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Modeling and Scheduling Home Appliances using Nature Inspired Algorithms for Demand Response Purpose

***Abstract**. Demand response (DR) refers to programs used in endeavors to reduce overall power consumption, manage consumption peak hour shifting, and reduce demand on service providers or utilities using different methods. This paper proposes a home appliance scheduler suitable for DR applications. In the proposed method, a controller controls thermal and shiftable loads, where thermal loads are empirical models that consider different factors. They produce the load profile of the home in consideration of different input parameters, e.g., setpoints and user tolerance ranges, and various factors, e.g., the room's physical structure and the external environment. A scheduler uses the controller to implement load shifting using the whale optimization algorithm, particle swarm optimization, and gray wolf optimization (GWO) algorithms for three different occupancy and price schemes. Acceptable results were obtained by applying the models using various outer temperatures and user tolerance ranges. The results also demonstrate cost reduction of 38.59% with GWO for the first occupancy scheme.*

***Streszczenie.** Demand Response (DR) oznacza programy do redukcji poboru mocy, doboru czasu pracy, odbiorników energii elektrycznej. W artykule zaproponowano program użycia urządzeń domowych spełniający wymagania DR z uwzględnieniem termicznych warunków pracy. . Zaproponowano algorytmy optymalizacji. (**Modelowanie i programy użycia domowych odbiorników energii elektrycznej z wykorzystaniem algorytmów optymalizacji**)*

Keywords: Demand Response (DR), GWO, WOA, PSO.
Słowa kluczowe: zarządzanie odbiornikami energii, DTR - demand response, algoryt,my optymalizacji.

Introduction

Demand response (DR) occurs when a signal is sent by a utility to indicate the current power demand, and the user's response to the signal to reduce total power consumption or power cost in kilowatt hours [1] in this process is sometimes referred to as demand side management (DSM). DSM can be performed manually by switching appliances on or off to satisfy the demand signal, or the appliances can be controlled automatically using home energy management systems (HEMS) or home energy management controllers [2]. HEMSs use various techniques and algorithms to schedule home appliances to reduce overall costs depending on the DR signals. The combination of accurate house appliances controllers that consider many appliance and environmental parameters with effective scheduling algorithms results in powerful HEMS and hence; distinct power cost reduction.

A. Overview of Home Appliance Modeling

Here, various modeling and scheduling techniques discussed in the literature are introduced. Note that thermal loads are the focus of this HEMS, and different metaheuristic algorithms are explored to perform scheduling.

Thermal load modeling using white, black, and gray box models [3] have been proposed. These methods can be used to model thermal loads in both dynamic or static ways for use in load management and monitoring. An extended comparison between the three models and their use in temperature prediction and load management was introduced by F. Amara et al. [3]. White box models primarily depend on information about the building's structure [4], and they are represented by differential equations comprising dynamic, static, linear, or nonlinear equations. However, white box models prone to errors due to inaccuracy in setting the air flow rate into a room or the rate of opening and closing windows [6].

Black box models only show the relationship between the input and outputs of the system. Such models are typically used in error detection rather than optimization. Gray box models combine features of both white and black box models. In addition, gray box model consider parameters with physical and empirical significance such as the wall's materials and thickness [5].

B. Load Scheduling and DR

DR can be implemented in different schemes, e.g., time of use (ToU), critical peak price, and others depending on the priorities. The ToU scheme is most frequently implemented in the literature [6].

Two excellent nature-inspired day-ahead metaheuristic scheduling models have been developed [7], i.e., the binary multi-objective PSO and hybrid bird swarm/cuckoo search algorithms. The main objectives of these algorithms are to schedule home appliances away from peak periods by changing their on/off status for the next day while maintaining user comfort by reducing wait times. It has been proven that these two algorithms outperform existing algorithms relative to cost reduction [6]. Note that control over an appliance's settings is not always possible because various appliances can only can be turned on or off, which could have significant effect on cost reduction and maintaining user comfort by allowing users to set tolerance ranges for each appliance rather than a general tolerable wait time.

Gray wolf optimization (GWO) has been used previously to facilitate energy conservation. For example, in [8] and [9], GWO was used to manage energy consumption in two power grids. Here, both grids were equipped with storage units, and GWO was employed to determine when power would be delivered to or taken from the grid for storage unit operation [8].In addition, GWO was applied to optimize the cost and size of storage units [9] in a similar case study. Here, it was found that GWO outperformed other relevant algorithms, e.g., PSO, the bat algorithm, and an improved bat algorithm, where the cost reduction of up to 25% and 33.2% can be achieved in the two sources, respectively. However, this was done on a large scale, and load controllability for single households was not considered.

The whale optimization algorithm (WOA) is another new metaheuristic algorithm that has been proven effective in many applications. For example, Swalehe, Chumbo, and Marungsri [10] presented an appliance scheduling system using the WOA that considered multiple types of appliances, renewable energy sources, and storage units. This system achieves 40% electricity bill reduction without inclusion of renewable sources and approximately 53% with renewable sources. However, one drawback of this system is that it only optimizes appliance on/off time, i.e., it cannot control setpoints or adjust the comfort levels of thermal loads.

In addition, Sharma and Saxena [11] presented a WOA scheduler for residential and commercial grids. Here, three strategies were employed for DSM, i.e., peak clipping, strategic conservation, and load shifting. Comparing the results of this system to two other algorithms (biogeography-based optimization and evolutionary algorithm) demonstrated that better cost and peak load demand reduction can be achieved using these three DSM strategies.

Another WOA-based cost optimization application was proposed previously [12], where the WOA was used to find the optimal production and operation cost for a system while solving a constrained economical dispatch problem. This algorithm was applied to multiple IEEE test systems with multiple thermal units. The algorithm was compared to PSO and LaGrange optimization, and it outperformed these methods with quicker convergence.

This paper proposes a comprehensive HEMS framework that comprises control and scheduling of home appliances (primarily thermal loads) to reduce the total power costs using DR schemes. The main contributions of this work are the ability to control more factors for each appliance, controlling set points and user tolerance t levels for each appliance (rather than simply turning appliances on or off), and considering more contributing factors, e.g., the building's physical structure and external temperatures. We first discuss empirical modeling of appliances, a complete house controller, and scheduling, which, to ensure reasonable validity, was considered based on three different occupancy and price schemes. The methodology followed in the modelling of the controller and the schedule is described in the next section. Following that, the results of both the controller and scheduler are presented, and finally the conclusion states the main finding of this research.

Methodology

The methodology followed in modeling and controlling home appliances in the proposed HEMS framework is described in this section. Note that the modeling phase is explained in detail in the literature [12].

A. Thermal Load Modeling

Thermal loads consume the most power in a typical household, specifically during summer. To schedule thermal loads, many control aspects must be considered to realize effective scheduling. The proposed thermal load models utilize the medims' physical information (air or water density and capacity), and inputs settings to generate a load profile for the given appliance in a certain period.

- House heater model

All thermal loads considered in this paper are based on the house heating system, which utilizes information about the physical characteristics of rooms, the external temperature, and several differential equations. The empirical system contains three subsystems represented by three differential equations, i.e., the heater subsystem, the house subsystem, and the thermostat. Here, a conditional controller is used to represent the thermostat, while the other two subsystems are represented by these equations [13].

a) Heater subsystem

In the first subsystem, the change in heat is calculated according to the temperature difference and the room's physical parameters. The change in heat is expressed as follows:

$$(1)\quad \frac{dQ}{dt} = (T_{heater} - T_{room}).Mdot.c$$

where $\frac{\boldsymbol{dQ}}{\boldsymbol{dt}}$ is the heat change rate, T_{room} is the current room temperature, T_{heater} is the heating element's outcoming air temperature, M_{dot} is the flowrate of the air mass in the heater (kg/hour), and ***c*** is the air's heat capacity at a fixed pressure.

b) *House subsystem*

The indoor temperature shift is determined by the house subsystem using heat exchange obtained by Eq. 1. The indoor temperature shift can be calculated as follows:

$$(2)\quad \left(\frac{dQ}{dt}\right)_{losses} = \frac{T_{room}-T_{out}}{R_{eq}}$$

$$(3)\quad \frac{dT_{room}}{dt} = \frac{1}{M_{air}.c}.\left(\frac{dQ_{heater}}{dt} - \frac{dQ_{losses}}{dt}\right)$$

where M_{air} is the internal air mass, and R_{eq} is the equivalent thermal resistance in the room.

Note that user tolerance is governed by the following two temperature limits.

$$(4)\quad T_1 = setpoint - tolerance\ level$$

$$(5)\quad T_2 = setpoint + tolerance\ level$$

The thermostat of the heating model will work like regular thermostats; turning the heater on or off depending on the internal temperature, making sure to stay within the comfort range of the user which is defined by T1 and T2. The flowchart of the heating system program is shown in

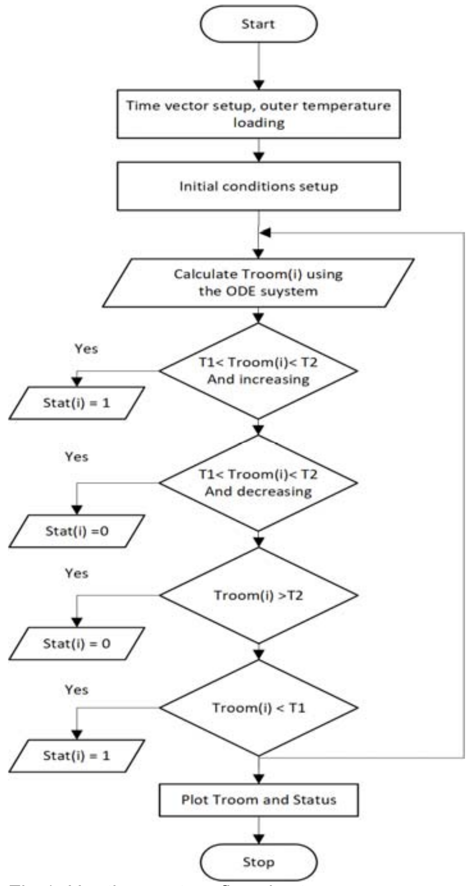

Fig.1. Heating system flowchart

Fig. 1.

- Air conditioner model

Air conditioners (AC) reduce the temperature of a room using the principals of matter state changes. Here, when a gas transforms from liquid to gas, heat is absorbed, which is released when it goes back to the liquid state. Absorbing heat cools the surrounding environment, which is the primary purpose of an AC unit [14].

The proposed HEMS's air conditioner model was the opposite in terms of the job and the thermostat. Note that small alterations were made when initializing the thermostat model and the model's constants. The AC model's results are highlighted in the Results and Discussion section.

- Refrigerator model

Refrigerators work like ACs; thus, the refrigerator controller model is similar to the AC model. However, some alterations were implemented in refrigerator model, i.e., physical constants, temperature setpoint limits, and the physical dimensions [15] [16]. Here, air density and specific heat capacity are unchanged because the medium is still air. Table 1 shows the constant values used in the refrigerator model.

- Water heater

Water is the heat transfer medium in water heaters. A typical tank-based water heater contains a large, insulated tank with one or two metal rods (i.e., heating elements), each of which is controlled by a separate thermostat. In addition, two pipes are connected to the tank: one for warm exiting water, and one for cold input water. When filled with cold water, the tank's higher rod is turned on to warm the top half of the water. Then, the lower rod follows until the water reaches the required temperature. Note that the heater model's physical constants were taken from a real experimental water heater used in a lab. Here, the fluid density and specific heat capacity are those of water (Table 1).

B. Shiftable Load Controller Models

Loads that can be shifted to a different time slot depending on the demand are referred to as shiftable loads. Such loads typically have a certain operation cycle with a pre-determined, uninterruptable duration for a successful running cycle. Two examples of such devices are washing machines and dishwashers. They are represented in a simple manner in this house controller. Here, users can set an initial working pattern for each appliance. This pattern provides insight into the likelihood of an appliance's operation timing (start and end time, in addition to the typical cycle duration and rated power consumption of the appliance).

Table 1. Physical constants of thermal appliances

Physical property	Air conditioner	Refrigerator	Water heater	Air heater
Density of fluid (kg/m^3)	1.2250	1.2250	1.0	1.2250
Temperature of fluid (˚C)	10	-5	75	50
Thermal conductivity (J/sec/m/C)	0.78 (Glass wool)	0.05 (Polyurethane)	0.05 (Polyurethane)	0.78 (Glass wool)
Dimensions (w . l . h (m))	10x 30 x 4	0.6x 0.6 x 1.8	0.450 x ∅ x 0.559	10 x 30 x 4
Flowrate (kg/min)	60	0.6	0.12	60
Wall thickness (m)	0.2	0.11	0.0381	0.2
Specific heat capacity (J/kg-K)	1005.4		1005.4	1005.4

C. Full House Controller

Combining the above models provides a full house controller comprising process functions executed according to the setup parameters (Fig. 2). Note that thermal and shiftable loads have different setup parameters. For example, shiftable loads do not require tolerance levels or set points, and thermal loads do not typically have an operation duration.

D. Load Scheduling Algorithms

The main objective of the scheduler is to reduce the total house energy costs and avoid peak prices. The DR signal is sent to the house as an input indicating the prices per minute for the next day. The cost of the full house's power consumption or the objective function is calculated as (Eq. 6) shows:

(6) $Cost = \sum_{i=1}^{n} \sum_{j=1}^{m} S_{ji} \times p_j \times r_i$

where *i* is an appliance counter, *j* is the minute of the day, S_{ji} is the total on status of the appliance (binary), r_i is the power rating of the i^{th} appliance converted from KWh to KW*minute, and p_j is the ToU DR price at the j^{th} minute (AED/KW*min).

The number of appliances considered in this study was five, where three are thermal loads and two are shiftable loads. The input to the cost function is a vector containing all setpoints of the thermal loads, comfort levels, and starting time for the shiftable loads, as expressed in Eq. 7:

(7) $x = [WM, DW, setpoint_{Ref}, tolerence_{Ref}, setpoint_{water\ heater}, tolerance_{water\ heater}, tolerance_{water\ heater}, setpoint_{AC}, tolerance_{AC}]$

where WM is the starting time slot for the washing machine, DW is the starting time slot for the dishwasher, $setpoint_{Ref}$ and $tolerence_{Ref}$ are the setpoints and tolerance ranges of the refrigerator, $setpoint_{water\ heater}$ and $tolerance_{water\ heater}$ are the setpoints and tolerance for the water heater, and $setpoint_{AC}$ and $tolerance_{AC}$ – the setpoints and tolerance for the AC, respectively.

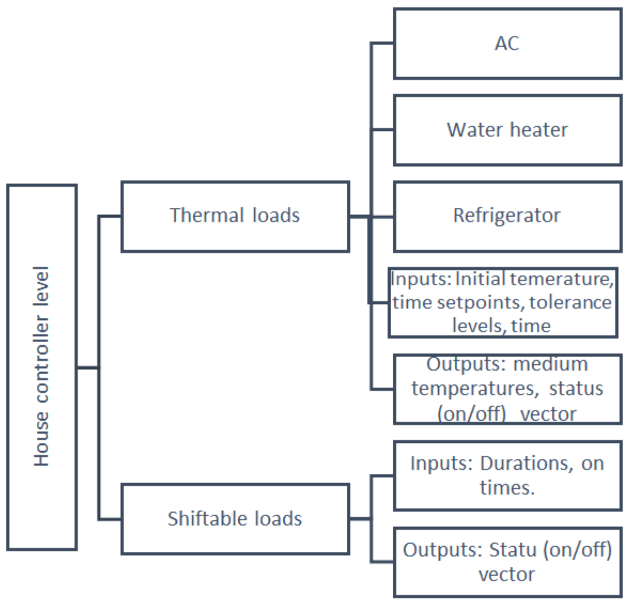

Fig.2. Structure of the complete house controller model

From Eq 7, it is clear that the problem dimension is eight because each individual appliance model has additional input parameters, e.g., initial temperatures and occupancy. Note that shiftable loads are uninterruptable, and their working cycle is fixed and cannot exceed typical limits. The upper and lower limits of the input vector (Eq. 7) are defined as follows:

$lb = [1\ 1\ 2\ 1\ 50\ 3\ 19\ 1\ ]$

$ub = [1440 - 90\ 1440 - 60\ 5\ 3\ 80\ 10\ 24\ 3\ ]$

where 1440 is the number of minutes in a day, and 90 and 60 are the working cycles of the washing machine and dishwasher, respectively. The main objective of this optimization problem is to minimize the consumption cost in DR programs; thus, the optimization problem can be expressed as follows.

(8) $min(\sum_{i=1}^{n} \sum_{j=1}^{m} S_{ji} \times p_j \times r_i\ )$

The flowchart of the scheduling process is shown in Fig. 3. To run the optimizers, the same input parameters are used for each algorithm, which is the initial setup vector for the appliances. The controller is called using the initial parameters, an initial load profile is evaluated, the cost is calculated, and then, if the cost is not the lowest, the optimizer is called to generate a new setup vector, which produces a lower cost when passed to the controller. This process is reseated until the minimum cost is obtained while maintaining the user's tolerance level.

PSO, GWO, and WOA are nature-inspired metaheuristic algorithms used by the optimizer. Applying these algorithms in the system (Fig. 3) produces the new low-cost load profile of the appliances. The same house controller or appliance models were used, only the optimization method of the scheduler was different for every trial.

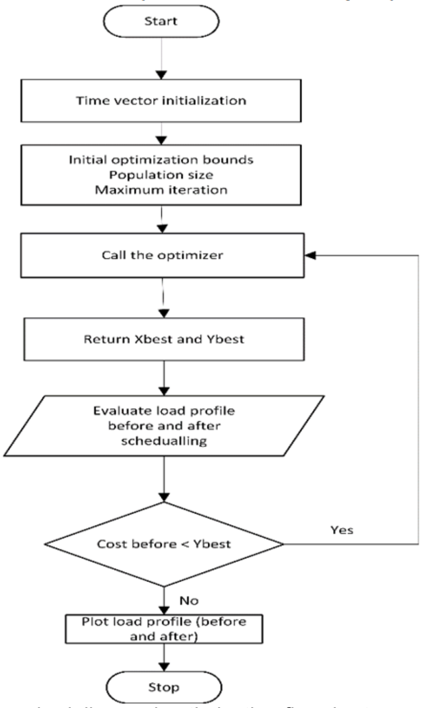

Fig.3. House scheduling and optimization flowchart

a) PSO

The PSO algorithm mimics the behavior of bird swarms when finding food, and the same applies to the WOA and GWO, which mimic the behavior of whales and wolves hunting for food, respectively. These algorithms have specific position and velocity equations, where the position of the closest particle (a bird, whale, or wolf) to the prey is calculated and updated in each iteration. The closer the particle is to the prey, the closer the optimizer is to the optimum solution. The position and velocity equations for the three algorithms are given as follows:

(9) $V_j^{i+1} = \omega^i \times V_j^i + C_1 \times rand_2 \times \left(X_{pbest_j}^i - X_j^i\right) + C_2 \times rand_2 \times \left(X_{gbest}^i - X_j^i\right)$

(10) $X_j^{i+1} = X_j^i + V_j^{i+1}$

where V_j^{i+1} is the velocity of the j^{th} particle at the i+1^{th} iteration, V_j^i is the same velocity at the i^{th} iteration, $rand_1$ and $rand_2$ are random values in the range [0, 1], and C_1 and C_2 are acceleration constants, respectively.

Here, new position X_j^{i+1} is evaluated by adding the evaluated velocity to the current position X_j^i of the j^{th} particle in the i^{th} iteration [17].

b) WOA

The WOA's position vector is calculated using the previous position and best possible position. Here, no velocity is involved; however, the distance of the current whale from the prey is used to evaluate the new position.

(11) $\vec{D} = \left|\vec{C}.\vec{X}_{best} - \vec{X}_i\right|$

(12) $\vec{X}_{i+1} = \left|\vec{X}_{best} - \vec{A}.\vec{D}\right|$

Here, i is the iteration, $\vec{X}_{best}$ is the best position, $\vec{X}_i$ is the current position vector, and $\vec{A}$ and $\vec{C}$ are coefficient vectors calculated in Eq. 13 and Eq. 14, respectively [18].

(13) $\vec{A} = 2\vec{a}.\vec{r} - \vec{a}$

(14) $\vec{C} = 2\vec{r}$

c) GWO

GWO, which uses the same general equations as the WOA with a slight difference, is expressed as follows:

(15) $\vec{X}_{j+1} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$

where $\vec{X}_1$, $\vec{X}_2$, and $\vec{X}_3$ are the positions of the three most dominant wolves in the pack [19].

In this study, the constants of the three algorithms were set according to acceptable values found in the literature (Table 2) [20], [18], [19].

Table 2. Algorithm constants and weights

Algorithm	Population size	Maximum iterations	Other constants
PSO	50	100	wMax = 0.9; wMin = 0.2 c1 = 2; c2 = 2
WOA	50	100	r1=rand() r2=rand(); b=1 l=(a2-1)*rand+1; a2=-1+t*((-1)/Max_iter)
GWO	50	100	r1=rand(); r2=rand(); C1=2*r2; C2=2*r2; C3=2*r2;

E. Special Testing Scenarios

To further test the proposed system, a baseline was created to compare the results of the optimizer. This baseline was a manual house profile, where the cost of the house for 24 hours is calculated based on three occupancy and price schemes. The occupancy variation realistically mimics the house occupancy during different days of the week. The first occupancy scheme included one period where the user was not in the house, the second included two, and the third included three. Figure 4 shows the baselines for the occupancy schemes. The first occupancy scheme is when the house is vacant once, the second is when it is vacant twice, and the third is when it is unoccupied at three different periods. Alternatively, Figure 5 shows the baselines for the price schemes during three different types of day: workdays, weekends, and school holidays. Here, the price signals vary from low to high during different periods depending on the demand at the given time.

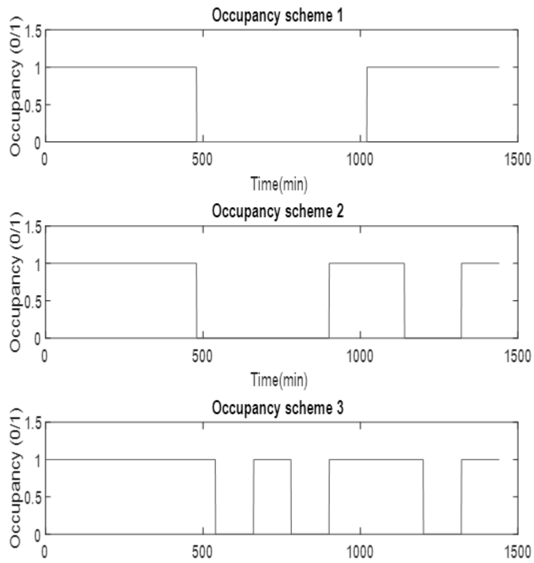

Fig.4. Occupancy schemes for testing

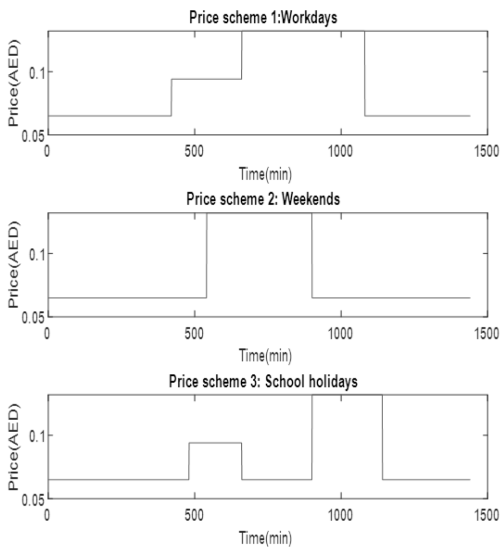

Fig.5. Price schemes for testing

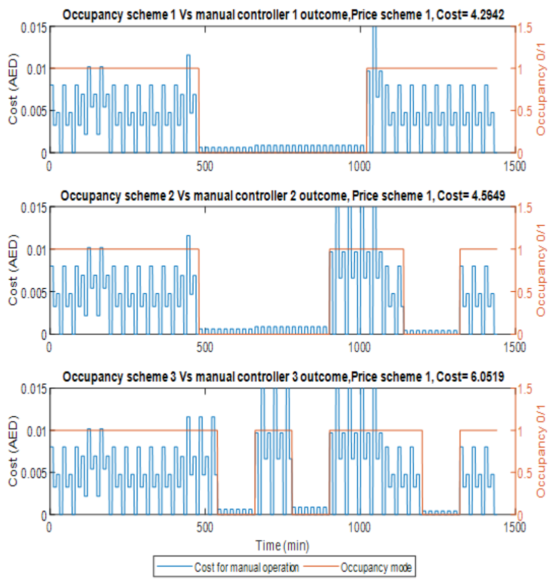

Fig.6. Baseline daily cost (AED) for three occupancy schemes

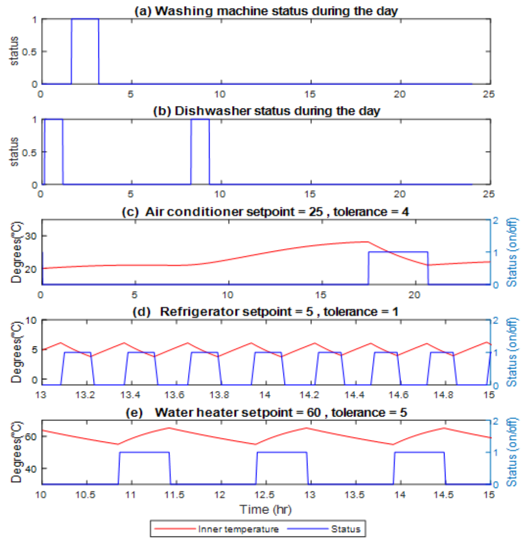

Fig.7. Full house controller profile

The cost per minute in the day was calculated for different combinations of price and occupancy scenarios to create baselines for comparison. Figure 6 shows an example of the cost obtained using price scheme 1 and the three occupancy schemes.

Results and Discussion

A. House Controller Model

As discussed previously, the combination of appliance models provides full house controller model. Figure 7 shows the output profiles of all modeled appliances, including the temperature in thermal loads and on/off cycles of shiftable loads. The thermal loads operated as expected, and the temperature fluctuated within the acceptable limit. Note that the room heater was excluded because this is not a common appliance in an Emirati household. The washing machine was only used once for 90 minutes, while the dishwasher was run twice for 30 minutes. More details about the controller results for each appliance can be found in the literature [21].

B. Load Scheduling and Optimization

To reduce the total cost, the appliances were scheduled according to the three occupancy schemes and the minutely, and full day costs were recorded and compared to the baseline. Here, PSO, WOA, and GWO were used to solve the optimization problem. Figure 8, Figure 9, and Figure 10 show the costs per minute of the loads after scheduling using PSO, WOA, and GWO with the three occupancy schemes and price scheme 1. As can be seen, for all three cases, the cost using the scheduler was always less than the baseline.

As can be seen from the figures, the cost was reduced with scheduling. Table 3 shows the corresponding appliance setup parameters for optimum cost reduction obtained by each algorithm using occupancy scheme 1 and price scheme 1. The best input parameters were similar for nearly all algorithms for the thermal loads (x(3) - x(8)). The first two elements of the input vector represent the starting point of the shiftable loads' cycle, which are typically discrete, and these represent the time sample (minute) when the shiftable zload cycle will start. Their values were either very small (at the beginning of the day) or very high (at the end of the day), which are low peak price periods.

Table 4 summarizes the cost reduction percentages using all algorithms relative to the baseline for a combination of nine occupancy and price scenarios.

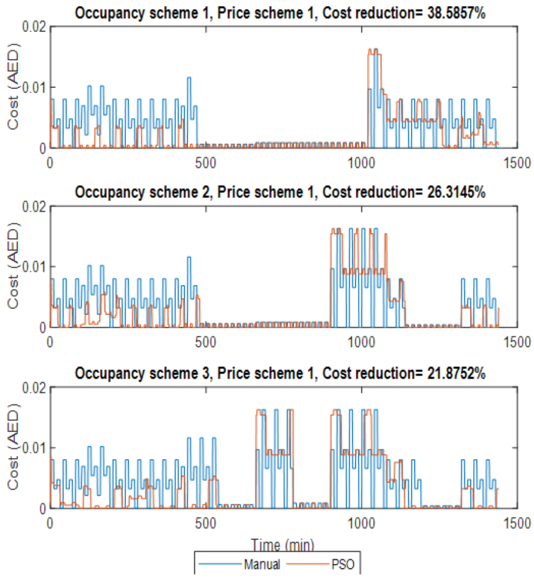

Fig. 8. Manual (baseline) controller cost vs PSO cost

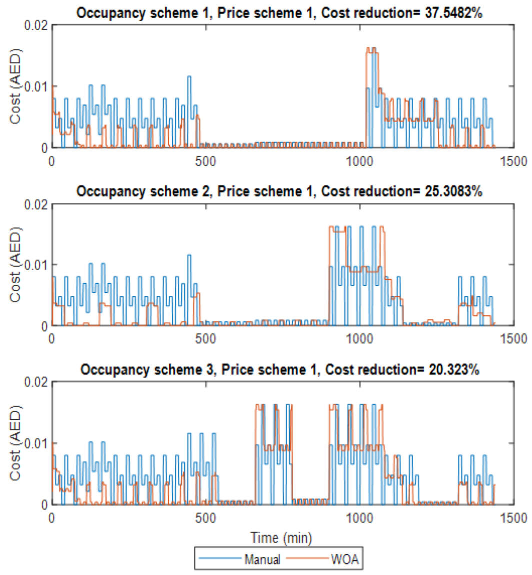

Fig. 9. Manual (baseline) controller cost vs WOA cost

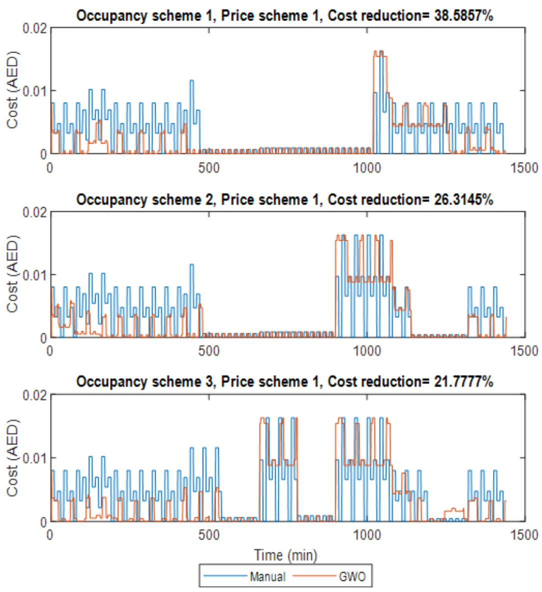

Fig.10. Manual (baseline) controller cost vs GWO cost

Table 3. Optimum appliance parameters using price scheme 1 and occupancy scheme 1

Algorithm	Xbest (appliances setpoints) [WM, DW, Ref_set, Ref_tol, Heater_set, Heater_tol, AC_set, AC_tol]	Ybest (cost in AED)	Cost Reduction
baseline	[1080, 60, 4, 2, 70, 2, 18, 2]	4.29	-
PSO	[154, 269, 5, 3, 50, 5, 24, 1]	2.64	38.59%
WOA	[1, 1380, 5, 1, 50, 3, 24, 1]	2.68	37.55%
GWO	[1225, 1307, 5 ,1, 50, 5, 24, 1]	2.64	38.59%

As can be seen, the cost reduction was consistent with all three algorithms, where price scheme 2 obtained the largest reduction. Note that that GWO obtained the largest reduction in nearly all scenarios, representing a slight difference to the results obtained by PSO. The WOA obtained the lowest cost reduction compared to the other two algorithms. Across all scenarios and algorithms, the largest reduction was obtained using price scheme 2 and occupancy scheme 1, where 44.64% cost reduction was obtained, and the lowest was obtained by the WOA using occupancy scheme 4 and price scheme 1.

Overall, despite the slight difference in results, we consider the results to be consistent and comparable, which proves the reliability of the proposed system and house controller model. A convergence test was then conducted to further test the system's consistency.

C. Consistency

To evaluate scheduling consistency when a single algorithm was applied, all three algorithms were run multiple times, and the minimum cost was recorded at each time. It is important for the system to be stable, i.e., giving the same expected minimum for the same input parameters. Figure 11, Figure 12, and Figure 13 show the convergence curves for each algorithm repeated multiple times with the same initial values.

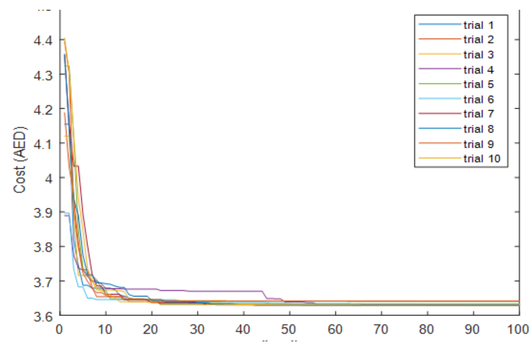

Fig.11. PSO consistency test

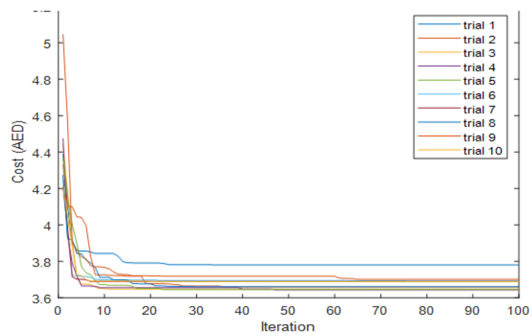

Fig.12. WOA consistency test

As can be seen, PSO and GWO were very consistent, whereas the WOA was inconsistent. Even though WOA has been tested on many multimodal systems and proven to be very powerful, it did not perform as expected with this system. Selecting constants for an algorithm can affect the results significantly, and WOA has many constants that are generated randomly or change randomly over time. We believe that tuning these parameters could improve the results. Generally, the results obtained by GWO were comparable to those obtained by PSO which is a well-known, reliable algorithm. These algorithms provided nearly identical results relative to the optimum cost and best input parameters.

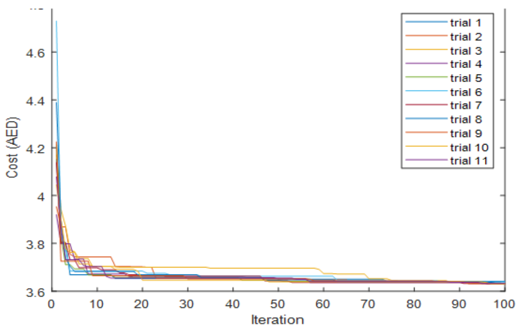

Fig.13. GWO consistency test results

Table 4. Cost reduction percentages comparison between baseline and PSO, WOA, and GWO

Algorithm		Occupancy scheme 1	Occupancy scheme 2	Occupancy scheme 3
PSO	Price scheme 1	38.59 %	26.31 %	21.88 %
	Price scheme 2	43.74 %	39.54 %	29.60 %
	Price scheme 3	34.25 %	24.60 %	24.58 %
WOA	Price scheme 1	37.55 %	25.31 %	20.32 %
	Price scheme 2	42.95 %	39.49 %	29.56 %
	Price scheme 3	34.46 %	24.57 %	24.06 %
GWO	Price scheme 1	38.59 %	26.31 %	21.78 %
	Price scheme 2	44.64 %	40.96 %	29.56 %
	Price scheme 3	34.46 %	22.71 %	24.95 %

Conclusion

In this paper, we have proposed a full house controller (HEMS) and load scheduler for use in DR and load scheduling applications using PSO, GWO, and the WOA. Empirical models of thermal loads were used to produce a load profile to predict temperature based on different setup parameters, e.g., the setpoints and tolerance ranges, in addition to other physical factors. The proposed model generates optimal input parameters (setpoints and tolerance ranges) for each appliance to reduce total consumption costs, which is significant because most comparable models only control the on/off status of the loads. The three algorithms provided very similar results, which verifies the consistency of the system and objective function (Eq. 6). In future, we plan to implement additional appliances and DR schemes to the system to make it more dynamic, realistic, and cater to more variable factors set by the user, such as special occasions when the house is extra occupied, or other comfort related factors.

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REFERENCES

[1] C. Goldman, M. Reid, R. Levy, and A. Silverstein, “Coordination of Energy Efficiency and Demand Response,” Ernest Orlando Lawrence Berkeley National Laboratory, LBNL-3044E, Jan. 2010. [Online]. Available: https://eetd.lbl.gov/sites/all/files/publications/report-lbnl-3044e.pdf.

[2] P. Siano, “Demand response and smart grids—A survey,” *Renew. Sustain. Energy Rev.*, vol. 30, pp. 461–478, Feb. 2014, doi: 10.1016/j.rser.2013.10.022.

[3] F. Amara, K. Agbossou, A. Cardenas, Y. Dubé, and S. Kelouwani, “Comparison and Simulation of Building Thermal Models for Effective Energy Management,” *Smart Grid Renew. Energy*, vol. 06, no. 04, pp. 95–112, 2015, doi: 10.4236/sgre.2015.64009.

[4] C. Verhelst, “Model Predictive Control of Ground Coupled Heat Pump Systems for Office Buildings,” Ph.D Dissertation, Katholieke Universiteit Leuven, Heverlee, Belgium, 2012.

[5] P. R. Novak, N. Mendes, and G. H. C. Oliveira, “SIMULATION OF HVAC PLANTS IN 2 BRAZILIAN CITIES USING MATLAB / SIMULINK,” presented at the Ninth International IBPSA Conference, Montreal, Canada, Aug. 2005.

[6] F. Shariatzadeh, P. Mandal, and A. K. Srivastava, “Demand response for sustainable energy systems: A review, application and implementation strategy,” *Renew. Sustain. Energy Rev.*, vol. 45, pp. 343–350, May 2015, doi: 10.1016/j.rser.2015.01.062.

[7] Z. A. Khan, A. Khalid, N. Javaid, A. Haseeb, T. Saba, and M. Shafiq, “Exploiting Nature-Inspired-Based Artificial Intelligence Techniques for Coordinated Day-Ahead Scheduling to Efficiently Manage Energy in Smart Grid,” *IEEE Access*, vol. 7, pp. 140102–140125, 2019, doi: 10.1109/ACCESS.2019.2942813.

[8] M. Abdulgader, S. Lakshminarayanan, and D. Kaur, “Efficient energy management for smart homes with grey wolf optimizer,” in *2017 IEEE International Conference on Electro Information Technology (EIT)*, May 2017, pp. 388–393, doi: 10.1109/EIT.2017.8053392.

[9] K. Nimma, M. Al-Falahi, H. D. Nguyen, S. D. G. Jayasinghe, T. Mahmoud, and M. Negnevitsky, “Grey Wolf Optimization-Based Optimum Energy-Management and Battery-Sizing Method for Grid-Connected Microgrids,” *Energies*, vol. 11, no. 4, p. 847, Apr. 2018, doi: 10.3390/en11040847.

[10] H. Swalehe, P. Chombo, and B. Marungsri, “Appliance Scheduling for Optimal Load Management in Smart Home integrated with Renewable Energy by Using Whale Optimization Algorithm,” *GMSARN Int. J.*, vol. 12, pp. 65–75, 2018.

[11] A. K. Sharma and A. Saxena, “A demand side management control strategy using Whale optimization algorithm,” *SN Appl. Sci.*, vol. 1, no. 8, p. 870, Jul. 2019, doi: 10.1007/s42452-019-0899-0.

[12] A. Kumar, V. Bhalla, P. Kumar, T. Bhardwaj, and N. Jangir, “Whale Optimization Algorithm for Constrained Economic Load Dispatch Problems—A Cost Optimization,” in *Ambient Communications and Computer Systems*, 2018, pp. 353–366.

[13] “Thermal Model of a House - MATLAB & Simulink.” https://www.mathworks.com/help/simulink/examples/thermal-model-of-a-house.html (accessed Jul. 30, 2018).

[14] “How Air Conditioners Work,” *archtoolbox.com*. https://www.archtoolbox.com/materials-systems/hvac/how-air-conditioners-work.html (accessed Mar. 30, 2019).

[15] O. Laguerre, “Heat Transfer and Air Flow in a Domestic Refrigerator,” in *Mathematical Modeling of Food Processing*, vol. 20100770, M. Farid, Ed. CRC Press, 2010, pp. 453–482.

[16] M. A. Fayazbakhsh, F. Bagheri, and M. Bahrami, “A Resistance–Capacitance Model for Real-Time Calculation of Cooling Load in HVAC-R Systems,” *J. Therm. Sci. Eng. Appl.*, vol. 7, no. 4, p. 041008, Dec. 2015, doi: 10.1115/1.4030640.

[17] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in , *IEEE International Conference on Neural Networks, 1995. Proceedings*, Nov. 1995, vol. 4, pp. 1942–1948 vol.4, doi: 10.1109/ICNN.1995.488968.

[18] S. Mirjalili and A. Lewis, “The Whale Optimization Algorithm,” *Adv. Eng. Softw.*, vol. 95, pp. 51–67, May 2016, doi: 10.1016/j.advengsoft.2016.01.008.

[19] S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey Wolf Optimizer,” *Adv. Eng. Softw.*, vol. 69, pp. 46–61, Mar. 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[20] S. Mirjalili, “A simple implementation of Particle Swarm Optimization (PSO) Algorithm,” *Mathworks.com*. https://www.mathworks.com/matlabcentral/fileexchange/67429-a-simple-implementation-of-particle-swarm-optimization-pso-algorithm (accessed Oct. 03, 2020).

[21] I. Haroun, “Home Appliance Modelling and Control for Demand Response Applications,” presented at the International Conference on Electrical and Computing Technologies and Applications, AURAK, Aug. 2019.