is used to convert the DC current from the PV system into AC current.

To utilize the electricity of the main grid, we use ESS to store electricity from the main grid at low price time and provide electricity for our home appliances at high price time. ESS also helps us exploit the PV system efficiently. The energy from a PV system is able to be stored in ESS at any time slot and reused in different time slot. Furthermore, our system supports selling energy to the outsiders such as smart electric vehicles, other houses, or even main grid. We assume that our MC can use AMI to transmit selling electricity.

IV. PROBLEM FORMULATION

To optimize electricity bill and PAR, we define mathematical models and constraints of all elements in our HEMS. In this section, we build mathematical formulas of RES, ESS, appliances and our cost function during a day time from 0 A.M.

TABLE 1. A comparison of HEMS: State of the art.

Paper	Algorithms (Techniques)	Integration		Objective			Scheduling Home Appliances	Selling Capability	Utilizing Main Grid	Supporting Selling Operation
		ESS	*RES*	*min Cost*	*min PAR*	*max UC*				
[9]	MINLP	✓		✓		✓	✓	✓	✓	
[10]	MINLP	✓	✓	✓		✓	✓	✓	✓	
[3]	meta-heuristic	✓	✓	✓	✓		✓			
[13]	meta-heuristic			✓	✓	✓	✓			
[14]	meta-heuristic	✓	✓	✓	✓	✓	✓			
[15]	meta-heuristic	✓	✓	✓	✓	✓	✓			
[17]	meta-heuristic			✓	✓	✓	✓			
[8]	MILP and meta-heuristic	✓	✓	✓	✓	✓				
[11]	DP and game theory	✓	✓	✓			✓	✓		✓
[12]	CP			✓		✓	✓			
[7]	MILP			✓			✓			
[6]	LP	✓		✓						
[20]	Kalman filter	✓	✓	✓						
[18]	Load shedding	✓	✓	✓			✓			
Our work	meta-heuristic	✓	✓	✓	✓		✓	✓	✓	✓

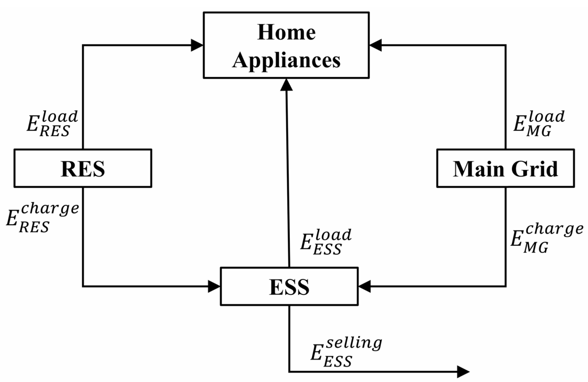

FIGURE 2. Electricity flows in our HEMS.

to 12 P.M.. We also divide a day into $T = 24$ time slots and the duration of each time slot is $\Delta t = 1h$.

A. ELECTRICITY FLOWS

Fig. 2 shows all electricity flows in our system. In our model, RES can be used to provide electricity for appliances in a house and store electricity in the ESS at any time slot in any quantity. The ESS can be used to provide electricity for appliances and sell electricity at any time slot in any quantity. If the electricity from RES and ESS is not enough for home devices, the electricity of the main grid is needed. Moreover, electricity from the main grid can be stored in ESS in the low price time slot and would be used in the high price time slot.

B. RENEWABLE ENERGY SOURCE

As shown in Fig. 1, our HEMS is equipped with a PV system as RES. According to [21] and [22], we use the following equation to calculate the output power P_{RES} of PV system in kW at time τ.

$$P_{RES}(\tau) = GHI(\tau) \cdot S \cdot \eta^{RES} \quad \forall \tau \; 0 \leq \tau \leq 24 \tag{1}$$

where GHI is the global horizontal irradiation (kW/m^2) at the location of solar panels. S is the total area (m^2) of solar panels and η^{RES} is the solar conversion efficiency of the PV system.

In time slot t with time slot's duration Δt, our PV system generates an electrical energy $E_{RES}(t)$ as follows.

$$E_{RES}(t) = P_{RES}(\tau) \cdot \Delta t \quad \forall t \; 1 \leq t \leq T \tag{2}$$

where τ is the real time in time slot t.

As shown in Fig. 2, this energy would be used for home load and ESS charging. Thus, we have the following equation.

$$E_{RES}(t) = E_{RES}^{load}(t) + E_{RES}^{charge}(t) \quad \forall t \; 1 \leq t \leq T \tag{3}$$

where $E_{RES}^{load}(t)$ is an energy quantity used for home load in time slot t. $E_{RES}^{charge}(t)$ is an energy quantity used to charge ESS in time slot t.

From (1), (2), and (3), we have following constraints for variables $E_{RES}^{load}(t)$ and $E_{RES}^{charge}(t)$.

$$0 \leq E_{RES}^{load}(t) \leq GHI(\tau) \cdot S \cdot \eta^{RES} \cdot \Delta t \quad \forall t \; 1 \leq t \leq T \tag{4}$$

$$0 \leq E_{RES}^{charge}(t) \leq GHI(\tau) \cdot S \cdot \eta^{RES} \cdot \Delta t \quad \forall t \; 1 \leq t \leq T \tag{5}$$

C. ENERGY STORAGE SYSTEM

The main role of ESS is to exploit the PV system and the electricity of the main grid more efficiently. Our ESS is able to store the energy of the main grid or RES in a time slot with low price and provide to home load in a time slot with high price. The parameters of our ESS used in this paper are shown in Table 2.

In a general case, ESS in our HEMS has two functions: a source to provide energy for home load and sell surplus energy to the outside, and a sink to store energy from RES and the main grid. Hence, with $\forall t \; 1 \leq t \leq T$, we have the following formulas.

$$E_{ESS}^{Discharge}(t) = \left(E_{ESS}^{load}(t) + E_{ESS}^{selling}(t)\right) \cdot \left(1 - mode^{ESS}(t)\right) \tag{6}$$

TABLE 2. The parameters of an ESS [21].

Parameters	Meaning
η^{ESS}	ESS efficiency
Ch_{rate}/Dh_{rate}	the maximum charge/discharge rate of ESS
EL_0	the initial energy level of ESS
EL_{min}	the minimum energy level of ESS
EL_{max}	the maximum energy level of ESS

$$E_{ESS}^{Charge}(t) = \left(E_{RES}^{charge}(t) + E_{MG}^{charge}(t)\right) \cdot mode^{ESS}(t) \tag{7}$$

where $E_{ESS}^{Discharge}(t)$ refers to an energy quantity which is drawn from ESS in a time slot t. $E_{ESS}^{Charge}(t)$ refers to an energy quantity stored in the ESS in a time slot t. $E_{ESS}^{load}(t)$ is an energy quantity used for home load in a time slot t. $E_{ESS}^{selling}(t)$ is an energy quantity used to sell to the outside in a time slot t. $E_{RES}^{charge}(t)$ is an energy quantity stored in ESS from RES in a time slot t. $E_{MG}^{charge}(t)$ is an energy quantity stored in ESS from the main grid in a time slot t. Because ESS is only able to be either charged or discharged in a time slot, $mode^{ESS}(t)$ is a binary variable which shows the status of ESS in slot t.

$$mode^{ESS}(t) = \begin{cases} 1 & \text{if ESS is charged.} \\ 0 & \text{if ESS is discharged.} \end{cases} \tag{8}$$

Assuming that $E_{ESS}^{Level}(t)$ is energy level of ESS after time slot t where $\forall t \ 1 \le t \le T$, we have the following formula.

$$E_{ESS}^{Level}(t) = E_{ESS}^{Level}(t-1) + E_{ESS}^{Charge}(t) \cdot \eta^{ESS} - E_{ESS}^{Discharge}(t)/\eta^{ESS} \tag{9}$$

where η^{ESS} is ESS efficiency. It is worth noting that η^{ESS} must be used in (9) because some energy is lost when charging or discharging an ESS, which is called round trip efficiency. When using ESS, we must satisfy the following constraints.

- The charge/discharge rate of ESS cannot exceed the Ch_{rate}/Dh_{rate}. It means that we are only able to put in or draw certain energy quantity in a time slot t with duration Δt.
- The energy level of ESS must be between EL_{min} and EL_{max}.

From above constraints, with $\forall t \ 1 \le t \le T$, we have the following constraints.

$$0 \le E_{ESS}^{Discharge}(t) = E_{ESS}^{load}(t) + E_{ESS}^{selling}(t) \le Dh_{rate} \cdot \Delta t \tag{10}$$

$$0 \le E_{ESS}^{Charge}(t) = E_{RES}^{charge}(t) + E_{MG}^{charge}(t) \le Ch_{rate} \cdot \Delta t \tag{11}$$

$$EL_{min} \le E_{ESS}^{Level}(t) \le EL_{max} \tag{12}$$

$$0 \le E_{ESS}^{load}(t) \le Dh_{rate} \cdot \Delta t \tag{13}$$

$$0 \le E_{ESS}^{selling}(t) \le Dh_{rate} \cdot \Delta t \tag{14}$$

$$0 \le E_{RES}^{charge}(t) \le Ch_{rate} \cdot \Delta t \tag{15}$$

$$0 \le E_{MG}^{charge}(t) \le Ch_{rate} \cdot \Delta t \tag{16}$$

Since we only consider our system during a day (no net accumulation for next day), energy level must be returned to the initial energy level at the end of the day. Thus, we have this constraint.

$$E_{ESS}^{Level}(T) = EL_0 \tag{17}$$

We assume that all energy to be sold come from ESS. If we want to sell energy generated from RES, it should be stored in ESS before selling. Note that the variable $E_{RES}^{charge}(t)$ has two constraints in (5) and (15). If our RES generates more energy than the sum of the energy needed by home appliances and the energy is able to stored in ESS in a time slot, the remain energy of RES will be wasted.

D. HOME APPLIANCES

In our system, we suppose that there are two different sets of appliances: shiftable appliances M and non-shiftable appliances N. The set of shiftable devices $M = \{a_1, a_2, a_3, \ldots, a_m\}$ includes the devices which can operate at any time slots whereby we can move the operation time of these devices to low price slots to save costs. The set of non-shiftable devices $N = \{b_1, b_2, b_3, \ldots, b_n\}$ have a fixed operation time slots defined by users. In a time slot t, the energy consumption of total appliances, $E_{total}^{appliances}(t)$, in a house is the sum of the energy consumption of shiftable set M, $E_M(t)$, and non-shiftable set N, $E_N(t)$, which are given in (18), (19), (20), with $\forall b_i \in N, \forall a_i \in M, \forall t \ 1 \le t \le T$.

$$E_{total}^{appliances}(t) = E_N(t) + E_M(t) \tag{18}$$

$$E_N(t) = \sum_{i=1}^{n} Power_{rate}(b_i) \times O(b_i, t) \times \Delta t \tag{19}$$

$$E_M(t) = \sum_{i=1}^{m} Power_{rate}(a_i) \times O(a_i, t) \times \Delta t \tag{20}$$

where $Power_{rate}(a_i)$ and $Power_{rate}(b_i)$ refer to the power rating of devices a_i, b_i which is given by producers. $O(a_i, t)$ and $O(b_i, t)$ are binary variables which show the status of devices a_i and b_i in a time slot t.

$$O(a_i, t) = \begin{cases} 1 & \text{if shiftable device } a_i \text{ is ON} \\ 0 & \text{if shiftable device } a_i \text{ is OFF} \end{cases} \tag{21}$$

$$O(b_i, t) = \begin{cases} 1 & \text{if non-shiftable device } b_i \text{ is ON} \\ 0 & \text{if non-shiftable device } b_i \text{ is OFF} \end{cases} \tag{22}$$

Since $O(b_i, t)$ has a fixed value, $E_N(t)$ also has fixed value. In a whole day of $T = 24$ hours, the total energy consumption of all appliances in our system is given by

$$\sum_{t=1}^{T} E_{total}^{appliances}(t) = \sum_{t=1}^{T} E_N(t) + \sum_{t=1}^{T} E_M(t). \tag{23}$$

When a shiftable device is moved to low price slots, the energy demand of this device is not changed because the operation time of each shiftable device does not change and it is not interrupted during operation. To provide enough energy for home appliances, we use 3 different sources as shown in Fig. 2: energy from RES E_{RES}^{load}, ESS E_{ESS}^{load}, and the main grid E_{MG}^{load} in a time slot t. Hence, we have the following formula with $\forall t$ $1 \leq t \leq T$.

$$E_{total}^{appliances}(t) = E_{RES}^{load}(t) + E_{ESS}^{load}(t) + E_{MG}^{load}(t) \tag{24}$$

$$\Rightarrow E_{MG}^{load}(t) = E_{total}^{appliances}(t) - E_{RES}^{load}(t) - E_{ESS}^{load}(t) \tag{25}$$

From (18), we have

$$E_{MG}^{load}(t) = E_N(t) + E_M(t) - E_{RES}^{load}(t) - E_{ESS}^{load}(t). \tag{26}$$

Because $E_{MG}^{load}(t) \geq 0$ and we assume that the main grid always provide enough electricity for the requirement of our home load. Thus, we have the following constraint.

$$0 \leq E_{RES}^{load}(t) + E_{ESS}^{load}(t) \leq E_N(t) + E_M(t) = E_{total}^{appliances}(t) \tag{27}$$

E. LOAD DEMAND AND COST FUNCTION

In this subsection, we build a formula of energy from the main grid called load demand in each time slot. We get the total energy cost for a day using the load demand and the prices of the main grid. According to [23], there are many kinds of electricity tariffs such as Time-of-Use pricing (ToU), Real-Time Pricing (RTP), Critical Peak Pricing (CPP) and so on. ToU and RTP are commonly used tariffs in most HEMSs. In this paper, we use Day-Ahead Pricing (DAP), a kind of RTP where the price of electricity changes on the hourly basis and remains constant in an hour. Customers are typically notified of DAP prices on a day-ahead basis.

We assume that the energy from RES and ESS is complimentary, whereby in a time slot t, load demand needed from main grid, $E_{LD}(t)$, includes $E_{MG}^{load}(t)$ and $E_{MG}^{charge}(t)$ as shown in Fig. 2. With $\forall t$ $1 \leq t \leq T$, we have the following formula.

$$E_{LD}(t) = E_{MG}^{load}(t) + E_{MG}^{charge}(t) \tag{28}$$

From (26), we have

$$E_{LD}(t) = E_N(t) + E_M(t) + E_{MG}^{charge}(t) - E_{RES}^{load}(t) - E_{ESS}^{load}(t). \tag{29}$$

In addition, we sell amount of energy, $E_{ESS}^{selling}(t)$, to the outside in a time slot t. Hence, the energy cost to be paid in a time slot t, $EC(t)$, is

$$EC(t) = E_{LD}(t) \times P_{MG}(t) - E_{ESS}^{selling}(t) \times P_{sell}(t). \tag{30}$$

where $P_{MG}(t)$ is the electricity price of the main grid in the time slot t. This value is determined by the electrical provider. $P_{sell}(t)$ is the price of selling energy in the time slot t. This value is decided by users. From (30), total cost we must pay for energy from the main grid during a day $T = 24$ hours, C_{day}, is

$$\begin{aligned} C_{day} &= \sum_{t=1}^{T} EC(t) \\ &= \sum_{t=1}^{T} \Big(E_{LD}(t) \times P_{MG}(t) - E_{ESS}^{selling}(t) \times P_{sell}(t) \Big). \end{aligned} \tag{31}$$

From (29), we have the following formula.

$$\begin{aligned} C_{day} = \sum_{t=1}^{T} \bigg(\Big(& E_N(t) + E_M(t) + E_{MG}^{charge}(t) - E_{RES}^{load}(t) \\ & - E_{ESS}^{load}(t) \Big) \times P_{MG}(t) - E_{ESS}^{selling}(t) \times P_{sell}(t) \bigg) \end{aligned} \tag{32}$$

Since our objective is to minimize the total energy cost during a day, objective function is defined as

$$\begin{aligned} & min(C_{day}) \\ & = min\Bigg(\sum_{t=1}^{T} \bigg(\Big(E_N(t) + E_M(t) + E_{MG}^{charge}(t) - E_{RES}^{load}(t) \\ & \quad - E_{ESS}^{load}(t) \Big) \times P_{MG}(t) - E_{ESS}^{selling}(t) \times P_{sell}(t) \bigg) \Bigg). \end{aligned} \tag{33}$$

Combining with (20), we have the objective function of our system as

$$\begin{aligned} min\Bigg(\sum_{t=1}^{T} \bigg(\Big(& E_N(t) + \sum_{i=1}^{m} Power_{rate}(a_i) \times O(a_i, t) \times \Delta t \\ & + E_{MG}^{charge}(t) - E_{RES}^{load}(t) - E_{ESS}^{load}(t) \Big) \times P_{MG}(t) \\ & - E_{ESS}^{selling}(t) \times P_{sell}(t) \bigg) \Bigg). \end{aligned} \tag{34}$$

In (34), $Power_{rate}(a_i)$, $E_N(t)$, and $Price_{MG}(t)$ are fixed values we already know. $O(a_i, t)$ are binary variables. $E_{MG}^{charge}(t)$, $E_{RES}^{load}(t)$, $E_{ESS}^{load}(t)$, $E_{ESS}^{selling}(t)$ are variables which must satisfy all constraints: (3), (4), (5), (10), (11), (12), (13), (14), (11), (16), (17), (27).

Usually, the price of the main grid is higher than the selling price. We assume that $P_{sell}(t) = \alpha \times P_{MG}(t)$ with $0 < \alpha \leq 1$. Thus, the objective function of our system becomes

$$\begin{aligned} min\Bigg(\sum_{t=1}^{T} \bigg(& E_N(t) + \sum_{i=1}^{m} Power_{rate}(a_i) \times O(a_i, t) \times \Delta t \\ & + E_{MG}^{charge}(t) - E_{RES}^{load}(t) - E_{ESS}^{load}(t) \\ & - \alpha \times E_{ESS}^{selling}(t) \bigg) \times P_{MG}(t) \Bigg). \end{aligned} \tag{35}$$

F. PEAK-TO-AVERAGE RATIO

PAR is a ratio of the peak load demand and the average of total load demand over a day, from $t = 1$ to $t = 24$. PAR tells the energy behavior of our system and it is directly related to the operation of the electricity main grid. The power supply companies always want to keep customers' PAR low. In our system, it is calculated as follows.

$$PAR = \frac{max(E_{LD}(t))}{\frac{1}{T}\sum_{t=1}^{T} E_{LD}(t)} \tag{36}$$

where $E_{LD}(t)$ is calculated by (29).

V. PARTICLE SWARM OPTIMIZATION ALGORITHM

The particle swarm optimization (PSO) is an evolutionary computation algorithm which simulates the behavior of organisms [24]. The PSO algorithm is usually used to solve continuous optimization problems. At the beginning of PSO algorithm, a population of particles is created and randomly placed at the search space of the problem to be optimized. At each iteration, each particle moves to a different position inside the search space to find an optimal solution. A new position is calculated using the current position and velocity. Generally, the new position $x_i(t+1)$ and velocity $v_i(t+1)$ of particle i at iteration $t+1$ is calculated by the following formula.

$$\begin{aligned} v_i(t+1) &= \omega \cdot v_i(t) + C_l \cdot r_l \cdot (lb_i(t) - x_i(t)) \\ &\quad + C_g \cdot r_g \cdot (gb(t) - x_i(t)) \end{aligned} \tag{37}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{38}$$

where ω is the inertia weight and is a constant, $v_i(t)$ is the velocity of particle at iteration t, C_l is the acceleration coefficients for personal best and is a constant, r_l is the random number distributed from 0 to 1 for personal best, $lb_i(t)$ is the personal best position of the particle at iteration t, $x_i(t)$ is the position of the particle at iteration t, C_g is the acceleration coefficients for global best and is a constant, r_g is the random number distributed from 0 to 1 for global best, and $gb(t)$ is the global best position at iteration t. After running a number of iterations, all particles will move to a best position (best solution) of the problem.

In our objective function, we have two kinds of variables: continuous variables such as $E_{MG}^{charge}(t)$, $E_{ESS}^{load}(t)$ and binary variables that only have 0 or 1 such as $O(a_i, t)$. The original PSO algorithm is only correctly operated in the continuous search space. For binary variables, we must use the binary particle swarm optimization (BPSO) given by Kennedy and Eberhart in [25]. In BPSO algorithm, the formula of each particle's velocity at iteration $t+1$ is the same as (37). To update the value of particle $x_i(t+1)$ at iteration $t+1$, instead of using velocity as (38), we use a sigmoid function $S(.)$ given by (39).

$$S(v_i(t+1)) = \frac{1}{1+e^{-v_i(t+1)}} \tag{39}$$

and

$$x_i(t+1) = \begin{cases} 1 & S(v_i(t+1)) > rand(). \\ 0 & S(v_i(t+1)) \leq rand(). \end{cases} \tag{40}$$

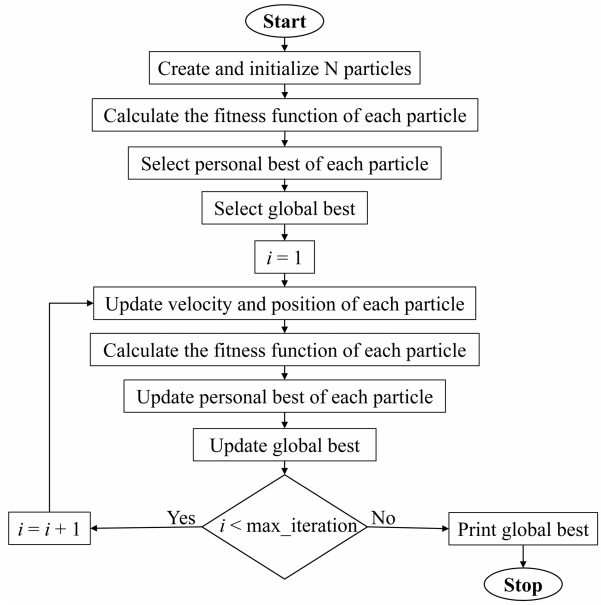

FIGURE 3. A flowchart of PSO algorithm.

TABLE 3. PSO and BPSO parameters.

Parameters	Value
ω	1
C_l	2
C_g	2
Swarm Size	1000
Number of iterations	250
Number of running times	10

where $rand()$ is function which generate a pseudo-random number in range [0.0, 1.0]. Fig. 3 shows the working flow of our PSO algorithm. The PSO and BPSO parameters used in our simulation are shown in Table 3.

VI. SIMULATIONS AND DISCUSSIONS

In this section, the results of our simulation are presented. We simulate the hourly energy use of the set of household appliances during a day. We divide a day into 24 time slots where time slot 1 begins from 0 A.M. to 1 A.M., time slot 2 from 1 A.M. to 2 A.M. and so on. Our HEMS was evaluated in two cases: (I) single-objective optimization and (II) multi-objective optimization. In the first case, with the support of RES and ESS, we focused on total energy cost optimization. Utilization of energy of the main grid at low price time slot and selling energy were evaluated in terms of total energy cost during a day. In the second case, we minimized our HEMS based on two objectives: total energy cost and PAR. In both cases, our program is run on Intel(R) Core(TM) i7-8700 CPU @ 3.20GHz (12 CPUs) and 16GB RAM with Windows 10 pro. The computational time of our program was about 10 minutes.

To compare results of our simulation with one of [3], the input parameters of our simulation were employed from [3] including home appliances, day-ahead pricing

TABLE 4. Description of the appliances.

Load Type	Appliances	Power Rating (kW)	Daily Usage (Hours)	Start Time
Shiftable	Washing machine	0.8	5	-
	Air conditioner	1.3	10	-
	Clothes dryer	0.7	4	-
	Water heater	1	8	-
	Dish washer	0.2	3	-
non-shiftable	Personal computers	0.2	18	7 A.M.
	Security cameras	0.1	24	0 A.M.
	Microwave oven	0.5	7	3 P.M.
	Refrigerator	0.9	20	2 A.M.
	Television	0.2	8	4 P.M.
	Lights	0.1	6	6 P.M.

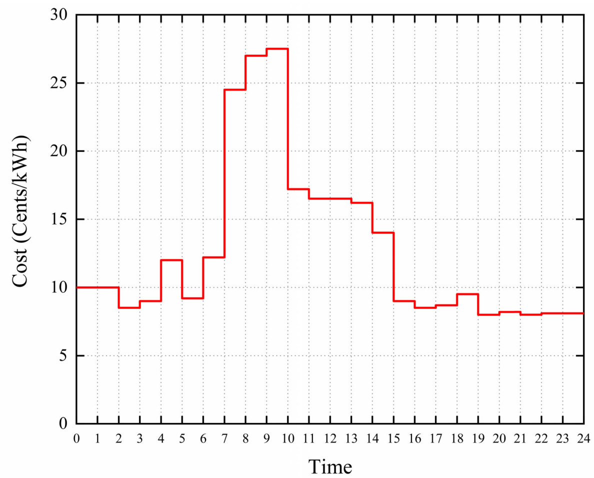

FIGURE 4. Hourly prices according to DAP signal.

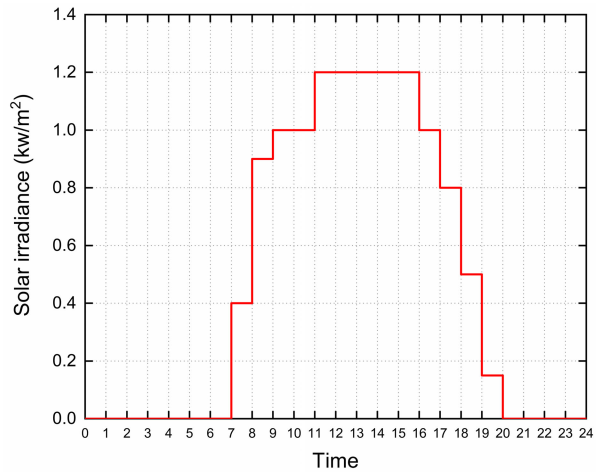

FIGURE 5. Solar irradiance to compute $P_{RES}(\tau)$.

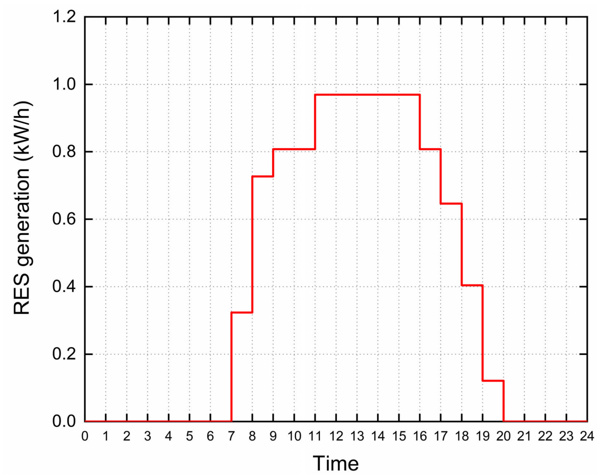

FIGURE 6. Hourly RES energy generated by the PV system.

TABLE 5. The input parameters of our ESS in the simulation.

η^{ESS}	Ch_{rate}/Dh_{rate}	EL_0	EL_{min}	EL_{max}
95%	0.3 kW	0.5 kWh	0.5 kWh	3 kWh

signal, solar irradiance and RES as shown in Table 4, Fig. 4, Fig. 5 and Fig. 6, respectively. There are 11 appliances that were divided into two categories: shiftable and non-shiftable. The shiftable appliances are devices whose operating time can be shifted to low price time slots whereas operating time of non-shiftable devices cannot be changed. All the appliances cannot be interrupted during operation. Table 4 shows the power rating and the length of operation time of all appliances. For the RES in our system, we used an electricity generation by PV system modeled in (1). Our RES mainly depends on energy conversion efficiency of the solar generator, the area of solar cells, solar irradiation. Our RES is configured to generate the same amount of energy as in [3].

In our system, we use ESS with the same configuration as in [3]. The parameters of our ESS are shown in Table 5. In [3], authors proposed a fixed plan for RES and ESS. In their work, 30% of energy from RES in each time slot is used for the charging of ESS, and the remaining energy is used for home load. The ESS is charged only from the PV system in the day time. The energy in ESS is only used for home load at high price time slot from t_{20} to t_{24}. In this paper, we propose a fully flexible general plan for RES and ESS. As described in Section IV, the energy from RES is not only used for home appliances but also to charge ESS with any quantity and at any time slot. An energy quantity of ESS also can be used for selling to the outside at any time slot.

A. CASE 1: SINGLE-OBJECTIVE OPTIMIZATION

In this case, we focus on minimizing total energy cost of our system during a day. We firstly assume that $P_{sell}(t) = P_{MG}(t) \forall t$ which means $\alpha = 1$.

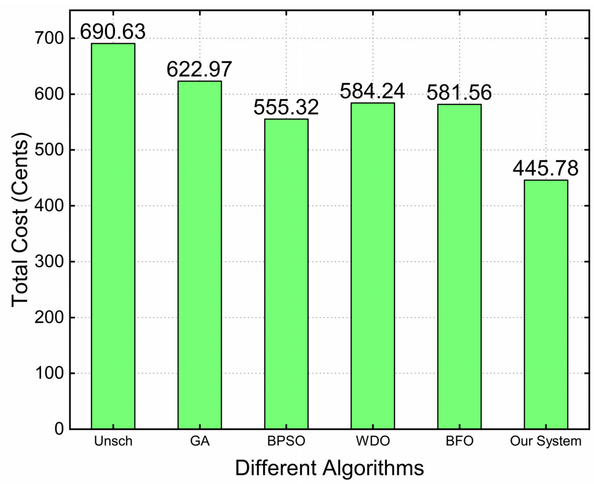

FIGURE 7. Total energy cost of different algorithms [3].

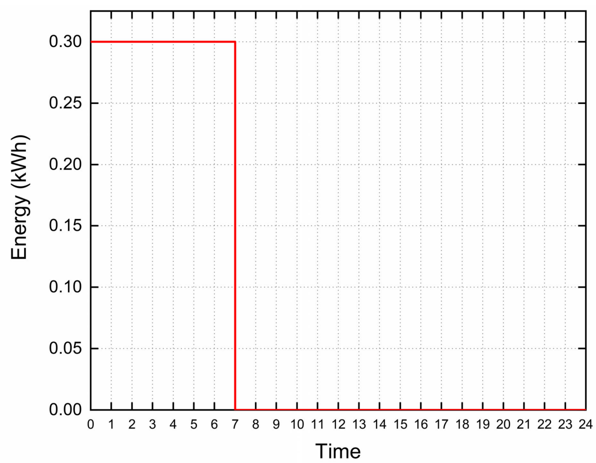

FIGURE 8. Hourly energy of the main grid stored in ESS.

1) TOTAL ENERGY COST

The comparison of total energy cost of our system and [3] is shown in Fig. 7.

Total energy cost of our system is 445.78 cents, the smallest energy cost among six algorithms. Compared with [3]'s BPSO algorithm, the total energy cost of our system is significantly reduced by 19.7%. To understand where this benefit comes from, we analyze an output of our simulation for all appliances to see how our HEMS utilizes energy of the main grid and ESS energy as shown in Fig. 8, Fig. 9, and Fig. 10 respectively.

Firstly, in order to decrease the total energy cost, our HEMS tries to utilize energy of the main grid by storing main grid's electricity in ESS at low price times such as 0 A.M., 1 A.M., 2 A.M. as shown in Fig. 8. This cheap energy will be used for home devices at high price time such as from 8 A.M. to 9 A.M. and from 9 A.M. to 10 A.M. (Fig. 9) or to sell to the outside at high price time such as from 7 A.M. to 8 A.M. and from 10 A.M. to 11 A.M. (Fig. 10).

Secondly, as illustrated by Fig. 11, most of the energy generated from RES is used for home devices for two reasons: The first reason is that RES generates energy at high price times. Hence, immediately using it for home devices is better than storing it in ESS. Furthermore, storing RES energy to ESS and discharging later lead to lose of energy due to round-trip efficiency. The second reason is that the amount of energy generated by RES is smaller than energy needed by home devices in all time slots. In this case, our HEMS prefers using it for home devices to storing it in ESS.

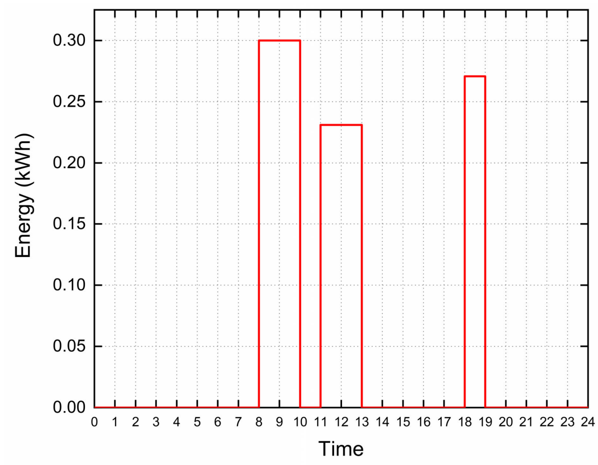

FIGURE 9. Hourly ESS energy used for home load.

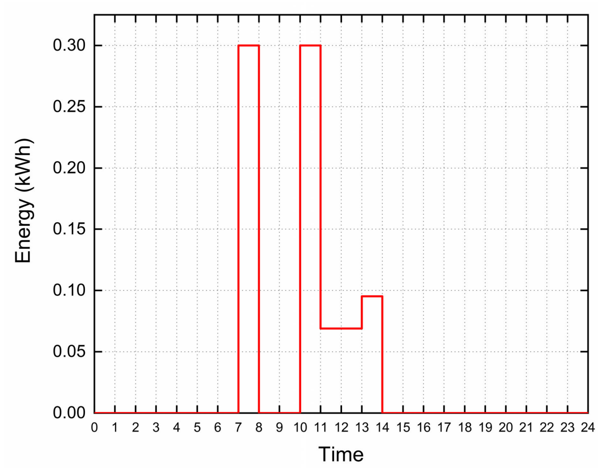

FIGURE 10. Hourly ESS energy used for selling.

TABLE 6. Schedule of the shiftable appliances.

Load Type	Appliances	Daily Usage (Hours)	Start Time
Shiftable	Washing machine	5	7 P.M.
	Air conditioner	10	2 P.M.
	Clothes dryer	4	7 P.M.
	Water heater	8	4 P.M.
	Dish washer	3	7 P.M.

Finally, Table 6 shows the schedule of each shiftable appliance which is the useful result of our algorithm. Our HEMS schedules our appliances to operate at low price time. With this schedule, we have hourly energy needed by home appliances (red line) and hourly load demand of our system from the main grid (blue line) at each time as shown in Fig. 12.

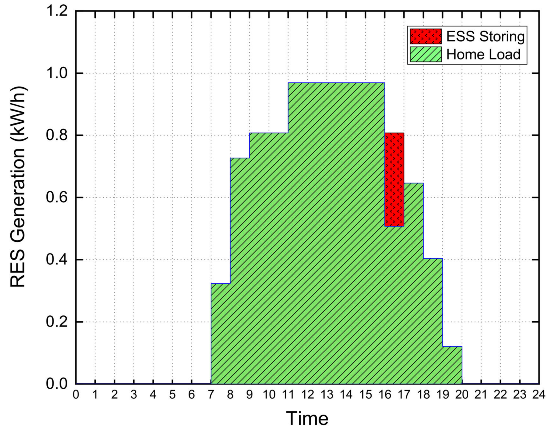

FIGURE 11. RES energy used for ESS storing and home load.

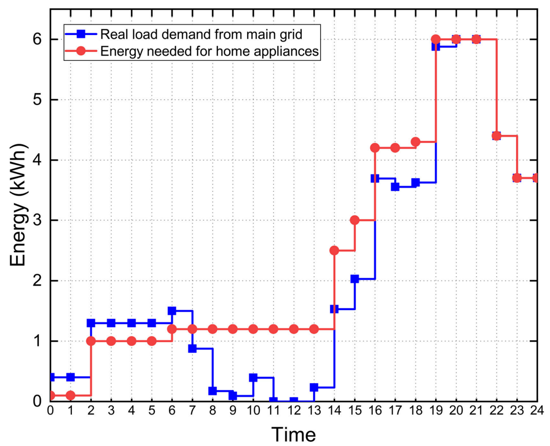

FIGURE 12. Hourly load demand from main grid.

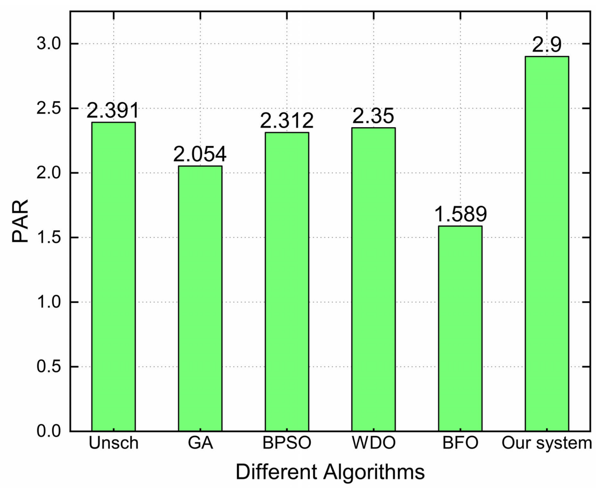

FIGURE 13. PAR of different algorithms [3].

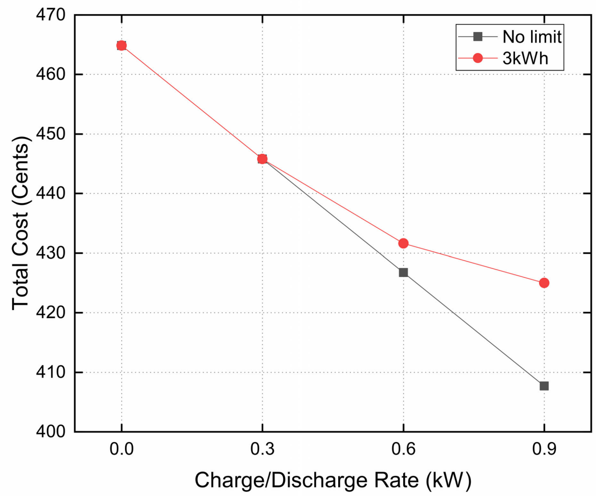

FIGURE 14. Average total energy cost with different Ch_{rate}/Dh_{rate} and capacity of ESS.

In detail, at low price time such as 7 P.M., 8 P.M., and 9 P.M., our system uses a lot of energy from the main grid for home devices. Moreover, at time from 0 A.M. to 7 A.M., because of utilization of cheap energy from the main grid, the load demand from the main grid is bigger than the energy which is required by the home appliances. Whereas, the need of energy of the main grid is very small at high price time such as 7 A.M., 8 A.M. because of the support of RES and ESS. Even our HEMS does not need energy of the main grid at time from 11 A.M. to 1 P.M since our ESS and RES have sufficient energy for home load at these time slots.

In summary, above three main factors make total energy cost of our system drop significantly. However, because we only focus on minimizing the energy cost, the average PAR of our system in this case is higher than algorithms of [3] as illustrated in the Fig. 13. There is a trade-off between decreasing the total energy cost and reducing the system's PAR. We thus try to balance these values in multi-objective optimization section.

2) OUR SYSTEM WITH DIFFERENT ESS

In this subsection, we consider the effects of Ch_{rate}/Dh_{rate} and capacity of ESS on minimizing the energy cost. Fig. 14 and Table 7 show the average total energy cost of our system with different Ch_{rate}/Dh_{rate} and ESS capacity when we run our simulation with same PSO parameters as shown in Table 3.

As shown in Table 7, the total energy cost has a steady decrease with increasing Ch_{rate}/Dh_{rate}. In particular, with 3 kWh of ESS capacity, average total energy cost is 431.61 cents and 425 cents for 0.6 kW and 0.9 kW of Ch_{rate}/Dh_{rate} respectively. Compared with total energy cost of $Ch_{rate}/Dh_{rate} = 0.3$ kW, the average energy cost of our system is reduced slightly by 3.2% and by 4.7%. Assuming that ESS has an infinite space to store energy (no limit), we get maximum benefit from increasing Ch_{rate}/Dh_{rate} parameter with a remarkable drop to 4.3% and 8.5% for 0.6 kW and 0.9 kW of Ch_{rate}/Dh_{rate} respectively. In addition, from results of our simulation, ESS capacity required to store enough energy is around 4 kWh and 6.5 kWh respectively. We get these results because with bigger Ch_{rate}/Dh_{rate} we can

TABLE 7. Average total energy cost with different Ch_{rate}/Dh_{rate} and capacity of ESS.

Ch_{rate}/Dh_{rate}	ESS capacity	average cost	average PAR
0.0 kW	-	464.84 cents	2.92
0.3 kW	3 kWh	445.78 cents	2.90
0.6 kW	3 kWh	431.61 cents	2.83
	no limit	426.74 cents	2.75
0.9 kW	3 kWh	425 cents	2.80
	no limit	407.69 cents	2.64

TABLE 8. Average total energy cost with different selling prices.

α	max energy cost	min energy cost	average energy cost
1	303.01 cents	297.76 cents	301.66 cents
0.9	311.86 cents	306.07 cents	309.44 cents
0.8	322.53 cents	316.08 cents	318.57 cents

store more energy of the main grid at low price time slot and use it for higher price time slot. Furthermore, Table 7 shows a trend to decrease PAR of our system when the Ch_{rate}/Dh_{rate} is increased.

The increasing of Ch_{rate}/Dh_{rate} helps to considerably decrease the average total energy cost of our system. However, to get maximum benefit from this increase, we must have an ESS with sufficient capacity to store energy.

3) OUR SYSTEM WITH SMALLER SELLING PRICE

In this subsection, the effect of smaller selling prices on total energy cost is considered. If energy generated from RES is always smaller than load demand of home appliances and selling price is smaller than price of the main grid at all time during a day, no energy should be sold to the outside. Hence, for this subsection, the area of solar cells is doubled to double the amount of RES energy at all time slots. To store all energy from RES, our ESS has $Ch_{rate}/Dh_{rate} = 0.9$ kW and its capacity is always enough to store energy from RES and the main grid (no limit). Table 8 shows the average total energy cost of our system with $\alpha = 1$, $\alpha = 0.9$ and $\alpha = 0.8$. It means that we consider three cases with $P_{sell}(t) = P_{MG}(t)$, $P_{sell}(t) = 0.9 \times P_{MG}(t)$, and $P_{sell}(t) = 0.8 \times P_{MG}(t) \forall t$ respectively.

With double amount of energy from RES, our average energy cost decreases by 26% from 407.69 cents (Table 7) to 301.66 cents (Table 8). In addition, the average energy cost of our system is increased when selling price is decreased. In particular, if selling price $P_{sell}(t)$ is reduced by 10%, the average energy cost rises to around 2.6%.

To see how our HEMS utilizes the RES energy and energy of the main grid in this case, we analyze an output of the best case of our simulation with $\alpha = 0.9$ as shown in Fig. 15, Fig. 16, Fig.17 and Fig. 18.

As depicted in Fig. 15, at peak-price time from 7 A.M. to 11 A.M., most of energy generated by RES is used for home load. Because RES energy is larger than energy demand from home devices at time from 8 A.M. to 11 A.M., the surplus energy is lost. The lost energy can not be stored in ESS because ESS is set to discharge mode. With this mode, energy from ESS can only be drawn out to sell to the outside at

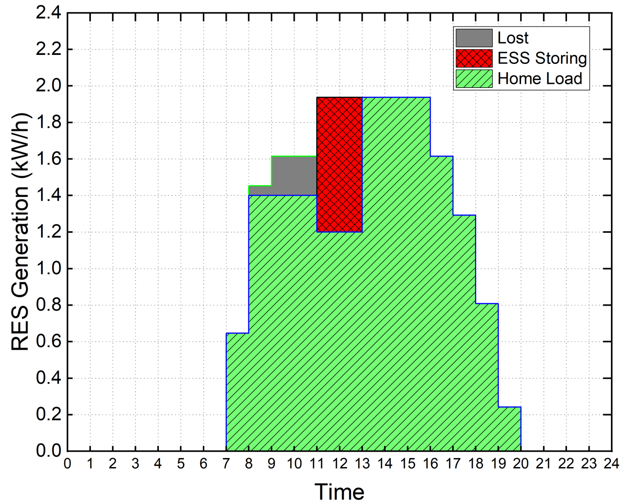

FIGURE 15. Hourly RES energy with double area of solar cells.

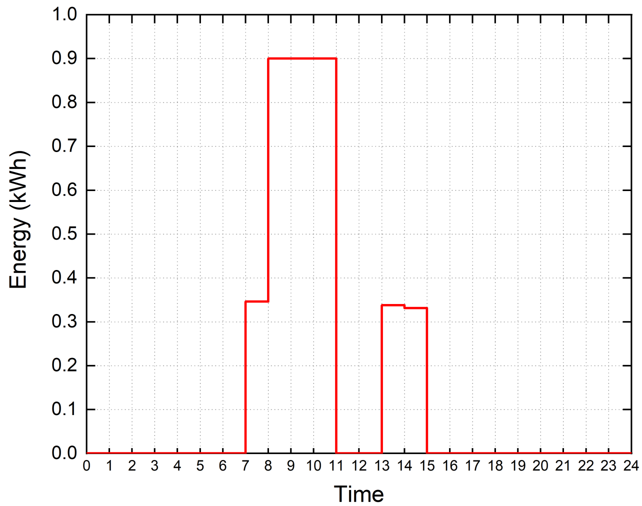

FIGURE 16. Hourly selling energy with double area of solar cells.

time from 7 A.M. to 11 A.M. (Fig. 16) or for home load at time from 7 A.M. to 8 A.M. (Fig. 17). It is worth noting that energy stored in ESS comes from two sources: energy from RES and energy of main grid at low price time (Fig. 18). With the support of cheap energy, the selling energy is maximum with 0.9 kWh at time from 8 A.M. to 11 A.M.

At time from 11 A.M. to 1 P.M., ESS is set to the charge mode after selling. With this mode, the surplus energy of RES, after providing for home load, is stored in ESS. At these time slots, the selling energy and ESS energy for home load are zero because ESS energy can not be discharged. At time from 1 P.M. to 3 P.M., ESS is set to the discharge mode. Hence, ESS energy can be drawn to sell to the outside and provide for home load again as shown in Fig. 16 and Fig. 17, respectively.

B. CASE 2: MULTI-OBJECTIVE OPTIMIZATION

PAR describes the behavior of the consumer's home load and it affects the operation of the main grid. As described

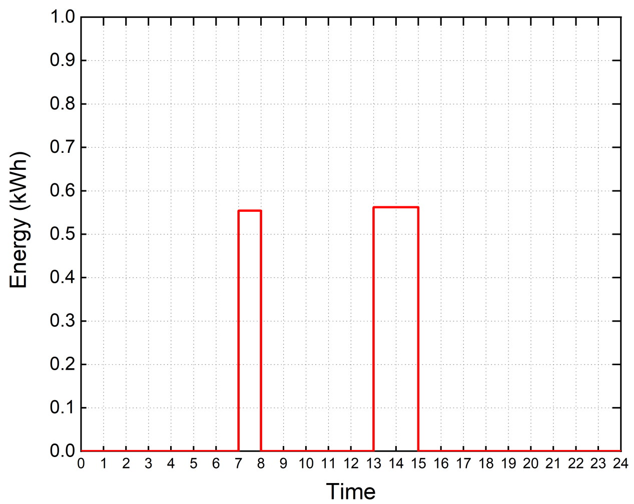

FIGURE 17. Hourly ESS energy for home load with double area of solar cells.

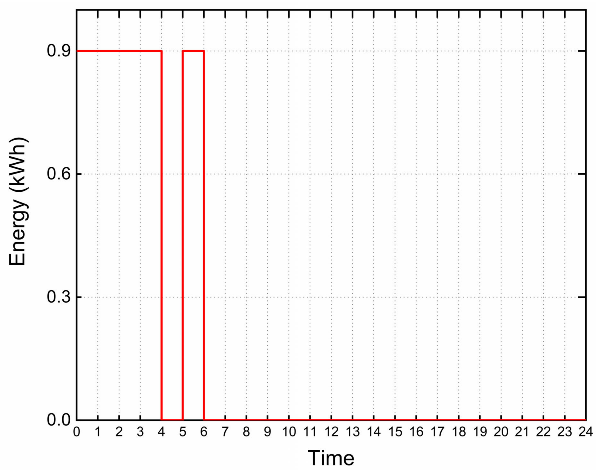

FIGURE 18. Hourly energy of the main grid stored in ESS with double area of solar cells.

in previous section, when we only focus on minimizing the total energy cost, our system's PAR remains very high as shown in Fig. 13. To solve this problem, we try to minimize two aspects: total energy cost and PAR at the same time. By using weight method of multi-objective optimization (MOO), we have a new objective function.

$$min(w_1 \times C_{day} + w_2 \times PAR) \tag{41}$$

where C_{day} is calculated by (34) and w_1 is the weight of variable C_{day} and is a constant. PAR is calculated by (36) and w_2 is the weight of variable PAR and is also a constant.

The input parameters of our simulation are the same as the single-objective optimization (SOO). Because of the complicated objective function, the running time of our simulation is slightly increased to 11.5 minutes. In this section, w_2 is set to a value bigger than the value of w_1 with the hope that PAR is decreased while C_{day} is increased to acceptable value. In our

TABLE 9. Average PAR and total energy cost with different w_2.

w_1, w_2	average PAR	average energy cost
$w_1 = 1, w_2 = 10$	2.396	472.69 cents
$w_1 = 1, w_2 = 20$	2.076	496.84 cents
$w_1 = 1, w_2 = 30$	2.019	517.02 cents

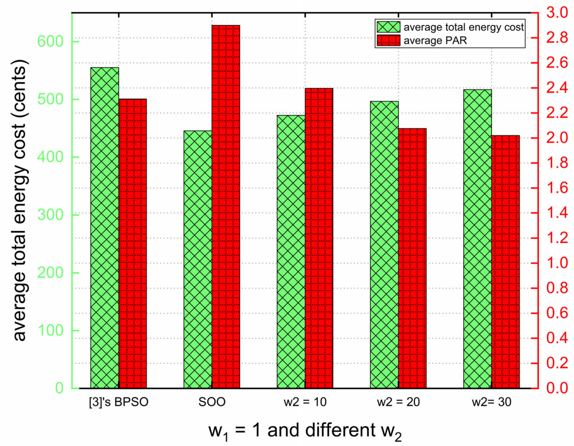

FIGURE 19. Average PAR and average energy cost with different w_2 and other algorithms.

simulation, we keep $w_1 = 1$ and change w_2 to achieve the PAR we desire.

Fig. 19 and Table 9 show the average total energy cost and average PAR of our system in 3 cases: ($w_1 = 1, w_2 = 10$), ($w_1 = 1, w_2 = 20$), and ($w_1 = 1, w_2 = 30$). A steady decrease in average PAR and a gradual increase in average total energy cost were observed with increasing w_2.

More specifically, with ($w_1 = 1, w_2 = 10$), average PAR of our system is 2.396, a decrease of 17.4% whereas we have a 6% increase in average energy cost, as compared with average PAR and total energy cost of our system in the SOO case. In this case, we still have higher average PAR than [3]'s BPSO algorithm. With ($w_1 = 1, w_2 = 20$), average PAR of our system is 2.076, a decrease of 28.4% compared with PAR of our system in the SOO case whereas our system's average total energy cost is only 496.84 cents. Compared to PAR and total energy cost of [3]'s BPSO algorithm, these values of our system is remarkable. By using MOO, our system has better performance in both elements: PAR and total energy cost. Our average PAR is smaller than the PAR of [3]'s BPSO algorithm by approximately 10.2% and our average energy cost is smaller than the energy cost of [3]'s BPSO algorithm by approximately 10.5%.

Table 10 shows the schedule of shiftable appliances in MOO best case of our system with $w_2 = 20$. The proposed HEMS schedules the appliances at appropriate time to decrease the PAR. It is worth noting that there is a big difference with the schedule of our appliances in SOO case (Table 6). From this schedule, we have hourly energy which is needed by home appliances and hourly load demand of our system from the main grid as shown in the Fig. 20.

TABLE 10. Schedule of the Shiftable appliances in MOO best case with $w_2 = 20$.

Load Type	Appliances	Daily Usage (Hours)	Start Time
Shiftable	Washing machine	5	1 A.M.
	Air conditioner	10	2 P.M.
	Clothes dryer	4	0 A.M.
	Water heater	8	4 P.M.
	Dish washer	3	3 P.M.

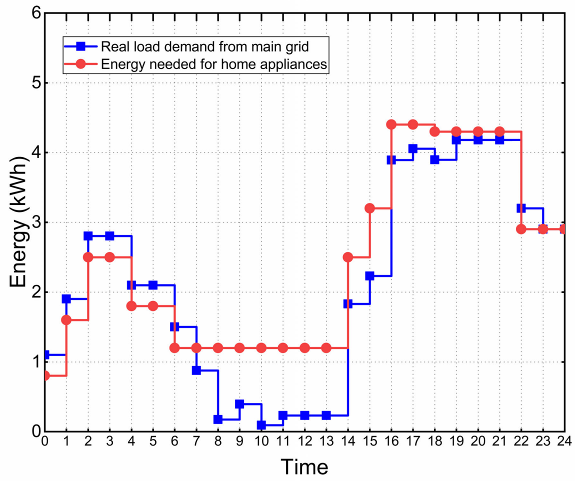

FIGURE 20. Hourly load demand of MOO best case from main grid with $w_2 = 20$.

As depicted in this figure, the biggest energy needed from the main grid is approximately 4.2 kWh from 7 P.M. to 8 P.M. and this value is spread through many time slots. This is a significant decrease as comparing with the biggest load demand of SOO case of 6 kWh in the Fig. 12. This result is the main reason help our system's PAR to decrease. At peak hours such as from 4 P.M. to 6 P.M., with the support of RES and ESS, the load demand from main grid also goes down, compared with energy needed for home appliances. This support also makes our PAR decrease.

VII. CONCLUSIONS AND FUTURE WORKS

This study presented a new HEMS with integration of RES and ESS. Our objective was to minimize energy cost and PAR of our system during a day. The algorithms we used in our system were the combination of PSO and BPSO. Our HEMS is able to utilize electricity of the main grid at low price time to provide for home appliances at high price time with the support of ESS and RES. In addition, our HEMS support selling electricity to the outside. To achieve our objective, we built general mathematical formulas for energy cost and PAR and evaluated our HEMS by performing extensive simulations. With new functions, energy cost of our HEMS was significantly reduced to 19.7%, as compared to previous results of BPSO algorithms in [3]. However, when our system only focuses on the minimization of energy cost, PAR of our system remains very high. In order to reduce PAR, we used the weighted method of MOO to minimize both energy cost and PAR. Simulation results showed that, with appropriate values of weight constants w_1, w_2, energy cost and PAR of our system can be decreased to values smaller than both energy cost and PAR of BPSO algorithm in [3]. In particular, with $w_1 = 1, w_2 = 20$, both energy cost and PAR of our system were reduced by approximately 10%. In terms of ESS parameters, simulation results also show that there is considerably reduction when Ch_{rate}/Dh_{rate} and the capacity of ESS are increased. Energy cost of our system was reduced by 4.3% and 8.5% with 0.6 kW and 0.9 kW of Ch_{rate}/Dh_{rate} respectively and ESS must have sufficient capacity to store energy.

With development of HEMSs, user-mode energy management architecture in global scale is suggested for SG [26]. Its main responsibilities are to maintain energy efficiency and energy reliability under uncertain electricity generation and demand of prosumers. In future, our HEMS need to cooperate with this system to improve operations of SG.

In our future system, besides electricity cost and PAR, user comforts, such as thermal comfort and consecutive tasks, will also be considered. Real-time optimization is another way to improve our system. With this technology, our system can be optimized with real-time usage data.

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