A novel recommender system for energy management based on fuzzy in smart home

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Abstract

Smart energy management systems in smart cities are efficient tools for customers to optimize electrical equipment. These systems in residential homes and proper energy management increased reliability, increased user comfort, and reduced subscriber costs. This article uses smart home shift able equipment with multi-objective evolutionary algorithms according to the operation constraints, customer welfare, demand, and time cost of electricity for proper time management. Therefore, the NSGA-II and MOGOA[4] multi-objective algorithms were used to simultaneously improve electricity consumption costs and the average daily load of subscribers. The proposed algorithm for equipment management is derived from the hybrid NSGA-II and Grasshopper Optimization Algorithm, abbreviated MOGOA. In addition, smart home solar panels and energy storage systems were used as a fuzzy recommender system for a smart home lighting system for optimal management of the resulting energy. The results indicated an acceptable reduction in costs and peak to average ratio (PAR), and also the use of fuzzy recommender for solar energy helped decrease electricity costs.

Keywords: Smart Home, Energy Management, Multi-objective Optimization, Fuzzy Recommender, Renewable Energy, NSGAII, Grasshopper Algorithm Optimization

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1- Introduction

Prevention of energy waste is one of the most critical issues that has been considered by developed countries in today's world because energy plays an essential role in human life.

Currently, there is a concern to improve consumption pattern and energy management due to the increase in the number of consumers, the change in consumption patterns, lifestyles of people in the community, and the need for rapid access to consumer needs due to time constraints and reduced energy supply sources (Sharma, Dua, Singh, Kumar, & Prakash, 2018). Therefore, proper planning in the use of electricity consumption and proper control of electrical equipment, and renewable energy in a smart home is a great help to reduce the cost of electricity consumed by customers and environmental pollutants. The construction of smart homes in smart grid infrastructure is currently one of the essential topics in smart energy management systems. Managing the use of smart home equipment is the most effective step that can be taken to have a sustainable city and optimal network management. Proper management and scheduling of equipment arrival time in smart homes have a significant impact on reducing electricity costs for customers and energy efficiency. As fossil fuel resources have dwindled and the world has faced global warming due to greenhouse gases, the efficient use of existing resources along with the use of renewable energy has become more in demand than ever before.

The construction of smart homes in smart grid infrastructure is currently one of the most important topics in smart energy systems and the most important infrastructure of smart cities. In addition, demand-side management is useful for both users and service companies. A new planning method for power consumption in homes equipped with energy storage devices has been proposed (Sharifi, & Maghouli, 2019). Short-term planning and the use of renewable energy along with demand management can be targeted by smart city managers (Logenthiran, Srinivasan, & Shun, 2012). Predicting customer loads during energy management should be considered as a key role in the efficient management of renewable resources. Accordingly, models of energy consumption patterns of the past days and their average should be used as a basis for predicting the load consumption pattern (Ahmad, Javaid, Alrajeh, Khan, Qasim, & Khan, 2015).

There are many different objectives for demand-side management (DSM) in smart grids. For example, the article (Mehrshad, Tafti, & Effatnejad, 2013) stated that an efficient energy consumption program should minimize the peak to average total energy demand ratio, total energy cost, as well as the daily electricity charge of each user. Various solutions have been proposed to solve this problem, including the use of renewable energy and off-grid batteries to meet the user's needs. Battery discharge, energy received from the grid for battery charging, and load estimation should be considered as decision variables (Mary, G. A., & Rajarajeswari, R. (2014., Rahim, Javaid, Ahmad, Khan, Khan, Alrajeh, & Qasim, 2016).

Article (Zhao, Lee, Shin, & Song, 2013) first outlined the energy management system (EMC) in a smart grid-based residential network and then proposed an efficient planning method for smart home energy use.

Some articles targeted the research and development of the General Demand Management Model (G-DSM) for residential users to reduce PAR, energy cost, and equipment waiting time by rapidly implementing the proposed algorithm. A combination of real-time pricing, genetics, IBR, and KP techniques has been used to achieve this objective (Dethlefs, Preisler, & Renz, 2015., Khan, Javaid, Mahmood, Khan, & Alrajeh, 2015).

onsidered power price changes between peak consumption and low consumption times, formed an optimization problem, and proposed an algorithm based on a genetic algorithm to be able to find the optimal program order for all the tasks of a smart home to reduce energy cost (Miao, Huang, & Chen, 2012).

Moreover, retailers should be considered in smart cities (Rasheed etal. 2016) and article (Meng, Zeng, Zhang, Dent, Gong, 2018) tried to show that an electricity retailer serves three different categories of customers, including those with an optimal energy management system installed in their smart home meters (C-HEMS), those with only a smart meter (C-SM), and those without a smart meter (C-NONE).

This article aimed to support retailers to make optimal day-to-day decisions about dynamic pricing despite customer fragmentation. Therefore, a two-tier decision-making framework was proposed so that retailers would first set their electricity prices for the next 24 hours as representatives of high-level representatives, and customers act as low-level agents and plan their energy consumption accordingly.

Eissa (2018) Provided a real-time energy management program, a combination of time-based programs, including real-time pricing models and incentive-based demand response programs. The primary purpose of this system is to reduce energy consumption during peak hours.

Han, Sun, & Fan (2018) Discussed the important issue of consumers' controllable burden, as well as s the optimal use of renewable energy sources. This complex and multivariate problem is solved using the first-order derivative method along with big data analysis. The simulations showed that the proposed approach is an efficient method for solving the problem of distributed energy management planning in addition to considering user participation.

Investigated energy consumption by the lighting system, which generally consumed 25% of the total electricity consumption in a building. Today, the lighting source of the building using fluorescent lamps has been considered. Previous studies have focused on controlling the power density of incandescent lamps, which are now rarely used. This paper presents a building lighting system based on a fuzzy logic scheme (Panjaitan, & Hartoyo, 2011).

Xiong, Chen, Kishore, & Yener (2011) Considered the total energy consumption of all appliances, but did not plan for each device separately. In this paper, residential home appliances are divided into two categories with the intermittent or uninterrupted degree, so that the simulated results are closer to the actual performance of the appliances. The objectives of this article are defined as minimizing electricity costs and peak consumption.

Managed storage systems based on energy prices and found that the battery is charged during low hours and the battery is discharged when the energy price is high. Although this procedure significantly reduces electricity bill amounts, implementing a hybrid pricing model is not efficient.

Therefore, smart city and time management of equipment used in smart homes, as well as management of renewable energy in smart homes, has been proposed as a new way to solve many urban problems and efficient control and management of smart cities (Guo, Pan, Fang, & Khargonekar, 2013). Smart home technologies (SHT): technologies that control devices remotely using an internet connection by smartphones or tablets. Smart homes are becoming widespread due to their energy efficiency, climate change, and the sustainability of buildings. The study explains a variety of technical, economic, social, political, and environmental smart home technology diffusion dimensions and its research, policy, and technology development implications. To do this, we need a design that is more innovative, sensitive, progressive, and comprehensive technology to advance the adoption of SHT and meet some of its promised climate and sustainability objectives (Del Rio, Sovacool, & Griffiths, 2021).

In this study (Alhasnawi, Jasim, Rahman, & Siano, 2021), a novel robust smart EMS and demand reduction for smart homes based on internet of energy is proposed. And also used an improved version of GWO, and ABC optimization algorithms to improve the system efficiency in terms of energy consumption cost and the user's satisfaction.

Today, problems such as pollution caused by fossil fuel consumption, population density, difficulties related to access to urban transportation have challenged different communities, and it has been the subject of their research.

In this regard, proper planning of energy resources has been demanded and considered more than before, which has led to less use of fossil fuels and optimal energy supply. On the other hand, proper use and management of energy in urban infrastructure can significantly reduce the costs of cities.

Urban smart grid system improves the economic status of a community, which is also beneficial for the environment. Residents of smart homes can implement smart grids and smart home features and can use this shiftable infrastructure to reduce electricity bills, as well as reduce the peak to average index.

Optimal energy management, maintaining the right temperature for the home, using clean energy, and reducing electricity costs are some of the critical issues in the smart city, especially in the smart home. The energy management system proposer and planner propose the most appropriate solution by analyzing the user's behavior in energy consumption and equipment, as well as considering the user's limitations to maintain the welfare of subscribers.

This research aimed to optimally manage energy in a smart home using careful planning and considering user constraints and considered the well-being of the subscribers when planning the use of the equipment as the most important constraints. The objective of optimal planning is to use equipment to minimize the cost of electricity and PAR using a multi-objective genetic algorithm and grasshopper algorithm.

2- Grasshopper algorithm

Determining the initial location of grasshoppers, which is represented by the X function, is the most basic step in solving the grasshopper algorithm. The new position of grasshoppers depends on three different parameters, including the gravitational force of the earth, the social relationship of the grasshoppers, and the wind flow at the moment the grasshoppers move (Mehrshad etal, 2013).

$$X(t+1)_i = S(t)_i + G(t)_i + A(t)_i X(t+1)_i = S(t)_i + G(t)_i + A(t)_i \tag{1}$$

Where i is the numerator of the number of grasshoppers and t indicates the numerator of the algorithm. S represents the social relationship of i^{th} grasshopper in t^{th} iteration, G illustrates the gravitational force of i^{th} grasshopper in t^{th} iteration, A shows the wind flow of i^{th} grasshopper in t^{th} iteration.

Social interaction of grasshoppers: This section is created to establish social interactions between grasshoppers whose reason is the group flight and movement of mature and immature grasshoppers, which is calculated as follows:

$$S_i = \sum_{\substack{j=1 \\ j\neq i}}^{npop} s(d_{ij}) * \widehat{d_{ij}} S_i = \sum_{\substack{j=1 \\ j\neq i}}^{npop} s(d_{ij}) * \widehat{d_{ij}} \tag{2}$$

$$\widehat{d_{ij}} = \frac{X(i)-X(j)}{d_{ij}} \widehat{d_{ij}} = \frac{X(i)-X(j)}{d_{ij}} \tag{3}$$

Where $d_{ij} d_{ij}$ indicates the distance of the i^{th} grasshopper from the j^{th} grasshopper and $\widehat{d_{ij}}\widehat{d_{ij}}$ shows the unit vector of i^{th} grasshopper to the j^{th} grasshopper, which can be calculated from Equation (1). In other words, the distance is normalized in Formula (1), and s also represents the function of power or intensity of social forces, which is calculated in Equation (4).

$$s(d) = f * e^{-\frac{d}{l}} - e^{-d} s(d) = f * e^{-\frac{d}{l}} - e^{-d} \tag{4}$$

Where d, f, l, and s are the distance of grasshoppers, the intensity of gravity, the scale of gravity length, and the effect of social interactions (gravity or repulsion) of grasshoppers, respectively. Grasshoppers try to attract grasshoppers far away and repel locals very close. Figure 1 shows the effect of one grasshopper on other grasshoppers (Arora, & Anand, 2019, Saremi, Mirjalili, & Lewis, 2017).

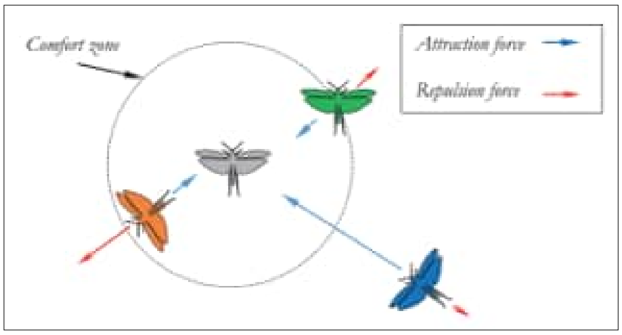

Figure (1): Initial correctional models between individuals in a community (Arora, & Anand, 2019)

The s function is highly dependent on the two parameters f and l, which affect the magnitude of the impact of social interactions. The drawing of the s-curve in terms of these two parameters shows that both graphs tend to zero after long distances so that the change interval should be mapped between 1 and 4 and taken into account in the calculations.

The final equation of the grasshopper optimization algorithm is given in Equation (5).

$$X(t+1)_i = c\left\{\sum_{\substack{j=1\\ j\neq i}}^{npop} c * \frac{ub-lb}{2} * s\left(\left|x_i(t)-x_j(t)\right| * \frac{X(i)-X(j)}{d_{ij}}\right)\right\} + \widehat{T(t)}$$

$$X(t+1)_i = c\left\{\sum_{\substack{j=1\\ j\neq i}}^{npop} c * \frac{ub-lb}{2} * s\left(\left|x_i(t)-x_j(t)\right| * \frac{X(i)-X(j)}{d_{ij}}\right)\right\} + \widehat{T(t)} \quad (5)$$

Where ub is the upper bound and ul is the lower bound of the range of changes of the decision variables, and $\widehat{T(t)}\,\widehat{T(t)}$ is the value of the best solution found to t^th^ iteration. The coefficient c mentioned to improve the answers is similar to the coefficient of inertia in the PSO algorithm. This coefficient, which will be considered as a reduction, can be considered linearly or non-linearly and calculated as follows:

$$c = c_{max} - t * \frac{c_{max}-c_{min}}{t_{max}} c = c_{max} - t * \frac{c_{max}-c_{min}}{t_{max}} \quad (6)$$

The value of t is equal to the number of iterations, c_{max} is the maximum value of c, which is usually set to 1, c_{min} is the minimum value of c and is equal to zero or close to zero, and t_{max} is the maximum number of iterations of the algorithm.

3- literature Review

Home residents can use this smart and shiftable infrastructure to reduce electricity bills and average peak after implementing smart grids and increasing smart home features. Energy management in smart homes is a complex task that requires efficient planning. The critical issue in energy management is demand management, whose task is to balance supply and demand and reduce the power consumption of subscribers during peak hours, as well as minimizing the cost of electricity consumed by subscribers during the day and night. Therefore, a method was proposed for planning the operation time of home appliances to achieve these objectives. Multi-objective evolutionary algorithms were used to properly manage the time of use of smart home equipment considering operating constraints. The solar panel of the fuzzy recommender system was also used for proper energy management. Solar panels and energy storage devices in smart homes can significantly reduce environmental pollutants and energy consumption, lowering subscribers' electricity costs. Figure 2 provides an overview of the proposed plan. This proposed energy management plan has two parts:

In the first part, a significant reduction can be observed in cost and PAR based on consumption pattern and number of user equipment, and scheduling of shiftable devices. A combination of multi-objective evolution algorithms of NSGA-II and Grasshopper were used to achieve these objectives Figure (5), and the results of the proposed method were compared with the method of the multi-objective genetic evolutionary algorithm by proposing a new multi-objective evolutionary algorithm. The reason for using multi-objective evolution algorithms is the simultaneous optimization of two objectives in this paper. It should be noted that there is another way to use the one-objective algorithm and weight factor, but this method cannot be used because the objectives are not the same and the unit of cost is in dollars and the unit of PAR is per unit. The NSGA-II multi-objective flowchart is shown in Figure (4) and the MOGOA multi-objective flowchart is depicted in Figure (5). The outline of the proposed design is taken from the general architecture of the smart home in the reference (Khalid, Javaid, Rahim, Aslam, & Sher, 2019).

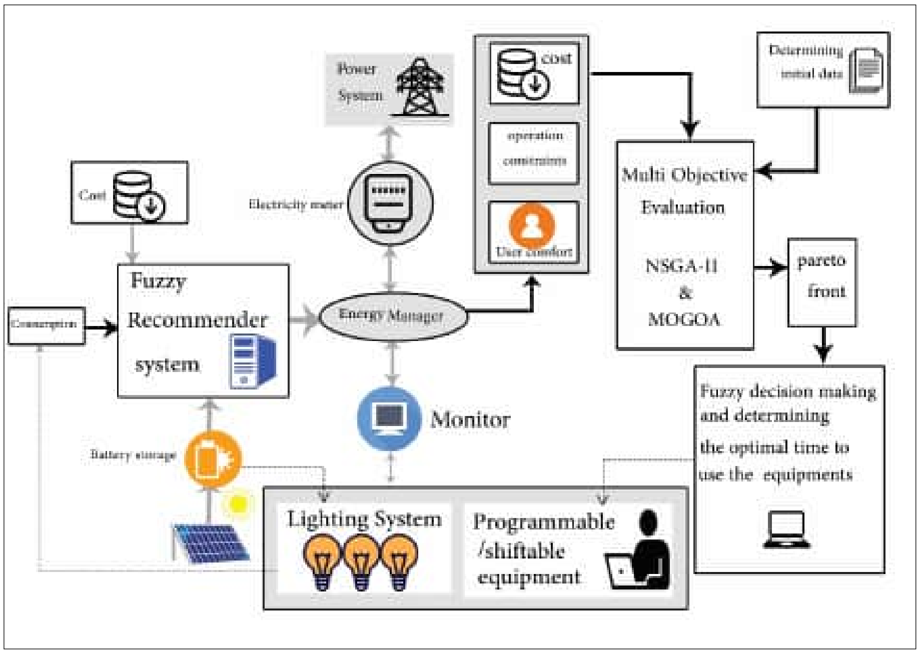

Figure (2): Flowchart of the proposed method

The second part is related to a plan based on a fuzzy-based recommendation system for energy management in the lighting system in a smart home using clean solar energy. In this proposal, the inputs include the amount of storage of the solar panel (battery or digital charger), the amount of energy consumption, the cost of consumption, and they are finally implemented according to the rules of the expert person. The output is the percentage of using solar energy recommended by the system. The amount of solar panel production was determined using fuzzy logic to be used optimally and on time. The first factor, which was considered as the input of fuzzy logic, was the amount of panel storage.

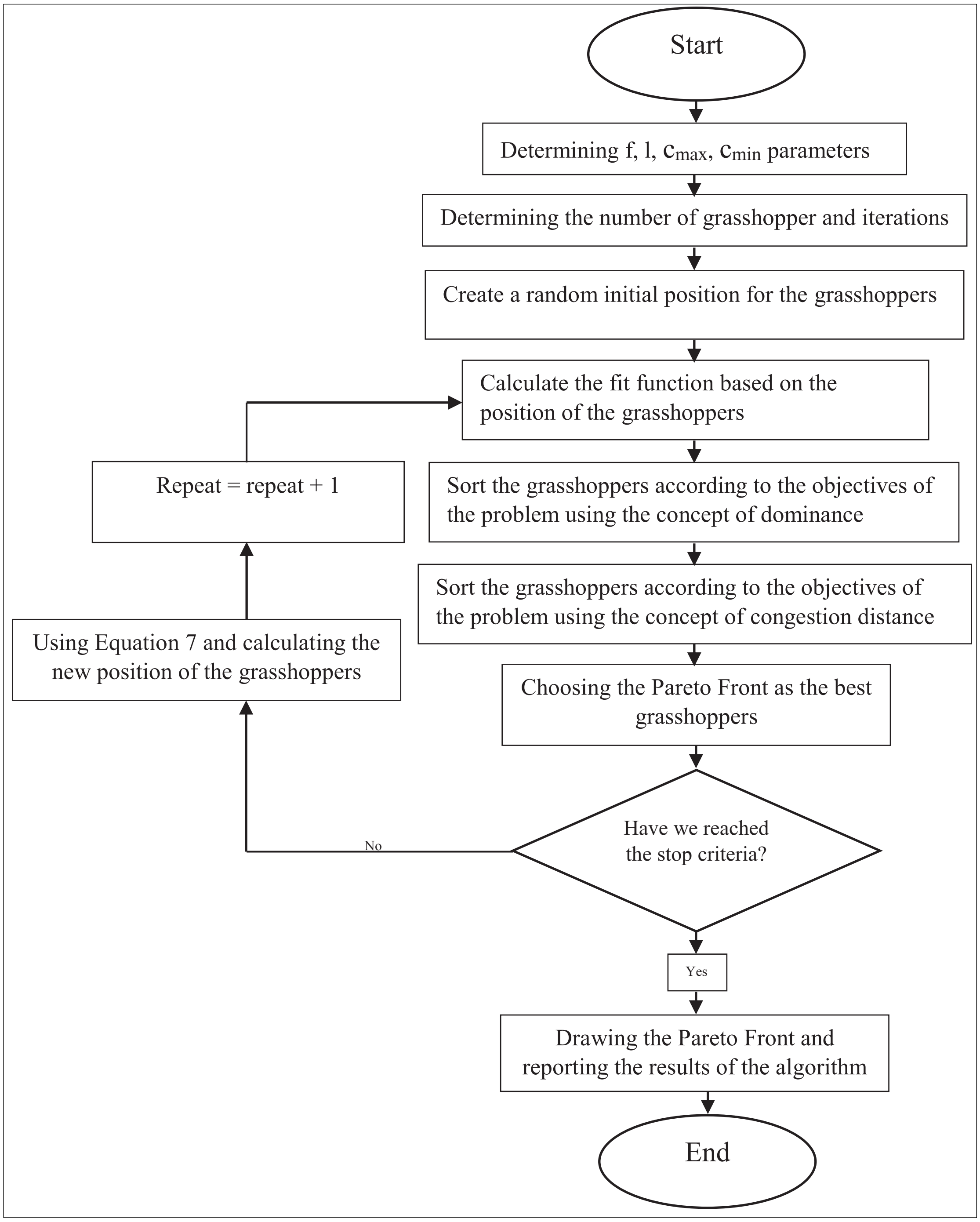

Figure (3): Multi-Purpose Grasshopper Optimization Algorithm

In this research, it has been tried to present a multi-objective grasshopper algorithm by combining a single-objective grasshopper algorithm and a multi-objective genetic algorithm. Calculating the new position of each grasshopper and determining its suitability is described in the previous sections and the flowchart is shown in Figure (3). Figure 3 indicates that values such as cmax, cmin, f, l should be determined to calculate the values of s and c.

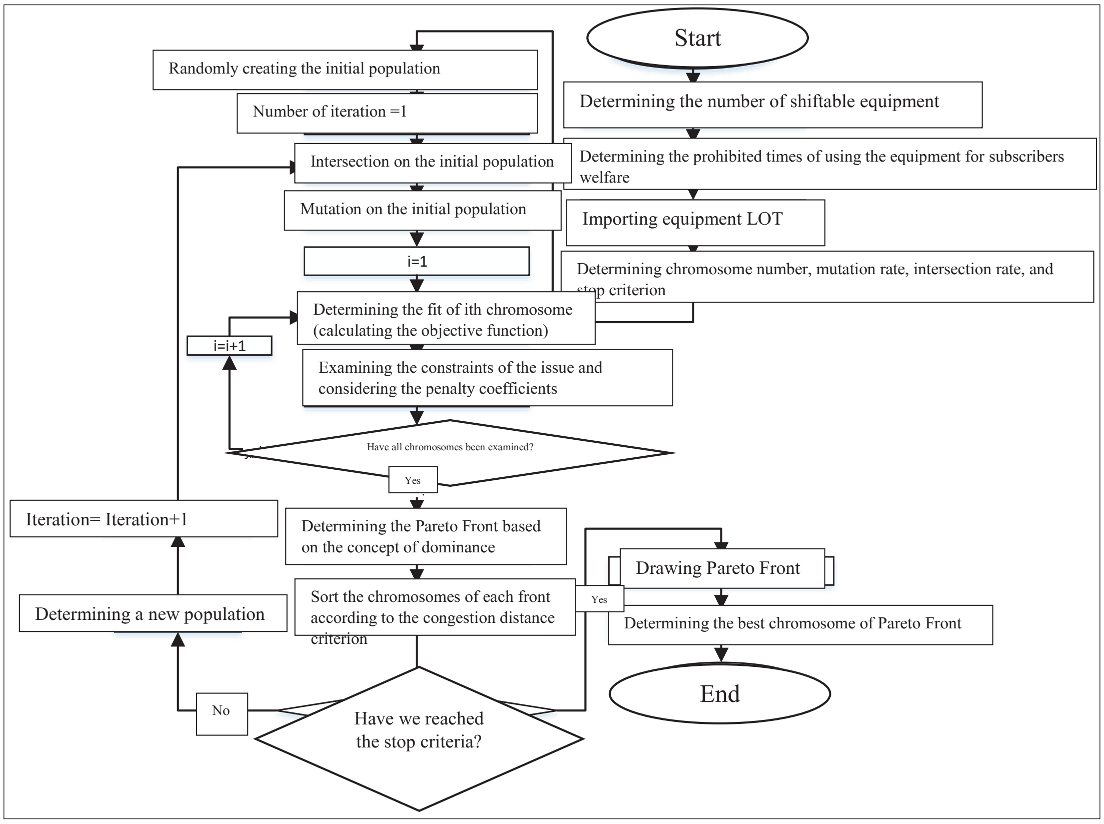

Figure (4): Flowchart of NSGA-II multi-objective optimization algorithm

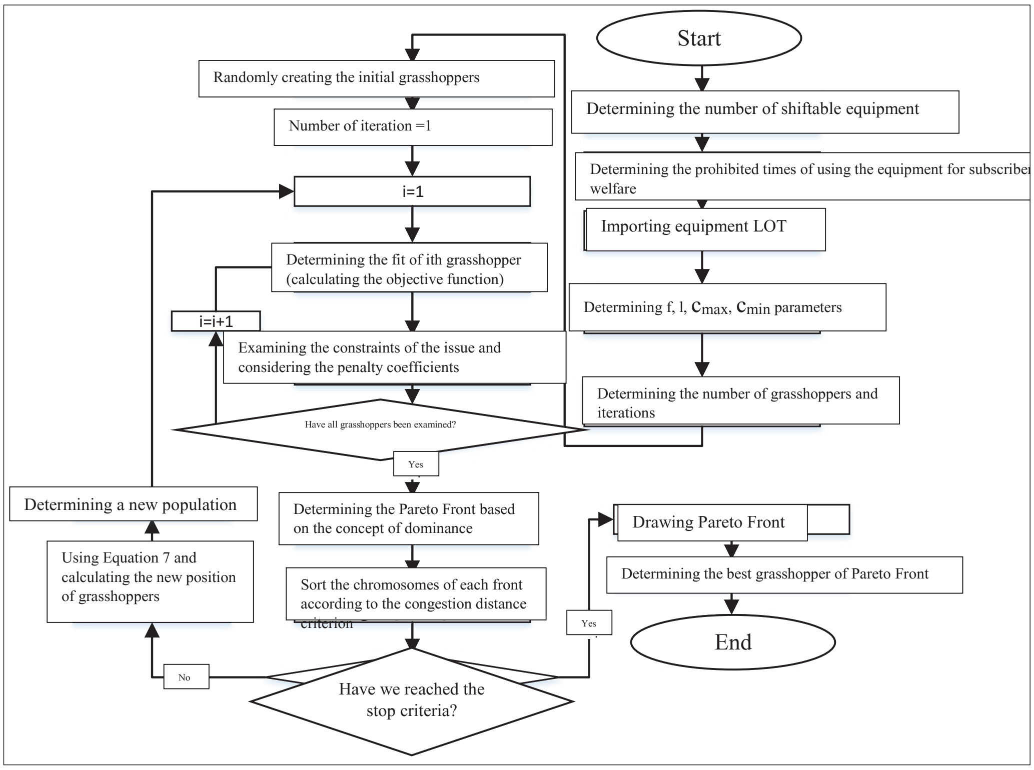

Figure 5. Flowchart of MOGOA multi-objective optimization algorithm

Objective functions

Multi-objective evolutionary algorithms were used to optimize the time of use of equipment in smart homes. The objective function is to minimize the average amount of subscriber's load consumption and to minimize the cost of subscriber's electricity consumption. First, all the equipment used in each slot was determined using multi-objective genetic algorithm chromosomes to calculate the amount of the subscriber's cost. Then, the electricity consumption cost of all equipment was calculated in each slot given the cost of each slot and the product of the cost of each slot multiplied by the power consumption of the intended equipment. The total cost of the subscription during the day and night is calculated by summing all the costs. The cost of the subscribers is calculated according to Equation 9, and the unit of cost is estimated based on tradition in which PD_iPD_i is the power consumption of i^{th} subscriber and $Costs_jCosts_j$ is the power cost of the j^{th} slot.

$$Cost = \sum_{j=1}^{120}\sum_{i=1}^{24} PD_i Costs_j Cost = \sum_{j=1}^{120}\sum_{i=1}^{24} PD_i Costs_j \qquad (7)$$

The peak amount of the subscriber boarding hours is determined based on the hours set to start working in the respective slots and using evolutionary algorithms to calculate PAR and this value is divided by the subscriber's average daily consumption load. In other words, PAR is the peak to average ratio (peak consumption) to the average daily consumption load, which is calculated according to Equation (10).

$$PAR = \frac{Max\ Power(Peak\ Load)=Load_{max}}{Avg\ Power=\frac{\sum_N Load}{N}} PAR = \frac{Max\ Power(Peak\ Load)=Load_{max}}{Avg\ Power=\frac{\sum_N Load}{N}} \qquad (8)$$

Different constraints of smart homes were included in the objective functions based on penalty coefficients to be applicable in the studies. The first constraint was the duration of each piece of equipment, which is represented by a LOT. In other words, when any equipment enters the circuit, the equipment must remain in the circuit until the end of its operation time and then leave the circuit. Another constraint for the proper management of smart home equipment is using all equipment in a full day and extending the length of the operational period of all equipment after entering the circuit and turning it on. One of the main goals of smart homes is to be considered as a constraint on optimizations. Customer satisfaction is one of the features of proper time management of equipment in smart homes. The scheduled time for the start of operation of any equipment was not in the prohibited range for the user as much as possible. This constraint was considered in the calculations due to the welfare of the subscribers.

Fuzzy Recommender

Energy storage and solar panels were used for optimal energy management for the lighting system. Input variables, panel or battery storage, cost, and subscriber's consumption (KW/h) were considered to draw membership functions of each input, including the range of changes and expert opinions. MATLAB software fuzzy toolbox is used to simulate the inputs.

Different rules were collected for collecting fuzzy inputs and fuzzy outputs by gathering information from reference articles and using expert opinions. The number of considered rules can be calculated according to fuzzy membership functions and based on language values intended for fuzzy inputs. A total of 45 fuzzy rules were considered given three inputs and 15 different modes for language variables. The number of rules has been reduced to 15 because some rules were similar and repeated in the same way (Figure 6).

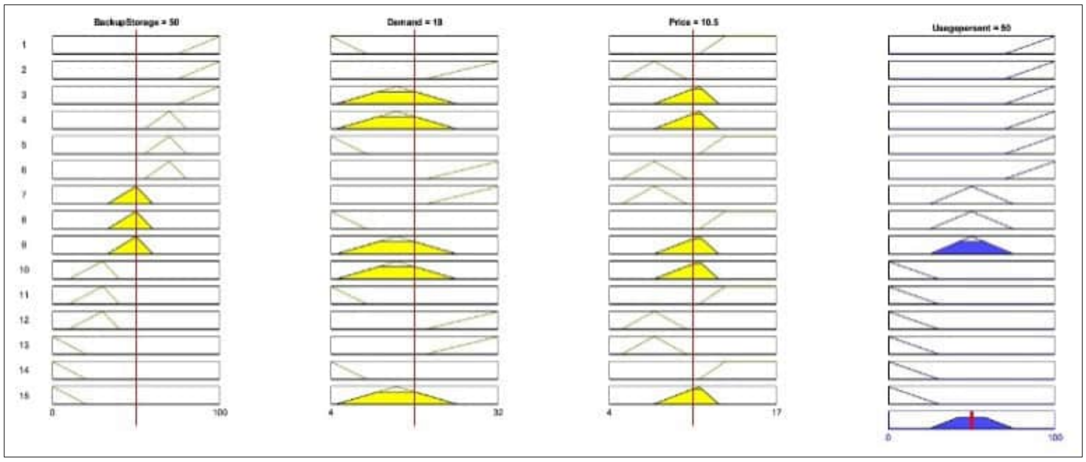

Figure (6): The number of rules has been reduced to 15

Figure 7(a) shows the membership of the panel save amount. The membership function of the panel save amount is divided into 5 different parts .

The second factor considered as the input of fuzzy logic was the amount of power consumption by the subscriber. Figure 7(b) demonstrates the membership of the subscriber consumption rate. The membership function of the panel save amount is divided into 3 different parts according to Table 1 and it has been tried to completely simulate the amount of subscriber's consumption by using the opinions of an expert.

The cost of electricity consumed by subscribers is the last membership function as input. The electricity consumption costs of the subscribers were considered as TOU based on 120 slots in 1 full day and given in the calculations of multi-objective evolution algorithms. The amount of electricity consumption was considered as a membership function. Subscriber electricity costs have a significant effect on panel output and panel setting points. Figure 7(c) presents the membership function of subscriber electricity costs.

According to the intended membership function, the values for the electricity consumption of the subscribers reached approximately the maximum amount of cost in the price ranges above 13, and this should be considered in fuzzy calculations. MATLAB software was used to implement fuzzy logic.

The language variables and features of the output membership function should also be determined before conducting fuzzy studies due to the completion of input information and determination of membership functions for inputs. The output variable and the output fuzzy membership function are plotted in Figure 7(d)

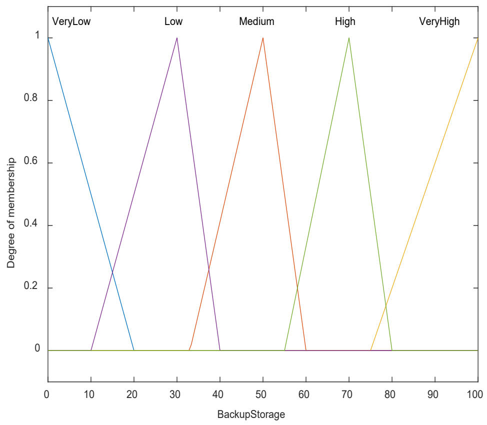

Figure 7(a). Membership function of saving the subscriber consumption panel _ fuzzy input

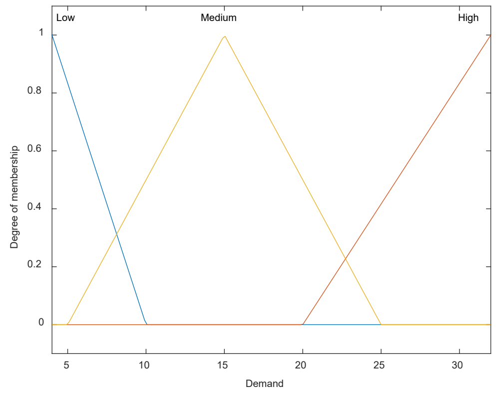

Figure 7(b). Subscriber Power Consumption Membership Function - Fuzzy Input

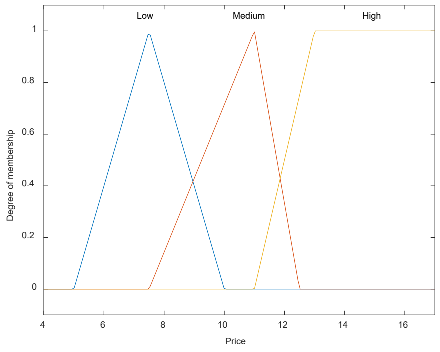

Figure 7(c). Membership function of electricity consumption of subscribers - fuzzy input

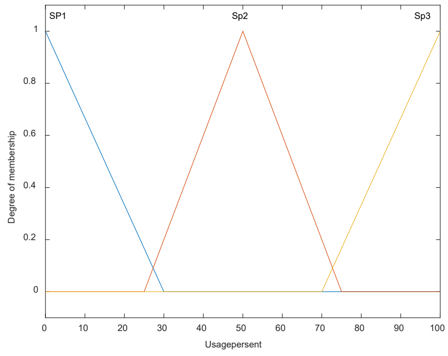

Figure 7(d). Membership function of Rate of using panel - Fuzzy output

Figure (7): Fuzzy input- Fuzzy output

4- Research findings

In this section, first, the test network is introduced, and the cost and average load consumption are studied in a full day considering the collective average behavior of consumers. The average daily load consumption of equipment (PAR) and the cost of electricity consumed by subscribers at the same time were optimized according to the TOU plan for subscribers.

User comfort and subscriber well-being were considered as one of the important constraints in simulations and evolutionary algorithms. The penalty coefficients of the prohibited times for the user were considered in all sections, increasing the subscribers' satisfaction in the presented program.

Test network

A reference network similar to the reference (Kishor, Yadav, & Kumar, 2009., Xiong, Tan, Yang, & Chen, 2013). was used to compare the performance of the proposed algorithms. In the test network, 24 pieces of equipment mentioned in the appendix are considered.

Table 1 indicates the intervals set by the user for a random daily consumption. All prohibited periods of using the devices were taken from the user, which increases the user's comfort and takes into account the users' welfare.

In addition, Table 1 presented the LOT index, which indicates the performance range of the desired equipment after entering the circuit. In this research, the period of 1 full day is divided into 120 slots, and the information is also displayed as a slot. According to these calculations, every 1 hour is defined as 5 slots, and each slot is defined as 12 minutes.

The cost of shared electricity must first be considered for test network analysis. Therefore, the TOU method has been used and the graph of cost changes per kilowatt-hour of subscribers' consumption per slot is shown in Figure (8).

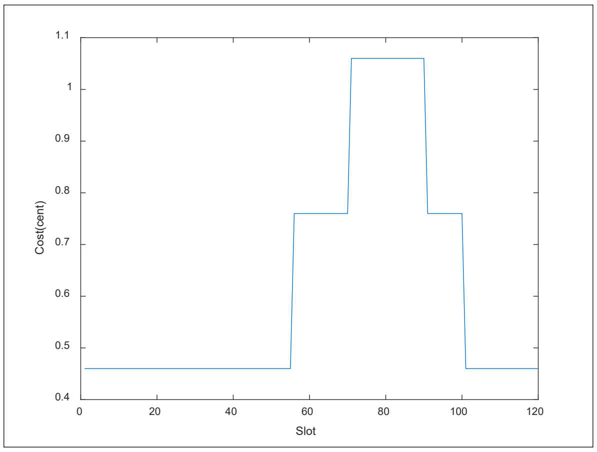

Figure (8): Cost changes per kilowatt-hour in 1 full day

Figure (8) shows the costs in cent/slot, which must be multiplied by 5 to calculate the cost of electricity consumed by subscribers on a cent/hour basis to match the reference article. The graph of subscriber's cost and power consumption can be plotted based on the average daily consumption defined in Table 1 considering the consumption costs of the subscribers.

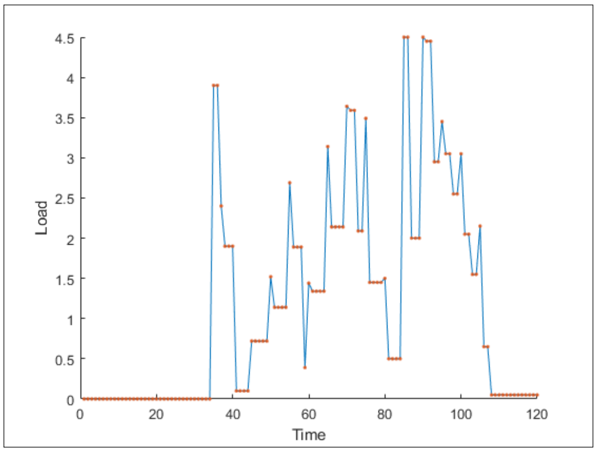

Figure (9): Subscriber's power consumption curve based on desired hours of equipment use (kW)

This cost and average power consumption are not the best possible conditions. The subscriber's average load per day is 3.7174 Figure (9) and the total cost per day for the time of the subscriber's desired consumption is calculated as much as 1107.7872 cents. Subscriber's behavior was corrected using evolutionary algorithms to reduce the cost and average boarding load of the subscriber.

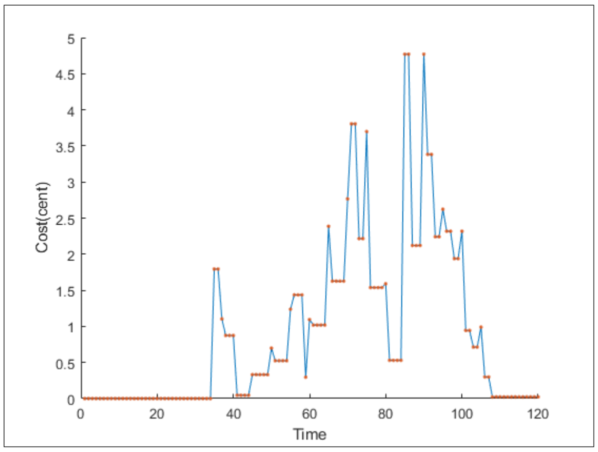

Figure (10): Subscribers' electricity cost curve based on desired hours of equipment use

Optimization using MOGOA multi-objective propeller algorithm

The results of the simulations were analyzed using the multi-objective grasshopper algorithm (MOGOA). The parameters of the two algorithms were similarly selected to compare the results of the multi-objective grasshopper algorithm and the multi-objective genetic algorithm. The population of primary grasshoppers and the number of iterations were considered as much as 100 and 500, respectively. The initial population of the multi-objective genetic algorithm and the number of iterations were considered as much as 100 and 500, respectively. c_{max} in the grasshopper algorithm was 1, c_{min} was 0, and the value of f was 0.5 and the value of l was 1.5.

The optimizer objectives in this algorithm were defined as improving the peak to average ratio index and reducing subscriber costs. The decision variable in the multi-objective grasshopper algorithm is the time the equipment enters the circuit, which should be considered in the multi-point optimization. The first point is the lack of using equipment in the prohibited range because of subscribers' satisfaction.

Figure (11) shows the improvement of the first Pareto Front in different iterations of the MOGOA algorithm, which could achieve the dominant Pareto Front overall its previous solutions after 500 repetitions. The second point is to consider the LOT in the calculations and observe it as much as possible. The main constraint is the requirement to use all equipment during a full day according to the LOT, and the equipment should be used in a full day and passed the LOT period. The stop criterion is the number of iterations of the multi-objective grasshopper algorithm. This algorithm presents the algorithm responses as a Pareto Front due to the use of the concept of dominance and congestion distance in the single-objective grasshopper algorithm and conversion of this algorithm into the proposed multi-objective MOGOA algorithm. All Pareto Front grasshoppers are valid as the responses to the problem are similar to the multi-objective genetic algorithm. Grasshoppers are considered at the beginning and end of the Pareto curve, which represents the best response in terms of cost and peak-to-average ratio index for comparison with multi-objective genetic algorithm to select the best grasshopper using a fuzzy decision-maker.

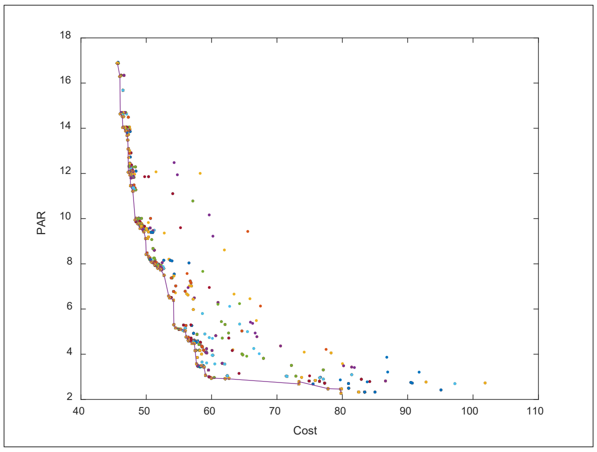

Figure (11): Pareto Front curve for different iterations of the algorithm

Figure (11) examined the most primitive and terminal chromosomes of the final Pareto Front. In the following studies, the mentioned chromosomes were analyzed with the chromosomes selected by the fuzzy decision-maker. Table 2 demonstrates the best grasshopper in terms of reducing cost as much as about 64%, as well as the best grasshopper regarding both objective and fuzzy decision maker compared to unplanned mode about 59% of subscribers' cost. Moreover, the best chromosome in terms of the peak to average ratio is about 41% compared to the unplanned mode, which is excellent because this grasshopper should not be expected to make complete cost recovery as the last grasshopper in terms of cost.

From the PAR point of view, the top grasshopper could improve the peak to average ratio of the PAR network after using the fuzzy decision-maker about 17% compared to the base article, which is excellent. In addition, the superior grasshopper had about 33% improvement in cost reduction using fuzzy decision make, which seems to be very desirable compared to the base article. The results of the simulations should be comprehensively reviewed and compared with the reference article. The best response from a PAR perspective was the NSGA-II algorithm. This algorithm could provide the best response in terms of cost. The responses provided for multi-objective algorithms were much better than those of the reference article, and the second point is to compare the algorithms in terms of convergence-to-response speed. The MOGOA algorithm converged to the final response at a speed of about 30% faster than the convergence speed of the NSGA-II algorithm. Therefore, the multi-objective grasshopper algorithm has a much higher speed from the point of view of convergence speed.

Table (1): Comparison of results from multi-objective algorithms		
	Subscriber's Total Cost (cent)	Peak-to-average ratio (PAR) for a full day
Unplanned consumption (NSGA-II)unsch	110.7872	3.7417
Top chromosome in terms of cost (NSGA-II)	25.7874	20.6897
Best Chromosome from Peak to Average Ratio Index (NSGA-II)	95.0182	1.511
Selection of superior Pareto Front chromosomes using fuzzy decision-maker (NSGA-II)	41.4964	2.2351
Best Grasshopper in terms of Cost (MOGOA)	39.076	16.7428
Best Grasshopper in terms of Peak to Average Ratio Index(MOGOA)	76.0848	2.1978
Selection of Superior Beam Front Grasshoppers Using Fuzzy Decision Maker (MOGOA)	44.4898	2.3222
BAT Algorithm [1]	66.1914	2.8533
HP Algorithm [1]	66.1782	3.3941
HFBA Algorithm [1]	66.4478	2.7958

Figure (12) compares the scheduling of all equipment in the chromosomes presented in Table 2. As can be seen, the schedule for all scenarios of the multi-objective grasshopper algorithm is plotted in the form of a bar chart, which allows the analysis of equipment one by one. The vertical axis is a full day slot, each slot is 12 minutes, and every five slots is an hour.

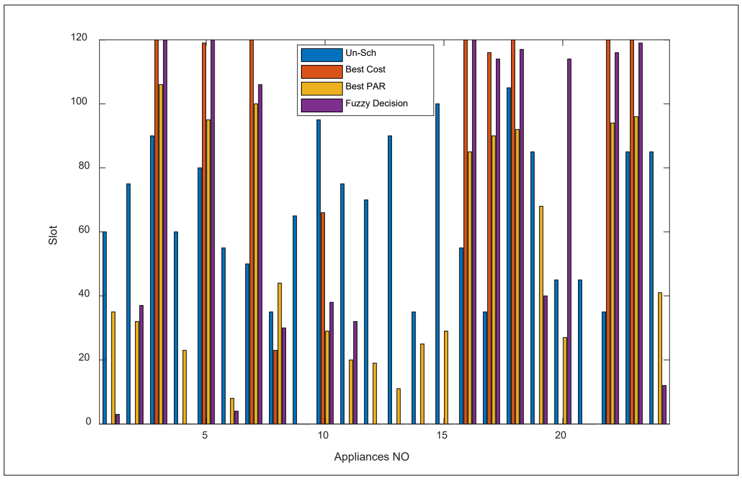

Figure (12): Comparison of scheduling programs in the MOGOA algorithm

Selected best grasshoppers are used by fuzzy decision-makers to evaluate the amount of improvement of the multi-objective grasshopper algorithm on the cost curves and the peak to average ratio index to subscribers' full-day average. For this purpose, it is better to first check the network from the point of view of subscribers' power consumption in a full day. Figure 13 indicates a reduction in the subscriber power consumption in this interval due to the increase in subscribers' costs in slots 56 to 100.

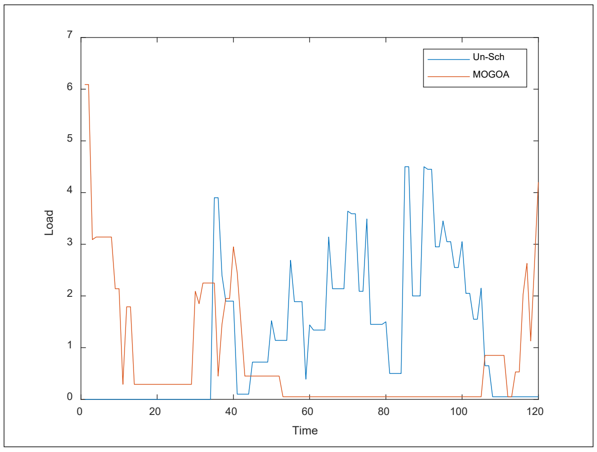

Figure (13): Subscribers' power consumption in a full day

The consumption costs of the subscribers in a full day are shown in Figure 14. Reducing the power consumption of subscribers at peak load and in response to the increase in electricity prices in slots 56 to 100 has clearly been able to reduce subscriber costs.

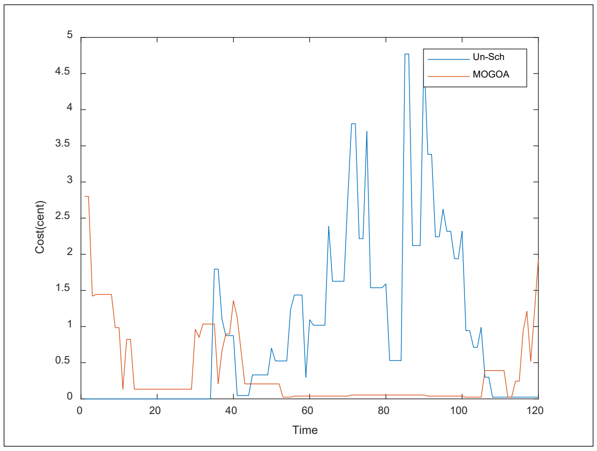

Figure (14): Cost of electricity consumed by subscribers in a full day (cent)

Use fuzzy recommender to manage solar panel

In this section, the energy management of the solar panel for the lighting system was performed using a fuzzy recommender. The effective inputs of the optimal production of the solar panel were determined by three factors, including the amount of panel storage, the amount of electricity consumed by the subscribers, and the cost of consumed electricity. The relationship between the factors affecting the optimal determination of panel output and output was calculated using fuzzy logic. The general method of fuzzy logic modeling is shown in Figure 15. As shown, the inputs and outputs are related using 15 rules, which were explained in the previous section.

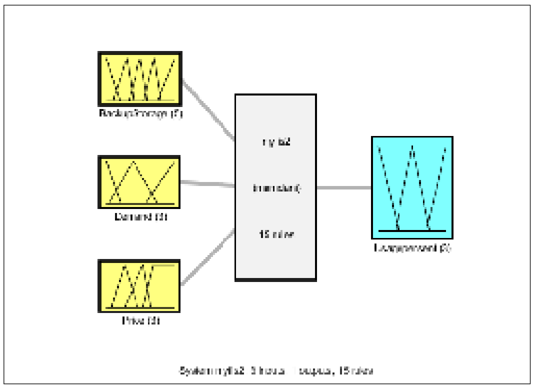

Figure (15): Relationship between fuzzy recommender inputs and outputs

The output membership function can also be calculated according to the rules of fuzzy logic and then, check the fuzzy level for different inputs.

In the next stage, the amount of panel adjustment was checked according to the input levels. Figure (20) shows the solar panel adjustment point changes based on the level of panel storage changes and consumption load. According to the figure, the fuzzy recommender system has selected a small amount for panel energy management use for low solar panel savings and low loads. The fuzzy recommender maximized the energy management value of the panel for large amounts of panel storage and high loads according to fuzzy rules.

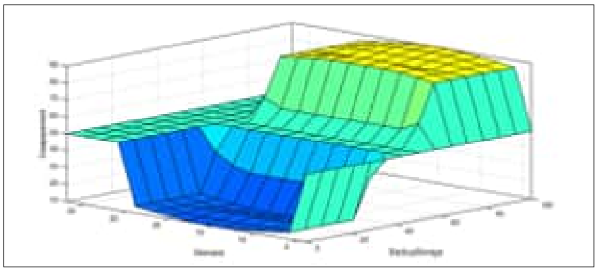

Figure (16): Interface level between panel storage - load consumption and panel energy management

Figure (16) shows the changes in the solar panel's energy management adjustment point based on panel storage and common electricity consumption costs. Fuzzy recommender reduced panel energy management for small amounts of panel storage and the cost of electricity consumed by subscribers. The fuzzy recommender prioritized the use of the panel and increased its value by increasing costs. This process was conducted by increasing the panel reserve, and the fuzzy recommender has functioned correctly according to the fuzzy rules.

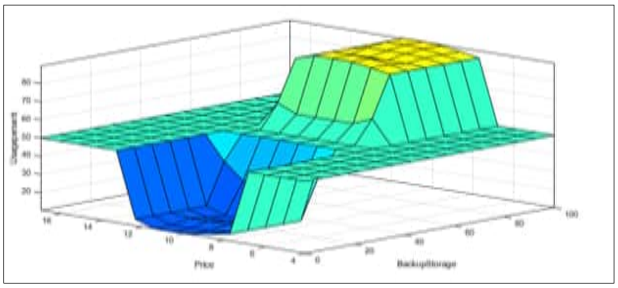

Figure (17): Interface level between panel storage - power cost and panel energy management

5- Conclusion

This article aimed to conduct optimal management based on time scheduling for smart home equipment. Therefore, all the basic limitations, including considering the LOT constraint, using all the equipment during a full day, and the constraint of the subscribers' welfare, were considered in the optimal planning. Multi-objective genetic algorithm and multi-objective grasshopper algorithm were used for optimization and it was observed that optimal management of equipment entry time into the circuit can minimize a very good percentage of subscribers' round-the-clock costs and peak-to-average load ratio. the best grasshopper from cost reduction point of view has been able to reduce about 64 % of common costs compared to non - planning and also the value for the best chromosome from peak to average ratio point of view is about 41 %, which is excellent.

in the proposed algorithm, selection of the best chromosome by using fuzzy decision - making has about 17 % improvement in PAR and for cost about 33 % improvement has been achieved than more desirable articles. as it was observed, the MOGOA algorithm was able to optimize the simulation targets to a suitable extent.

These results showed that energy can be managed by using equipment in smart homes using an optimization program. The use of a fuzzy recommender to manage the energy of the solar panel in lighting applications showed that the user should use the panel storage for the lighting system when the panel storage is high or very high. This method of using clean energy helps to reduce costs and pollutants. Also in this paper, studies have been performed for an experimental network. It is suggested that studies be implemented on the personal test network and the results be done by changing the purchase.In addition, in the future, instead of considering TOU for joint sales, other responsive load management schemes and the joint behavior modification of RTP and CPP can be used, and the issue can be examined from the type of cost scheme viewpoint.

Table (2): Specifications of applied equipment and determination of prohibited intervals								
Name of equipment	Unplanned usage hours (hours)	Unplanned use (Slot)	Start of the prohibited period (hours)	Start of the prohibited period (Slot)	End of prohibited period (hours)	End of prohibited period (Slot)	Power (KW)	LOT
AC1	12	60	22	110	5	25	1.00	5
AC2	15	75	22	110	5	25	1.00	5
AC3	18	90	22	110	5	25	1.00	10
Humidifier1	12	60	6	30	10	50	0.05	10
Humidifier2	16	80	19	95	22	110	0.05	10
Fan	11	55	1	5	3	15	0.05	119
Cloth Dryer	10	50	23	115	5	25	0.80	5
Rice Cooker1	7	35	23	115	5	25	1.80	5
Rice Cooker2	13	65	23	115	5	25	1.80	10
Rice Cooker3	19	95	23	115	5	25	0.50	2
Pool Pump	15	75	20	100	24	120	0.40	20
Water Pump1	14	70	24	120	6	30	1.50	2
Water Pump2	18	90	24	120	6	30	1.50	2
Electric Radiator1	7	35	10	50	14	70	0.50	2
Electric Radiator2	20	100	14	70	16	80	0.50	2
Water Heater1	11	55	22	110	24	120	1.50	3
Coffee Maker1	7	35	22	110	5	25	0.10	25
Dish Washer	21	105	6	30	14	70	0.60	2
Coffee Maker2	17	85	22	110	5	25	1.00	1
Washing Machine	9	45	14	70	16	80	0.38	5
Water filter	9	45	20	100	24	120	0.24	30
Electric Kettle1	7	35	24	120	5	25	1.50	1
Water Heater2	17	85	22	110	4	20	1.50	20
Electric Kettle2	17	85	20	100	4	20	1.50	1

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