Low Cost and Reliable Energy Management in Smart Residential Homes Using the GA Based Constrained Optimization

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Abstract

Recently smart grids have given chance to residential customers to schedule operation times of smart home appliances to reduce electricity bills and the peak-to-average ratio through the demand side management. This is apparently a multi-objective combinatorial optimization problem including the constraints and consumer preferences that can be solved for optimized operation times under reasonable conditions. Although there are a limited number of techniques used to achieve this goal, it seems that the binary-coded genetic algorithm (BCGA) is the most suitable approach to do so due to on/off controls of smart home appliances. This paper proposes a BCGA method to solve the above-mentioned problem by developing a new crossover algorithm and the simulation results show that daily energy cost and peak to average ratio can be managed to reduce to acceptable levels by contributing significantly to residential customers and utility companies.

Keywords
Energy efficiency, smart grids, home energy management system, power scheduling, multi-objective optimization.

1. Introduction

The increasing power demand for householders inevitably leads to an increase in electricity unit prices in many countries due to economic growth and long-term global political conflicts. As the smart grids gradually widen and the controllability of household appliances increases, it is possible to reduce both the daily cost of the energy supplied from the grid under certain tariffs and power loss in transmission lines based on the demand side management strategies. There have been many studies based on popular deterministic and metaheuristic algorithms to achieve this in household use and they are briefly mentioned below.

Zaibi et al proposed two types of management strategies that are compared in the way they share the hybrid power sources between the storage devices and the electrical and hydraulic loads [1]. Furthermore, energy management strategies from both the demand-side and generation-side were proposed to meet power demand and minimize the overall operation cost with day-ahead real-time weather forecasting and demand response for a typical residential home using an optimization technique. Monyeiab and Adewumiab put forward a combined energy management system based on the demands and constraints of consumers such as time of dispatch, cheaper tariff, minimum cost operation, low carbon emission, dynamic pricing [2]. Another investigation such as by Shakouri and Kazemi was carried out to lower energy cost for householders using the multi-objective mixed-integer linear programming and the results verify that the proposed model covering few scenarios worked well to reduce the daily energy cost to an acceptable level [3]. Lokeshgupta and Sivasubramani studied about home energy management for residential consumers to lower both their electricity bills and utility companies' peak load demand, and it is believed this can be achieved by smart energy storage systems [4]. Another investigation by Ghalelou et al was about optimal energy management of interconnected multi-smart apartment buildings considering energy flow among them using mixed-integer programming [5]. Sharifi and Maghouli developed a novel scheduling procedure for power consumption in homes equipped with energy storage devices and claim that their proposed optimal power scheduling method reduced electricity bills and improve peak-to-average ratio while considering residents' comfortability [6]. Golmohamadi et al proposed a novel approach to optimize the behavior of household appliances based on retail electricity price considering the uncertainties of electricity price and wind/solar power using stochastic programming [7]. Veras et al studied scheduling loads in a home energy management system based on a multi-objective demand response optimization model to determine the scheduling of home appliances for the time horizon using the non-dominated sorted genetic algorithm [8]. Hussain et al proposed an efficient home energy management controller based on genetic harmony search algorithm to reduce electricity bills, peak to average ratio as well as maximizing user comfort for a single home and multiple homes with real-time electricity pricing and critical peak pricing tariffs [9]. Jordehi developed a new binary particle swarm optimization (PSO) with quadratic transfer function named as quadratic binary PSO for scheduling shiftable appliances in smart homes with 10 appliances, where the number of decision variables was 264 [10]. Zhu et al investigated to efficiently solve a complex combinatorial problem based on the scheduling of household appliances in multiple smart homes using an improved cooperative heuristic approach and the obtained results verify that the proposed algorithm worked well [11]. Yahia and Pradhan conducted an experimental study of the home appliances scheduling problem from realistic aspects and the residential load scheduling problem based on minimization of electricity cost was solved for consumer preferences [12]. B. Lokeshgupta and S. Sivasubramani used a multi-objective mixed-integer linear technique with the battery storage system for multiple residential consumers to reduce their electricity bills while utilities primary goal to reduce their system peak load demand [13]. Veras JM et al introduced a home energy management system (HEMS) that aims to schedule the use of home appliances based on the price of electricity in real-time and on the consumer satisfaction in which the multi-objective optimization model solved using the non-dominated sorted genetic algorithm (GA) [14]. Yi Liu et al developed a satisfaction model for different types of household appliances to minimize the energy expense considering different demand response strategies such as demand-limit-based and injection-limit-based [15]. Boyang Li et al studied cost-effective runtime scheduling designed for the schedulable and non-schedulable appliances to schedule the appliances and rechargeable battery cost-effectively while satisfying users' preferences using the iterative alternative algorithm [16]. George Ifrim et al proposed a shifting optimization algorithm for a small community of 11 modern houses with 8 photovoltaics and smart appliances that can be remotely controlled via tablets or mobile phones to reduce the electricity bills and peak power loads [17].

2. System Description and Proposed Method

A typical home energy management system (HEMS) connected to a smart grid is simply shown in Figure 1. The demand-side management (DSM) controller plays a major role in controlling and monitoring household appliances through a local communication network and constantly communicates with the smart grid to acquire the electricity price depending on the tariff in use. The smart meter is the key player being employed to measure power absorbed from the smart grid and delivers it to the smart home appliances (SHA). Besides, it receives the necessary information from the user preferences to send it to the DSM controller. The smart meter also communicates the SHA for on/off control. The SHA used here are divided into 4 categories based on their operating condition. They are namely fully time shiftable, partly time shiftable, non-time shiftable, and power shiftable. A washing machine, a dishwasher, and a clothes dryer are described as fully time shiftable appliances (FTSA); a vacuum cleaner, a hairdryer, and a toaster are called partly time shiftable appliances (PTSA), and a refrigerator, an indoor and outdoor lighting are named as non-time shiftable appliances (NTSA). Power shiftable appliances (PSA) are considered to be an electric vehicle and a water tank and power delivered to the PSA are assumed to constant. Accordingly, each appliance has a rated power as well as start-end times and operation time. In general, time-of-use tariffs have a variable rate during the day. For larger residential consumers, the time-of-use tariff that a lower energy rate typically applies throughout the night is common, and in this investigation, the time-of-use tariff is assumed to be employed for electricity pricing. From this perspective, the residential electricity tariff of Turkey in 2019 is 0.5445, 0.7997, and 0.3405 Turkish liras per kWh at the periods from 06.00 to 17.00, 17.00 to 22.00 and 22.00 to 06.00 respectively. Three different households are used to achieve the objectives and they are given in Tables I, II, and III. The total daily energy consumption of all three households are the same.

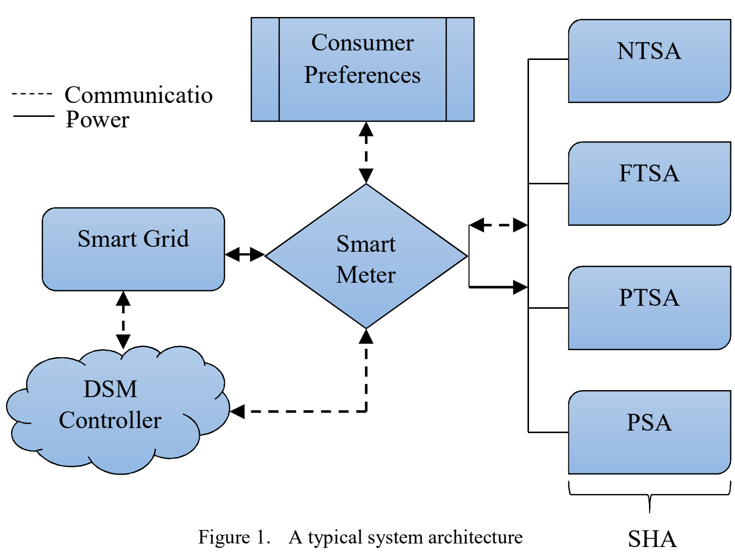

Figure 1. A typical system architecture

TABLE I.
A set of typical appliances for 1st household

Appliance	Operation range (h)	Operation time (min)	Average power (kW)
Fully Time Shiftable			
Dishwasher	1-24	60	1.80
Washing machine	1-24	60	0.80
Clothes dryer	1-24	60	2.50
Partly Time Shiftable			
Iron	20-24	60	1.00
Vacuum cleaner	10-14	90	0.50
Oven	17-20	45	2.00
Hair dryer	6-8	5	2.10
Toaster	6-9	10	1.20
Electric kettle	6-9	10	2.10
TV	10-24	480	0.10
Air conditioner	9-24	420	1
Non-Time Shiftable			
Fridge	1-24	1440	0.15
Indoor lighting	7-8, 19-24	480	0.20
Outdoor lighting	1-7, 19-24	780	0.10
Fully Power Shiftable			
Storage devices	**Operation range (h)**	**Capacity (kWh)**	**Average power (kW)**
Electric vehicle	1-24	8	2.0
Water pump	1-24	0.5	0.3

TABLE II.
A set of typical appliances for 2nd household

Appliance	Operation range (h)	Operation time (min)	Average power (kW)
Fully Time Shiftable			
Dishwasher	1-24	60	1.80
Washing machine	1-24	60	0.80
Clothes dryer	1-24	45	2.50
Partly Time Shiftable			
Iron	7-21	30	1.00
Vacuum cleaner	7-12	45	0.50
Oven	12-18	45	2.00
Hair dryer	6-9	5	2.10
Toaster	6-9	10	1.20
Electric kettle	6-9	10	2.10
TV	8-24	480	0.10
Air conditioner	8-24	420	1
Non-Time Shiftable			
Fridge	1-24	1440	0.15
Indoor lighting	7-8, 19-24	480	0.20
Outdoor lighting	1-7, 19-24	780	0.10
Fully Power Shiftable			
Storage devices	**Operation range (h)**	**Capacity (kWh)**	**Average power (kW)**
Electric vehicle	1-24	10	2.0

TABLE III.
A set of typical appliances for 3rd household

Appliance	Operation range (h)	Operation time (min)	Average power (kW)
Fully Time Shiftable			
Dishwasher	1-24	90	1.80
Washing machine	1-24	90	0.80
Clothes dryer	1-24	75	2.50
Partly Time Shiftable			
Iron	16-22	75	1.00
Vacuum cleaner	9-13	90	0.50
Oven	15-20	90	2.00
Hair dryer	6-10	25	2.10
Toaster	6-10	25	1.20
Electric kettle	6-10	25	2.10
TV	6-24	660	0.10
Air conditioner	8-24	600	1
Non-Time Shiftable			
Fridge	1-24	1440	0.15
Indoor lighting	7-8, 19-24	480	0.20
Outdoor lighting	1-7, 19-24	780	0.10

The flowchart of the GA application is depicted in Figure 2. The process of the GA is generating an initial population randomly that contains a set of individuals within given constraints in which each contains a solution to the problem, calculating the fitness values for each individual, selection, crossover, and mutation. Here, operation times of the electrical household appliances, which are shifted in time and power, are generated by random binary strings, and their fitness values are calculated for each binary string. The most fitted individuals are selected using the top-pop size selection method in which the GA sorts the population from the best values to the worst values, and the half-top of best values will be selected based on their fitness value, and the selected individuals are employed to obtain different individuals using crossover and inversion mutation operations which are key operators in optimization process by the BCGA for HEMS.

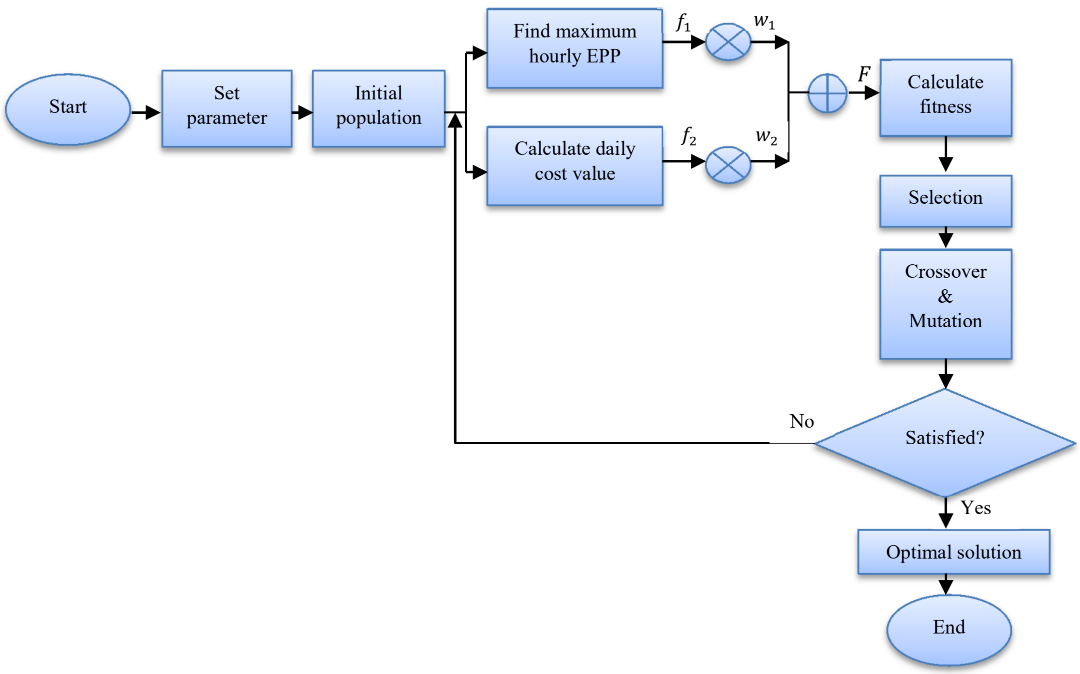

Figure 2. Flowchart of genetic algorithm optimization

3. Problem Formulation

The current optimization problem can be formulated to both minimize daily energy costs and peak power demand. This is simply a multi-objective constrained optimization problem that may be solved by the BCGA with the newly developed crossover implementation and the optimization problem is solved for three cases. The first case is to minimize daily energy costs, the second case is to reduce peak power consumption, and the third case is to reduce both cost and peak power consumption. For this optimization, three households with different electrical appliances having starting-ending times and operation time as shown in Tables 1, 2, and 3 were formed for each case. The total power consumption for each household is equal to each other for a fair comparison of the results from various aspects. To perfectly apply crossover and mutation operations to individuals, the time resolution is assumed to be 5 minutes. This means that a day corresponds to 288-time slots and each appliance runs for at least 5 minutes or multiples of 5 minutes. So, the time slot vector for each appliance is denoted as:

$$T \triangleq \{1, 2, 3, \ldots, 287, 288\}, \forall t \in T \tag{1}$$

As mentioned above, the electrical household appliances divided into 4 categories. So, the power consumption vector for each household appliances category is denoted as:

$$U_a \triangleq \{U_a^1, U_a^2, \ldots, U_a^{288}\},\ X_b \triangleq \{X_b^1, X_b^2, \ldots, X_b^{288}\},\ Y_c \triangleq \{Y_c^1, Y_c^2, \ldots, Y_c^{288}\},\ Z_d \triangleq \{Z_d^1, Z_d^2, \ldots, Z_d^{288}\},$$

$$\forall a \in NTSA, \forall b \in FTSA, \forall c \in PTSA, \forall d \in PSA, \forall t \ \in T \tag{2}$$

We assume that the power consumption per time slot for all appliances is fixed. So, the power consumption of each household appliances category during time slot t is given by:

$$U_a^t = \frac{U_a^*}{12} \times B_a^t, X_b^t = \frac{X_b^*}{12} \times B_b^t, Y_c^t = \frac{Y_c^*}{12} \times B_c^t, Z_d^t = \frac{Z_d^*}{12} \times B_d^t \quad (3)$$

Where $B_a^t, B_b^t, B_c^t, B_d^t \in \{0,1\}$ are binary integer, 1 if the appliance operates in time slot t, and 0 otherwise.

The total power consumption for each household appliances category is given by:

$$U = \sum_{a=1}^{A} \sum_{t=1}^{T} U_a^t, X = \sum_{b=1}^{B} \sum_{t=1}^{T} X_b^t, Y = \sum_{c=1}^{C} \sum_{t=1}^{T} Y_c^t, Z = \sum_{d=1}^{D} \sum_{t=1}^{T} Z_d^t,$$

$$\forall a \in NTSA, \forall b \in FTSA, \forall c \in PTSA, \forall d \in PSA, \forall t \in T \quad (4)$$

This first single-objective optimization problem is to minimize the electricity daily cost by shifting operation time of shiftable appliances from higher-cost on-peak hours to lower-cost off-peak hours which can be formulated by calculating the cost of each category of appliances and given by:

$$Min\ F_1 = Cost_{NTSA} + Cost_{FTSA} + Cost_{PTSA} + Cost_{PSA} \quad (5)$$

Where,

$Cost_{NTSA} = \sum_{a=1}^{A} \sum_{t=1}^{T} U_a^t \times e(t),\ Cost_{FTSA} = \sum_{b=1}^{B} \sum_{t=1}^{T} X_b^t \times e(t), Cost_{PTSA} = \sum_{c=1}^{C} \sum_{t=1}^{T} Y_c^t \times e(t),$

$Cost_{PSA} = \sum_{d=1}^{D} \sum_{t=1}^{T} Z_d^t \times e(t), T \triangleq \{1,\ 2,\ 3, \dots, 287, 288\}, \forall\ t \in T$ and $e(t)$ is unit electricity price at time slot t.

The second single-objective is to minimize the electricity peak power demand and given by:

$$\text{Min}\ F_2 = \sum_{i=1}^{n} P_i^t \leq PPD \quad (6)$$

where $PPD = (\sum_{a=1}^{A}\ U_a^t + \sum_{b=1}^{B}\ X_b^t + \sum_{c=1}^{C}\ Y_c^t + \sum_{d=1}^{D}\ Z_d^t), \forall\ t \in T$.

Two objective functions that are to be optimized. They can be reduced to a single objective function, thus providing an easier solution. The multi-objective optimization problem given by Equations (5) and (6) was solved by the BCGA for each household and the formulation of the multi-objective optimization problem given by:

$$\text{Min F} = \omega_1 F_1 + \omega_2 F_2 \quad (7)$$

where ω_1 and ω_2 are the weight coefficients, $\omega_1 + \omega_2 = 1$ and $\omega_1,\ \omega_2 \in [0, 1]$.

4. Results and Discussions

In this section, we describe the simulation results and the discussion of our proposed method, to test the validity of the proposed method, the smart grid-connected houses having various household appliances with and without the storage devices. The 1st load profile has smart electrical appliances with two storage devices that are an electric vehicle and a water pump. The 2nd load profile has also smart electrical appliances with one storage device that is an electric vehicle. The 3rd load profile has smart electrical appliances without storage devices. We consider the total daily energy consumption of all the three load profiles are equal to make a fair comparison between them. Cost and power calculations were made based on three objectives such as only cost, only power, and cost and power in the households.

The proposed method is performed using MATLAB to solve the BCGA optimization problem. The parameters used for GA, number of generations $G = 100$, the population size of each generation $N = 100$, the probability of crossover $P_c = 0.9$, and the probability of mutation $P_m = 0.03$. As mentioned above, we proposed a weighted-sum method that combines multi-objective functions into a single objective function which can represent all cases, in the only cost reduction case $w_1 = 1, w_2 = 0$, in the only power reduction case $w_1 = 0, w_2 = 1$, and in the cost-power reduction case $w_1 = 0.5, w_2 = 0.5$.

Figure 3 shows the unscheduled and scheduled daily cost results for optimal operations of household appliances in the three load profiles for the three cases. In only cost reduction case, attempts to reduce the cost regardless of the peak load by shifting the operation time of the electrical appliances to the hours when the electricity price was cheapest, the cost reached its highest values in the three load profiles: ৳1.21 in the 1st time slot, ৳1.50 in the 14th time slot, and ৳1.59 in the 15th time slot respectively, when the electricity price is lower. In the case of only power reduction, tries to avoid peak hours regardless of the cost by shifting the operation time of the electrical appliances to the hours in which the electricity price might be higher, the cost reached its highest values in the three load profiles: ৳1.61 in the 19th time slot, ৳1.38 in the 21st time slot, and ৳1.45 in the 18th time slot respectively when the electricity price is higher. In the case of cost and power reduction, it implies making a balance in the operating times of the electrical appliances and for that reason, the appliances load profile is smoother at most of the time slots. The average cost values in the three load profiles for the three scheduled cases and unscheduled cases are shown in Table IV. The minimum average cost values were found in the case of only cost reduction, and maximum in the cases of only power reduction and unscheduled as expected. In the cost-power case, the average cost values are closer to the only cost case.

TABLE IV.
The average cost in the three load profiles for the three scheduled cases and unscheduled case

Case	LP1	LP2	LP3
Unscheduled	৳0.67	৳0.75	৳0.76
Only cost	৳0.61	৳0.60	৳0.66
Only power	৳0.72	৳0.71	৳0.71
Cost-power	৳0.62	৳0.60	৳0.70

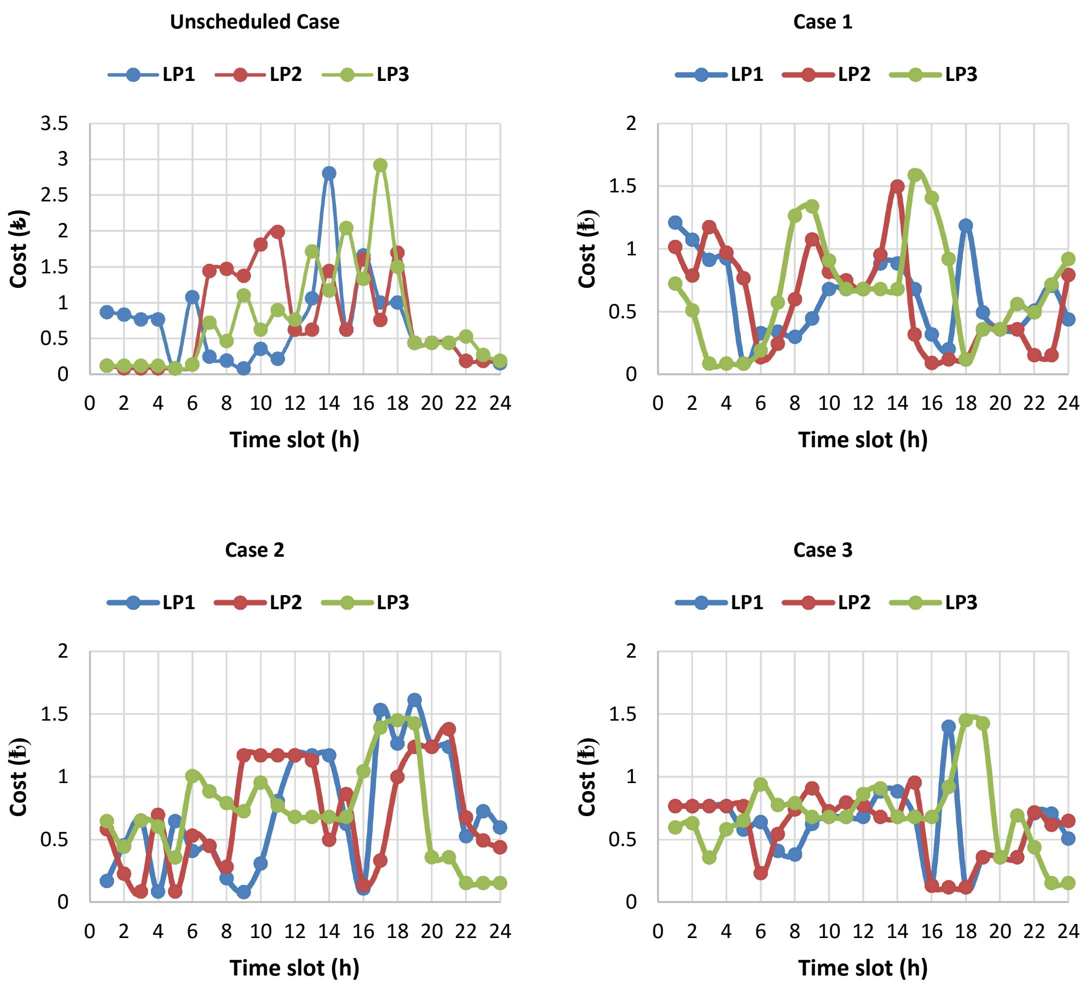

Figure 3. Variation of unscheduled and scheduled daily cost with time slot under the three cases

Figure 4 shows the unscheduled and scheduled daily power consumption results for optimal operations of household appliances in the three load profiles for the three cases. The total power consumption in the three load profiles is the same as 31.875 kW. The variation of power consumption in the three load profiles for the three scheduled cases and the unscheduled case is shown in Table V. In the case of only cost reduction, which is based only on reducing daily energy costs, the power consumption reached the highest values within 1-5 time slots in the 1st and 2nd load profiles when the electricity price is lower, while in the 3rd load profile reached its highest value within 15-16 time slots in which the electricity price is might be higher due to the 3rd load profile doesn't contain power storage devices. In the case of only power reduction, which is based on reducing only peak power rather than cost, the power consumption reached the highest values in the three load profiles: 2.15 kW within 12-14 time slots, 2.15 kW in within 9-12 time slots, and 1.92 kW in the 3rd and 16th-time slots respectively. In the case of cost-power reduction, we obtained the lowest power consumption in the cases of only power and cost-power but in the case of cost-power was smoother than only power case. It seems that the proposed approach method worked well to reduce power consumption during the day.

TABLE V.
The variation of power consumptions in the three load profiles for the three scheduled cases and unscheduled case

Case	LP1	LP2	LP3
Unscheduled	0.15-5.15 kW	0.25-3.65 kW	0.25-3.75 kW
Only cost	0.25-3.55 kW	0.15-3.45 kW	0.15-2.92 kW
Only power	0.15-2.15 kW	0.25-2.15 kW	0.45-1.92 kW
Cost-power	0.15-2.25 kW	0.15-2.25 kW	0.45-1.92 kW

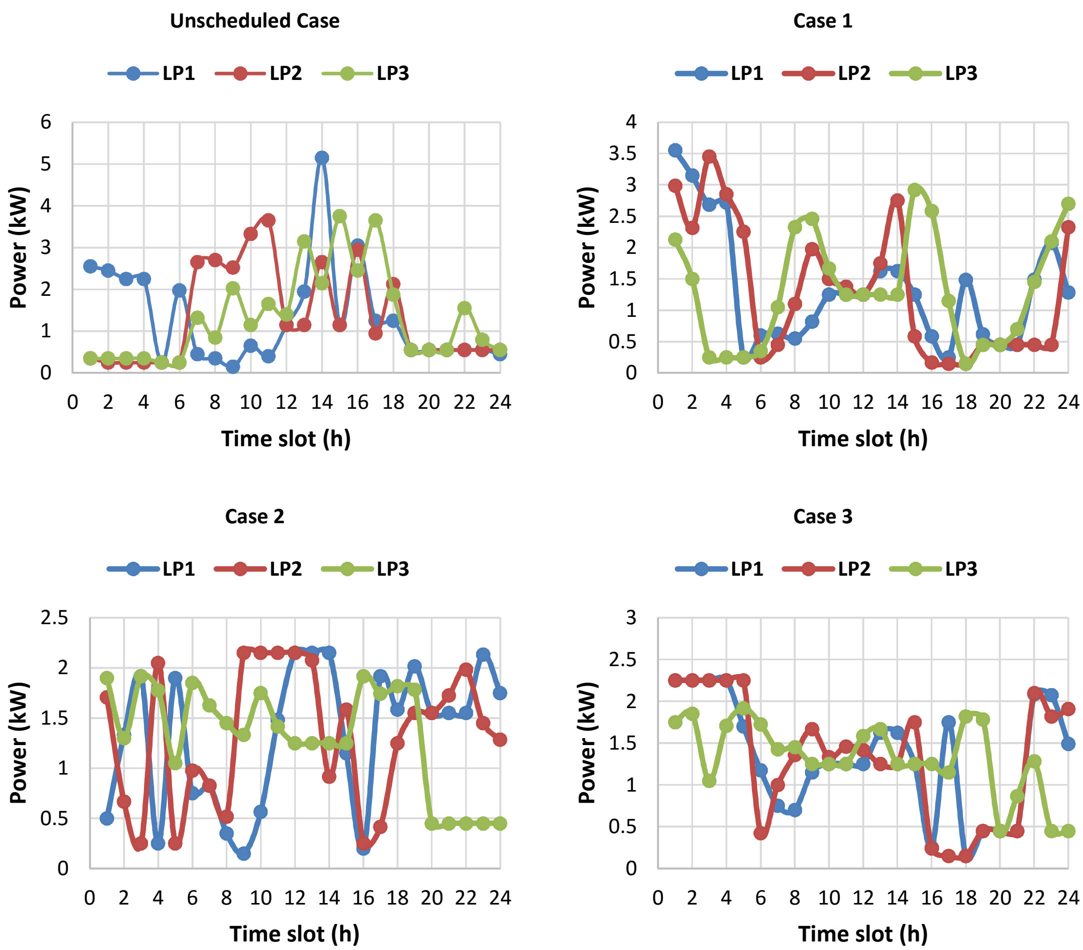

Figure 4. Variation of unscheduled and scheduled daily power consumption with time slot under the three cases

Figure 5 shows the comparison results of daily cost and peak power between the scheduled and unscheduled in the three load profiles for the three cases and the results are shown in Table VI. From the results, we obtained that the cost-power case is the best way to reduce the total cost and peak power demand in the HEMS during the day. If we want to understand the effect of the power storage devices on HEMS, in the third load profile which doesn't contain storage devices, we see the total cost in the third load profile was higher than the first and second load profiles which mean power storage devices play a major role in reducing the cost for HEMS.

TABLE VI.
The results of daily cost and peak power for the scheduled and unscheduled in the three load profiles for the three cases

Case	LP1		LP2		LP3	
	Cost	Peak Power	Cost	Peak Power	Cost	Peak Power
Unscheduled	৳15.44	4.95 kW	৳17.95	3.65 kW	৳18.26	3.75 kW
Only cost	৳14.68	3.55 kW	৳14.29	3.45 kW	৳15.93	2.92 kW
Only power	৳17.24	2.15 kW	৳17.05	2.15 kW	৳17.05	1.92 kW
Cost-power	৳14.85	2.25 kW	৳14.29	2.25 kW	৳16.77	1.92 kW

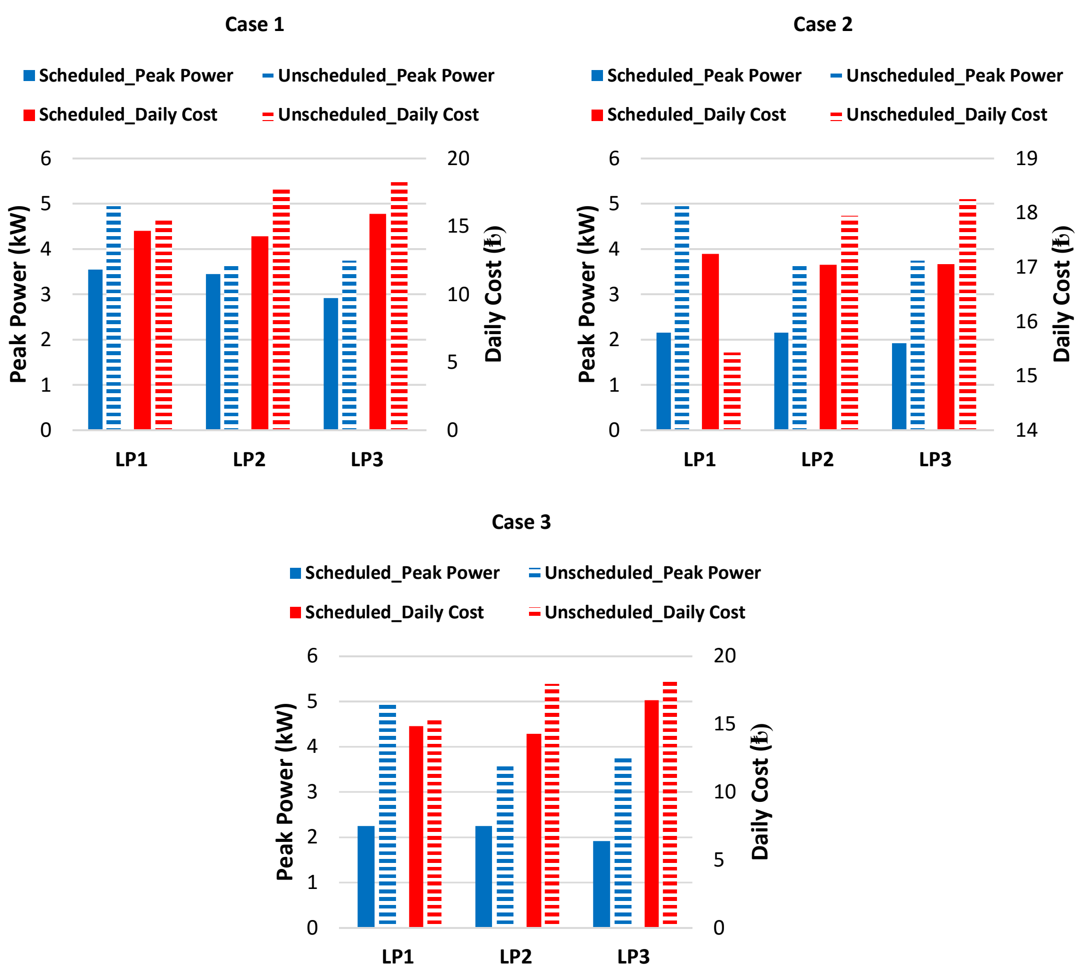

Figure 5. Unscheduled and scheduled daily cost and peak power under the three cases

5. Conclusion

The proposed method is capable of solving the multi-objective constrained optimization problems under consideration to reduce both daily energy cost and peak power demand under various cases because the BCGA perfectly adapts itself to the nature of on/off control household appliances in certain operation times. It is verified that the proper optimization of operation times is highly crucial in a HEMS including few constraints, fully time shiftable, partially time shiftable, non-time shiftable, and power shiftable household appliances. It is also verified that the power storage devices play a major role in reducing the cost of HEMS. Small-time resolution is highly influential on the optimization process through the BCGA since it creates more ones in the strings in a population for proper crossover and mutation operations. It may be said that the convergence time is short in this optimization process and the real-time control of the household appliances may be possible in case of sudden changes in consumer preferences. It can be concluded from the results, the advantages, and the efficiency of using HEMSs in residential homes by reducing both daily cost and peak power and the benefits for utility companies by reducing the peak power demand which leads to increase capacity, efficiency, and reliability in the distribution network.

Nomenclature

t: Time slot number
T: Maximum time slot number which is 288
n: Total number of household appliances
a: Non-time shiftable household appliance index
b: Fully time shiftable household appliance index
c: Partially time shiftable household appliance index
d: Power shiftable household appliance index
A: Total number of non-time shiftable household appliances
B: Total number of fully time shiftable household appliances
C: Total number of partially time shiftable household appliances
D: Total number of power shiftable household appliances
$e(t)$: Unit electricity price at time slot t
P_i^t: Power demand of household appliance i at time slot t
PPD: Peak power demand
U_a^t: Power of non-time shiftable household appliance a at time slot t
X_b^t: Power of fully time shiftable household appliance b at time slot t
Y_c^t: Power of partially time shiftable household appliance c at time slot t
Z_d^t: Power of power shiftable household appliance d at time slot t
B_a^t: Binary digit for household appliance a at time slot t
B_b^t: Binary digit for household appliance b at time slot t
B_c^t: Binary digit for household appliance c at time slot t
B_d^t: Binary digit for household appliance d at time slot t
ω_1: The first weight coefficient
ω_2: The second weight coefficient

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