ISSN: 2251-9246
EISSN: 2345-6221

pp. 1:8

Synchronizing of Smart Homes in Microgrids using Whale Optimization Algorithm

Farhad Nourozi[1], Navid Ghardash Khani[2*]

[1]Department of Electrical Engineering, Ahrar Institute of Technology and Higher Education, Rasht, Iran, farhadnorouzi97@gmail.com
[2]Department of Electrical Engineering, Bandar Anzali Branch, Islamic Azad University, Bandar Anzali, Iran, navid_gh@aut.ac.ir

Abstract

The household energy management system (HEMS) can optimally schedule home appliances for transferring loads from peak to off-peak times. Consumers of smart houses have HEM, renewable energy sources and storage systems to reduce the bill. In this article, a new HEM model based on the time of usage pricing planning with renewable energy systems is proposed to use the energy more efficiently. The new meta-heuristic whale optimization algorithm (WOA) and the common meta-heuristic of particle swarm optimization (PSO) are used to achieve that. To improve the performance, a mapping chaos theory (CWOA) is proposed. Also, an independent solar energy source is used as a support of the microgrid to achieve a better performance. It is concluded that the energy saving achieved by the proposed algorithm is able to decrease the electricity bill by about 40-50% rather than the WOA and PSO methods. The proposed system is simulated in MATLAB environment.

Keywords: Chaos Whale optimization (CWOA), Distributed Energy Resources (DER), Household Energy Management System (HEMS), Particle Swarm Optimization (PSO), Renewable Energy Systems (RES), Smart time Scheduling (SS)
Article history: Received 2024/01/14; Revised 2024/02/20; Accepted 2024/03/10, Article Type: Research paper

1. Introduction

The smart grid phrase refers to modernizing the electrical grid by merging different technologies such as distributed manufacturing, planable loads, communicational systems and storage devices which are used effectively for electricity transmission sustainably, economically and safely. Energy management plays a vital role in preserving sustainability and smart grid reliability, which in turn helps prevent power outages. Energy management is a complex task on the side of consumers and requires efficient time scheduling of home appliances with minimum suspension to reduce the peak to average ratio (PAR) and energy consumption costs. Distributed energy resources (DER), which are placed alongside the final consumer loads, provide a replacement for constructing new central mass production power plants or establishing transmission lines or renewing them. DERs are relatively small energy resources with a nominal capacity of several kilowatts in residential buildings to several megawatts in the distribution grid. DER can be commonly used as micro turbines and diesel generators or in the form of renewable energy sources (RES) such as photovoltaic (PV), wind turbines and biomass converters. Due to the concerns of climate change, RES is intensely preferred over common resources. Even though the periodicity of the RES is one of the biggest problems with integrating it, the RES random output factors and the uncertain consumer behavior make it hard to keep production balanced and make system operators want to work there. Energy storage has the potential to alleviate uncertainty regarding the existence of production and demand, but this approach is currently inappropriate or excessive on a large scale. As a result of population growth and the spread of residential customers, today's electrical energy consumption is on the rise. One of the most important methods to manage and reduce the electricity bill is the household energy management system, especially for devices such as washing machines, air conditioners, etc. As household energy management gets more complicated, synchronization and efficient scheduling of home appliances has become essential in a way that, by determining an optimization issue and choosing a suitable optimization solution, certain benefits can be obtained for residential consumers and help the electrical energy providers with energy usage reduction. This has caused many models and algorithms to be proposed and improved in the field of synchronization and household energy management while considering different concerns. Authors in [1] proposed a short term power load forecasting using learning models for energy management in a smart community. For the purpose of energy management in a smart community, they focused on investigating and evaluating machine learning models for accurately predicting user power profiles. The simulation results show that the Radial Basis Function (RBF) kernel is the best machine learning model for forecasting the short term power consumption of a single household. Eight regression models were evaluated for the purpose of predicting the power consumption of a single household. A pyramid-CNN based deep learning model for power load forecasting of similar-profile energy customers based on clustering is investigated in [2]. They significantly improved forecasting results for randomly selected users from different clusters. Customers' MAPE improved by up to 10% as a result of the clustering-based model training strategy. The summary of the study is that energy customers can be grouped into clusters and then a representative model could be developed/ trained, which can accurately forecast power load for individual energy-customer. Moreover, towards energy efficiency and power trading, exploiting renewable energy in cloud data centers is investigated in [3]. Authors utilize real-time data requests, weather data, and pricing data for performing simulations and the cost and carbon emission of cloud DCs. In [4] authors proposed a deep learning framework for short term power load forecasting. A case study of individual household energy customer results affirms the effectiveness and productiveness of the proposed method to mitigate energy.

Authors in [5] proposed quality learning (RSOTHA-QL), a real-time scheduling of household appliances' operational times based on reinforcement learning. The proposed RSOTHA-QL design operates in two phases. In the first phase, the Q learning factors operate in response to the smart home's environment and receive a reward. The amount of reward for planning the operation time of home appliances is used in the next step to ensure minimal energy consumption. In the second phase, the dissatisfaction derived from the home appliance operation schedule of the household user is maintained by classifying home appliances into three groups of deferrable, non-deferral and controllable. A combined resistance stochastic optimization model for smart home energy management in daily and real-time energy markets in which the uncertainties of energy prices and PV production in the proposed model is proposed by authors in [6]. A flexible resistance optimization method for creating a problem-solving equation and uncertainty management of the day-ahead market prices are used when PV production is assumed to be at its worst. In [7] authors proposed a daily energy management algorithm for synchronizing smart homes with reproducible energy resources and energy. Daily decentralized synchronization with home appliance time scheduling and energy sharing among smart homes vary to minimize the consumer electricity bills in pricing. In another study, authors proposed an algorithm based on local search for minimum conflict, combined with Grey Wolf Optimizer for the power time scheduling matter in the smart home [8]. The home appliance time scheduling issue of the smart home is in accordance with the variable pricing outlines for flattening users' power consumption. The aim of the method is reduction in electricity bills and to improve the user's comfort and to maintain the power systems' function [8]. In [9] authors focused on the energy management of a smart home equipped with a plug-in electrical vehicle (PEV) and home and PV battery storage which offers an energy price signal for the entire energy storage equipment connected to the smart home system. The combination of methods including optimization and prioritization is demonstrated in this article according to the rule. The proposed algorithm creates a priority order between PEV, home batteries and the imported power from the grid based on the energy resources. The proposed energy the executives calculation is after the base expense of complete energy for the brilliant home and the PEV proprietor while satisfying the family power requests and the stockpiling hardware charge necessities. For residential appliance time scheduling, authors in [10] presented the model of demand-side management based on optimization evolutionary algorithms for binary particle swarm, genetic algorithm, and cuckoo search). The model is reproduced in the hour of purpose (ToU) valuing climate for three sorts of customary homes, smart homes and smart homes with RES. The mentioned research focused on the field of smart homes synchronization with chaotic whale optimization algorithm (CWOA) in providing loads for efficient timing determination for distributed resources. The smart distribution possibility of scheduled resources by an EMS decentralized energy management system which is able to ideally schedule the entire storage and production resources in microgrids.

Table.1.
The comparison between present study and some other similar methods

Reference	Method	Advantage	Disadvantage
Current Study	CWOA	Simple implementation No need for gradient information (can pass through local optimal points) Includes a wide range of samples.	The sampled data is limited
[11]	Genetic Grey Wolf Algorithm	Simple process Easily generalizable	Inability to solve problems with sampling discontinuities.
[12]	Genetic Algorithm	The nature of random search in the sampling area The best answers because of competition (survival conflict)	High executive and practical costs
[14]	Ant Colony Optimization	Convergence to the optimal answer is guaranteed.	Includes additional mechanisms such as retreat and local search mechanisms.

2. Smart Home Synchronization Modeling

One of the most important challenges for renewable energy systems is their power production unpredictability, because of wind speed or sun irradiation variations, which complicates energy management. Also, for energy consumption by electricity consumers, not all consumers can be bound to consume specific devices at a specific time, which also complicates the power management study to reduce energy costs. In this case for modeling the smart home synchronized system, the EMS is used efficiently in a household for home appliance synchronization to consume energy from the grid and RES stored energy. The HEMS includes several pieces of equipment. Home grid (HG), electrical appliances and a home display device. The household owns home appliances, smart time scheduling (SS) and a decision system which is embedded in HEMS and synchronizes equipment. Three types of consumers are considered. A household's daily energy consumption is exclusively simulated and operates as a consumer and producer of electrical energy, which is called a professional consumer. A household equipped with a RES system or local energy production is a smart counter which provides energy price signals and a collection of electrical appliances which consume energy. In this model, each day is divided into 25 time periods. The SS efficiently calculates the ON-OFF schedule of home appliances. Each home contains a collection of appliances ℕ= $\{a_1, a_2 \ldots a_N\}$ and |ℕ|=N. Assume that the observation period is H and there are two types of loads, which are intermittent loads and base loads. The first collection includes a washing machine, a clothes-dryer, an electrical auto and an electrical water heater.

Similarly, the second collection includes a refrigerator and a light source. When the intermittent equipment is activated, it can be postponed at any time. For a synchronization matter, the number of portable devices is more than zero hence $A>0$. The goal of the user is obtained with optimized control measures for portable loads. Assume that $\alpha_{ai,}$ is a collection of portable equipment that hasn't been scheduled in the h time period and base loads. This assumption is considered because the user isn't willing to reschedule those loads. Each home appliance has a constant number of time intervals (LOT) and each home appliance must operate within 24 hours and accomplish its duty. Each home appliance can only tolerate a certain amount of delay (ζ_{ai}) which is demonstrated as (1) because the SS operates based on charge transfer.

$$\zeta_{ai} = 24 - \beta_{ai} \tag{1}$$

Where, the βai refers to the LOT of the ai. Upper and lower limits of ζai are given as mentioned in (2).

$$\Psi_1 \leq \zeta_{ai} \leq \Psi_2 \tag{2}$$

Where Ψ_1=24−β_{Max} and Ψ_2=24−β_{Min}. If h_i is the energy consumption of a_i appliance in h time period, then the demand of the entire household (E_T) is calculated as below.

$$E_T = \sum_{i=1}^{N} \sum_{h=1}^{24} (h_i) \tag{3}$$

It is assumed that the household produces 40% of the demand by RES. The user must be connected to the main power grid, by considering the production hourly for a photovoltaic module ($E_{RES,h}$ $\forall$ $h\in\{1,2,\ldots,24\}$), the daily production is given as mentioned in (4).

$$E_{RES} = \sum_{h=1}^{24} E_{RES,h} \tag{4}$$

By assuming this collection, $A=\{a_1,a_2,\ldots,a_N\}$, these home appliances are connected to SS-related HEMS. The goal of this matter is minimizing the electricity bills which are modeled from (5) to (9).

$$f = Min \sum_{h=1}^{24} \sum_{i=1}^{N} E_{Cost_{a_{i,h}}} \quad (5)$$

$$\sum_{h=1}^{24} \sum_{i=1}^{N} E_{h,a_i} = E_{grid}, \forall B \quad (6)$$

$$\sum_{h=1}^{24} \sum_{i=1}^{N} E_{T,h} = E_{grid,h} + E_{RES,h}, \forall I \quad (7)$$

$$\zeta_{Max,} \leq 24 - \beta_{ai} \quad (8)$$

$$\sigma_{h_i} \in \{0,1\} \quad (9)$$

Equation (5) is the minimizing function goal. Equation (6) refers to energy demand and balance in the B state. According to (7), the energy demand is always achieved by grid and reproducible energy resources. Equation (8) demonstrates the maximum waiting time that each appliance can tolerate. In (9), a binary variable that indicates whether an appliance is ON or OFF has been provided.

3. Whale Optimization Problem Solving Method

The primary concept of Whale Optimization Algorithm (WOA) is described, modeled and demonstrated in this part. Finally, an operator is proposed for function improvement of (WOA) in this article. One of the biggest whales is humpback whales. Their favorite kind of prey is Krill), floating crustaceans similar to shrimp (and small flocks of fish. Fig. 1 illustrates the whales' feeding behavior. The intriguing issue with respect to the humpback whales is their exceptional hunting strategy [15]. The feeding behavior is called the bubble-net feeding method. Humpback whales prefer a flock of krill or small fish near the surface. It is deduced that this method of feeding is accomplished by producing particular bubbles in the shape of a "9" or along a circle, as shown in Fig.1.

A) Modeling and optimization algorithm

Humpback whales can identify the place of baits and surround them. The target bait or a point close to it is assumed by the WOA algorithm to be the best currently optimized answer. After the best search factor is determined, the other search factors attempt to modernize their positions through the best factor. This behavior is defined in the following equations.

$$D = \left| \vec{C}.\vec{X^*(t)} - \vec{X(t)} \right| \quad (10)$$

$$\vec{X(t+1)} = \vec{X^*(t)} - \vec{A}.D \quad (11)$$

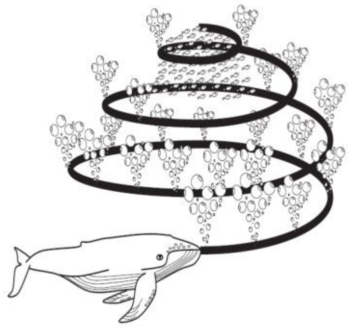

Fig. 1. Bubble-net feeding behavior of humpback whales [10]

Where t indicates the current repetition $\vec{C}$ & $\vec{A}$ the coefficient vectors, $\vec{X^*(t)}$the position vector of the best current obtained answer, $\vec{X}$ the position vector, | | the absolute value and "." is the element to element multiplication. It is also worthy of note that if a better answer exists; $\overrightarrow{X*}$ must be updated in each repetition. The vectors $\vec{a}$and $\vec{c}$are calculated as follows.

$$\vec{a} = 2\vec{a}.\vec{r} - \vec{a} \quad (12)$$

$$\vec{c} = 2\vec{r} \quad (13)$$

Where $\vec{a}$ along the repetition period and efficiency reduces linearly from 0 to 2 and $\vec{r}$ is a random vector between 0 and 1. The (X,Y) position of a searching factor can be updated in accordance with the position of the current best factor (X^*,Y^*). Different locations around the best factor can be obtained relative to the current position by adjusting the values of vectors $\vec{A}$ and $\vec{C}$. Equation (11) allows each research factor to update its vicious position to the current best answer and simulates the bait surrounding. A similar concept can improve with n dimensions in a search environment, and the research factors will move toward the cube cloud around the best currently obtained answers. As mentioned before, humpback nails also attack the bait with the bubble-net method. This method is formulated as follows mathematically.

B) The bubble-net attack method (the efficiency phase)

Two approaches have been developed to imitate the humpback whales' bubble-net behavior as follows.By reducing the amount of $\vec{a}$, this behavior can be achieved by (12). Pay close attention to the region of fluctuation of $\vec{A}$ also decreases when the vector $\vec{a}$ is reduced. In other words, $\vec{A}$ has a random value between $-a$ to$+a$ that decreases over the repetition period from 2 to 0. The new position of the research factor can be determined anywhere between the main position of the factor and the position of the best current factor by adjusting random values of the $\vec{A}$ between -1 and +1 to. The Spiral update position method begins by determining the distance between the whale in (X, Y) and the prey in (X^*, Y^*). Next, it mimics the spiral motion behavior of humpback whales to create a spiral equation describing the positions of the whale and prey.

$$\vec{X}\,(t+1) = \overrightarrow{D'}.e^{bl}.cos(2\pi l) + \overrightarrow{X^*}\,(t \tag{14}$$

While $\overrightarrow{D'}$=|$\overrightarrow{X^*}$ (t)−$\vec{X}$ (t)|, is a constant for determining the logarithmic spiral structure and x shows the whale's distance from the prey (the most accurate position to date), l is a random number between -1 and$+1$. In close proximity to their prey, humpback whales swim in a narrower circle and simultaneously leave a spiral trail. We assume that there is a 50% possibility of selecting between the shrinking siege mechanism and the spiral model for updating the whales' position along the optimization for simultaneous simulation of these behaviors. The modeling is as follows.

$$\vec{X}(t+1)= \quad \overrightarrow{X^*(t)}-\vec{A}\ .\vec{D}\ , \quad if\ p<0.5\overrightarrow{D'}.e^{bl}.\cos(2\pi l)+\overrightarrow{X^*(t)},\ if\ p\geq 0.5 \tag{15}$$

Where p is a random parameter that can varied from 0 to 1. Humpback whales also use the bubble-net method to randomly search for baits. The following is the search's mathematical model.

C) Searching for baits (Discovery Phase)

When searching for prey (discovery), a similar strategy based on fluctuations in the $\vec{A}$ vector can be utilized. Actually, humpback whales search at random based on where they are. To force the search factor to the distance from a source whale, random values of $\vec{A}$ greater than or equal to 1 are used. In contrast to the efficiency phase, the position of a search factor in the discovery phase is determined by an update of a randomly selected search factor rather than the most effective search factor that has been discovered thus far. The WOA algorithm is able to carry out an inclusive search thanks to this mechanism and |$\vec{A}$ |>1. The following is a mathematical model.

$$\vec{D}\ = \left|\vec{C}\,.\overrightarrow{X_{rand}}\ - \vec{X}\,\right| \tag{16}$$

$$\vec{X}\,(t+1)=\overrightarrow{X_{rand}}\,-\vec{A}\,.\vec{D} \tag{17}$$

Where $\overrightarrow{X_{rand}}$ is the current population's chosen random position vector (a random whale).The WOA algorithm begins with a series of random responses. In every reiteration, research factors update their positions comparative with the haphazardly picked arbitrary component or the most fitting response acquired till now. In order to provide discovery and decrease efficiency, the parameter a is reduced from 2 to 0. When $|A|$ is less than 1, the best answer is chosen. While $|A|$ is greater than 1, a random search factor is used to update the search factors' positions. WOA can move between a circular movement and a spiral movement depending on the amount of p. The WOA algorithm finally comes to a stop by obtaining a stop indicator. Because it has the capacity for discovery as well as efficiency, WOA could theoretically be regarded as an all-encompassing optimizer. Therefore, the proposed cube cloud mechanism proposed by authors in [15] which determined a search area in the neighborhood of the best answer and allows other search factors to take advantage of the best current history within that range. Adaptive changes of the A search vector allows the WOA algorithm to slowly transfer between discovery and efficiency. While a reduction is dedicated to discovery, some repetitions are dedicated to discovery (|A|≥1) and the rest to efficiency (|A|<1). Significantly, WOA only includes two main internal parameters that must be adjusted (C&A).

D) Algorithm improvement with chaos operator

Chaos operators and the other revolutionary operators can be entirely contained in the WOA formulation for creating the humpback whale's behavior. A Chebyshev Chaos Map is proposed by authors in [16] to improve the function of the WOA method. This map causes the numbers in the whole search area to be distributed, and as a result, the discovery function of the optimization algorithm is improved. The equation of this map is given in (18).

$$x_{i+1} = \cos(icos(xi)) \tag{18}$$

The beginning point of the map based on the chaos map range can be selected between 0 and 1 or -1. It is also necessary to note that the initial amount can have a significant effect on the chaos mapping fluctuations pattern. This chaos mapping is used for the entire production steps of answers in the WOA algorithm. The parameters used in modeling, are defined in Table. 2 as following.

4. Simulation Results

To analyze the proposed function designed for smart home appliances, the daily energy consumption of a series of home appliances is simulated. Characteristics which include home appliances numbers, utilization time and power of appliances are assumed as mentioned in Table 3. In the ToU pricing plan, the electricity bills are offered at different rates during different time periods. Fig. 3 illustrates the sent ToU signal by the power grid for final consumers. The controlling parameters in WOA and PSO algorithms are proposed in Table. 4.

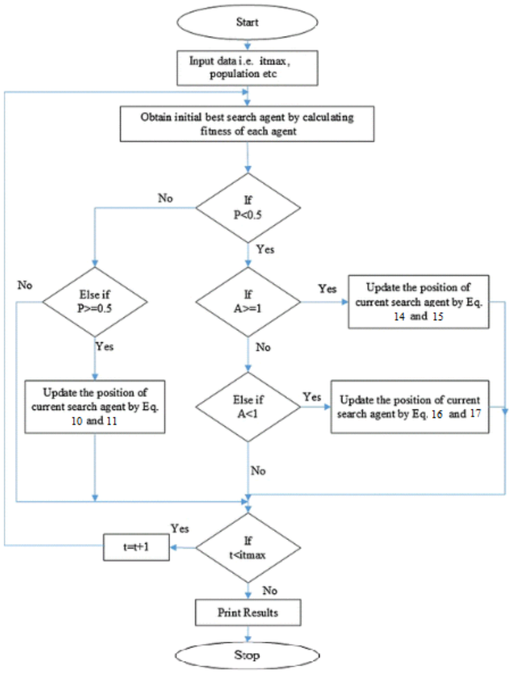

Fig. 2. Flow chart of Whale optimization algorithm

Table.2.
Definition of the parameters

Parameter	Definition
h	Time of Usage
D	Distance to Target
$X(t+1)$	Position in the next iteration
X^*	Position vector is the best answer
t	Present iteration
P	Random Parameter (Between 0 to 1)
l	Spiral position (between 0.5 to 1)
LOT	Number of fixed time intervals, for each consumer
ζ_{ai}	The amount of time delay for i_{th} consumer
Ψ	Delay time range (upper limit and lower limit)
$\delta_{h,ai}$	A binary variable is given that is between 0 and 1
$E_{h,ai}$	Consumption of energy related to the device by time
$\vec{A}$	Range oscillation vector
C	Vector Coefficient
$\vec{r}$	Random vector between 0 and 1
η	Efficiency
b	A coefficient for determining the shape of a logarithmic helix

In the simulation process, an independent solar energy source is used as a support for the microgrid. Although the photovoltaic power production as renewable energy source depends on the radiation value of the sun and the time of sunset and sunrise, but for the simplicity of simulation the power generated by the RES is assumed as illustrated in Fig. 4.

A) *Without presence of HEMS*

Common consumers have no HEM structure, so in case of need they only use the grid energy for providing their electrical energy. The energy attained from the grid is consumed by appliances at different time intervals. Fig. 5 illustrates the load power demand behavior in several scenarios using demand response. The unscheduled part of Fig. 5 refers to the load power demand variation during daily time without the presence of HEM and the photovoltaic system.

Table.3.
The considered home appliances with their characteristics [10].

Power (KW)	***Utilization Time***	***Appliances***	***Type***
1	1 to 2 and 13 to 15	Washing machine	A
4	1 to 5,9 to 11 and 19 to 21	Dryer	
3	5 to7, 9 to 10 and 20 to 24	Electrical auto	
4.5	1 to 2, 4 to 5, 19 to 21 and 17 to 22	Water heater	
1	24 hours	Refrigerator and fridge	B
1.5	24 hours	Light	

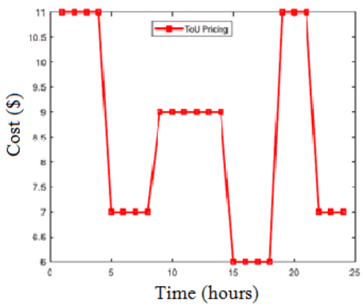

Fig. 3. Pricing plan of time usage [10]

Table.4.
Controlling parameters in WOA and PSO algorithms

Control Parameter	***Value***
Maximum repetition	600
Decision Factors	24×6
Population	100
Spiral position (l) in WOA	0.5-1

B) *With presence HEMS*

It is deduced from Fig. 5, that smart time scheduling (SS) ensures that loads are moved to the hours with the lowest expanses in addition to shifting them from high peak hours to low peak hours. Smart home consumers who have the HEM structure efficiently consume energy and by transferring loads during the peak hours to nonpeak hours gain certain advantages by considering different priorities and limits of the user. With this type of structure, many consumers can be encouraged to participate in efficient utilization of energy by planning their appliances. In the professional consumer state with HEM, utilizing the pricing plan and RES energy efficiently, the electricity bills are minimized. Considering this scenario, in smart houses, HEM and RES production combine along with the energy storage system. The SS utilizes the stored energy of RES where the grid energy expanses are maximized and transferred loads and then minimizes the electricity bills significantly. To analyze the energy cost of the consumers in different scenarios the calculation is done and finalized in Fig. 6 which illustrates the energy cost profile during the day in different methods. It is inferred that the best algorithm to reduce the energy cost is CWOA-RES method which is able to reduce the bill cost for about 58%. Daily savings of consumers and the amount of PAR ratio for owning a HEM structure is demonstrated in Table.5 in comparison to the common consumers. It is inferred from the results that the maximum amount of energy saving is obtained by the CWOA proposed method.

5. Conclusion

The household energy management system (HEMS) allows the user to time schedule the home appliances for load transfer from high peak hours to non-peak hours. HEM predicts the efficient time for home appliances, efficiently utilizes the grid energy and allows the consumers to pay the minimum electricity bills while fulfilling the comfort level of the user. In this article, a new HEM model is proposed based on the ToU pricing plan with RES. In order to efficiently use the grid energy and RES, in the proposed model, the WOA new meta-heuristic algorithm and the PSO common meta-heuristic optimization algorithm have been used. Also, to improve the WOA function, a map based on the chaos theory is proposed for utilizing the whole search area which is called CWOA method. The results illustrate that this method has a better performance than other ones. Moreover it is obtained from the simulations that the energy saving is achieved regarding the minimization of electricity bills for consumers by the proposed method. By using the PSO, WOA and the CWOA algorithms and the proposed model, electricity bills and energy consumption peaks have significantly decreased. It can be inferred from the simulation results that the CWOA proposed algorithm has a better function relative to PSO and WOA methods.

Regarding the PAR relationship, the functions of WOA and CWOA were better than PSO. In terms of practical limitations, this can be attributed to the high cost of solar panels and sophisticated online smart systems that must be installed by local power distribution companies. For future studies it is suggested to compare other optimization algorithms with the methods presented in this paper. Also, considering the effect of the variable intensity of solar radiation on the power generation of the solar panel on the simulation results can enrich the research.

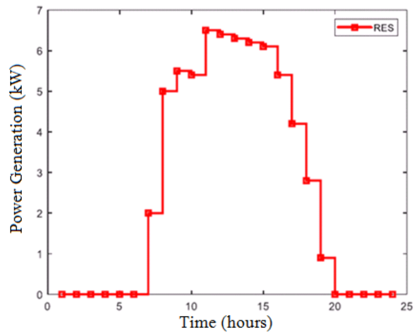

Fig. 1. Electrical power generation of PV during a day

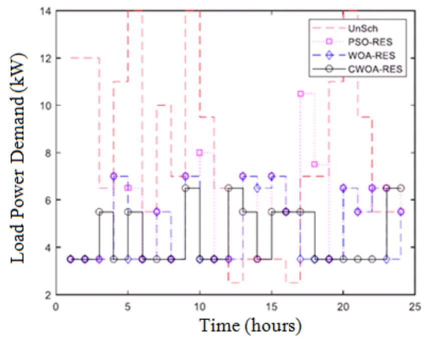

Fig. 2. Load power demand profile during a day

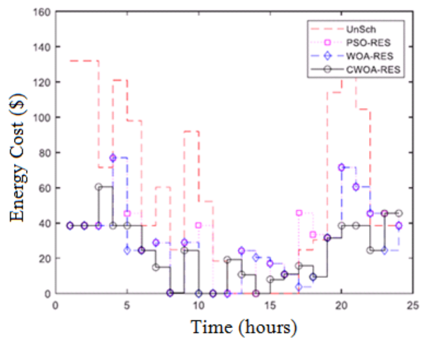

Fig. 3. Energy Cost profile during different methods

Table.5.
Considered home appliances and their characteristics

PAR	*Bill Saving (%)*	*Total cost ($)*	*Optimization method*
4.5	0	1383.88	Without planning
1.88	43	783.59	Coordinated with PSO
1.46	52	657.38	Coordinated with WOA
1.44	58	576.6	Coordinated with CWOA

References

[1] K. Aurangzeb, "Short Term Power Load Forecasting using Machine Learning Models for energy management in a smart community," 2019 International Conference on Computer and Information Sciences (ICCIS), 2019, pp. 1-6, doi: 10.1109/ICCISci.2019.8716475.

[2] K. Aurangzeb, M. Alhussein, K. Javaid and S. I. Haider, "A Pyramid-CNN Based Deep Learning Model for Power Load Forecasting of Similar-Profile Energy Customers Based on Clustering," in IEEE Access, vol. 9, pp. 14992-15003, 2021, doi: 10.1109/ACCESS.2021.3053069.

[3] S. Aslam, S. Aslam, H. Herodotou, S. M. Mohsin and K. Aurangzeb, "Towards Energy Efficiency and Power Trading Exploiting Renewable Energy in Cloud Data Centers," 2019 International Conference on Advances in the Emerging Computing Technologies (AECT), 2020, pp. 1-6, doi: 10.1109/AECT47998.2020.9194169.

[4] K. Aurangzeb and M. Alhussein, "Deep learning framework for short term power load forecasting, a case study of individual household energy customer," 2019 International Conference on Advances in the Emerging Computing Technologies (AECT), 2020, pp. 1-5, doi: 10.1109/AECT47998.2020.9194153.

[5] M. Khan, J. Seo and D. Kim, "Real-Time Scheduling of Operational Time for Smart Home Appliances Based on Reinforcement Learning," in IEEE Access, vol. 8, pp. 116520-116534, 2020, doi: 10.1109/ACCESS.2020.3004151.

[6] Alireza Akbari-Dibavar, Sayyad Nojavan, Behnam Mohammadi-Ivatloo, Kazem Zare, Smart home energy management using hybrid robust-stochastic optimization, Computers & Industrial Engineering, Volume 143, 2020, doi:10.1016/j.cie.2020.106425.

[7] B. Celik, R. Roche, D. Bouquain and A. Miraoui, "Decentralized Neighborhood Energy Management With Coordinated Smart Home Energy Sharing," in IEEE Transactions on Smart Grid, vol. 9, no. 6, pp. 6387-6397, Nov. 2018, doi: 10.1109/TSG.2017.2710358.

[8] Sharif Naser Makhadmeh, Ahamad Tajudin Khader, Mohammed Azmi Al-Betar, Syibrah Naim, Ammar Kamal Abasi, Zaid Abdi Alkareem Alyasseri, A novel hybrid grey wolf optimizer with min-conflict algorithm for power scheduling problem in a smart home, Swarm and Evolutionary Computation, Volume 60, 2021, 100793, doi:10.1016/j.swevo.2020.100793.

[9] S. Aznavi, P. Fajri, A. Asrari and F. Harirchi, "Realistic and Intelligent Management of Connected Storage Devices in Future Smart Homes Considering Energy Price Tag," in IEEE Transactions on Industry Applications, vol. 56, no. 2, pp. 1679-1689, March-April 2020, doi: 10.1109/TIA.2019.2956718.

[10] N. Javaid, "An Intelligent Load Management System With Renewable Energy Integration for Smart Homes," in IEEE Access, vol. 5, pp. 13587-13600, 2017, doi: 10.1109/ACCESS.2017.2715225.

[11] Qinghua Gu , Xuexian Li and Song Jiang, “Hybrid Genetic Grey Wolf Algorithm for Large-Scale Global Optimization”, Hindawi Complexity Volume 2019, 18 pages, doi:10.1155/2019/2653512.

[12] A. Al-Duais, M. Osman, M. H. Shullar and M. A. Abido, "Optimal Real-Time Pricing-Based Scheduling in Home Energy Management System Using Genetic Algorithms," 2021 IEEE 4th International Conference on Renewable Energy and Power Engineering (REPE), 2021, pp. 243-248, doi: 10.1109/REPE52765.2021.9617067.

[13] S. Korjani, A. Serpi and A. Damiano, "A Genetic Algorithm Approach for Sizing Integrated PV-BESS Systems for Prosumers," 2020 2nd IEEE International Conference on Industrial Electronics for Sustainable Energy Systems (IESES), 2020, pp. 151-156, doi: 10.1109/IESES45645.2020.9210700.

[14] F. Lezama, R. Faia, J. Soares, P. Faria and Z. Vale, "Learning Bidding Strategies in Local Electricity Markets using Ant Colony optimization," 2020 IEEE Congress on Evolutionary Computation (CEC), 2020, pp. 1-8, doi: 10.1109/CEC48606.2020.9185520.

[15] Seyedali Mirjalili, Andrew Lewis, “The Whale Optimization Algorithm, Advances in Engineering Software,” Volume 95, 2016, Pages 51-67, doi:10.1016/j.advengsoft.2016.01.008.

[16] Petra Snaselova, Frantisek Zboril, Genetic Algorithm using Theory of Chaos, Procedia Computer Science, Volume 51, 2015, Pages 316-325, doi:10.1016/j.procs.2015.05.248.