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A Cost-Effective Optimization for Scheduling of Household Appliances and Energy Resources

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ABSTRACT In literature, proposed approaches mostly focused on household appliances scheduling for reducing consumers' electricity bills, peak-to-average ratio, electricity usage in peak load hours, and enhancing user comfort level. The scheduling of smart home deployed energy resources recently became a critical issue on demand side due to a higher share of renewable energy sources. In this paper, a new hybrid genetic-based harmony search (HGHS) approach has been proposed for modeling the home energy management system, which contributes to minimizing consumers' electricity bills and electricity usage during peak load hours by scheduling both household appliances and smart home deployed energy resources. We have comparatively evaluated the optimization results obtained from the proposed HGHS and other approaches. The experimental results confirmed the superiority of HGHS over genetic algorithm (GA) and harmony search algorithm (HSA). The proposed HGHS scheduling approach outperformed more efficiently than HSA and GA. The electricity usage cost for completing one-day operation of household appliances was limited to 1305.7 cents, 953.65 cents, and 569.44 cents in the proposed scheduling approach for case I, case II, and case III, respectively and was observed as lower than other approaches. The electricity consumption cost was reduced upto 23.125%, 43.87% and 66.44% in case I, case II, and case III, respectively using proposed scheduling approach as compared to an unscheduled load scenario. Moreover, the electrical peak load was limited to 3.07 kW, 2.9478 kW, and 1.9 kW during the proposed HGHS scheduling approach and was reported as lower than other approaches.

INDEX TERMS Demand side management, demand response program, home energy scheduling, smart grid, metaheuristic algorithm.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The traditional power utility or grid is one-way or unidirectional in nature and utilities have no real-time information of electricity demand from consumers [1]. Therefore, information and communication technologies (ICT) implementation and advancement in technologies (e.g. Sensors, control

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systems, and instruments) enable transforming the traditional electric power grid into the next-generation electric power grid is also called a "smart grid" [2]. The European Commission defines a smart grid as: "A smart grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and those that do both in order to efficiently deliver sustainable, economic, and secure electricity supplies" [3]. Over the last decade, the integration of environment friendly and clean renewable energy sources (RESs) in power systems have become

necessary due to rising demand for electricity and global warming issues. The smart power grid introduces several new ideas, concepts, and technologies that enable the integration of RESs electricity generation in the power system. The most significant feature of smart power system technologies is mutual communication between utilities and consumers that helps to improve the reliability and efficiency of the smart power grid [4].

In order to meet consumers' electricity demand, a demand response (DR) program is applied to enhance the power system's operational efficiency and minimize electricity usage during peak load hours in residential areas. In the last decade, researchers have focused on demand side management (DSM) problems by making load demand sensitive to the electricity tariff in smart grid [5], [6]. Being engaged with environment friendly concerns and increasing demand for electricity, in the last decade, residential consumers have focused on the integration of RESs in their premises. The integration of the RESs on demand side can help the consumer to minimize the electricity bill by purchasing less electricity from the electric utility. Solar energy is one of the most popular RESs and electricity generation from it is available during the daytime and it does not assist to minimize the peak load demand without installation of an energy storage system (ESS) such as batteries [7], [8].

The residential sector usually contains three variant types of energy resources: utility, RESs energy output (mainly solar), and electric storage batteries. The proper management of available energy resources in the power system, both on the demand side and generation or supply side allows expanding the efficient use of electricity. In the context, a higher share of RESs energy generation in a smart home, the management of demand side integrated energy resources is recently becoming a critical issue. In recent decades, DSM problems (e.g. home energy scheduling) have attracted growing attention among the smart grid research community; more than 2000 research studies have been documented since the 1980s [9]. In literature, monetary incentive based various forms of DSM systems are being deployed by the utility for flexible electricity load flattening amongst residential consumers. The DSM system is a prominent component in the smart grid that encourages residential consumers to control electricity usage in their premises, through DR programs. In European countries and the United Kingdom, the DR programs have been explored since the 1970s [10], to enhance the power system operational efficiency and minimize electricity usage in residential areas during peak load hours.

The DR program utilizes an advanced metering infrastructure (AMI) based smart meter for two-way information flow amongst consumers and utility. The AMI based smart meters also facilitate utilities to control and change customers' electricity demands, and to achieve their main goals such as revenue protection and efficient electricity load management. Based on features DR programs are classified into two types such as price-based programs and incentive-based programs. Consumers gladly schedule the operation of

household appliances on their premises based on electricity tariffs in price-based programs. A grid utility can directly access and schedule the usage of household appliances by giving monetary benefits to consumers for controlling electricity usage during peak load hours [11], in case of the incentive-based DR programs. Both DR programs play a key role to enhance the operational efficiency of power systems as well as offer financial benefits to consumers by making load demand sensitive to electricity price signals.

B. LITERATURE REVIEW

In recent literature, numerous studies [12]–[28] have been documented, in which various forms of home energy management (HEM) system proposed for solving the home energy scheduling problem with attention to minimize consumer's electricity bill by utilizing DSM system features. In study [12], authors proposed a HEM system based on graph search algorithm - Dijkstra, in which to reduce a consumer's electricity bill during peak hours and computational efforts are considered as objective functions. In study [13], operations of household appliances have been optimally scheduled by considering the objective to reduce consumers' electricity bills and electricity usage during peak hours. In the above study, authors proposed a scheduling controller for the HEM system based on binary backtracking search algorithm (BBSA), under the user's priority and user's comfort constraints. In [14], HEM system architecture has been proposed for reducing peak-to-average ratio (PAR) and consumer's electricity bill based on genetic algorithm (GA). In [15], authors applied an approach for constructing a HEM system based on the fusion algorithm of particle swarm optimization (PSO) and harmony search algorithm (HSA) to schedule household appliances. In which objectives such as to minimize consumers' electricity bills and to meet user's comfort are considered. In [16], authors employed a hybrid of teacher learning based optimization (TLBO) and GA for modeling HEM systems to schedule household appliances with objectives such as reducing consumers' electricity bills and user discomfort. In study [17], Ozkan developed a real-time HEM system based on an appliance-based rolling wave planning (Ab-RWP) method. In real-time HEM system household appliances are scheduled based on user-defined priority order, for achieving the goals of reducing consumers' electricity bills and improving energy efficiency.

In [18], authors proposed an optimization approach using bat algorithm and flower pollination algorithm for modeling the HEM system with attention to reduce consumers' electricity bills and enhance user's comfort. Besides, authors also proposed fuzzy controllers to optimize the illumination system and electricity usage in heating/cooling. In [19], a meta-heuristic based model of the HEM system has been proposed by utilizing enhanced differential evolution (DE) and HSA to optimize the electricity consumption, enhance user comfort and reduce consumer's electricity bill and PAR under real-time pricing (RTP) electricity tariff. In [20], authors proposed a two-tier HEM system model using earthworm algorithm

and cuckoo search (CS) algorithm to optimize electricity consumption, enhance user's comfort, and reduce consumer's electricity bill and PAR in load demand. The first-tier scheduled household appliances and second-tier uncertainties during task execution are incorporated by the rescheduling of household appliances in the proposed HEM system. In [21], authors proposed four metaheuristic scheduling algorithms for modeling the HEM system to analyze cost efficiency of electricity consumption under critical peak pricing (CPP), day-ahead RTP, and inclined block rate (IBR) tariffs. In [22], the authors applied a hybrid of bird swarm algorithm (BSA) and CS algorithm and a multi-objective binary BSA for modeling the HEM system. In which objectives such as to reduce user discomfort, PAR in load demand, and consumer's electricity bill are considered. Besides, authors applied dynamic programming for coordination between household appliances to achieve real-time scheduling on user's demand. In [23], the HEM controller based on five metaheuristic algorithms is modeled to schedule the household appliances by enhancing user comfort and reducing consumer's electricity bill and PAR in load demand. In the above paper, metaheuristic algorithms such as GA, binary PSO, bacteria foraging algorithm (BFA), and a hybrid of wind driven optimization and GA have been evaluated under RTP electricity tariff to analyze objectives. In [24], authors proposed dynamic programming and two metaheuristic approaches GA and binary PSO for modeling the HEM system to schedule household appliances. Besides, authors also proposed a hybrid of PSO and GA to model the HEM system for smart home load scheduling. In the above paper, proposed approaches have been evaluated under day-ahead RTP and CPP electricity tariffs with attention to reduce electricity consumption in peak hours, consumer's electricity bills, and user's discomfort.

In [25], authors utilized the mixed integer linear programming (MILP) method to develop an energy management framework to facilitate the utility of a residential area for better managing demand and supply. In [26], authors proposed an approach for modeling HEM systems based on mixed integer nonlinear programming (MINLP), considering residential consumer's needs and ToU pricing. In the proposed model, a graphical user interface is provided for adjustments of day-ahead residential consumer's desired tasks, and household appliances are categorized based on task classification, i.e. environmental controlling tasks, energy-based tasks, and time-based tasks. In [27], authors applied MILP for modeling the HEM system by incorporating the value of lost load based operational priority in scheduling the household appliances. In the proposed model, authors considered operation constraints, electricity tariff model (e.g. IBR), and value of lost load based operational priority from a consumer perspective to schedule household appliances. In study [28], authors introduced an approach based on residential DR programs for modeling HEM systems to schedule appliances of various categories with attention to reduce consumers' electricity bills under the budget limit. In which MINLP and generalized benders decomposition (GBD) techniques and time-of-use

TABLE 1. Abbreviations.

Abbreviation	Algorithms and terms
Ab-RWP	Appliance-based rolling wave planning
ACO	Ant colony optimization
AMI	Advanced metering infrastructure
BBSA	Binary backtracking search algorithm
BFA	Bacteria foraging algorithm
BSA	Bird swarm algorithm
CPP	Critical peak pricing
CS	Cuckoo search
DE	Differential evolution
DER	Distributed energy resources
DR	Demand response
DSM	Demand side management
EA	Evolutionary algorithm
ESS	Energy storage system
EST	Earliest start time
GA	Genetic algorithm
GBD	Generalized benders decomposition
HEM	Home energy management
HGHS	Hybrid genetic-based harmony search
HM	Harmony memory
HMCR	Harmony memory consideration rate
HMS	Harmony memory size
HSA	Harmony search algorithm
IBR	Inclined block rate
LFT	Latest finish time
MILP	Mixed integer linear programming
MINLP	Mixed integer nonlinear programming
NREL	National renewable energy laboratory
PA-rate	Pitch adjustment rate
PAR	Peak-to-average ratio
PSO	Particle swarm optimization
PV	Photovoltaic
RESs	Renewable energy sources
RTP	Real time pricing
TLBO	Teacher learning based optimization
ToU	Time-of-use

(ToU) tariff are utilized. The abbreviations of different terms and methods are specified in Table 1.

In the recent decade, various studies [29]–[42] also have been documented to solve home energy scheduling problems for the smart home with only RESs integration, or both RESs and ESS integration. In study [29], authors proposed a hybrid of stochastic programming and robust optimization model for the HEM system by incorporating the uncertainties of solar photovoltaic (PV) electricity output and electricity tariffs. In the proposed model, the smart home is considered as a prosumer that participates in the real-time and day-ahead energy market to achieve maximum profit under consumer's comfort constraints. In study [30], an effective HEM system has been modeled based on a stochastic MILP framework to reduce consumers' electricity bills and the computational burden of the home energy scheduling problem. In the proposed model, the home is furnished with a solar PV module and ESS batteries, and various dynamic electricity pricing models such as ToU, RTP, and IBR are considered to alleviate consumers' electricity bills. In [31], authors proposed a mathematical model based on stochastic MILP to develop a HEM system for the smart home in which RESs and storage devices are integrated. A scenario-based stochastic modeling methodology is applied in the proposed model to reduce energy cost by considering the stochastic RESs electricity output, time-varying electricity tariffs, weather conditions, household appliances energy usage pattern, ESS capacity, and real-time electric sales prices. The work presented in [32] proposes a HEM system model based on PSO to schedule the household appliances and ESS usage for reducing

consumers' electricity bills in a microgrid-connected smart home. In [33], authors developed HEM controllers based on ant colony optimization (ACO), binary PSO, and GA with considering objectives to reduce user's discomfort, consumer's electricity bill, and PAR of load demand. In [34], authors developed a hybrid method using GA and binary PSO to design a HEM controller. In study [35], authors designed a hybrid approach using GA and PSO for modeling HEM system by integrating RESs and ESS. In both studies, household appliances are scheduled by considering objectives to reduce PAR of load demand and consumer's electricity bill. In [36], authors applied a decomposed-weighted-sum PSO approach for modeling the HEM system by integrating RESs and ESS in smart homes. The proposed approach's ultimate objectives are to minimize net cost of energy, electricity usage during peak hours, and time-based user's discomfort. Besides, the authors also proposed an innovative approach for performance analysis of the applied metaheuristic algorithm. In [37], authors modeled the HEM system for scheduling household appliances under RTP and IBR electricity tariffs by integrating RESs and balancing demand and supply. The HEM system is based on the GA, binary PSO, and genetic wind-driven optimization to schedule household appliances with ultimate objectives such as reducing consumer's electricity bill and PAR in load demand.

In [38], authors proposed a three-step simulation method based on a heuristic approach to design the HEM system for eco-efficient operations of the household appliances in a smart home by utilizing deployed RESs and ESS at home. In the proposed approach, household appliances have been scheduled to achieve objectives such as reduce the total cost of electricity, emission, and time-based user's discomfort. In [39], authors proposed the HEM system by considering the integration of RESs and ESS to reduce consumer's electricity bill in response to the ToU and CPP electricity tariffs by the scheduling of appliances. The proposed HEM system was designed using the earliglow algorithm with attention to reduce consumer's electricity bills, user waiting time, and PAR in load demand. In [40], authors developed an efficient HEM system based on MILP for scheduling the household appliances and optimally utilizing the electric vehicles to reduce energy cost. In the proposed HEM system, RESs including wind turbine and solar PV module and ESS are deployed at home for balancing demand and supply with attention to reduce electricity load burden on utility, PAR in load demand, and consumer's electricity bill in response to the RTP electricity tariff. In [41], authors applied three metaheuristic algorithms including binary PSO, GA, and CS to design a HEM system for efficient scheduling of household appliances by considering RESs integration. In the above study objectives such as to reduce electricity consumption in peak hours and consumers' electricity bills in response to the ToU tariff are considered. In [42], authors developed various DSM models based on metaheuristic algorithms for managing electricity consumption and user comfort to human preferences. In the proposed model, authors aim to handle the

uncertainty of RESs electricity output and efficient utilization of ESS. The ultimate objectives of the proposed model are to handle the integration of RESs and reduce carbon emission, PAR in load demand, user discomfort, and consumer's electricity bill.

In the research literature, proposed approaches mostly have focused on scheduling of household appliances for modeling HEM systems with the primary objective to reduce consumer's electricity bills. Although home energy scheduling problems have been addressed in literature, there are still research gaps in the power system field (e.g., the scheduling of smart home deployed energy sources). In studies [34], [35], authors have focused on scheduling of household appliances with objectives such as to reduce consumers electricity bill and PAR of load demand. However, to reduce electricity usage during peak load hours and scheduling of smart home deployed energy resources are ignored in these studies.

C. CONTRIBUTIONS AND STRUCTURE OF PAPER

The metaheuristic algorithm at the core of the HEM system plays a significant role to exploit flexibility for the scheduling of household appliances. In the context of the residential sector demand side problems (e.g., home energy scheduling problem), to propose an efficient metaheuristic approach for modeling the HEM system is still needed, which contributes to minimizing the residential consumers' electricity bills. Moreover, the HEM system should be capable of exploiting flexibility for scheduling the operations of household appliances and deployed energy resources such as utility power, RESs power output, and ESS batteries. This work is an extension of [43], our conference paper already published and has the following knowledge contributions in academic research.

- We have designed a new hybrid genetic-based harmony search (HGHS) approach, in which the local search capability of HSA is improved by integrating it with GA.
- We have proposed the HGHS approach for modeling the HEM system to reduce consumer's electricity bill and electricity usage in peak load hours through scheduling the operation of household appliances and deployed energy resources in consumers' premises with maximum utilization of RESs power output.

The rest of this paper is structured as follows: The proposed system formulation is given in section II. In section III, we have briefly explained the proposed approach. Section IV presents simulation results obtained from the proposed approach and finally, concluding remarks are written in the last section.

II. PROPOSED SYSTEM FORMULATION

The proposed HEM system is for a typical home furnished with n household electrical appliances. It assumed that $A = \{a_1, a_2, \dots, a_n\}$ represents a set of household appliances, which are classified into inflexible appliances and flexible appliances. In the research literature, inflexible appliances (e.g., interior lighting) are referred to as baseline

TABLE 2. Nomenclature.

Symbol	Description
A^{pv}	Area of solar PV module (m^2)
A^{wt}	Rotor swept area of wind turbine (m^2)
β	Array efficiency temperature coefficient
δ	Time interval duration (h)
EE_t^{ess}	Electrical energy in ESS at timeslot t (kWh)
EP_t^{ch}	Electrical power storage charge rate at timeslot t (kW)
EP_t^{dch}	Electrical power storage discharge rate at timeslot t (kW)
EP_t^{grid}	Electrical power consumed from power grid in timeslot t
EP_{total}^{grid}	Total electrical power consumed from power grid per day
EP_t^{load}	Electrical load demand at timeslot t
EP_{total}^{load}	Total electrical load demand of household per day
EP_t^{pv}	Electrical power (kW) output of solar PV module at timeslot t
EP_t^{res}	Electrical power (kW) output of RESs at timeslot t
$EP_t^{res,max}$	Maximum electrical power (kW) output of RESs at timeslot t
EP_{total}^{res}	Total electrical power (kW) output of RESs per day
EP_t^{wt}	Electrical power (kW) output of wind turbine at timeslot t
EPC_t^{grid}	Cost of electricity consumed from power grid in timeslot t
EPC_{total}^{grid}	Total cost of electricity consumed from power grid per day
ER_a	Daily energy requirement for appliance a
η^{ess}	Electrical power storage charge/discharge efficiency
η^m	Module efficiency of solar PV
η^{pc}	Power conditioning equipment efficiency in solar PV module
η^{pv}	Power coefficient of solar PV module
η^{wt}	Power coefficient of wind turbine
I_b	Direct normal solar irradiance
I_d	Diffuse solar irradiance
I_t	Solar irradiance on a tilted surface (kW/m^2) at timeslot t
kW_g	Electrical power grid capacity (kW) at timeslot t
λ_t	Represents electricity RTP signal at timeslot t (cents/kWh)
R_b	Tilt factor for direct normal solar radiation
R_d	Tilt factor for the diffuse solar radiation
R_r	Tilt factor for the reflected solar radiation
ρ	Air density (Kg/m^3)
T_c	Solar PV cell temperature ($^{\circ}C$)
T_r	Reference temperature for solar PV cell efficiency
T_t^{out}	Outdoor temperature ($^{\circ}C$) at timeslot t
ε	Power rating (kWh)
ε_a	Power rating of household appliance a (kWh)
v_{in}	Cut-in wind velocity/speed (m/s)
v_{nom}	Nominal wind velocity/speed (m/s)
v_{out}	Cut-out wind velocity/speed (m/s)
v_t	Average wind velocity (m/s) at timeslot t

loads or real-time appliances. In a smart home, the flexible household appliances can be scheduled based on the proposed approach. The RESs including wind turbines and a solar PV module are integrated at home. The ESS is also installed in a home to reduce the peak load demand. The electricity is supplied from three energy resources such as a utility, RESs electricity generation, and ESS batteries to complete the operations of household appliances.

In the proposed HEM system model, the electricity consumption cost minimization is the main objective to reduce electrical peak load and minimum electricity purchase from the utility. On the other hand, to maximize the utilization of RESs power output is our goal. The RESs installation cost is not considered and RESs power output is free of cost. The subsections contain the mathematical formulation and description of RESs, ESS, proposed HEM system, household electrical load, and objective function. Moreover, we have considered RTP tariff signals for consumer's electricity cost calculation in this work.

A. RENEWABLE ENERGY SOURCES

We assumed that a standard wind turbine and solar PV module with an open rack array are installed in a smart home. For the 15th June, we obtained half-hour base solar PV module performance such as data solar irradiance (W/m^2)

and ambient temperature ($^{\circ}C$) and wind speed (m/s) for city Houston, Texas, U.S. from PVWatts® calculator designed by national renewable energy laboratory (NREL). The half-hour base solar irradiance, ambient temperature, and wind speed graphically are plotted in Figures 1, 2, and 3 respectively. The solar PV power output with area $A^{pv}(m^2)$ calculated by [44]:

$$EP_t^{pv} = \eta^{pv} \cdot A^{pv} \cdot I_t \cdot (1 - 0.005(T_t^{out} - 25)), \quad (1)$$

where, EP_t^{pv} is maximum electrical power (kW) generation of solar PV module at timeslot t, η^{pv} is power coefficient of solar PV module, A^{pv} is solar PV module area (m^2), I_t is solar irradiance on a tilted surface (W/m^2) and T_t^{out} is outdoor temperature ($^{\circ}C$) at timeslot t. The description of nomenclatures are specified in Table 2. Solar irradiance on a tilted surface I measured as [45]:

$$I = I_b \cdot R_b + I_d \cdot R_d + (I_b + I_d) R_r, \quad (2)$$

where, I_b and I_d represent direct normal solar irradiance and diffuse solar irradiance. R_b , R_d , and R_r represent a tilt factor for direct normal solar radiation, diffuse, and reflected solar radiation, respectively. The solar PV module efficiency η^{pv} defined as follows [45]:

$$\eta^{pv} = \eta^m \cdot \eta^{pc} [1 - \beta(T_c - T_r)], \quad (3)$$

where η^m represents module efficiency, η^{pc} represents power conditioning equipment efficiency, β represents array efficiency temperature coefficient, T_c represents cell temperature, and T_r is reference temperature for cell efficiency.

Wind turbine power output for a location depends on wind speed (velocity), wind turbine's rotor swept area, and air density. The total electrical power available in timeslot t from the wind turbine calculated as [46]:

$$EP_t^{wt} = 0.5 \cdot \eta^{wt} \cdot A^{wt} \cdot \rho \cdot v_t^3, \quad (4)$$

where EP_t^{wt} is maximum electrical power output of wind turbine (kW) at timeslot t, η^{wt} is power coefficient of wind turbine, A^{wt} is rotor swept area of wind turbine (m^2), ρ represents air density (Kg/m^3), and v_t represents average wind velocity (m/s) at timeslot t.

The power output and performance curve of a wind turbine highly depends on the model. Therefore, wind turbine system equation modeling is strongly inclined by the wind turbine's electrical power curve. The electrical power output of wind turbine is based on both cut-in speed v_{in} and cut-out speed v_{out} in the model [45]:

$$EP_t^{wt} = \begin{cases} 0.5 \cdot \rho \cdot \eta^{wt} \cdot A^{wt} \cdot \min(v_t, v_{nom})^3, \\ \forall t : v_{in} \leq v_t \leq v_{out}, \\ 0, \\ \forall t : v_t \leq v_{in} \text{ and } v_t \geq v_{out}. \end{cases} \quad (5)$$

In our proposed model, the electrical power generation from RESs (EP_t^{res}) is the sum of electrical power generation from a solar PV module and wind turbine at timeslot t. The electrical power generation from RESs (EP_t^{res}) defined as:

$$EP_t^{res} = EP_t^{pv} + EP_t^{wt} \quad \forall t = 1 : T. \quad (6)$$

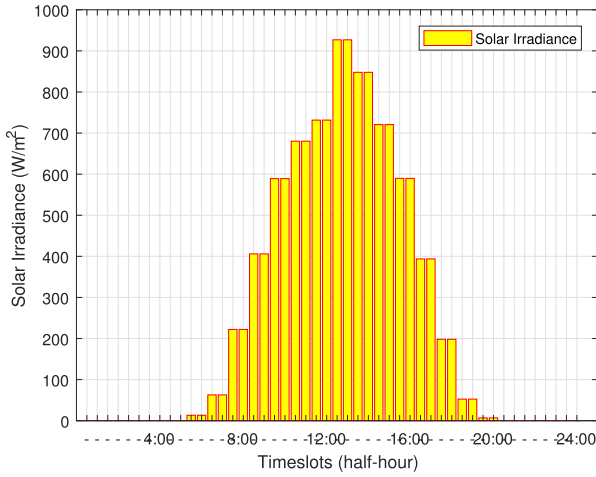


FIGURE 1. Forecasted solar irradiance.

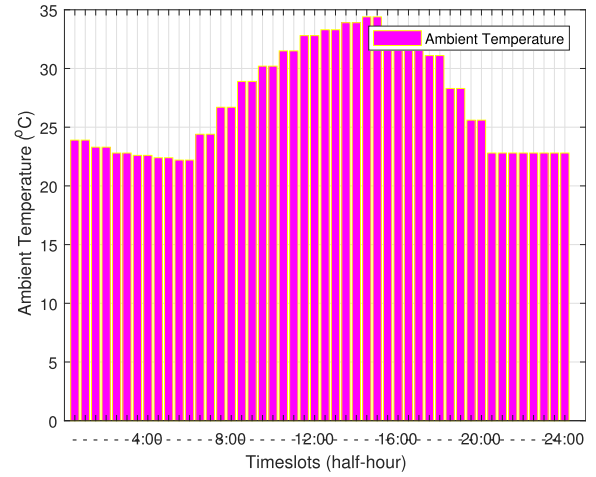


FIGURE 2. Forecasted ambient temperature.

Similarly, total electrical power generation from RESs for a day (EP_{total}^{res}) calculated by the following formula:

$$EP_{total}^{res} = \sum_{t=1}^T (EP_t^{pv} + EP_t^{wt}). \quad (7)$$

It is assumed that EP_{max}^{res} is the maximum electrical power generation capacity of RESs. The electrical power generation from RESs (EP_t^{res}) at timeslot t must be in the following range:

$$0 \leq EP_t^{res} \leq EP_{max}^{res} \quad \forall t = 1 : T. \quad (8)$$

B. ENERGY STORAGE SYSTEM

In the ESS, electrical energy stored during timeslot t based upon the rate of charging and discharged the batteries. Turn-around efficiency of ESS is considered to overcome the loss of electrical energy during the process of charging and discharging. The electrical energy storage level in ESS batteries at each timeslot t can be calculated as [44]:

$$EE_t^{ess} = EE_{t-1}^{ess} + \delta \cdot \eta^{ess} \cdot EP_t^{ch} - \frac{\delta \cdot EP_t^{dch}}{\eta^{ess}}, \quad (9)$$

where EE_t^{ess} is electrical energy storage level in ESS at timeslot t (kWh) and EE_{t-1}^{ess} is electrical energy storage level in ESS at timeslot $t-1$ (kWh), δ is time interval duration (h), η^{ess} is charge/discharge efficiency, EP_t^{ch} represents charge rate of electrical power (kW) at timeslot t , and EP_t^{dch} represents discharge rate (kW) at timeslot t .

Here, we assume that EE_{min}^{ess} and EE_{max}^{ess} are boundary limits of energy storage level in ESS batteries, respectively and EE_t^{ess} indicates the electrical energy storage level in ESS batteries at timeslot t ($t \in T$). The ESS batteries charging and discharging limits are defined by the manufacturer and model as [44]:

$$EP_t^{ch} \leq EP_{limit}^{ch}, \quad (10)$$

$$EP_t^{dch} \leq EP_{limit}^{dch}, \quad (11)$$

$$EE_{min}^{ess} \leq EE_t^{ess} \leq EE_{max}^{ess}, \quad (12)$$

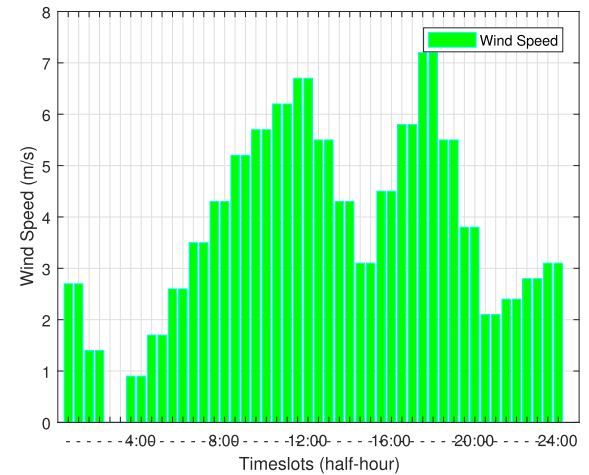


FIGURE 3. Forecasted wind speed.

where EP_{limit}^{ch} and EP_{limit}^{dch} are maximum limits of ESS charge rate and discharge rate. These ESS batteries limit support to maintain the storage and prevent damage and reduce the capacity of batteries. Let EE_{ini}^{ess} be the electrical energy storage level of ESS batteries at the beginning. So EE_t^{ess} electrical energy storage level limit in ESS batteries can be defined as $EE_{ini}^{ess} \leq EE_t^{ess} \leq EE_{max}^{ess}$. The initial EE_{ini}^{ess} electrical energy storage level is measured as $EE_{ini}^{ess} = EE_{min}^{ess}$ at the start of day. Furthermore, ESS batteries electrical energy storage level cannot exceed their capacity and should always be positive.

C. HOME ENERGY MANAGEMENT SYSTEM

We have assumed that the smart home mainly comprises HEM system, AMI based smart meter, household appliances, and main display panel. A wired home area network is utilized for two-way communication purposes between them. The predominant component is the HEM system, which is responsible to schedule the operations of household appliances following RTP tariff. It also controls the electrical power output of RESs and the condition of ESS in a smart

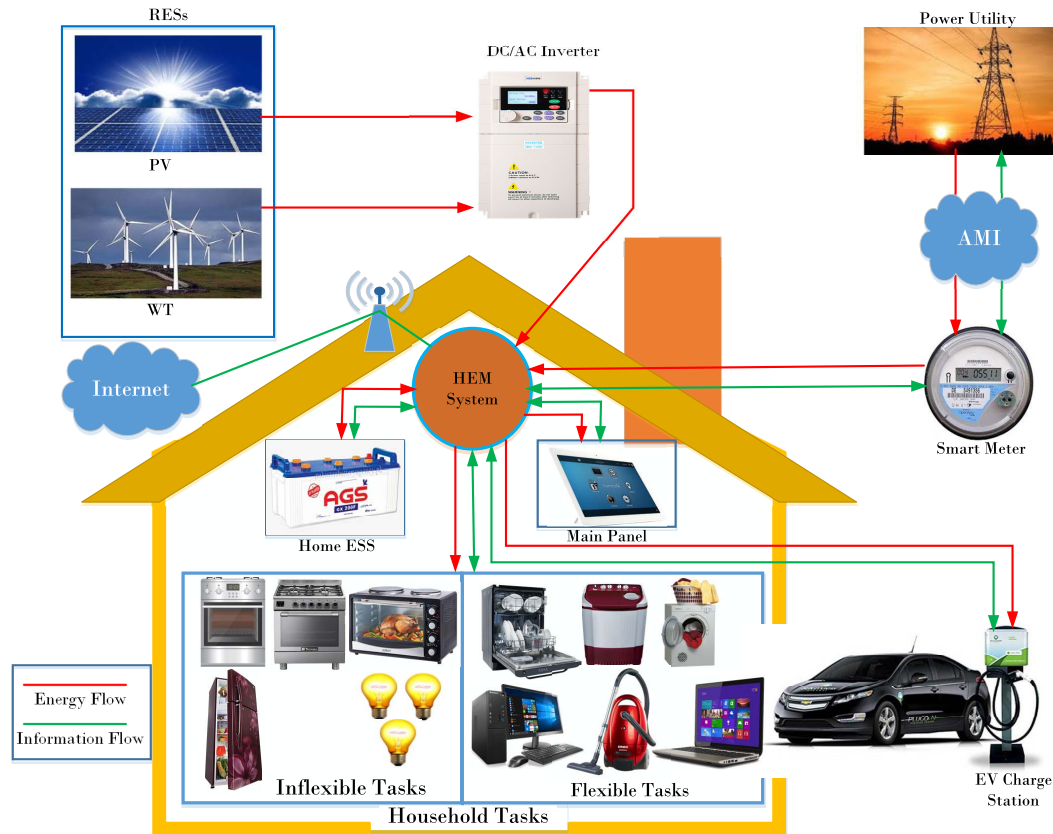


FIGURE 4. HEM system architecture.

TABLE 3. Power Rating of Household Appliances [47].

Appliance's Name	ϵ (kWh)	EST	LFT	Time window (h)	δ (h)
1 Dish washer	1	9	17	8	2
2 Cooker hob	3	8	9	1	1
3 Desktop	0.3	18	24	6	3
4 Vacuum cleaner	1.2	9	17	8	1
5 Electrical Vehicle (EV)	3.5	18	8	14	3
6 Cooker oven	5	18	19	1	1
7 Laptop	0.1	18	24	6	2
8 Microwave	1.7	8	9	1	1
9 Fridge	0.3	0	24	24	24
10 Interior lighting	0.84	18	24	6	6
11 Spin dryer	2.5	13	18	5	1
12 Washing machine	1	9	12	3	2

home to achieve the objective. To obtain feasible time for executing the operations of household appliances from the defined operation time window of individual appliances and shifting electrical load between power grid, RESs power output, and ESS based on a strategy to minimize the power usage cost are goals of the proposed HEM system. The proposed HEM system also offered features such as transmitting household appliances power consumption data to utility and receiving price-based DR signals for RTP tariff from utility through AMI based smart meter. It assumed that one day-ahead, a smart meter communicated RTP tariff-based DR signals from the utility to the HEM system. The Figure 4 contains a complete conceptual architecture of the proposed HEM system.

D. HOUSEHOLD ELECTRICAL LOAD

We have assumed that the one-day scheduling time period is divided into 48 half-hour time intervals (timeslots) $t \in T, \forall T = \{t_1, t_2, \dots, t_{48}\}$. The description of household appliances, their constant power ratings, operation time window, and usage hours per day are taken from [47] and shown in Table 3. It is assumed that ϵ_a represents the power rating of a household appliance and $\alpha_t = [0, 1]$ shows the ON/OFF status of household appliances. The smart home load demand per timeslot t (EP_t^{load}) for all household appliances defined as:

$$EP_t^{load} = \sum_{a \in A} \epsilon_a \cdot \alpha_t \quad \forall t = 1 : T. \quad (13)$$

Similarly, total smart home load demand per day (EP_{total}^{load}) for all household appliances defined as:

$$EP_{total}^{load} = \sum_{t=1}^T \left(\sum_{a \in A} \epsilon_a \cdot \alpha_t \right). \quad (14)$$

In the smart home, ESS batteries and RESs including a solar PV module and wind turbine are deployed as mentioned above. In case RESs electricity generation and electrical energy in ESS batteries are not enough to fulfill electrical load demand of a smart home, electricity is purchased from the utility to complete operations of household appliances. Therefore, the electrical energy purchased from utility in

timeslot t (EP_t^{grid}) to complete operations of household appliances is calculated as:

$$EP_t^{grid} = EP_t^{load} - EP_t^{res} \pm EE_t^{ess} \quad \forall t = 1 : T. \quad (15)$$

Similarly, total electrical energy purchased from utility per day (EP_{total}^{grid}) to complete the operations of household appliances can be calculated as:

$$EP_{total}^{grid} = \sum_{t=1}^T \left(EP_t^{load} - EP_t^{res} \pm EE_t^{ess} \right), \quad (16)$$

where EP_t^{load} is smart home load demand, EP_t^{res} is electrical power generation from RESs, and EE_t^{ess} is the electrical energy storage status in ESS batteries at timeslot t . EE_t^{ess} positive sign represents batteries charging and EE_t^{ess} negative sign means batteries are discharging. It assumed that λ_t represents electricity RTP tariff (cent/kWh) at timeslot t . The smart home electricity cost based on electrical energy purchased from utility in timeslot t (EPC_t^{grid}) can be calculated as:

$$EPC_t^{grid} = EP_t^{grid} \cdot \lambda_t \quad \forall t = 1 : T. \quad (17)$$

Similarly, the smart home consumer's electricity bill for electrical energy purchased from power grid per day (EPC_{total}^{grid}) can be measured as:

$$EPC_{total}^{grid} = \sum_{t=1}^T \left(EP_t^{grid} \cdot \lambda_t \right). \quad (18)$$

E. OBJECTIVE FUNCTION

In our proposed optimization scheduling approach, the objective function is expressed as:

$$\min f = \sum_{t=1}^T \left(\sum_{a \in A} \varepsilon_a \cdot \lambda_t \cdot \alpha_t \right), \quad (19)$$

subject to;

$$EP_t^{grid} \leq EP_t^{load} \leq (kW_g) \quad \forall t = 1 : T, \quad (20a)$$

$$\sum_{t=1}^T EP_t^{grid} \leq \sum_{t=1}^T EP_t^{load}, \quad (20b)$$

$$T_{min} \leq t \leq T_{max}, \quad (20c)$$

$$\varepsilon_a \cdot \alpha_t \geq 0 \quad \forall t = 1 : T, \quad (20d)$$

$$\sum_{t=1}^T \varepsilon_a \cdot \alpha_t = ER_a \quad \forall a \in A. \quad (20e)$$

The objective of our home energy scheduling problem is to reduce the cost of consumed electricity from the power utility, subject to constraints (20a-20e). The electrical power consumed from the power grid in timeslot t should be smaller than or equal to load demand for all household appliances at each timeslot, as described by constraint (20a). The total electrical energy consumed from the power grid per day should be smaller than or equal to load demand for all household appliances per day, as described by constraint (20b). According to the constraint (20c), timeslot t should be greater

than or equal to the minimum timeslot of T and smaller than or equal to the maximum timeslot of T . According to the constraint (20d), electricity usage of any household appliance in a particular timeslot t must be a non-negative value. Constraint (20e) imposed to make sure that household appliances can fulfill their one-day electrical needs.

III. PROPOSED APPROACH

In this section, first, we have shortly explained the original GA. Secondly, we have described the original HSA. Lastly, we have explained the proposed approach for modeling a HEM system to schedule the operations of household appliances and smart home deployed energy resources.

A. GENETIC ALGORITHM

The GA is an evolutionary programming based universal metaheuristic approach. In literature, the GA applied in numerous fields such as machine learning, pattern recognition, combinatorial optimization, functional optimization, scheduler, and optimization controller. The GA is influenced by mutation and crossover operators for finding a feasible solution to the optimization problem from the search space or available solutions. In the process of generating a new population, chromosomes (strings [0, 1]) are proficient to produce a new offspring (child) chromosome, and the crossover operator is applied on chromosomes to generate a new offspring chromosome. Generally, two parent's binary substrings are swapped based on selection of a one-point crossover operator for generating offspring (child). The mutation operator in GA randomly turns over bits based on a very small probability in chromosomes (strings [0, 1]). The mutation operator plays an important role in stabilizing the genetic diversity in the newly generated population. However, due to some deficiencies such as prematurity, high calculation time, and slow convergence speed, the GA may only promise to provide a local optimum solution to the optimization problem. In study [48], it perceived that merging the GA with EA considerably enhanced the efficiency of the hybrid approach.

B. HARMONY SEARCH ALGORITHM

The HSA is also an evolutionary programming approach and it is based on musician's behaviours such as memory-based or experience-based play, pitch adjusted play, and random play for finding the best harmony [49]. The initially produced harmony memory (HM) consists of some arbitrarily generated solutions and a harmony memory size (HMS) for under consideration optimization problems. At the initial stage, HM consists of a uniform distribution of upper and lower bounds of the optimization problem [49]. The search space gives a basis to arbitrarily produce the elements of new harmony. Mathematical it is formulated as follows:

$$x_{i,j} = l_j + \text{rand}().(u_j - l_j) \quad j = 1, 2, \dots, HMS, \quad (21)$$

where $x_{i,j}$ is the j^{th} element of harmony $x_i \in \{x_1, x_2, \dots, x_N\}$; l_j is lower limit and u_j is upper limit of the i^{th} search dimen-

sion. $rand()$ generates uniformly distributed of real numbers in $[0, 1]$ randomly.

In the next step, the improvisation process is started after the generation of the initial HM. On the basis of harmony memory consideration rate (HMCR) and pitch adjustment rate (PA-rate), a new harmony is generated by applying a random selection technique. The HMCR value is formulated as follows: [50]:

$$v_{i,j} = \begin{cases} x_{rnd,j} & rand() < HMCR, \\ l_j + rand(0, 1).(u_j - l_j) & else, \end{cases} \quad (22)$$

where $x_{rnd,j}$ represents the randomly selected harmony x_{rnd} of j^{th} element.

On the basis of PA-rate, the newly obtained elements of harmony in the above operation are changed with neighbors. It is defined as follows:

$$v_{i,j} = \begin{cases} v_{i,j} \pm rand(0, 1).bw_j & rand() < PA - rate, \\ v_{i,j} & else, \end{cases} \quad (23)$$

where bw_j represents bandwidth of j^{th} element.

In the above step, the value of the harmony vector $v_{i,j}$ is determined and assigned to the harmony vector x^{new} as follows: $x^{new} = v_{i,j}$. A comparison is conducted between harmony vector x^{new} and harmony vector x^{worst} . If harmony vector x^{new} is better than old harmony vector x^{worst} , in that case, harmony vector x^{new} is added in HM and old harmony vector x^{worst} is removed from HM.

C. PROPOSED APPROACH TO MODEL HOME ENERGY MANAGEMENT SYSTEM

A hybrid approach is one of the well-known and efficient strategy for improving the optimization performance of algorithms, in which good features of an algorithm are combined with other optimization methods. In recent literature, various studies have been documented for improving optimization performance of algorithms based on hybrid approaches. In study [51], authors have proposed a hybrid approach for household appliances electric load forecasting using a convolutional neural network (CNN) and long short-term memory (LSTM). The similar hybrid approach is applied in study [52] for forecasting the electricity tariff and household appliances electric load.

In the original HSA, the new harmony is randomly generated based on HMCR and PA-rate by considering an available solution vector (set of solutions) instead of only two parents as in GA. However, sometimes the random approach does not guarantee efficacious new solutions, and in that case, HSA may not generate convenient harmony. The algorithm's efficiency can be enhanced by tuning its parameters and/or hybridizing it with features of another optimization algorithm. Chromosomes in GA and Harmony in HSA and populations in GA and HM in HSA have similar behaviors for finding a feasible solution to the optimization problem.

In this research work, we proposed HGHS through appropriate integration of harmony in HSA with chromosomes

Algorithm 1 HGHS

```

1 Parameters initialization: problem size (dimension) or
  number of control variables (N), HMCR HMS, PA-rate
  and bandwidth bw distance;
  /* HM initialization */
2 for j = 1:HMS do
3   for i = 1:N do
4     |  $x_{i,j} = l_j + rand(0, 1).(u_j - l_j)$ ;
5   end
6 end
7 while Criteria is not met do
8   for j = 1:HMS do
9     | Fitness evaluation of individual harmony in HM;
10  end
11 Find the worst vector  $x^{worst} \in HM$ ;
12 for i = 1:N do
13   | /* memory consideration */
14   | if  $rand() < HMCR$  then
15     |  $v_{i,j} = x_{rnd,j}$ , where  $j \in (1, 2, \dots, HMS)$ ;
16     | /* pitch adjustment */
17     | if  $rand() < PA - rate$  then
18       |  $v_{i,j} = v_{i,j} \pm rand(0, 1).bw_j$ ;
19     end
20   else
21     | /* random selection */
22     |  $v_{i,j} = l_j + rand(0, 1).(u_j - l_j)$ ;
23   end
24    $x^{new} = v_{i,j}$ ;
25   /* Update HM */
26   if  $f(x^{new}) < f(x^{worst})$  then
27     |  $x^{new}$  included in HM;
28     |  $x^{worst}$  excluded from HM;
29   end
30   /* GA crossover operator and
31   mutation operator */
32   Select harmonies as parents for GA from HM;
33   Generate new (population) HM via Crossover and
34   mutation;
35 end

```

of GA and HM of HSA with the population of GA. The proposed approach is applied for modeling the HEM system to schedule operations of household appliances and integrated energy resources. The main procedure of the new algorithm begins with parameter initialization including population size, HMS, generations, number of iterations (NI), random bandwidth (bw) distance, and probability of mutating HM, crossover, HMCR, and PA-rate. In the next step, the fitness of each harmony in HM is evaluated and the worst vector x^{worst} is identified in HM. The optimization performance and convergence speed of the HSA are controlled by HMCR and PA-rate. Based on HMCR and PA-rate values, the new harmony vector x^{new} elements are selected randomly in the

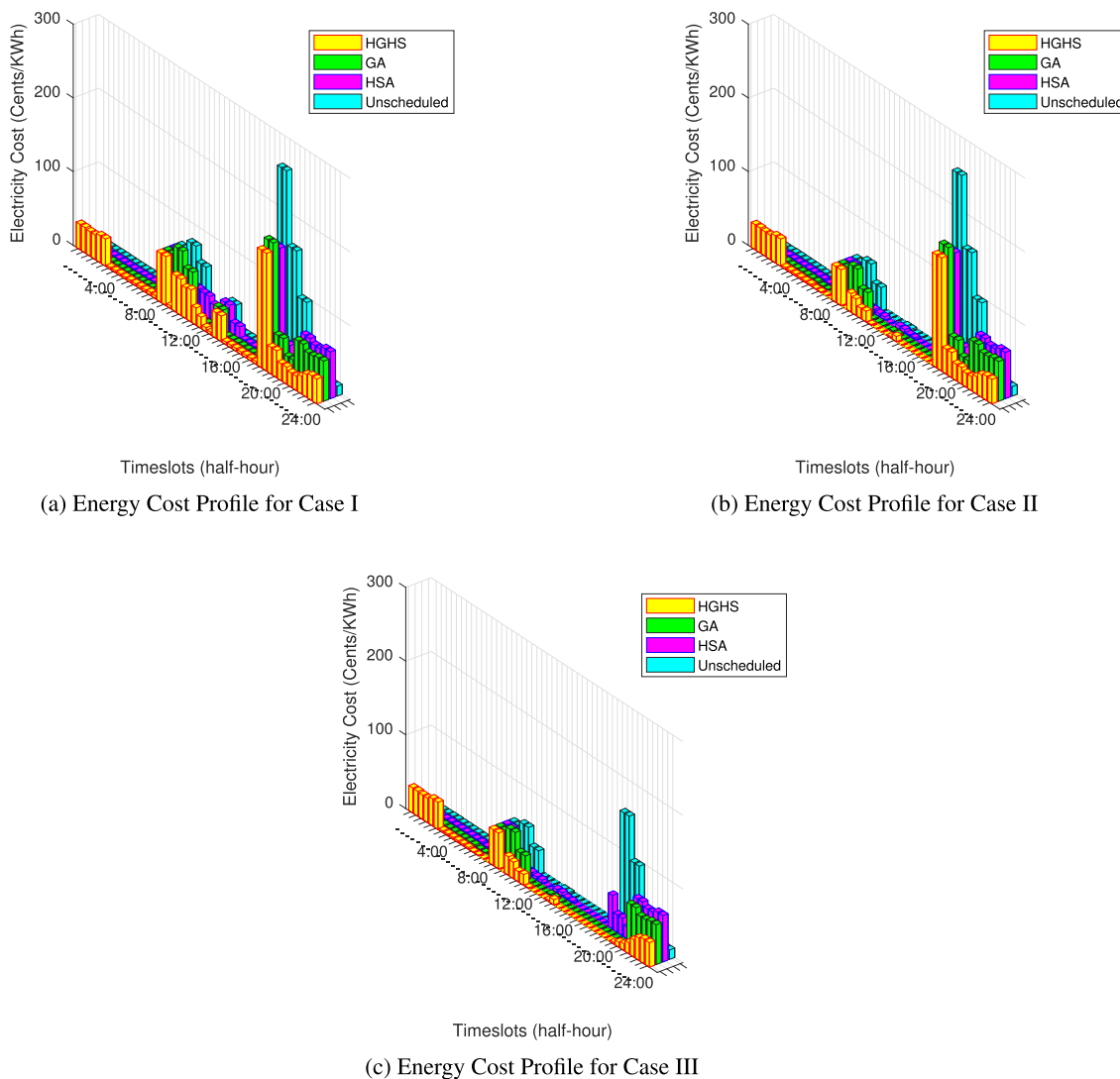


FIGURE 7. Smart home energy cost profile.

PV module are accurate. The wind turbine and solar PV module electrical power output tolerate a mean absolute error of 10% of the estimated power output in any timeslot t of the installed capacity for power production. One-third of the remaining 90% electricity is consumed for charging ESS batteries, which are utilized during peak load hours to minimize electricity consumption cost and electrical peak load. Two-third of the remaining 90% electricity is instantly consumed to complete scheduled operations of household appliances. The electricity from the utility is available as a backup all the time to complete operations of household appliances if the smart home estimated load demand did not fulfill from RESs electrical power output and ESS batteries. In the ESS, most advanced technology based deep-cycle and lead-acid batteries are used because of their efficiency, high reliability, and low cost. Although, these batteries have a relatively small volume of energy storage as compared to other types of batteries [53].

In this work HEM system is modeled by implementing the proposed HGHS load scheduling algorithm, GA and HSA in MATLAB R2017a. The simulation results are obtained by executing proposed HGHS, GA, and HSA on Intel Core-i5 CPU and 8GB memory-based computer. The following cases are considered to measure the performance and effectiveness of the proposed hybrid approach:

- Case I, home without RESs and ESS deployment
- Case II, home with only RESs deployment
- Case III, home with both RESs and ESS deployment

A. ELECTRICITY CONSUMPTION COST

The simulation results about electricity usage cost for the above mentioned three cases are described here. In case I, the electricity consumption cost profiles of scheduled loads based on the proposed HGHS, GA, and HSA load scheduling algorithms and unscheduled load are plotted in Figure 7a.

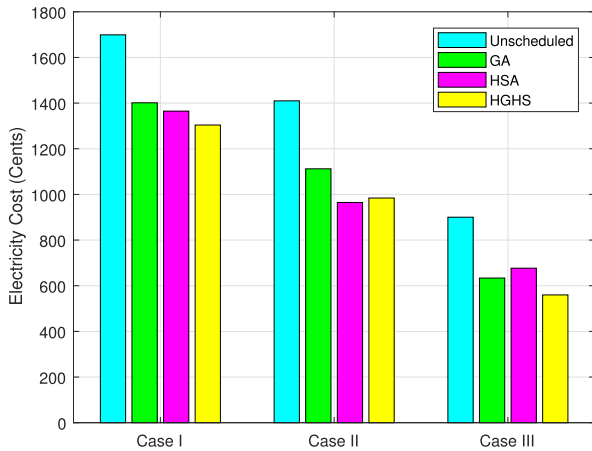


FIGURE 8. Total electricity cost.

The unscheduled electricity consumption cost during timeslots 37 and 38 was 261.1906 cents, whereas the GA based scheduled cost was obtained 170.1381 cents in the same timeslots. During timeslots 37 and 38, the electricity consumption cost was limited to 159.7321 cents in both HSA and HGHS based scheduling approaches. For case II, the electricity consumption cost profiles of scheduled loads based on the proposed HGHS, GA, and HSA load scheduling algorithms and unscheduled load are plotted in Figure 7b. During timeslots 37 and 38, the electricity consumption cost for unscheduled load was limited to 254.8318 cents and for scheduled load based on GA is limited to 163.7793 cents, respectively. The maximum electricity cost was 153.3733 cents during timeslots 37 and 38 for both HSA and HGHS based scheduling approaches. For case III, the electricity consumption cost profiles of scheduled loads based on the proposed HGHS, GA, and HSA load scheduling algorithms and unscheduled load are plotted in Figure 7c. In this case, electricity consumption cost was reduced during many timeslots. During timeslots 37 and 38 costs are reduced and the maximum electricity consumption cost was reported during timeslots 39 and 40 for the unscheduled load.

To complete operations of household appliances, the electricity cost during timeslots 39 and 40 was limited to 158.8048 cents for the unscheduled load. The maximum 62.9346 cents electricity consumption cost of HSA based scheduled load was reported during 43 and 44 timeslots and 59.0856 cents was reported during 43 and 44 timeslots for GA based scheduled load. Similarly, during timeslots 17 and 18, the electricity consumption cost was limited to 48.5055 cents in HGHS based scheduling approach.

For early described three cases, the total power consumption cost for one-day scheduling operations of household appliances using GA, HSA, and HGHS approaches and an unscheduled scenario are shown in Figure 8. In case I, the power consumption cost of one-day scheduling was 1699 cents for an unscheduled scenario. The electricity consumption cost was reduced and limited to 1401.4 cents, 1366 cents, and 1305.7 cents for GA, HSA, and HGHS scheduling approaches, respectively. In case I, electricity con-

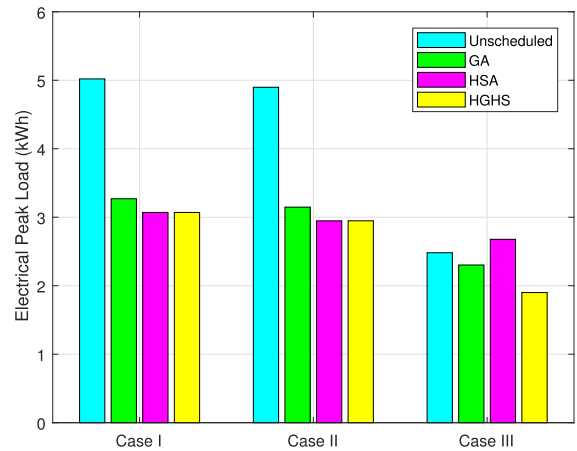


FIGURE 9. Electrical peak load.

sumption cost was 23.125% reduced for one-day scheduling operations of household appliances using the proposed load scheduling algorithm HGHS. Simulation results indicate that in case II, total electricity consumption cost for one-day scheduling operations of household appliances was reduced and limited to 1409.8 cents for an unscheduled load scenario. Electricity purchase cost from the utility was limited to 1112.2 cents, 998 cents, and 953.65 cents for GA, HSA, and HGHS based scheduling approaches, respectively. In case II, by integrating RESs electrical power output in the HEM system model up to 43.87% electricity consumption cost was reduced using the proposed hybrid approach.

In case III, by integrating both RESs electrical power output and ESS batteries in the HEM system total electricity cost for one-day scheduling operations of household appliances was significantly reduced. In this case, electricity consumption cost was limited to 900.14 cents, 633.65 cents, 641.44 cents, and 569.44 cents for an unscheduled scenario and GA, HSA, and HGHS approaches, respectively. The proposed hybrid approach HGHS outperforms more efficiently than GA and HSA by purchasing minimum power from the utility and reducing electrical peak load. The power consumption cost was 66.44% reduced using the proposed load scheduling approach.

B. ELECTRICAL PEAK LOAD

In the proposed HEM system model, the electrical peak load in an unscheduled scenario and scheduling of smart home household appliances using GA, HSA, and HGHS is shown in Figure 9. In case I, the electrical peak load was reported as 5.02 kW in an unscheduled scenario. In this case, the electrical peak load during home energy scheduling based on GA, HSA, and proposed HGHS approaches was limited to 3.27 kW, 3.07 kW, and 3.07 kW, respectively.

In case II, the electrical peak load values were reduced due to RESs electrical power output integration in the smart home. The electrical peak load during scheduled load scenarios based on GA, HSA, and the proposed HGHS scheduling approach was limited to 3.1478 kW, 2.9478 kW, and 2.9478 kW, respectively. In an unscheduled load scenario it

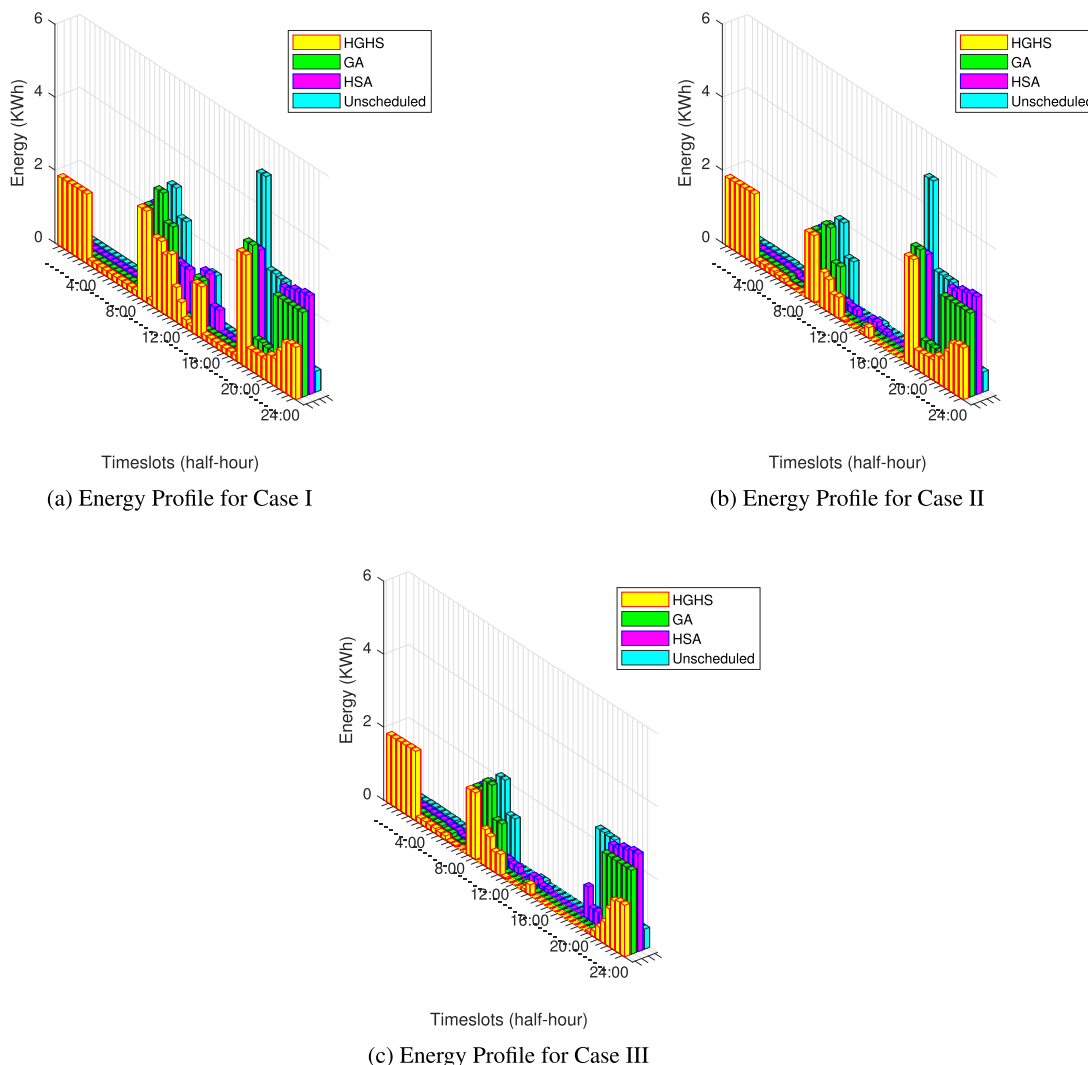


FIGURE 10. Smart home energy profile.

was 4.8978 kW. In case III, by integrating both RESs and ESS in the proposed HEM system electrical peak load is significantly reduced and it was limited to 2.4817 kW in an unscheduled load scenario. In scheduled load scenarios based on GA, HSA, and the proposed HGHS approach, the electrical peak load was limited to 2.3026 kW, 2.7726 kW, and 1.9 kW, respectively.

C. GRID ELECTRICITY USAGE

The grid electricity usage profiles of scheduled loads based on GA, HSA, and proposed HGHS approach and unscheduled load scenario are shown in Figure 10a, for case I. In this case, maximum energy 5.0200 kWh consumed in timeslots 37 and 38 to complete operations of household appliances based on the unscheduled scenario. During timeslots 37 and 38, electricity consumption was limited to 3.2700 kWh for the GA-based scheduling approach, and electricity consumption was limited to 3.0700 kWh for both HSA and HGHS approaches. By integrating RESs electrical power genera-

tion in the proposed HEM system, electricity usage from the grid was reduced in case II. The grid electricity usage profiles of scheduled loads based on the proposed HGHS, GA, and HSA load scheduling algorithms and unscheduled load are plotted in Figure 10b. In this case, to complete the operation of household appliances based on an unscheduled scenario, 4.8978 kWh energy was used during timeslots 37 and 38. Similarly, during timeslots 37 and 38 maximum of 3.1478 kWh energy was consumed for a GA-based scheduling approach, whereas maximum energy consumption was limited to 2.9478 kWh for HSA and HGHS scheduling approaches.

For case III, Figure 10c, represents the utility electricity usage (purchase) profiles of scheduled loads based on the proposed HGHS, GA, and HSA load scheduling algorithms and unscheduled load. By integrating RESs electrical power generation and ESS batteries in the HEM system, the electricity usage from the utility significantly reduced during specific timeslots for scheduling the operation of household appliances. In this case, utility electricity consumption is limited

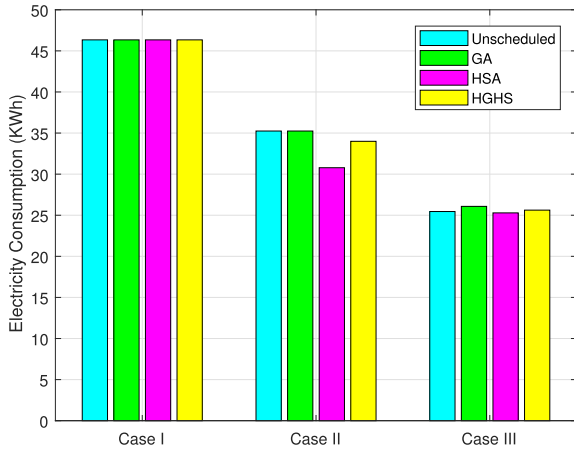


FIGURE 11. Total energy consumption.

to 2.4817 kWh during 39 and 40 timeslots in unscheduled load. Using the HSA approach, utility energy consumption is limited to 2.4997 kWh during timeslots 45 and 46 to schedule the operation of household appliances. Similarly, electricity purchase from the utility is limited to 2.3026 kWh during timeslots 43 and 44 in the GA based scheduling approach. In experimental results based on the proposed HGHS load scheduling approach, electricity purchase from the power utility is limited to 1.9000 kWh during timeslots 5 and 6 to complete the operations of household appliances.

For three cases as earlier described, the graphical simulation results of electricity purchased from the utility for one-day under unscheduled load scenario and GA, HSA, and HGHS scheduling approaches presented in Figure 11. In case I, in which RESs electrical power generation and ESS batteries did not integrate into the HEM system model, total electricity consumed from the grid in one-day was limited to 46.34 kWh for the unscheduled load as well as for GA, HSA, and HGHS scheduling approaches. By integrating RESs electrical power generation in the proposed HEM system model, the electricity consumption from the grid was reduced in an unscheduled load scenario and under load scheduling approaches. In case II, aggregate electricity usage from the grid for one-day was limited to 32.712 kWh, 32.079 kWh, 35.248 kWh, and 35.248 kWh for scheduled loads based on the proposed HGHS, HSA, and GA load scheduling algorithms and unscheduled load, respectively. In case III, simulation results indicate that electricity usage (purchase) from the grid significantly reduced for scheduling operation of household appliances by integrating both RESs electrical power output and ESS batteries into the HEM system model. In this case, the electricity usage from the grid for one-day during load scheduling scenarios based on GA, HSA, and proposed HGHS approach was limited to 26.079 kWh, 25.264 kWh, and 25.201 kWh, respectively. In unscheduled load scenario it was 25.452 kWh. The proposed load scheduling algorithm HGHS outperforms and significantly reduces electricity consumption from the power grid.

TABLE 4. Possible cases based on load and tariff - without integration of RESs and ESS in smart home.

Scenarios	Load (kWh)	Price (cents/kWh)	Cost (cents)
Min load, Min price	0.1500	17.5200	2.6280
Min load, Max price	0.1500	63.9900	9.5985
Max load, Min price	5.0200	17.5200	87.9504
Max load, Max price	5.0200	63.9900	321.2298

TABLE 5. Possible cases based on load and tariff - with only RESs integration in smart home.

Scenarios	Load (kWh)	Price (cents/kWh)	Cost (cents)
Min load, Min price	0	17.5200	0
Min load, Max price	0	63.9900	0
Max load, Min price	4.8978	17.5200	85.8092
Max load, Max price	4.8978	63.9900	313.4093

TABLE 6. Possible cases based on load and tariff - with both RESs and ESS integration in smart home.

Scenarios	Load (kWh)	Price (cents/kWh)	Cost (cents)
Min load, Min price	0	17.5200	0
Min load, Max price	0	63.9900	0
Max load, Min price	2.4817	17.5200	43.4796
Max load, Max price	2.4817	63.9900	158.8048

The electricity consumption patterns during one-day scheduling in a single home based on GA, HSA, and HGHS scheduling approaches indicate that household appliances are scheduled within a defined operational time window and without creating a peak in any hour of the day. Moreover, experimental results represent that the electrical peak load in the case of the proposed load scheduling algorithm HGHS reduced significantly.

D. FEASIBLE REGION

The area represents a set of points that are not eliminated by any constraint of the problem is a feasible region. The scheduling of household appliances based on the RTP electricity tariff ranges from 17.5200 to 63.9900 cents/kWh at timeslot in the proposed HEM system. The objective function is subject to the constraints like operational time windows and to reduce electrical peak load and electricity usage from the power grid. In this section, we have considered four different scenarios to simulate the feasible region of the objective function for the early described three cases. In which, the points P1 and P2 represent electricity cost for two scenarios such as min load demand (kWh) with min price (cents/kWh) and min load demand (kWh) with max price (cents/kWh), respectively. The points P3 and P4 represent electricity cost for the other two scenarios such as max load demand (kWh) with min price (cents/kWh) and max load demand (kWh) with max price (cents/kWh), respectively. In case I, the feasible region for the cost minimization objective is plotted in Figure 12a, in which the unscheduled load is in range [0.1500 5.0200] kWh. The possible scenarios based on electrical load and RTP signal to calculate the

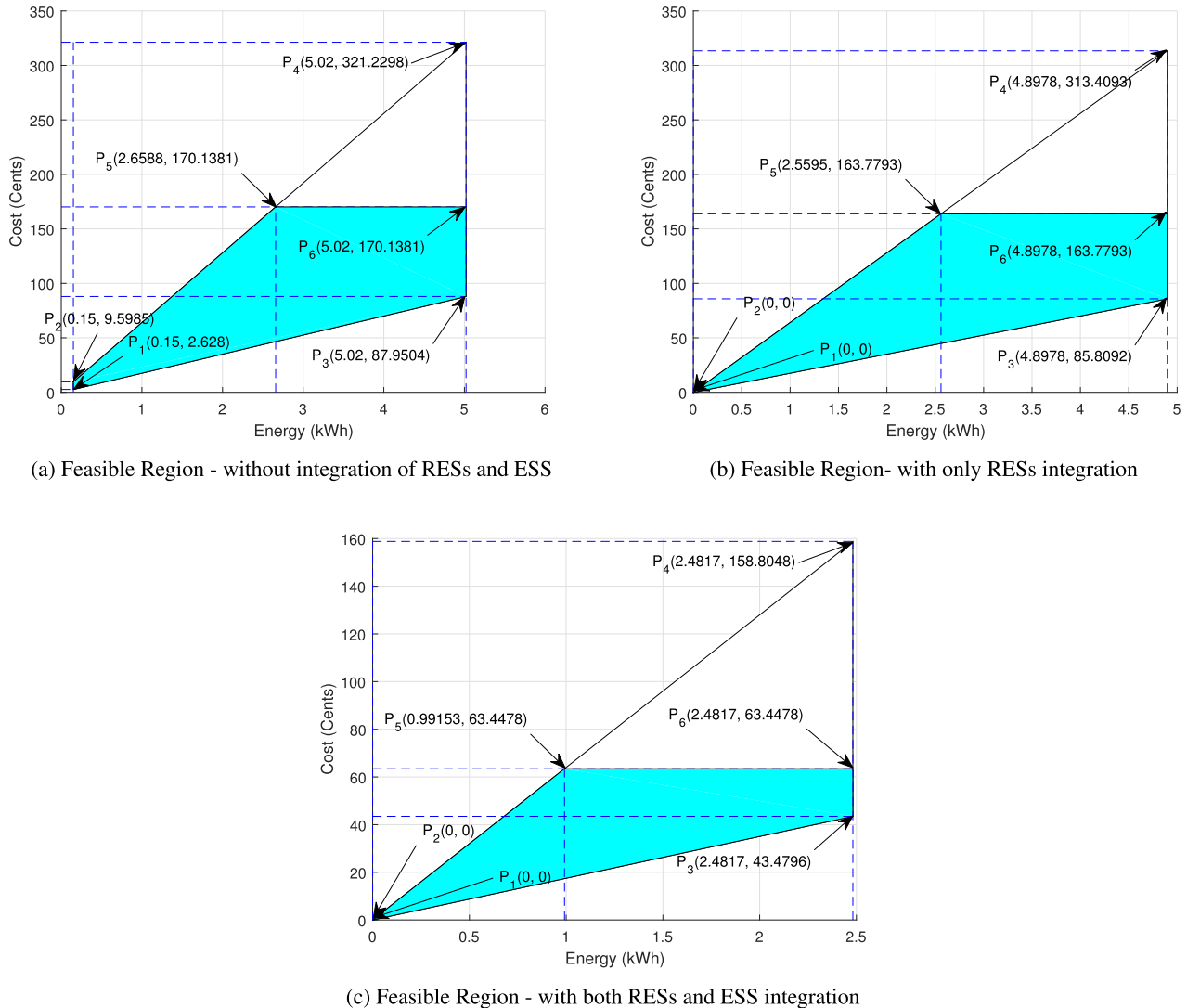


FIGURE 12. Electricity cost feasible region.

electricity cost specified in Table 4. The electricity cost feasible region (which includes eliminated and non-eliminated points) contains the points $P_1(0.1500, 2.6280)$, $P_2(0.1500, 9.5985)$, $P_3(5.0200, 87.9504)$, and $P_4(5.0200, 321.2298)$. The maximum energy cost at any timeslot in scheduling based on GA, HSA, and HGHS approaches should be less than the maximum electricity cost in an unscheduled load scenario. The shaded area of a plotted graph in Figure 12a surrounded by coordinates (P_1, P_2, P_3, P_5 , and P_6) represents the electricity cost feasible region. Point $P_5(2.6588, 170.1381)$ indicates that the scheduled load at timeslot is limited to 2.6588 kWh, where electricity cost is highest. Point $P_6(5.02, 170.1381)$ represents that load of 5.02 kWh did not schedule at any timeslot, where the electricity cost is more than 170.1381 cents. Figure 12b represents the feasible region of objective function for case II. In this case, by integrating RESs electrical power generation into the HEM system model, unscheduled load reduces and ranges

from 0 to 4.8978 kWh. For case II, Table 5 represents the possible scenarios on the basis of electrical load and cost of electricity purchased from the power utility. Points $P_1(0, 0)$, $P_2(0, 0)$, $P_3(4.8978, 85.8092)$ and $P_4(4.8978, 313.4093)$ represent the electricity cost region. The shaded area of a plotted graph in Figure 12b surrounded by coordinates (P_1, P_2, P_3, P_5 , and P_6) indicates the electricity cost feasible region for case II. In the feasible electricity cost region, point $P_5(2.5595, 163.7793)$ indicates that at any timeslot where the electricity cost is maximum, the scheduled load did not exceed 2.5595 kWh. The point $P_6(4.8978, 163.7793)$ represents the load of 4.8978 kWh scheduled at any timeslot where the electricity cost is less than 163.7793 cents. For case III, Table 6 represents the possible scenarios for calculating the cost of electricity consumed from utility based on electricity tariff and electrical load in any timeslot. In this case, the unscheduled electrical load further reduces and ranges from 0 to 2.4817 kWh by integrating RESs electrical power

generation and ESS batteries into the HEM system model. In Figure 12c, points P1(0, 0), P2(0, 0), P3(2.8417, 43.4796) and P4(2.8417, 158.8048) represent the possible region of objective function for case III. The coordinates of P1, P2, P3, P5, and P6 points form a shaded area that indicates the electricity cost feasible region for case III. In this case, P5(1.0178, 65.1277) and P6(2.4817, 65.1277) define two limits. The first limit based on P5(1.0178, 65.1277) is defined as the scheduled load is limited to 1.0178 kWh at any timeslot where electricity cost is a maximum of 65.1277 cents. The second limit based on P6(2.4817, 65.1277) is defined as the load of 2.4817 kWh scheduled at a timeslot where the price is less than 65.1277 cents.

V. CONCLUSION

In this study, we have proposed the HGHS approach for modeling the HEM system. The purpose of this HEM system model is to schedule the operations of household appliances, maximum utilization of RESs power output, optimally charging/discharging of ESS batteries, and reducing electricity purchase from the power grid or utility. The minimization of electricity consumption cost is the main objective subject to reduce electrical peak load and minimum electricity purchase from the power utility. In the proposed HEM system model, a day-ahead electricity RTP tariff is used for the scheduling of household appliances under the defined operational time window constraints for each household appliance. The performance and effectiveness of the proposed HEM system model are measured on the basis of three case studies for the scheduling of household appliances. The experimental results indicate that the performance of the proposed HGHS scheduling approach significantly increased by integrating RESs and installing ESS batteries into the proposed HEM system model. The proposed HGHS scheduling approach optimally scheduled the household appliances and deployed energy resources, which helped to reduce electricity consumption cost. The electricity consumption cost for completing one-day operation of household appliances was limited to 1305.7 cents, 953.65 cents, and 569.44 cents in the proposed scheduling approach for case I, case II, and case III, respectively and was observed as lower than other approaches. The electricity consumption cost was reduced upto 23.125%, 43.87% and 66.44% in case I, case II, and case III, respectively using proposed scheduling approach as compared to an unscheduled load scenario. Moreover, the electrical peak load was limited to 3.07 kW, 2.9478 kW, and 1.9 kW during the proposed HGHS scheduling approach and was reported as lower than other approaches.

Although the proposed HGHS scheduling approach has the flexibility to explore a search space in an equitable amount of time. However, the proposed approach takes a long time as compared to other algorithms for scheduling the operations of household appliances. It may be a challenging task to obtain significant results in the case of applying a proposed approach for scheduling the household appliances at community level. The experimental results encourage further study in future

work for long-term optimization scheduling of a set of smart homes and modeling the stochastic nature of electricity generation from RESs.

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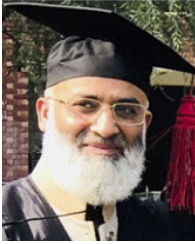
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