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HOME ENERGY MANAGEMENT SYSTEM FOR DEMAND RESPONSE PURPOSES

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Declaration of Original Work

I, Isra Adam Hussein Haroun, the undersigned, a graduate student at the United Arab Emirates University (UAEU), and the author of this thesis entitled "*Home Energy Management System for Demand Response Purposes*", hereby, solemnly declare that this thesis is my own original research work that has been done and prepared by me under the supervision of Dr. Hussain Shareef, in the College of Engineering at UAEU. This work has not previously been presented or published or formed the basis for the award of any academic degree, diploma or a similar title at this or any other university. Any materials borrowed from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged in accordance with appropriate academic conventions. I further declare that there is no potential conflict of interest with respect to the research, data collection, authorship, presentation and/or publication of this thesis.

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Abstract

The growing demand for electricity has led to increasing the efforts to generate and satisfy the rising demand. This led to suppliers attempting to reduce consumption with the help of the users. Requests to shift unnecessary loads off the peak hours, using other sources of generators to supply the grid while offering incentives to the users has made a significant effect. Furthermore, automated solutions were implemented with the help of Home Energy Management Systems (HEMS) where the user can remotely manage household loads to reduce consumption or cost. Demand Response (DR) is process of reducing power consumption in a response to demand signals generated by the utility based on many factors such as the Time of Use (ToU) prices. Automated HEMS use load scheduling techniques to control house appliance in response to DR signals. Scheduling can be purely user dependent or fully automated with minimum effort from the user. This thesis presents a HEMS which automatically schedules appliances around the house to reduce the cost to the minimum. The main contributions in this thesis are the house controller model which models a variety of thermal loads in addition to two shiftable loads, and the optimizer which schedules the loads to reduce the cost depending on the DR signals. The controllers focus on the thermal loads since they have the biggest effect on the electricity bill, they also consider many factors ignored in similar models such as the physical properties of the room/medium, the outer temperatures, the comfort levels of the users, and the occupancy of the house during scheduling. The DR signal was the hourly electricity price; normally higher during the peak hours. Another main part of the thesis was studying multiple optimization algorithms and utilizing them to get the optimum scheduling. Results showed a maximum 44% cost reduction using different metaheuristic optimization algorithms and different price and occupancy schemes.

Keywords: Demand Response, Home Energy Management System, Scheduling, Modelling.

Title and Abstract (in Arabic)

نظام اداره استهلاك الطاقة المنزلية لغرض الاستجابة للطلب

الملخص

مع تزايد الطلب على الطاقة بسبب ازدياد الكثافة السكانية وازدهار الصناعة، أصبح من الضروري ترشيد استهلاك الكهرباء المنتجة او زيادة معدل الإنتاج. من الجهود المبذولة حاليا لتلبية احتياج المستهلك من، الحملات التوعوية بضرورة تقليل الاستهلاك خلال ساعات الذروة، استخدام معدات ذات استهلاك منخفض، وتغيير بعض السلوكيات والممارسات من أجل الحفظ على الطاقة. على صعيد آخر، فقد تم تطوير أنظمه ذكيه تساعد المستهلك على اتخاذ قرارات سليمه، من خلال الاطلاع على نموذج الطلب الذي يتم توفيره من قبل مزودي الخدمة. يحتوي نموذج الطلب على أسعار مختلفة للطاقة خلال اليوم، يتمكن المستخدم بمساعدة الأنظمه الذكية من جدولة الأجهزة المنزلية لتخفيض استهلاك الكهرباء وتقليل التكلفة.

الهدف من هذه الأطروحة هو تصميم نظام تفاعلي لتنظيم وترشيد عمليه استهلاك الكهرباء في المنازل لأغراض الاستجابة لإشارات الطلب (Demand Response) من مزودي الخدمة. يتكون النظام من نماذج محاكاة للأجهزة المنزلية يتم من خلالها محاكاة وإنتاج السجل الاستهلاكي لكل جهاز تحت اعدادات معينة. تأخذ هذه النماذج بعين الاعتبار العديد من العوامل مثل درجات الحرارة الخارجية، المواصفات البنيوية للمبنى، والراحة المستهلك ومعلومات تواجده داخل المنزل. تساعد هذه التفاصيل بالإضافة الى المجدول الآلي على إنتاج جدولة جديدة وآليه للأدوات المنزلية لتخفيض استهلاك الكهرباء وتقليل تكلفتها. تم تصميم المجدول باستخدام عدة خوارزميات للتحقق من فاعلية النظام. تمكن النظام من تحقيق تخفيض كبير في تكلفة الطاقة لليوم الواحد.

مفاهيم البحث الرئيسية: نظام الاستجابة للطلب، انظمه الإدارة المنزلية، النموذجة، الجدولة.

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Warmest regard goes to my family and friends, my parents who kept praying for me, supported me in my downs before my ups, waiting for the moment when I achieve my goals.

Finally, to my students, who I love from the bottom of my heart, they were always a priority. I hope that with everything I give to them, I'm opening doors showing them the endless possibilities in front of them, teaching them to love and appreciate themselves, and never think that they can't do anything because of who they are or where they come from.

Dedication

To my beloved parents Adam & Hanan, my family, friends, and the future me

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List of Abbreviations

AC	Air Conditioner
ANN	Artificial Neural Networks
BPNN	Back Propagation Neural Networks
DW	Dishwasher
DR	Demand Response
DE	Differential Evolution
DSM	Demand Side Management
EMC	Energy Management Controllers
ENN	Elman Neural Networks
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HEMS	Home Energy Management System
HVAC	Heating Ventilating and Air Conditioning
MAPE	Mean Absolute Percentage Error
MILP	Mixed Integer Linear Programming
MLP	Multilayer Perceptron
MPC	Model Predictive Control
MSE	Mean Square Error
ODE	Ordinary Differential Equation
PAR	Peak to Average Ratio
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
ToU	Time of Use

WM	Washing Machine
WNN	Wavelet Neural Networks
WOA	Whale Optimization Algorithm

Chapter 1: Introduction

1.1 Overview

Goldman et al. [1] defined Demand Response (DR) as a term that refers to the user's response to the demand signals produced by the utility over time to reduce the overall power consumption or the power cost. DR can be purely manual, where the user controls individual loads to satisfy their purpose, or it can be automatic through Home Energy Management Systems (HEMS). HEMS can also be called Energy Management Controllers (EMC) [2]. HEMS utilize various techniques and algorithms to schedule house appliances in the best way to reduce the overall cost depending on the DR signals.

1.2 Relevant Literature

The literature provided a lot of information about house modelling and optimization techniques for scheduling. Appliances modelling will be presented first followed by optimization or scheduling techniques provided in the literature. Study Systems -in this case home appliances- models can be classified into Empirical and Non-Empirical models depending on the need for observation and the study purpose.

1.2.1 Home Automation and Smart Houses

Smart homes and smart applications are the interest focus of many, especially electric appliances manufacturers. Initially, home automation started with simple gateways, that simply keeps the house connected, then it evolved into more effective systems that can make decisions on behalf of the user to improve their power consumption experience. Plenty has been done in literature to develop and present many smart home models or systems that convert the process of controlling home appliances from purely user dependent into a more autonomous approach where all appliances are connected to the network and are controllable with a finger touch.

Kushiru et al. [3] presented a complete Residential Gateway Controller where appliances are connected through the network and the user can control them using Plug and Play mechanism. Two networks are utilized in the system, Wide Area Network outside the house, and three sub networks to be used inside the house depending on the type of the appliance and the control level. All of this was created using a composite operating system designed for better performance and memory reduction. By keeping the user informed of the performance of their appliances, this will help them make wiser decisions when it comes to energy consumption.

Two other sources [4] and [5] discussed the history of residential gateways and how important it is to maintain reliability and speed transmitting data from and to the main house controller. They presented multiple models using different communication techniques to connect the house before introducing any controllability features.

Moreover, Zhang, Qun, and Ji [6] presented a lighting system where the house controller controls a two stories building's lighting, turning lights on/off, adjusting the lights intensity in a room depending on the natural light level. The system structure was very simple, consisting mainly of light sensors, photoresistors, and control circuits utilizing rheostats to reduce the brightness of the light bulbs according to the natural light. The system contributed significantly in reducing the energy consumption.

A more sophisticated model that involve more controllability and load management is presented in [7], with a wireless in home Management system designed for cost reduction. It was compared to other optimizer-based management systems and it proved to reduce the cost of electricity, decrease the user's contribution to the peak load, and lightening the house's environmental fingerprint. Its cost reduction was close to that obtained from optimizer-based HEMS.

Moreover, the addition of energy generation in modern HEMS has started to become more frequent. Han et al. [8] and Hou et al. [9] showcased two interesting models where energy production is part of the HEMS. Han et al. [8] was utilizing Solar panels and wind turbines, while [9] used an Electric vehicle and a storage unit as the renewable element. A sophisticated Zigbee network was used in [8] to connect appliances, and a smart user interface was also developed to keep the user involved in this process. Renewable sources had their own servers separate from other power consuming appliances. Both references used optimizer-based schedulers and managed to reduce the consumption cost with the help of load scheduling and renewable energy sources.

Thus far, most of the presented models were real life implemented models where the loads are physically connected to the system through a control circuit and a communication scheme. Many efforts were made in developing scheduling algorithms to be implemented in real HEMS. These algorithms need to be tested on home appliances models to verify their performance. This main group of appliances targeted by this thesis are thermal appliances, which contribute greatly to the electricity bill. It is very important to consider many variables when modeling such appliance, as there are many factors that play a significant part in the performance of the appliance's model. Many thermal loads such as the Air Conditioner (AC), room heater, and refrigerator are affected by several factors such as the outer temperature, room occupancy, and the physical structure of the room. In the following section different modelling techniques are studied to decide on the best way to model thermal appliances to be used in a HEMS for the purpose of DR.

Thermal load controllers can be divided into Empirical and non-Empirical models depending on the need for real input data to create them. Each of these model categories will be explained in the following section with presenting related literature.

1.2.1.1 Empirical Models

White, black, and grey box thermal load modelling approaches [10] refer to the modelling of thermal loads in both a static or dynamic format for the purpose of load monitoring and management. Static models, are time independents models, while dynamic models aren't [11]. Amara et al. [10] introduced an in-depth comparison between the white, black, and grey box models for the thermal load prediction and load management.

1- White box model

White box models are mostly dependent on the building knowledge [13], they can be represented by differential equations which can be static, dynamic, linear or nonlinear. They can be tuned to find the values of all the contributing factors such as the walls' thermal conductivity, materials, number of windows, and air flow. They can produce some unavoidable errors due to the impossibility of defining the rate at which windows are opened and closed, or the exact flow rate into a room.

2- Black box model

black box models are powerful statistical models which are mostly used in error detection rather than optimization purposes. This is because they are automatically tuned, unlike white box models which require manual tuning. However, this can be a disadvantage especially when applying the model under hard conditions (minimum building system data) as it does not provide realistic outputs [13]. black box models reflect the relationship between the input and output without relating it to the building's structure, hence there is no need for manual tuning. Like white boxes, black boxes can be static, dynamin, linear or nonlinear, and they are known for their processing speed and simplicity of equations. Static black boxes examples include linear regression linear), and polynomials such as Levenberg Marquardt (nonlinear). Dynamic black boxes on the other hand include transfer function models such as Artificial Neural Networks (ANN), and Autoregressive Moving Average ARMA (linear), and polynomials such as Wiener /Hammerstein and Volterra models (nonlinear) [12].

3- Grey boxes

Grey boxes on the other hand are a combination of both black boxes and white boxes, where the parameters are both empirical and have a physical significance [14]. Since they are hybrid, their complexity depends on the inputs and equations which are different for every application. Grey boxes can be used in models where the significance of a factor is studied [15], when there is a lack of information about some physical quantities of the building, when there are difficulties in experimentally collecting the system's information [16], and when the occupants usage pattern of appliances is uncertain [10]. Grey box thermal models are usually represented by Resistance Capacitance (RC) circuits mimicking the building where R and C are the building's physical properties and the electric current (I) is the air flow.

An example of both a grey and a black box thermal models were presented in [10], the grey model was a first order differential equations system whereas the black box system was a linear ANN model. Initial parameters where assumed for the grey model, which were later tuned to get better response. Overall, the grey box model showed outstanding results with minimum error compared to the black box model where the estimated temperature deviated from the real data to a great extent. This is likely due to the nonlinearity of the heater's thermal model and the way it was chosen to be modeled using a simple ANN that might not accommodate for all the nonlinearities [10].

1.2.1.2 Empirical Thermal Appliances Models

A great discussion on modelling of residential AC using a self-learning grey-box method for the purpose of potential demand response was presented in [17]. The grey box model simulates the thermal model of a residential unit by representing it as an RC circuit where the air flow rate equates the electric current. The resistance and capacitance are physical values related to the structure of the room or the walls. In this model, three values of R and C were tuned using parameter preprocessing and optimization techniques such as Particle Swarm Optimization (PSO), Trust Region Algorithm (TRA), and the Genetic Algorithm (GA) to achieve accurate prediction results. Historical data of the outer and inner temperatures were used to train the model. The data were divided into training and testing sets, and the validation was done by calculating the Root mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Mean Absolute Error (MAE) of the predicted data with respect to the training set. The RMSE was around 0.24 and 0.28 for the training and validation sets respectively using the three optimization methods, however the GA took the longest runtime compared to the other two methods. The model was used in different Demand Response schemes, with different setpoints and operation modes, yet aging, comfort levels were not considered, hence the user-system interaction is limited.

A thermal model of a two-story high house using a novel hybrid modeling approach was presented in [18] consisting of the gray box (RC model) method and the black box which is a machine learning method. The heat transfer model was a first order differential equations model. The indoor temperature of the house is basically the average of the top and bottom levels' indoor temperatures. The RC model was validated with a training set and the temperatures of both the heater and the AC matched the RC system output with and RMSE of 0.456 and 0.619 for both the training and testing sets. PSO was used in the next stage to tune the results and produce a more accurate estimate of the indoor temperature. The model considers setpoints of the loads, however it doesn't consider the comfort levels which can be a drawback.

Holland et al. [19] described the comparison between two methods of thermal load modelling using differential equations (grey-box model), and their role in Demand Side Management (DSM) and load shifting applications. The model was for an enclosure that resembles a room where the first attempt was by representing it as a first order differential equation system and the second attempt was using a second order differential equations. In each model, the heat exchanged through the walls is calculated to obtain the total indoor temperature, utilizing the thermal energy balancing rule. The systems are like any grey-box models where the thermal system is represented by an RC circuit where the resistances and the capacitances represent the physical medium that the heat goes through (wall or any heat source). The order of the system is defined by the number of capacitors in the circuit, in this paper the highest number of capacitors (order) is two. In order to tune the thermal capacitances and resistance values of the model, a Proportional Integral Derivative (PID) controller was used alongside a real enclosure with a heating system, the error between the models and the real system is calculated at every time sample and the feedback tuned the variables to best resemble the real system. The error was minimized using two algorithms; Gauss-Newton (GNA) and Levenberg-Marquardt (LM) least squares search algorithms. The results concluded that the second order system gave better fitting results than the first order system, with fitting percentages of 90.9% for the second order system and 21.7% for the first order system. The only drawback of such system was the fact that it was trained in an indoor environment, where the outer temperature of the enclosure is not the real outside temperature, therefore it might not give the same accuracy when applied in a real building setup.

A controller and a scheduler model for residential units ACs were studied in [20]. The controller was a grey box model which uses the room's physical characteristics to predict the temperature of the room during a certain time period. The models were first introduced in [21], and they were adapted to include the dehumidifying effect of the AC. The optimizer that performed the scheduling was IBM ILOG CPLEX Optimizer which adopts the Knapsack Problem to solve the optimization problem. The main goal of the algorithm was to maintain the power consumption bellow 20 kW for all the 20 AC's taking part in the simulation. The goal was achieved in the whole group; however, the comfort levels were violated in some units. A great alternative to this drawback would have been converting this into a multi objective problem that minimizes the consumption of smaller groups of ACs, thus improving the comfort level and enabling the expansion of the system over a greater number of AC's.

Thermal appliances where modeled by a dynamic model presented in [22], where the indoor temperature and the Heating, Ventilating, and Air Conditioning (HVAC) system was represent by a set of dynamic equations that accommodated comfort levels and a set of thermal gains as constants (β's). It also included a Photovoltaic (PV) model that provided the unit with energy when discharging. The optimization was done using a Model Predictive Controller (MPC) stochastic optimizer, with the inclusion of chance constraints to maintain the user's comfort. The load reduction levels in the two test houses were about 95% higher than the required reduction by the utility.

A complete home energy management system which includes the models of several appliances such as the HVAC, PV, and human indoor thermal comfort was showcased in [23]. The HVAC was modeled as a thermodynamic third order state space model, the same as what [24] and [25], where the ambient temperature and solar irradiation are considered along with the building parameters to predict the indoor temperature of a building. Comfort was modeled separately, hence it was not included in the thermal model. The optimization was done using the Natural Aggregation Algorithm (NAA) [26], which mimics group living animals. The results of the HEMS showed better optimization of power consumption compared to other algorithms such as the PSO and Differential Evolution (DE).

two important points in the field of energy management systems and cost reduction applications were discussed in [27]. It presented the use of Model Predictive Control (MPC) in both controlling thermal loads and in tuning the controller's weights to optimize power consumption. The double control/tuning system was applied on three thermal loads, an AC, a water heater, and a refrigerator. The model represented the problem as a discrete linear state-space model which can be solved using a Linear Time Invariant (LTI) equations. The system was tested by running it on the three appliances for 24 hours using a varying price signal signifying peak hours, mid peak, and low peak prices. The setpoints and comfort levels can be set at the beginning, which is a positive point, then the controller will tune the weights of the MPC based on the price signal to give the lowest consumption. Studying the energy with respect to MPC weights, all three appliances seem to be within the limes initially set, however, there were some limits violations when cost and temperatures where tested with respect to MPC weights. This could be because the limits are rigid, meaning that the setpoints are fixed once only, with no possibility of changing them or the comfort levels to reduce costs, or it could be due to the non-linearity of the system and the fact that an LTI model was used to solve and optimize it, even though non-linear factors such as the weather existed.

1.2.1.3 Non-Empirical Models

Modelling and forecasting of thermal loads using Artificial neural networks and an ensample approach was showcased in [28] . The dynamic short-term load forecasting; which mainly forecasts the load within the next hour uses a benchmark that sets the current heat (Q(t)) to predict the next heat value (Q(t+1)). The inputs of the system are not depending on the time or the calendar in any way to increase the system's accuracy when dealing with unexpected scheduling events. This can be considered as a drawback, since the future load will depend on the current load and the time and day data.

Moreover Berelli et al. [29] introduced a load management system for the purpose of scheduling using ANN to improve the PV plant exploitation and energy independent micro grid. the modelling and scheduling depended on the load demand, the battery state, and the weather forecast. The ANN's purpose was to create a scheduled load profile of the day based on the input values. Two groups of ANNs (ANN1 and ANN2) were used with different inputs, ANN1 will "predict which loads of the day (n) operate (basic load cycle), while the ANN2 to establish which loads to recover or anticipate from day (n − 1) and (n + 1) respectively". The ANN model used was multilayered with two hidden layers and back propagation learning algorithm. The model predicted the power of the residential loads (thermal and shiftable loads) with no focus on the setpoints or the comfort levels of every thermal load, which can be a disadvantage.

The use of Elman Neural Networks (ENN) and Wavelet Neural Networks (WNN) in hourly predicting the thermal loads in a microgrid were highlighted in [30]. In WNN, forward propagation is used for the signal, while the error uses backward propagation. In this hybrid model. Two cases of historical data from Haidian Writers Association were given to the two algorithms, then the expected thermal load, entropy, and hyper entropy were evaluated and compared to the actual data. Overall, WNN gave more accurate results than ENN. The output did not specify the status of the individual appliances during the 24 hours period, instead only the total thermal load was evaluated. Moreover, no mention of any control parameters of the appliances was provided, which can be a major drawback if this model was to be used in DR scheduling.

Alternatively, a Non-linear Autoregressive Neural Network (NAR) method used in indoor temperature forecasting was presented in [31] . The neural network is a Multilayer Perceptron (MLP) that uses many regressors to predict the temperatures every 15 minute, the study and analysis was done for data up to 2 hours onwards. An MLP neural network is a feedforward single hidden layered, and fully connected network. It has only one hidden layer that uses a hyperbolic tangent activation function. The importance of this model is the fact that it uses 13 regressors, which is a large number, however, a 15 minutes time period can be considered large when applying a dynamic DSM system. Mean Square Difference (MSD), Mean Absolute Difference (MAD), and Mean Bias Difference (MBD) methods were used to validate the prediction. The RMSD for the whole building's indoor temperature ranged between 0.471 and 1.184 at time step 1 and 16. Overall the results were satisfactory, but the system lacked the controllability factors that enables it to be used in a DSM system as the paper claims it plans to do.

Shi et al. [32] showcased an indoor temperature and relative humidity prediction model using Backpropagation Neural Networks (BPNN). The prediction was done every 10 minutes for a time window of 6 to 72 hours ahead. The study was done in an industrial building in Chongqing, and the temperature and humidity were measured suing SHT15 sensor. The inputs to the model are the indoor temperature, humidity, and outer temperature and are used for training, whereas the outputs are the predicted temperature and relative humidity. Overall, the error of the temperature prediction was lower than that of the relative humidity prediction. The MAE values ranged from 0.1 to 0.09 for temperature prediction over various time windows. As for the relative humidity, a large error range of 0.4 to 10.34 was calculated which could be unacceptable especially if the system will be used in decision making controllers. Overall, the system is purely prediction and it does not offer any controllability of the thermal load or consideration of the user's comfort level.

The use of Support Vector Machines (SVM) and BPNN in indoor prediction was presented in [33]. The two techniques were applied on four test cases and the results were compared. The inputs to both models were the current indoor temperature (from a sensor), the outdoor temperature, the solar radiation and the wind speed. The Gaussian function was used as the kernel in the SVM model, and the parameters were obtained by cross validation to be ($C = 2$, $g = 0.5$, and $\varepsilon = 0.01$). for the BPNN model, the networks consisted of three layers with four inputs and one output which is the predicted temperature. Overall, SVM showed better indoor prediction than BPNN, with the Mean Square Error (MSE) of the SVM ranging from 0.1 to 0.4 in the four test cases, while the BPNN's MSE ranged from 0.5 to 0.9 for the four test cases.

Furthermore, Liu et al. [34] discussed multiple hybrid methods and application in indoor temperature prediction. The two main methods are particle swarm - least squares support vector regression (PSO-LSSVM), and DE Algorithm - least squares support vector regression (DE-LSSVM). They are optimized versions of typical time series and artificial intelligence methods (ARX and LSSVM respectively). In the first case, PSO was used to tune the LSSVM, whereas DE was used to tune the second LSSVM. The inputs to the system were historical data and metrological information. Overall, the error of the hybrid methods PSO-LSSVM and DE-LSSVM was lower than that of the LSSVM by itself of the ARX model. For example, the MAPE of one of the test cases improved by a 0.66%-0.81% range while the RMSE improved between 0.01 and 0.013. The downside of the model is its computational complexity or run time if this model was used for the purpose of dynamic load scheduling and controlling. This is mainly due to the many coefficients or variables that will need to be tuned in addition to the appliances' controlling variables.

Kavakioglu [35] discussed the modelling of thermal loads using partial least squares "These loads were modeled as functions of eight input variables such as relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area and glazing area distribution" [35]. The RMSE of both the cooling and heating loads where ranging between 2.892 and 5.737 which are considerably higher than other methods in the literature. It was also concluded that some of the input variables (orientations and glazing area distribution) do not contribute much to the output heating and cooling loads.

A high accuracy residential thermal load prediction model was discussed in [36]. Data were collected using wireless sensors distributed over different rooms in certain housed. Prediction was done using regression-based optimization model (called Matchsticks). Matchstick links between the heating scheduler and the actual house controller. It takes the historical sensor data (for training), current sensor data, along with the scheduler program to predict the temperature in the next time period. Model fitting was done using MATLAB's curve fitting function called lsqcurvefit. Evaluating the system with different time windows, shorter windows gave less error. Overall, the system saved a significant amount of gas in multiple houses when used with a controller, two households saved 3.3% and 2.3% in gas respectively. One of the main drawbacks of using training sets in a system, is the presence of sudden temperature changes (not related to the thermal inputs). This could reflect on the future predictions, which is exactly what happened in one of the units studied in this article.

Baniasadi et al. [37] provided a complete home energy management system that includes both the controlling and the optimization units for the purpose of DR application. The appliances included a Ground Source Heat Pump (GSHP), Water Storage Tank (WST), and a Fan Coil Unit (FCU). A real model “SELAB” was used with the MATLAB controller model for comparison and verification. SELAB was simulated in MATLAB as a heat dynamic state space model, where the output is the indoor temperature (Ti) and the building’s lumped thermal mass temperature (Tl. The thermal energy management system (TEMS) utilizes a dynamic setpoint approach which is best to reach the optimum performance. Overall, applying this system reduced the energy consumption by 13.3%, while the cost was improved by 25.31% which is a huge improvement.

A thermal comfort model that uses infrared thermal imaging, is presented in [38] to replace the set-points based controllers. The system consists of 3 main parts; sensors (temperature and humidity), Environment control devices (such as heat pumps and fans), and an HMI which is an interface to collect the user’s perception of the environment via a smart device. The user’s comfort or perception of the heat is measured by analyzing the infrared images of the occupants and the heat coming out of their bodies. To evaluate the system, a testbed was created, where the comfort levels of the participants are measured through infrared imaging and an HMI (for verification purposes). From the collected data, it was shown that over time, the user’s comfort levels were raised while the system was maintaining the indoor temperature at a reasonable range based on their infrared data. The main disadvantage of such model is the assumption that a room can have only one user, where the controller tries to maintain her/his comfort level, applying the controller in a room full of people can be challenging.

With proper load modelling, HEMS need to be every effective when it comes to load scheduling, especially is used for the purpose of DR. Load scheduling and optimization has been greatly discussed in literature, the following section discussed this point and presents the related literature.

1.2.2 Load Scheduling and Optimization

1.2.2.1 General Metaheuristic Approaches

Load scheduling refers to the process of balancing electrical loads throughout the day to reduce either cost or power consumption in response to a demand signal generated by the utility. Scheduling can be done using rule based techniques, or using optimization. [39] and [40] presented Mixed Integer programming optimization model to reduce power consumption cost ToU prices shifting some loads off the peak hours. [39] also included scheduling an Electric vehicle which can greatly affect the grid during peak hours. Both models successfully managed to reduce the consumption cost without creating a moving peak which tends to form with imbalance scheduling in addition to reducing the Peak to Average Ratio (PAR) during peak hours [39]. The research in [40] also managed to increase the household incentive due to shifting loads during peak hours. However, [40] only included shiftable loads where thermal loads have the most significant effect on the electricity bill. It also did not consider any user settings, only the on/off status was changed during different time slots to reduce the overall consumption.

Another interesting model was presented in [41] where the proposed HEMS used the ToU to reduce the consumption during peak hours with the loads classified into four categories, each with its own mathematical model to achieve the most reduction. Loads are divided into Uncontrollable Appliances without Storage, Controllable Appliances without Storage, Controllable Appliances with Indirect Storage, and Controllable Appliances with Direct Storage. This classification will ensure that this model can cover almost all appliances types for better performance. An interesting point that this research considered was representing thermal loads as indirect storage appliances, where energy is stored but in a different form other than electricity. The scheduling was done on 4 stages, adding more elements to the system at every case. Results showed that maximum cost reduction was achieved with more appliances included in the scheduling, and as a result, reducing the peak to valley differences.

Two excellent nature inspire day ahead metaheuristic scheduling models were developed in [42], namely Binary Multi-objective PSO and a hybrid of Bird Swarm and Cuckoo Search Algorithms. The main objectives of the two algorithms are to schedule the house appliances away from the peak period by changing their on/off status for the next day while keeping the user's comfort by reducing the waiting time. Three electricity tariff modules were tested using their models, Real Time Pricing (RTP), Time of Use (ToU), and Critical Peak Price (CPP), however, results showed that the pricing scheme does not affect the results in a significant way. Dynamic programming was implemented for coordination purposes among the appliances, and it proved to have the most effect on reducing cost and reducing the PAR. Comparing the two algorithms with two famous algorithms; the Multi-objective Particle Swarm Optimization, and Multi-objective Cuckoo Search Algorithm proved that the proposed algorithms outperformed them in terms of cost reduction. Controllability over each appliance's settings is not possible, this could have a significant effect in cost reduction and maintaining the user's comfort by allowing the users to set their tolerance ranges for every separate appliance instead of the general tolerable waiting time for them.

Another comparison was done between a Mixed Integer Linear Programming (MILP) model and a metaheuristic method (GA) was done in [43] in a HEMS that aimed in reducing electricity cost for a variety of loads ranging from shiftable, uninterruptible, and thermostatically controlled loads. Renewable energy generation was also incorporated in the system, scheduling was done based on the ToU price for both buying and selling power. The metaheuristic GA model managed to give better results compared to the MILP where the computational speed was 1 minute for the GA and 15 minutes for the MILP, indicating the mathematical complexity of the MILP.

1.2.2.2 Grey Wolf Optimizer (GWO)

Grey wolf optimization was used in a few sources when it comes to energy conservation. [44] uses a GWO to manage energy consumption in a grid. The grid has storage units and the algorithm decides when power is delivered to the grid or taken from the grid from the storage units. The system does not have control of individual appliances in every house, it controls the grid. Comparing it to a similar PSO system, it proved to save cost by about 25%.

Furthermore, another GWO controlled microgrid was presented in [45], where the cost and battery sizes in a simulation grid was optimizes. It was compared to multiple algorithms such as the PSO, the Bat Algorithm, and an improved Bat Algorithm, and it proved to outperform them by reducing the operational cost of the microgrid by 33.185%.

GWO was also used in green smart house scheduling with the presence of storage unit, as [46] presented an overall day ahead scheduling of household appliances to reduce total power consumption. In this thesis, the GWO optimizes when the storage unit is to be charged or discharged to obtain the best cost reduction. Prices are provided by the utility as DR signals the night before. The system proved to reduce the house's energy cost significantly, even when compared to other algorithms such as the PSO. User comfort is also considered in this model, which is an important point.

1.2.2.3 Whale Optimization Algorithm (WOA)

WOA is also a new metaheuristic algorithm that has proven to be effective in many applications. Swalehe, Chumbo, and Marungsri [47] presented an appliance scheduling system using WOA with multiple types of appliances including renewable energy sources and storage units. The system managed to achieve 40% reduction without the inclusion of renewable sources, and about 53% when they are included. One of the drawbacks of this system is that it only optimizes the on/off time of the appliances, not being able to control setpoints of any of the thermal loads.

Sharma and Saxena [48] on the other hand presented a WOA scheduler for two types of grids, a residential and a commercial grid. Three strategies were used for the DSM, Strategic Conservation, peak clipping, and load shifting. Comparing the results of this system with two other algorithms proved to achieve better cost and peak load demand reduction using the three DSM strategies.

Another cost optimization application was introduced in [49] where the WOA was used to find the optimal production and operation cost for a system while solving a constrained economical dispatch problem. The algorithm was applied on multiple IEEE test systems with varying number of thermal units. The algorithm was compared with PSO and LaGrange optimization and it outperformed them with a quicker convergence.

1.3 Statement of the Problem

As the literature showed, thermal appliances were modeled in different ways depending on the purpose. In multiple cases, the models were not considering some essential parameters such as the outer temperature, occupancy building's physical structure, and user comfort. These parameters will guarantee a more accurate load profile, which is very essential if the models are to be used in DR applications. Moreover, the schedulers discussed in the literature did not consider changing important load parameters, majority of them were designed to turn on/off appliances or shifting them away from the peak hours, without having any control over the individual appliance's settings. Having control over the individual appliance's operation parameters can give more accurate scheduling results and it will maintain the user's comfort. For example, an AC's setpoints can be adjusted to accommodate with the peak prices instead of getting turned off and disturbing the user's comfort.

1.4 Objectives of the Thesis

1- To come up with accurate and realistic models of home appliances especially thermal loads considering more controlling parameters for the purpose of DR load scheduling,

2- To build a full house controller (interface) where the user can input desired settings and be able to view the load profiles for those settings

3- To implement an effective load scheduling model that optimizes the appliances settings and schedule the loads around the house to reduce the cost to its minimum in response to a DR signal. Multiple heuristic algorithms are to be studied and used to optimize and schedule the HEMS appliances. The intended HEMS is to work daily, receiving the DR price signal from the utility and controlling the appliances to achieve minimum cost.

1.5 Scope of Work

The process of creating the HEMS includes firstly studying existing thermal load models and deciding on the most important control parameters to be added to the HEMS's model. Then the mathematical models for the thermal loads are to be developed and simulated with verifying their load profiles under multiple input settings. A full house controller is to be created where the users can initialize their desired settings for the day and be able to view the minutely load profile of their house using their settings. Thermal models are the focus of the HEMS since they are the biggest contributors to the electricity bill, however, some shiftable loads are to be added to the model to study their effect on the overall scheduler. Multiple metaheuristic optimization algorithms are to be used to optimize the system and schedule the loads to get the minimum cost.

1.6 Thesis Outline

Firstly, chapter 1 includes the overview of the thesis, objective, scope of work, and literature review. Following that chapter 2 contains the methodology followed to create the loads models and the full house controller. Then chapter 3 discusses the methodology followed to apply the optimizer and the scheduling system structure. Furthermore, the results of the full HEMS including the controller and the optimizer are discussed in the results and discussion section. Finally, the conclusion highlights the main findings from this research, restating the objectives with discussing the opportunities of future work.

Chapter 2: Appliances Modelling

2.1 Thermal Loads Modelling

Thermal loads are the most power consuming appliances in a UAE household, especially during summer. To properly schedule such loads, they must be well modelled with multiple control aspects that can be tuned for effective scheduling.

2.1.1 House Heater Model

The base for all the thermal loads in this research is the house heater model, which is a grey box model that depends on the outer temperature, physical room characteristics and a set of differential equations [50]. The physical contents are all initialized according to common values for typical house heaters. The empirical system consists of 3 subsystems and 3 main differential equations. The house model, the heater model and the thermostat. The thermostat is represented by a simple controller, whereas the other two subsystems are defined by the following equations.

- Heater subsystem

$$\frac{dQ}{dt} = (T_{heater} - T_{room}).M_{dot}.c \qquad (1)$$

Where $\frac{dQ}{dt}$ is the heat flow from the heater into the room, *c* is the heat capacity of air at constant pressure, M_{dot} is the air mass flowrate through the heater (kg/hr), T_{heater} is the temperature of the hot air coming of the heater, and T_{room} is the room temperature at that minute.

- House subsystem

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

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

Where M_{air} is the mass of the air inside the house, and R_{eq} is the equivalent thermal resistance of the house. The adopted model was implemented in MATLAB, the script consists of two modules, the ODE function which contains all the initial constants and the differential equations system, and a CALL function that gives the ODE system its input and plots the output for that input. ODE45 was the differential equations solver used in this module. The differential equation system is a 3-state model where the changing variables are T_{room}, Q_{losses}, and Q_{heater}. The initial conditions for the three variables are given to the ODE module as a vector. The output contains the calculated T_{room}, Q_{losses}, and Q_{heater}. The CALL module initializes the time vector, set points, tolerance ranges, room occupancy and outer temperatures and calls the ODE module every minute to produce the next minute's room temperature. All temperatures are represented in Celsius, while the time unite is 1 minute.

The differential system models the heat exchange in the room as a simple RC circuit where the flow of energy mimics the flow of current and the thermal internal wall resistance mimics the circuit's equivalent resistance. It was important to understand the relationship between the room's structure and the value of every constant to adjust the model for other thermal appliances. The minutely outer temperature is a real outer temperature vector where the corresponding sample is fed into the system, at every iteration of the ODE. The initial inner temperature was also changing where the current inner temperature will serve as an intimal T_{room} for the next sample. Another important variable that keeps updating is the status vector, for every iteration, the temperature is evaluated, and the status is defined through the thermostat. The upper and lower limits of the temperatures are defined by the tolerance ranges set by the user as the following:

$$T1 = \text{setpoint} - \text{tolerance range} \qquad (4)$$

$$T2 = \text{setpoint} + \text{tolerance range} \qquad (5)$$

Status is also governed by the occupancy, if the room is vacant, there is no point of keeping the heater on, therefore it will stay off even if the limits are exceeded, this will have a significant effect in reducing the power consumption. The flowchart of the program is shown in Figure 1.

2.1.2 Air Conditioner Model

Air conditioners are cooling devices which reduce the temperature of the room based on the concepts of matter's state change. When a gas changes its status from liquid to gas, it absorbs heat, whereas heat is released when going from gas to liquid. Absorbing heat leads to cooling down the medium which is exactly the purpose of the AC.

The working cycle of air conditioners refers to the operations that the refrigerant (in this case gas) goes through in order to change status or cool down the medium. It starts by the compressor phase where it pulls the warm refrigerant increasing its pressure and its temperature. The refrigerant then travels to the condenser where it goes through several fins with a running fan that helps it release its heat to the air and reducing; and therefore, reducing its temperature. The hot air then gets evicted to the exterior of the building.

During this process, the refrigerant changes its stat from gas to a high temperature liquid. The liquid is then passed to a valve that converts it into a mist. This

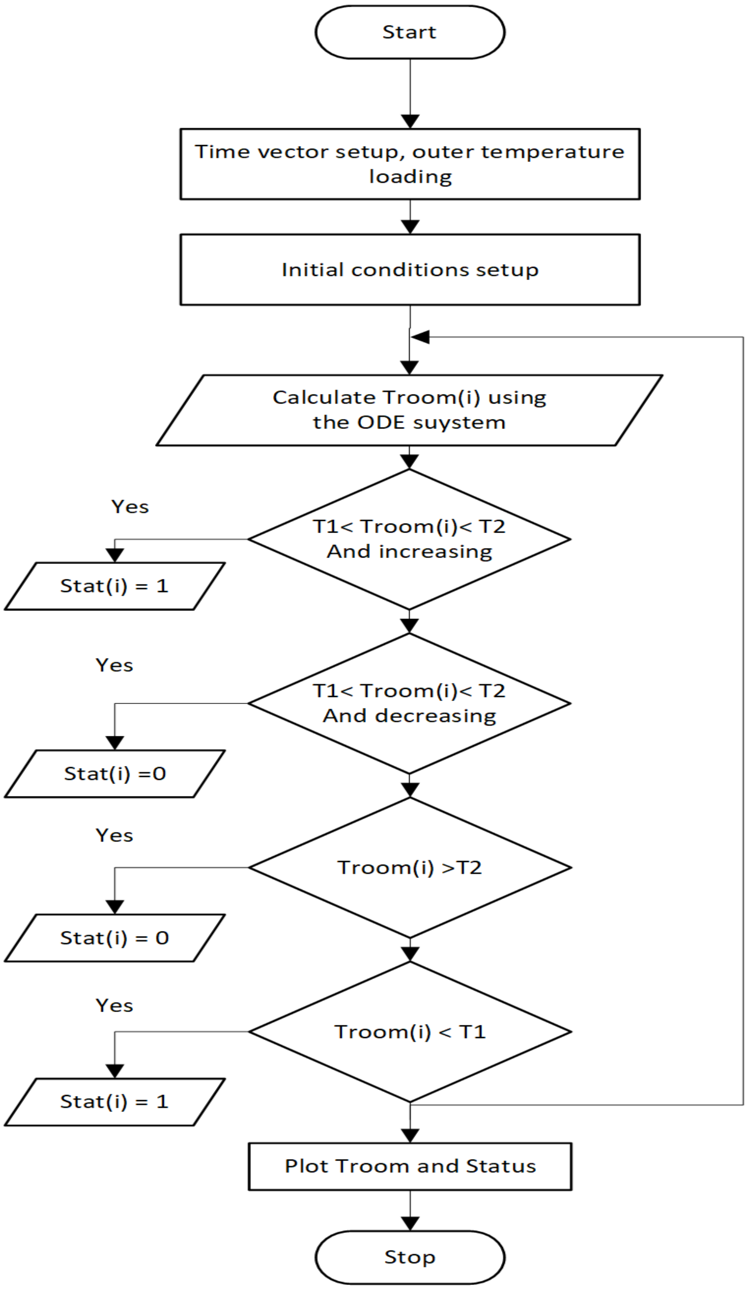

Figure 1: Heating system flowchart

sudden drop of pressure results in rapid cooling of the refrigerant, which is then passes to the evaporator coil located in front of a fan that circulates the room's air resulting in cooling it. The refrigerant losses its temperatures to the air and goes back to the compressor repeating the same process all over. Figure 2 shows the components of the system and the cooling cycle of the AC [51].

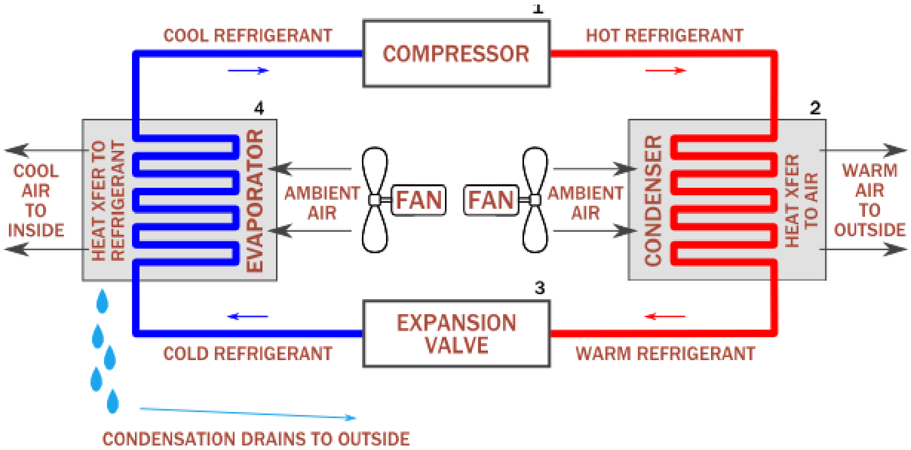

Figure 2: Air conditioner cooling cycle

The air conditioner model for the proposed HEMS was exactly the opposite of the heater's model. Minor changes were made on the heater model such as the heater (or AC) output air temperature, and the thermostat model. The outer temperature was kept the same as the one used in the heater; the results of the AC will be shown in the results section. The flow chart of the AC is the opposite of the room heater's model as shown in Figure 3.

2.1.3 Refrigerator Model

Refrigerators function the same way as air conditioners do, the same cycle happens inside the thermostat system of the refrigerator. The refrigerator's model was like that of the AC in terms of the thermostat subsystem, however many changes were made on the setup. Firstly, the dimensions of the room were changed into the refrigerator's dimensions. The refrigerator model that was used in the model was obtained from a study done on domestic appliances [52]. Other constants such as the thermal conductivity and the wall thickness were taken from other studies, considering that the insulation used in most refrigerators is Polyurethane foam [53]. The specific heat capacity and air density were kept the same since the medium is still air. Table 1 shows the values of all the constants in the refrigerator model. The refrigerator program runs just like the program in the flowchart (Figure 3), the results will be discussed in the results section.

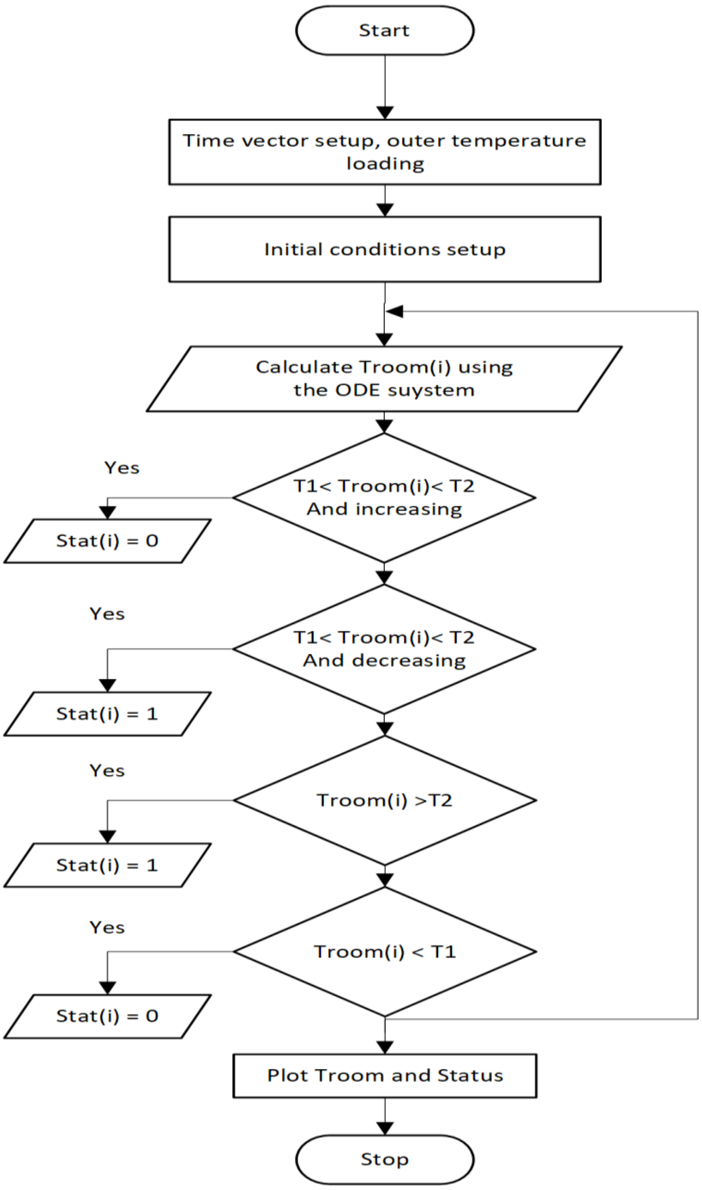

Figure 3: Cooling thermostat system (AC)

2.1.4 Water Heater Model

Water heaters work differently compared to other cooling and heating systems. For a start, the medium that heat is transferred through is water instead of air. Tank based water heaters consists of a large insulated tank that has one or two long rods that work as the heating elements. If two Heating elements exist, each heating element will be controlled by a separate thermostat. These types of heaters have two pipes, one for cold input water, and another one for warm output water. Figure 4 displays an example of the working cycle of a two heating elements heater.

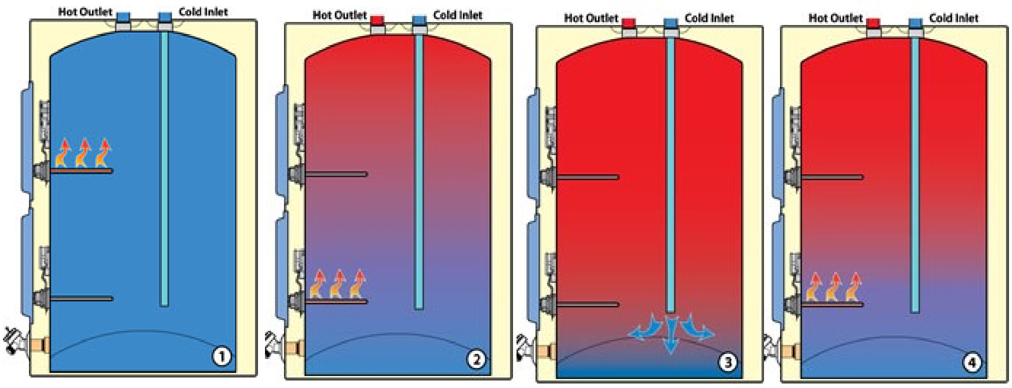

Figure 4:Working cycle of a water heater system

When the tank is filled with cold water, the higher rod will be on to heat the top part of the water, due to the high temperature, the density of the water will get lower, causing it to stay on top of the cold water, hence faster heating compared to when the lower rod is turned on first. Once the top is hot enough, the lower rod will be turned on until the whole tank reaches the desired temperature. When cold water flows into the tank, it sinks to the bottom and starts to gain heat from the surrounding, causing the total temperature to get lower [54]. Once the temperature is lower than the minimum of both thermostats, the heater will be turned on again until it is restored.

The same flowchart in Figure 1 is followed in modeling the water heater system for the proposed HEMS. As mentioned earlier, in water heaters the heat conducting fluid is no longer air but water, and the inner area of the room (tank) is no longer rectangular but cylindrical. The heater dimensions were used to calculate the inner area through the area of a cylinder equation. The insulating material was like that of a refrigerator; therefore, the thermal conductivity constant is the same. The dimensions were taken from a real model used in the labs for research; Florence FWH-50-15F model. The specific heat constant and the fluid density were changed to that of the water, along with the volume of the container which was 50 L. The values of all the constants are shown in Table 1 as well, the results are shown in the results section.

Table 1: Physical properties of the thermal appliances

	Air heater	Air conditioner	Refrigerator	Water heater
Dimensions (l.w.h (m))	30x10x4	30x10x4	0.6x0.6x1.8	0.450x0.559
Fluid density (kg/m^3)	1.2250	1.2250	1.2250	1.0
Fluid temperature (ºC)	50	10	-5	75
Thermal conductivity (J/sec/m/C)	0.78 (glass wool)	0.78 (glass wool)	0.05 (Polyurethane)	0.05 (Polyurethane)
Flowrate (kg/min)	60	60	0.6	0.12
Wall thickness (m)	0.2	0.2	0.11	0.0381
Specific heat capacity (J/kg-K)	1005.4	1005.4	1005.4	4185.5

2.2 Shiftable Loads

Shiftable loads are the loads which can be shifted in time depending on the user's desire. They tend to have a certain cycle duration which cannot be interrupted for a successful job. Washing machines and dishwashers are two examples of such loads. The way they were represented in the house model was simple, since they are unpredictable, and solely dependent on the user's actions, the user will give an initial profile of each appliance at the beginning. The profile will give information on when each appliance is likely to operate (an operation window; start and end time), how long is the operation cycle of the appliance, and what is the rated power consumed by it. The dishwasher and the washing machine were chosen as the shiftable loads in this model. The following section will show how these loads are incorporated in the full house model.

2.3 Full House Model

After modelling the individual loads, they were all combined in a full house model that will take the inputs of all the submodules and perform the optimization and scheduling. Firstly, the thermal loads were converted into functions which can be easily called by the house model. Then, the appliances' setup vectors are created for each appliance. The setup vectors of thermal loads differ a bit from that of the Shiftable loads, as Shiftable loads do not require a set point or a tolerance range, and the thermal loads do not have an operation duration. Figure 5 summarizes the house controller module which is to be used in the scheduling.

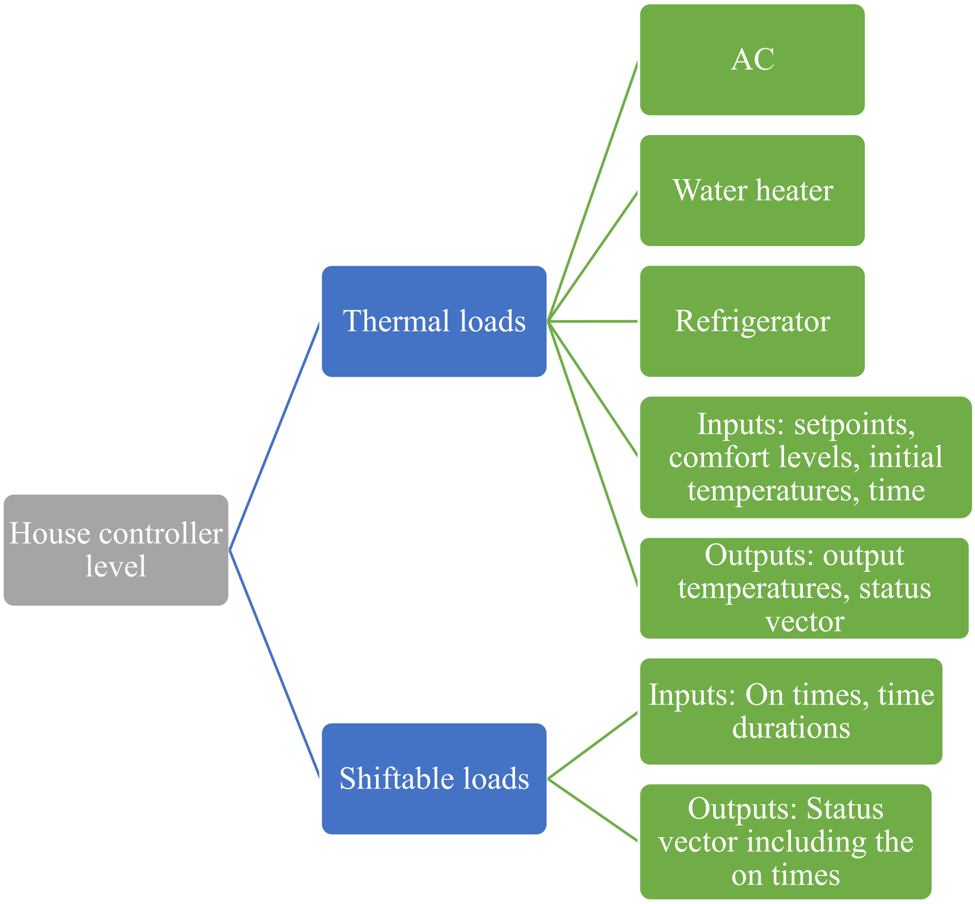

Figure 5: Full house controller model structure

The Significance of the house model lies in its accuracy and reliability to be next used in DR scheduling. In order to ensure realistic scheduling, the models must reflect reality (surrounding effecting factors) and typical human choices. The next chapter discusses the optimization techniques used to implement auto household loads scheduling for DR purposes using the developed models in this chapter.

Chapter 3: Optimization and Scheduling

3.1 Related Material

Multiple algorithms were explored to implement the scheduling including PSO, WOA, and GWO. Each of them will be explained first before explaining how they were used in the optimization.

3.1.1 Particle Swarm Optimization (PSO)

PSO is a nature inspired algorithm developed to solve nonlinear continues functions [55]. It originated from studying the behavior of bird swarms when looking for food, knowing that a single food source is available without really knowing where it is. In every iteration, the position and velocity of every particle is updated with respect to the best position. The best position is evaluated using a fitness function which the system is trying to reach its minimum. The position of the j^{th} particle at iteration i refers to the possible solution to the minimization function, which is best when it produces the minimum distance to the food position (function minimum). The particle's velocity and position are updated through equations 6 and 7.

$$V_j^{i+1} = \omega^i \times V_j^i + C_1 \times rand_2 \times \left(X_{pbest_j}^i - X_j^i\right) + C_2 \times rand_2 \times \left(X_{gbest}^i - X_j^i\right) \quad (6)$$

$$X_j^{i+1} = X_j^i + V_j^{i+1} \quad (7)$$

Where V_j^{i+1} represents the velocity if the jth particle at the $i+1$ 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], C_1 and C_2 are the acceleration constants. The 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 at the i^{th} iteration.

The position and velocity are also governed by two best values, the particle's local best across all iterations $X^{i}_{pbest_j}$, and the global best among the whole population X^{i}_{gbest}.

3.1.2 Whale Optimization Algorithm (WOA)

WOA is also a nature inspired algorithm, where the feeding process of Humpback whales is modelled [56]. Whales feed in large groups, with different modes or phases when looking for prey or when attacking. These modes are, encircling prey, search for prey, and spiral updating position. Like the PSO, the swarm consists of particles where the position of every particle X_{i+1} is calculated from the best position particle as shown in equations 8 and 9:

$$\vec{D} = \left|\vec{C}.\vec{X}_{best} - \vec{X}_i\right| \qquad (8)$$

$$\vec{X}_{i+1} = \left|\vec{X}_{best} - \vec{A}.\vec{D}\right| \qquad (9)$$

Where 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 as stated in equations 10 and 11:

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \qquad (10)$$

$$\vec{C} = 2\vec{r} \qquad (11)$$

Where $\vec{a}$ is a number linearly decreasing from 2 to 0 with every iteration and $\vec{r}$ is a vector randomly generated in the range [0,1]. When looking for prey, the whales behave in two ways depending on the hunting phases; exploration and exploitation. A 50% probability is assumed for every phase, and according to its value and the value of $|A|$ the position vector gets updated differently.

- Exploration phase (p<0.5)

In this phase the whales are still searching in the whole space, depending on the value of $|A|$the positions are changed as the following:

a- If $|A| \geq 1$ the position updates the same way as shown in equations 8 and 9.

b- Alternatively, when $|A| \geq 1$, in this case the new equations will be as shown in equation 12 and 13:

$$\vec{D} = \left|\vec{C}.\vec{X}_{rand} - \vec{X}_i\right| \qquad (12)$$

$$\vec{X}_{i+1} = \left|\vec{X}_{rand} - \vec{A}.\vec{D}\right| \qquad (13)$$

Where the new position uses a random position $\vec{X}_{rand}$ instead of $\vec{X}_{best}$.This phase is useful to search for the global best.

- Exploitation phase (p ≥ 0.5)

When they get closer to the prey, a spiral updating of the position happens as shown in equations 14 and 15:

$$\overrightarrow{D'} = \left|\vec{X}_{best} - \vec{X}_i\right| \qquad (14)$$

$$\vec{X}_{i+1} = \overrightarrow{D'}.e^{bl}.cos(2\pi l) + \vec{X}_{best} \qquad (15)$$

Where *l* is a number in the range [-1,1], and b is a constant. The pseudocode for the WOA is as shown in Figure 6.

```
Initialization: Swarm population (dim*population size)
Find the fitness for every element in the swarm
Locate the initial Xbest
While (j<Max iterations)
For i=1:Population size
Update constants
If_a(p<0.5)
    If_b (|A| >= 1)
        Xj+1 is evaluated using equ. 14
    Else if_b
        Xj+1 is evaluated using equ. 10
    End if_b
Else if_a
    Xj+1 is evaluated using equ. 16
End if_a

End for
Check for bounds
Evaluate fitness for all particles
Update Xbest and iteration
End while
```

Figure 6: WOA pseudocode

3.1.3 Grey Wolf Optimizer (GWO)

GWO is another nature inspired optimization algorithm, and like the PSO and WOA, the wolf packs represent the swarm that is observed during hunting. A hunting pack is divided into 4 categories, first, alpha wolves, which are the leaders and the rest of the pack follows them. Beta wolves come second to the alpha, they help alpha wolves make decisions and the rest of the pack follows them. Omega wolves come last, they are called the scapegoat, although very low in ranking yet they affect the pack's structure if missing. Finally, Delta wolves are the rest of the pack which do not belong to any of the other three categories [57]. The mathematical model of the GWO is very close to that of the WOA. The general position updating equation is the same as shown in equation 8 and 9. However, A and D are calculated as shown in equation 19 and 20.

$$\overrightarrow{A} = 2\vec{a}.\overrightarrow{r_1} - \overrightarrow{a} \qquad (19)$$

$$\vec{C} = 2\overrightarrow{r_2} \qquad (20)$$

Where in this case instead of one r there are two, both being a random number in the period [0,1]. The pack is divided into the 4 categories, the distance vector between each type of the wolves and the best position is calculated as shown in equations 21-23.

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\vec{X}_\alpha - \vec{X}_i\right| \qquad (21)$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\vec{X}_\beta - \vec{X}_i\right| \qquad (22)$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\vec{X}_\beta - \vec{X}_i\right| \qquad (23)$$

Where $\overrightarrow{C_1}$, $\overrightarrow{C_2}$, and $\overrightarrow{C_3}$ are randomly generated vectors, $\vec{X}_i$ represents the wolves' current position and $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ represent the positions of the wolves in each category. Following equations 21-23 three new positions of the wolves can be calculated as stated in equations 24-26:

$$\vec{X}_1 = \left|\vec{X}_\alpha - \overrightarrow{A_1}.\vec{D}\right| \qquad (24)$$

$$\vec{X}_2 = \left|\vec{X}_\beta - \overrightarrow{A_2}.\vec{D}\right| \qquad (25)$$

$$\vec{X}_3 = \left|\vec{X}_\delta - \overrightarrow{A_3}.\vec{D}\right| \qquad (26)$$

Where A1, A2, and A3 are also random vectors. Taking the average of the three vectors will give the wolf's new position as shown in equation 27.

$$\vec{X}_{j+1} = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \qquad (27)$$

The pseudocode for the GWO is shown in Figure 7.

```
Initialization: pack population (dim*pack size)
Initialize constants a,C,A.
Find the fitness for every element in the pack
Generate the first 3 best solutions Xα Xβ Xδ
While (j<Max iterations)
For i=1:Population size
  Update position (equation 28)
End for
Check for bounds
Evaluate fitness for all particles
Update the 3 best positions
Update constants
Update iteration
End while
```

Figure 7: GWO pseudocode

3.2 Optimization Problem Formulation

3.2.1 Objective Function

The main objective of the scheduler is to reduce the total house cost and avoiding peak prices. The DR signal is sent to the house as an input, indicating the minutely prices for the next day. The cost of the full house's power consumption can be calculated as equation 28 shows:

$$Cost = \sum_{i=1}^{n} \sum_{j=1}^{m} S_{ji} \times p_j \times r_i \qquad (28)$$

Where i is the appliance counter, j is the minute of the day, S_{ji} is the minutely status of the appliance, r_i is the power rating on the i^{th} appliance converted into KWminute, and finally p_j represents the price at the j^{th} minute.

The number of appliances in this research was 5, three of them are thermal loads and 2 are shiftable loads. The input to the cost function is a vector containing all the setpoints of the thermal loads, the comfort levels, and the starting time for the shiftable loads as shown in equation 29.

$$x = [\,WM\,, DW\,, setpoint_{Ref}, tolerence_{Ref}, setpoint_{water\ heater},$$

$$tolerance_{water\ heater}, setpoint_{AC}, tolerance_{AC}] \qquad (29)$$

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 setpoints and tolerance for the water heater, and $setpoint_{AC}$ and $tolerance_{AC}$ are the setpoints and tolerance for the AC. The problem dimension is 8, each of the individual appliance model has its own additional input parameters such as the initial temperatures and the occupancy. The Shiftable loads are uninterruptable, their working cycle is fixed and cannot exceed the typical limits. The upper and lower limits for the input vector are shown as the following.

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

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

Where 1440 is the number of minutes in a day, and 90 and 60 are the working cycles of the washing machine and the dishwasher respectively. The optimization problem can then be restated as shown in equation 30:

$$min(\sum_{i=1}^{n}\sum_{j=1}^{m} S_{ji} \times p_j \times r_i \ ) \qquad (30)$$

The flowchart for the scheduling process is shown in Figure 8. To run the optimizers, the same input parameters were used for every algorithm. The constants were set as acceptable values used in the literature. Table 2 shows the values for the constants for every algorithm.

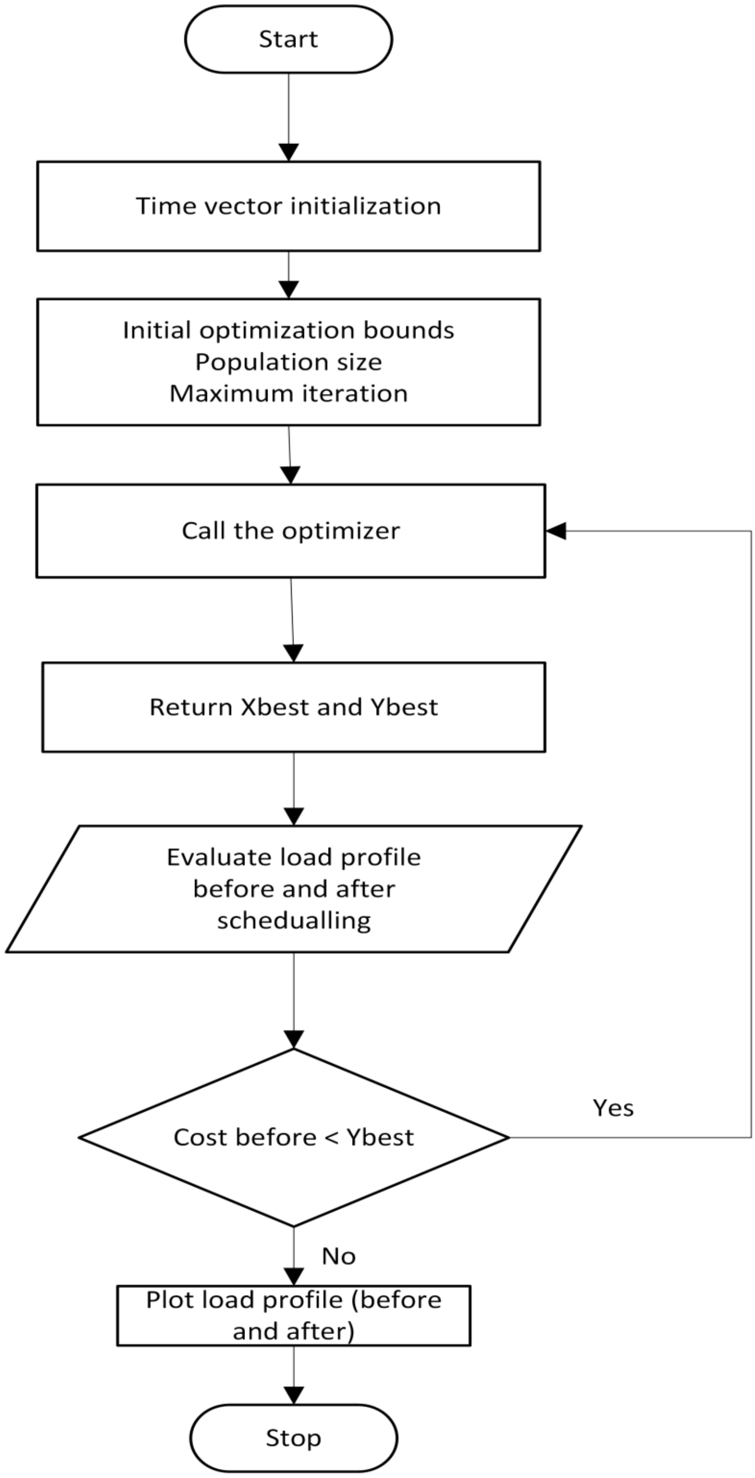

Figure 8: Load scheduling flowchart

Table 2: Algorithms configuration parameters

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;`

3.2.2 Special Comparison Schemes Preparation

To further test the system, a baseline was created to compare the results of the optimizer with it. This baseline was a manual house profile where the cost of the house for 24 hours is calculated based on 3 occupancy schemes and 3 price schemes. The occupancy variation is to realistically mimic the occupancy of the house during different days of the week. The first occupation scheme included one period where the user is not in the house, the second included two, and the third included three. Moreover, 3 price signals where used to calculate the total cost, a realistic DR signal can have different variation depending on the day of the week and the occupancy. Figure 9 shows the 3 occupation schemes and Figure 10 shows the 3 prices schemes.

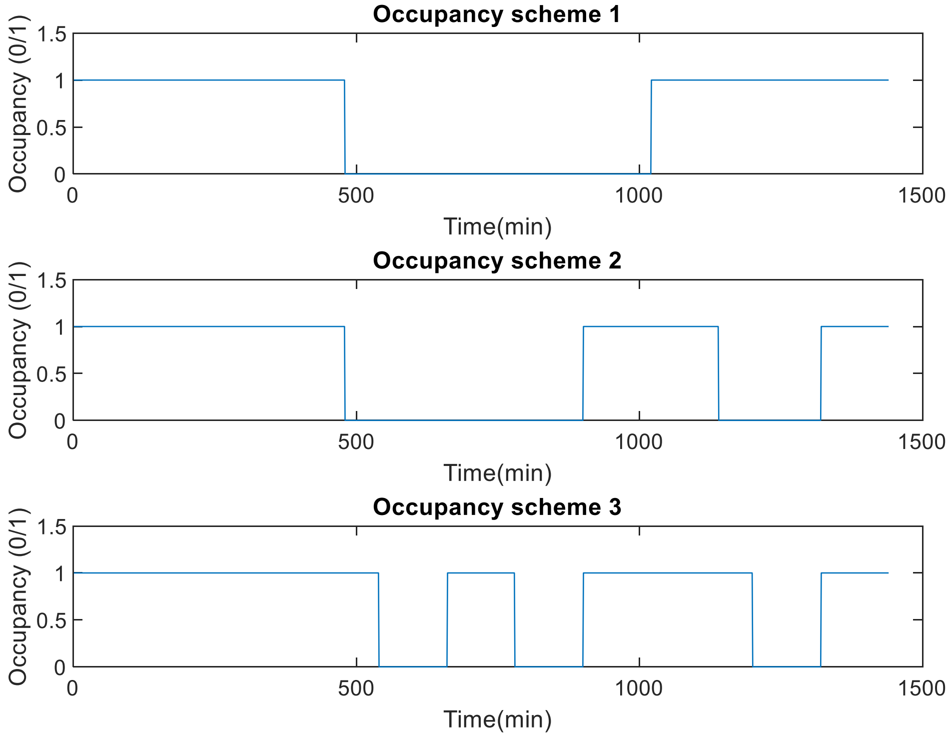

Figure 9: Occupancy schemes for testing

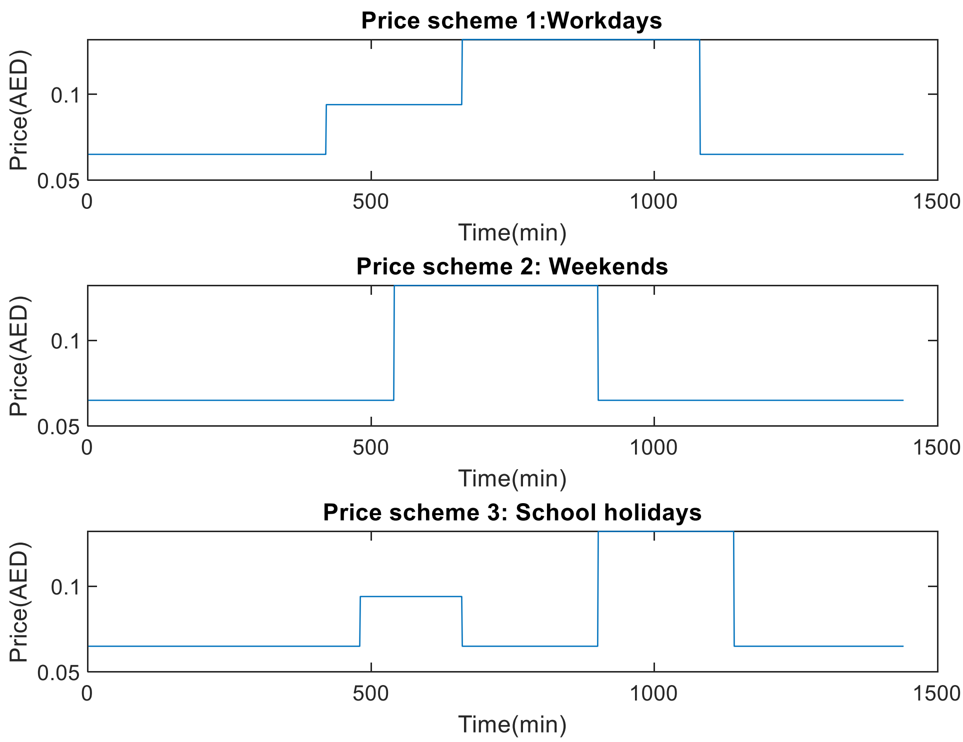

Figure 10: Price schemes for testing

Chapter 4: Results and Discussion

4.1 House Controller Model

4.1.1 Thermal Loads

4.1.1.1 House Heater

To verify the house heater model, it was run with multiple set points and multiple tolerance ranges. The outer temperature was taken from Meteoblue [58] website and it was interpolated to have a minute by minute log instead of the hourly log. The outer temperature was negatively offset to mimic a cold weather where the heater is needed. Figure 11 shows the heater's output under different operation settings. Firstly, with a set point of 28°C and 4°C tolerance range, it is seen that the swing is very large, hence the on cycles for the compressor are less frequent. Secondly, in Figure 11b, with a smaller tolerance range, hence the on cycles where more frequent than the previous case. Moreover, changing the setpoint will affect the duration of the on cycles as shown in Figure 11c where the setpoint was dropped to 20 with a comfort level of 4. The width of the on cycles is now less, since it is not required to work longer to heat up the room, the outer temperature plays an important role in keeping the temperature of the room low as well. Changing the tolerance range to a lower temperature means more on cycles which are shorter of course as shown in Figure 11d.

The power consumption for the heater model will be logically higher for the higher setpoints and the figures confirm; with the total on time for Figure 11d is 149 minutes whereas it's 329 minutes for Figure 11b.

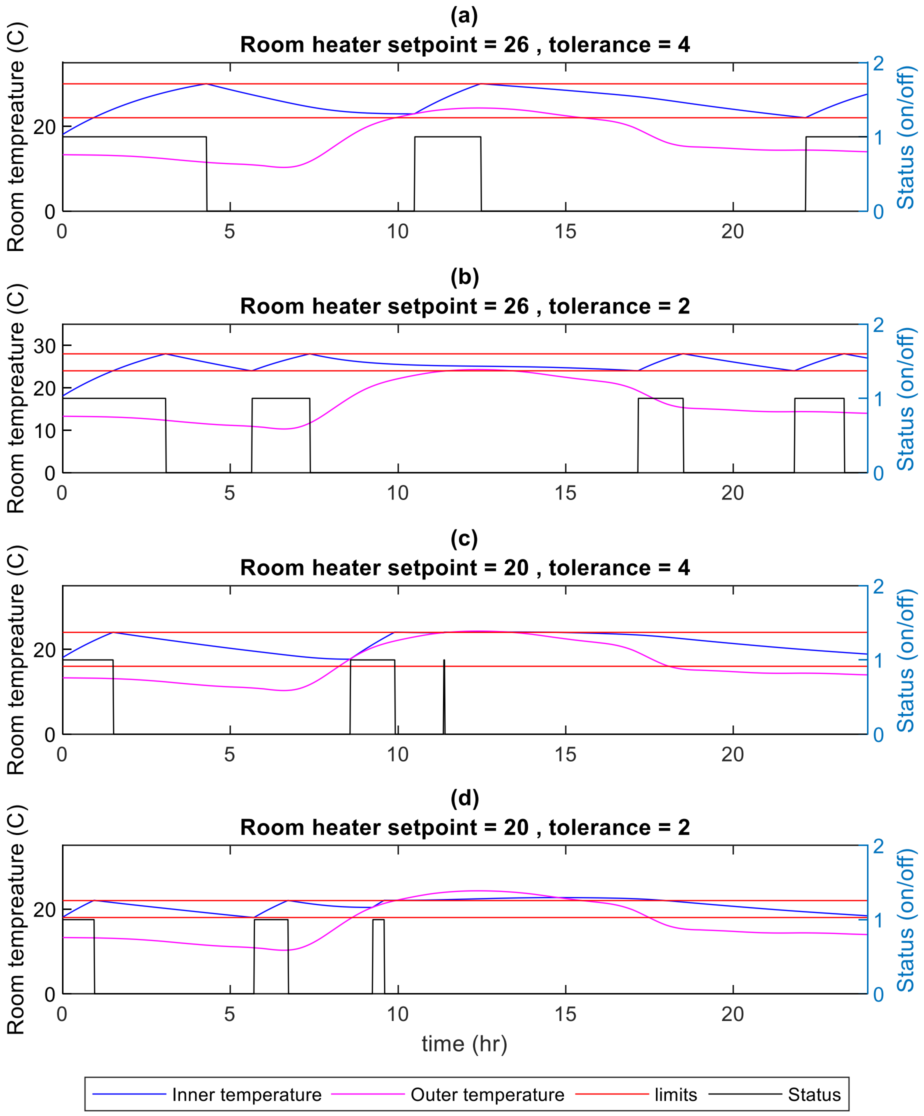

Figure 11: House heater controller output

4.1.1.2 Air Conditioner

As for the air conditioner, it was also verified in a similar way, the outer temperature was the same as the one used in the heater. The outer temperature was raised to mimic a hot day as well and the output was plotted for 24 hours.

Firstly, for higher set points and tolerance ranges (Figure 12a), it was noticed that the on cycles are narrower compared to the lower temperature setting (Figure 12c). This is because the compressor will have to work longer to reach lower temperatures (cooling). It is also noticed that the cooling cycles are mainly around the times when the outer temperatures are rising (at noon time) which is expected since the walls are not insulated, and they conduct some of the outer heat inside. On the other hand, when changing the tolerance ranges, as expected, reducing the tolerance ranges will cause

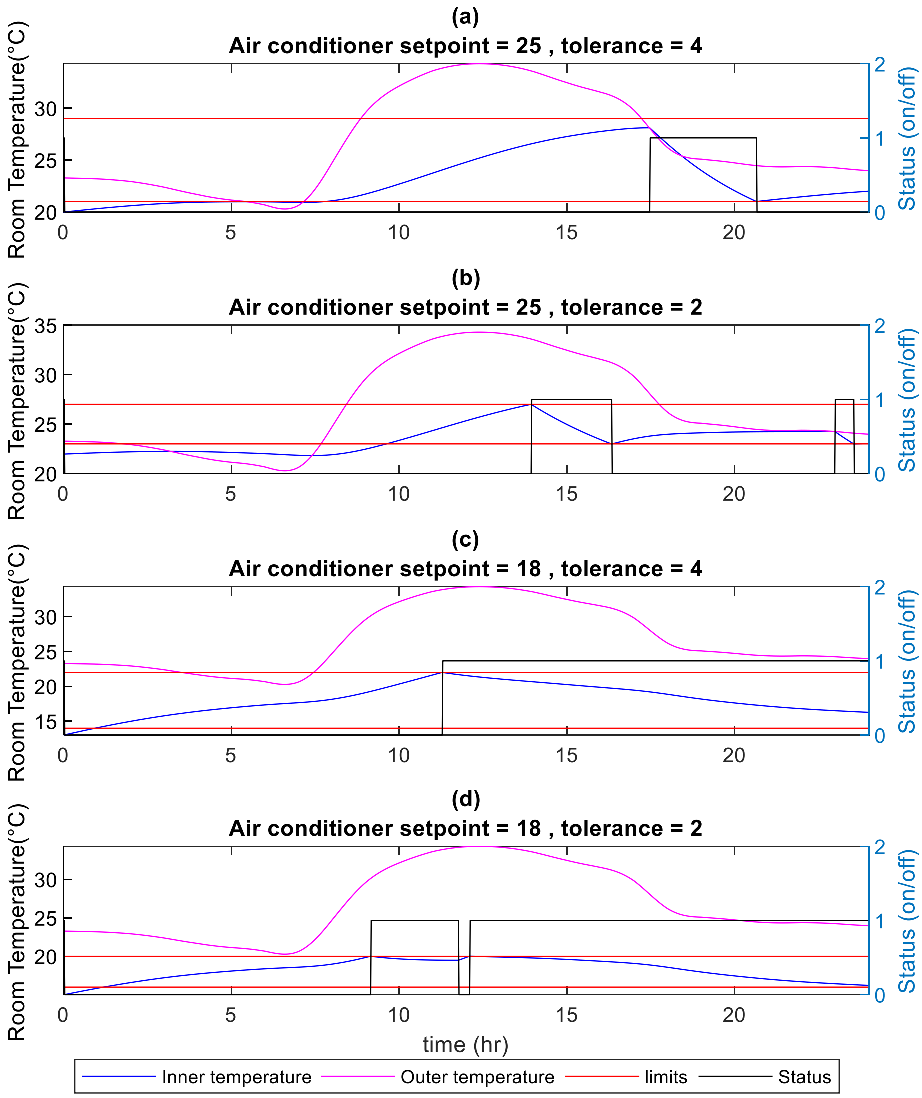

Figure 12: Air conditioner controller output

the compressor to work more frequently to maintain the indoor temperature within the two limits (Figure 12b,d). finally, as expected, the on time for lower temperatures was more, reaching 1738 minutes of the 24 hours period for the 18°C setpoint (Figure 12b) and 811 minutes for a 25°C set point (Figure 12d).

4.1.1.3 Refrigerator

The same analysis was done on the refrigerator, since it is a cooling device, it was expected to have similar behavior as the AC. Figure 13 shows the output of the refrigerator under multiple operation conditions. The outer temperature was a small

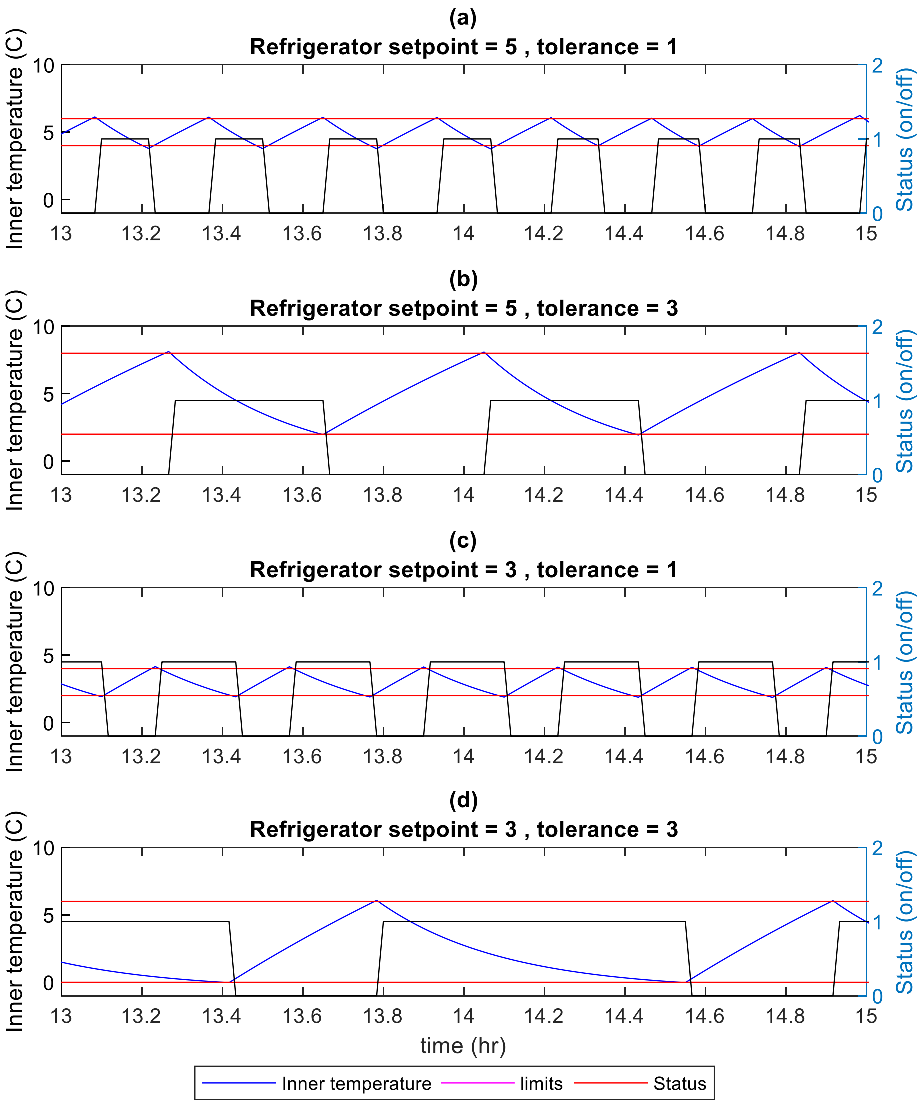

Figure 13: Refrigerator controller output

sine wave simulating the room temperature. The simulation was run over a period of 48 hours but only 2 hours were displayed on the figures for clarity. As shown in the figure and confirming the expectations, wider tolerance ranges yielded less frequent on/cycles (Figure 13b,d), whereas narrower comfort levels yielded more frequent cycles (Figure 13a,c). As for the duration of the on/off cycles, higher set points gave resulted in less on time as shown in Figure 13b, with only 927 minutes out of the 48 hours, whereas it reached 1279 minutes with the 3°C setpoint (Figure 13d).

4.1.1.4 Water Heater

As for the water heater, it was also simulated for 48 hours, but only 5 hours were plotted as shown in Figure 14. Since it is a heating device, it is expected to have a similar behavior to the room heater model. With smaller tolerance ranges (Figure 14a,c) the on/off cycles were more frequent, whereas with wider comfort levels (Figure 14b,d) it is the opposite. As for the setpoints, higher set points gave more on time as the compressor will need more time to reach the higher temperature setting. This is verified in the figures as the in time for Figure 14b was 1320 minutes whereas it was only 505 minutes for Figure 14d which was a lower setpoint.

4.1.2 Full House Model

With all the appliances' predictive models ready, they were all combined and run in one program. Figure 15 shows the combined system output including the shiftable loads (washing machine and dishwasher). The blue pulses represent the status, with varying amplitude depending on the figure scale. The thermal loads are exactly as what was discussed in the previous sections, the room heater was excluded as it is not a common appliance in an Emirati household. The washing machine was operated once for an hour and a half, whereas the dishwasher was operated twice, once in the afternoon and once at night for a duration of half an hour. With the system setup, optimization can be done on it knowing how the load will look like in the day and the typical power consumption of a load.

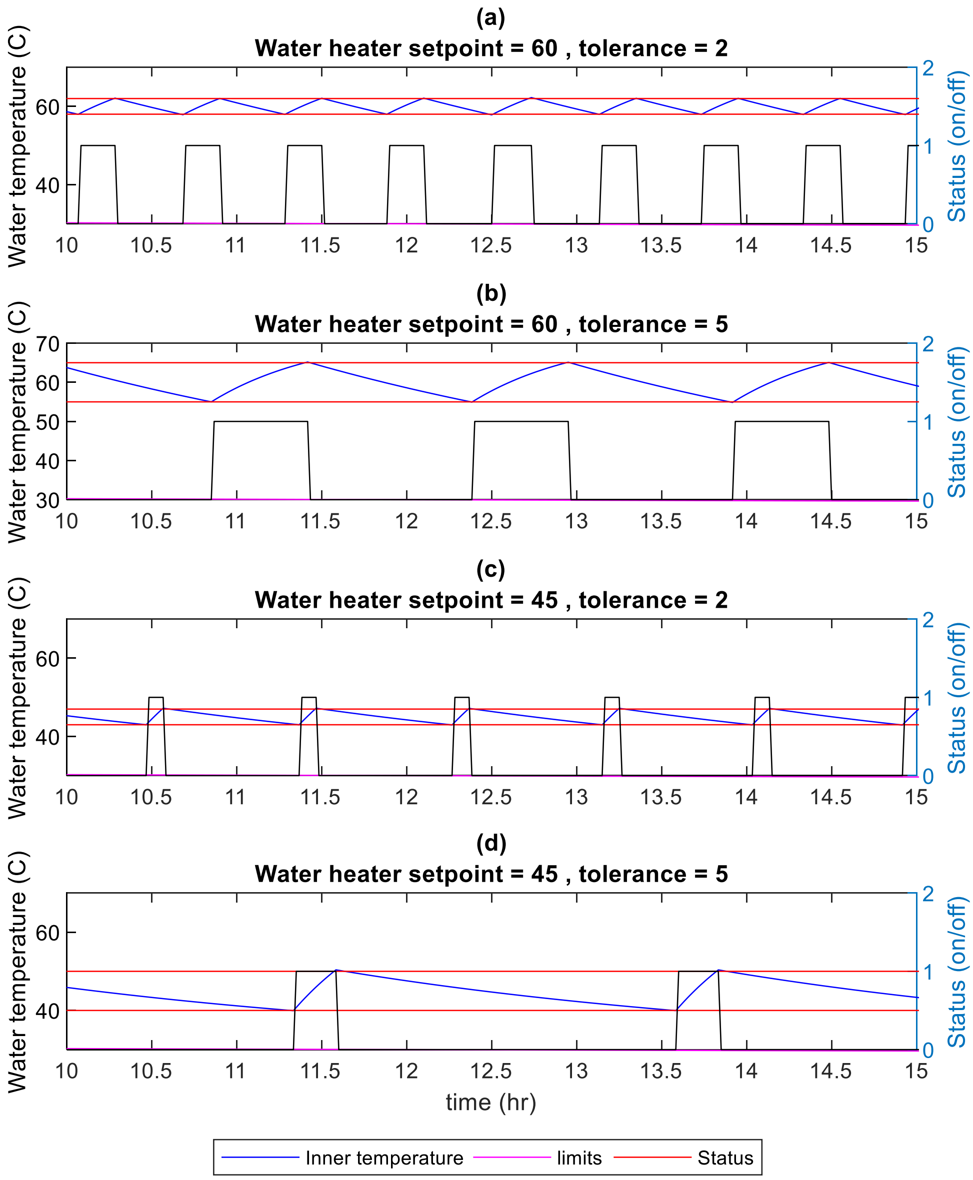

Figure 14: Water heater controller output

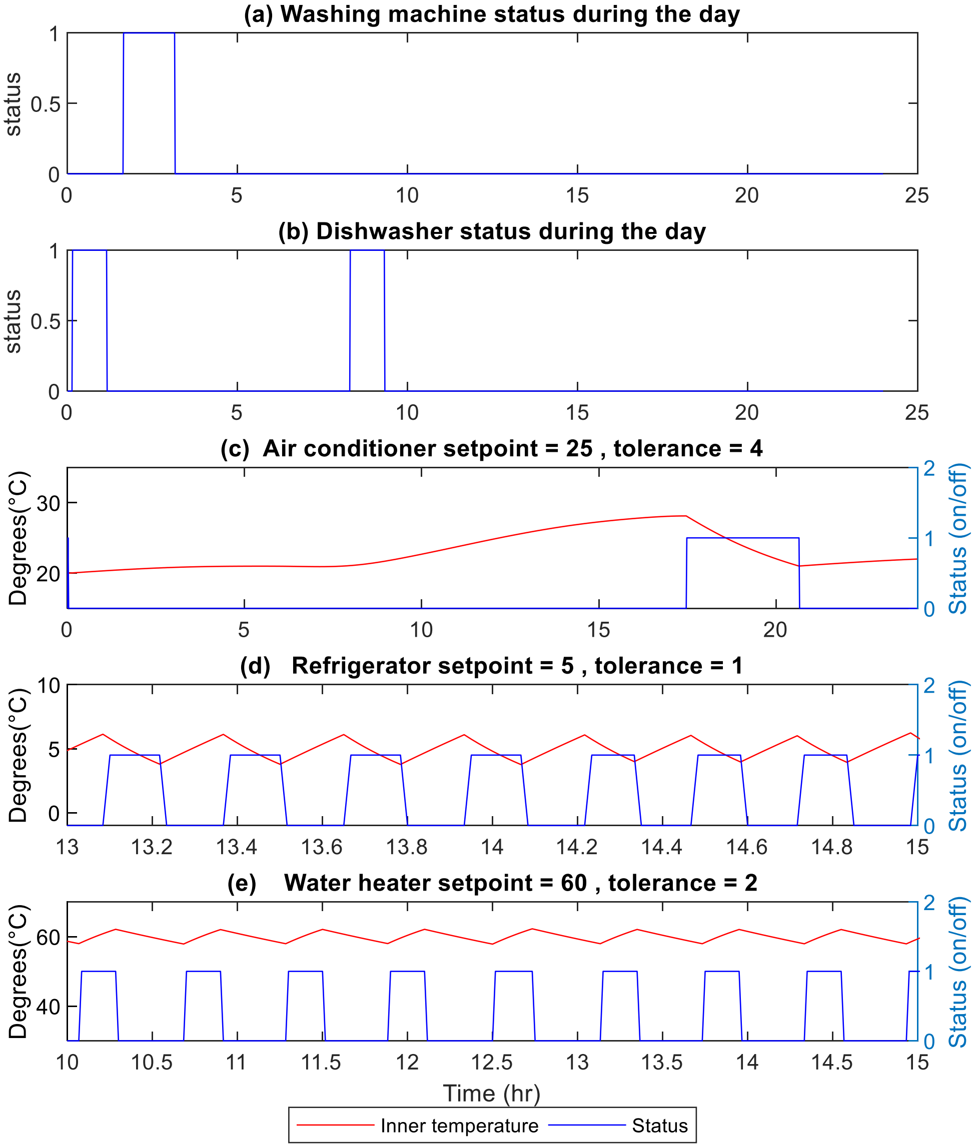

Figure 15: Full house controller output

4.2 Optimization and Scheduling

4.2.1 Baseline Scenarios

Using the above mentioned 3 price and occupancy schemes, and using information of the typical operation patterns of operation for some thermal loads [59], the manual baseline patterns were created for comparison with the optimization results as shown in Figures 16-18; where each figure shows the corresponding cost of consumption using the a certain price scheme and the three occupancy schemes. The cost of each scenario is shown on the top of the subfigure and summarized in Table 3.

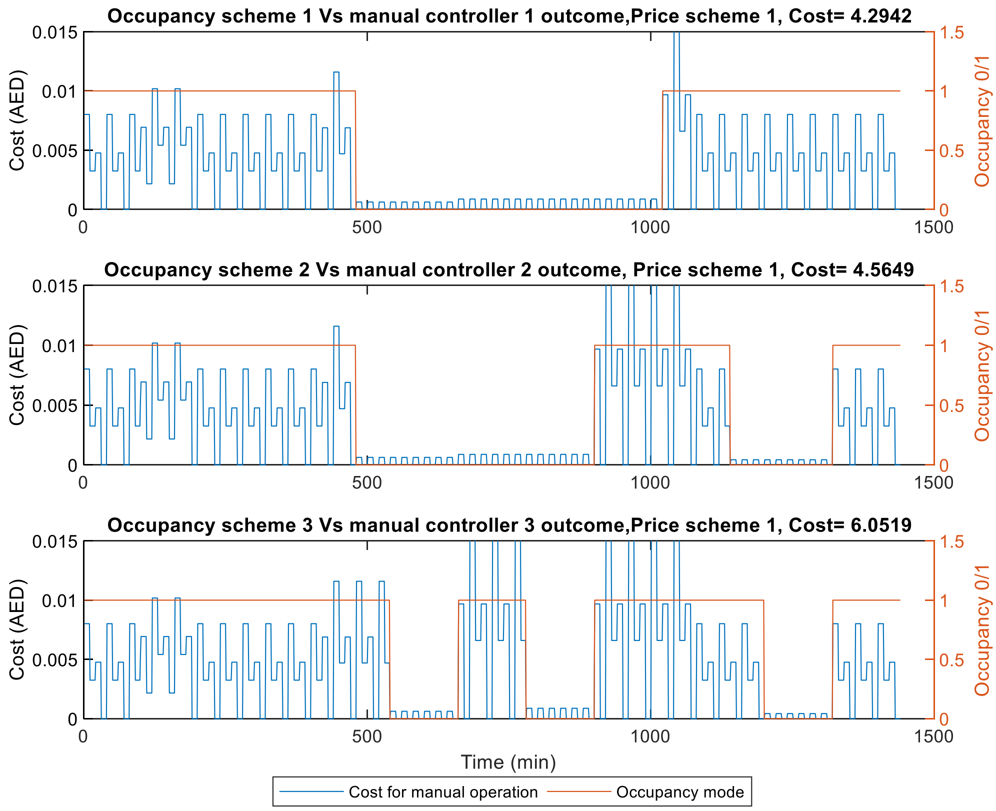

Figure 16: Price scheme 1 baseline daily cost for the 3 occupancy schemes

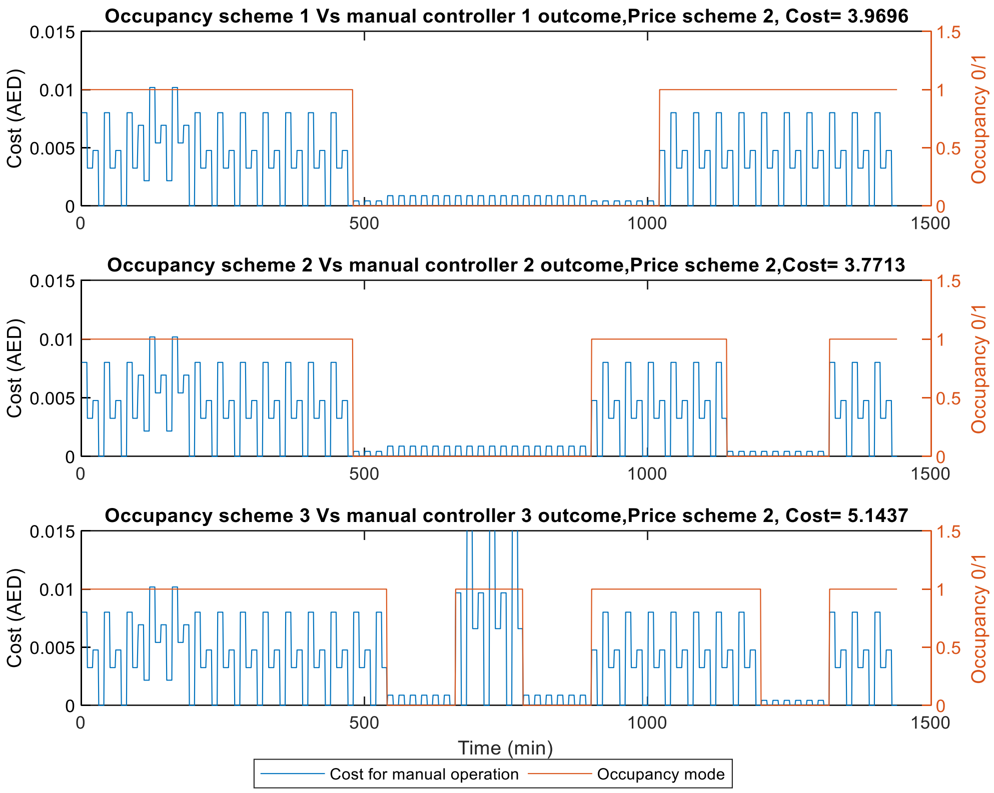

Figure 17: Price scheme 2 daily cost for the 3 occupancy schemes

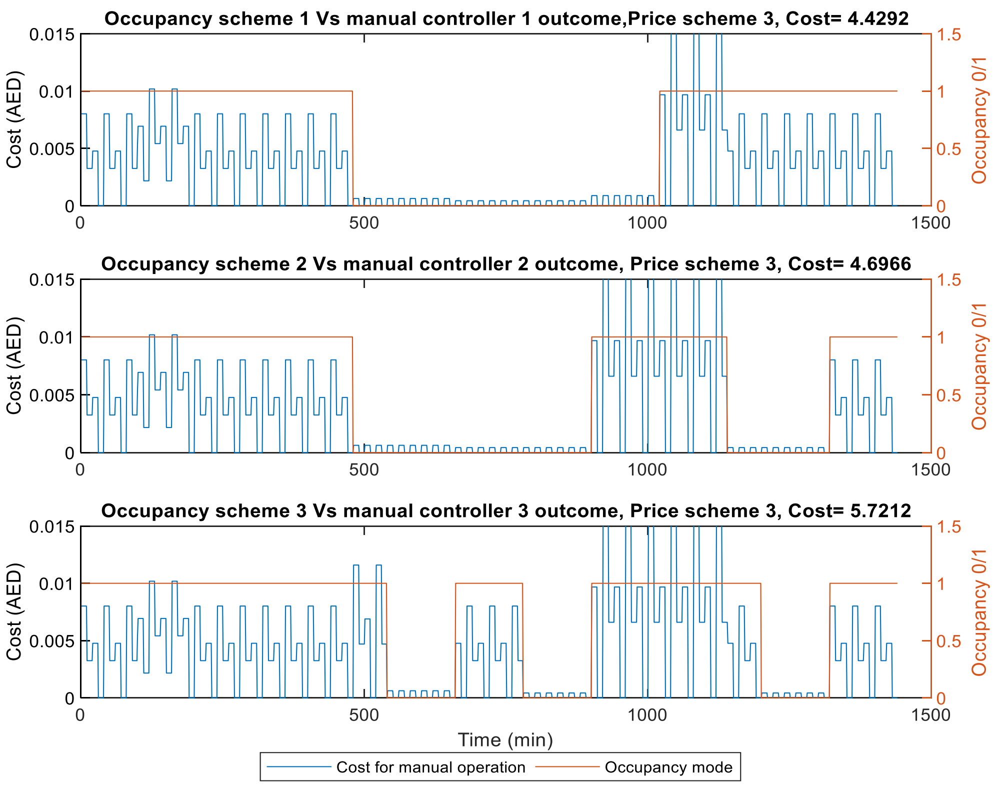

Figure 18: Price scheme 3 daily cost for the 3 occupancy schemes

Table 3: Cost of a single day consumption for 9 scenarios (AED)

	Occupancy scheme 1	**Occupancy scheme 2**	**Occupancy scheme 3**
Price scheme 1	4.29	4.56	6.05
Price scheme 2	3.97	3.77	5.14
Price scheme 3	4.43	4.70	5.72

4.2.2 Scheduling vs Manual Load Control Comparison

As mentioned before, verification of the system requires a variation of test scenarios, hence the 9 cases of manual baselines were created using 3 different occupancy modes and 3 different price schemes. The optimizers were run using these different price and occupancy schemes and the outputs were compared to their corresponding manual output.

4.2.2.1 PSO

The first algorithm to be tested was the PSO, the cost of consumption was calculated using the 9 scenarios and it was compared to the manual cases. Figures 19-21 show the results of the comparison.

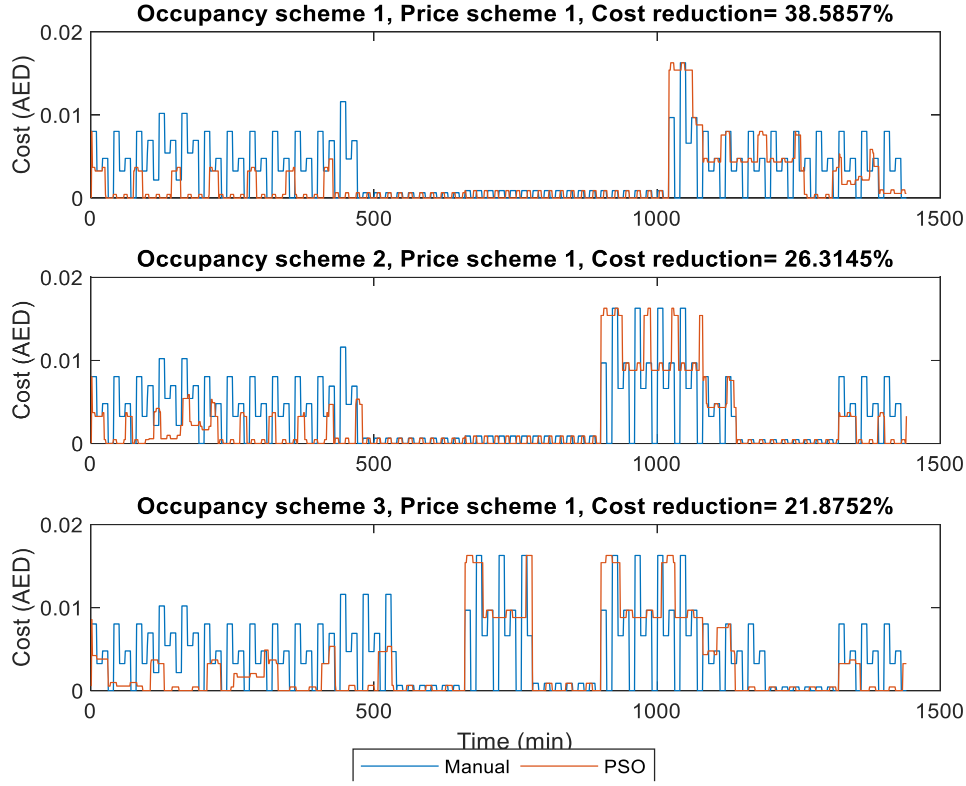

Figure 19: Manual controller cost vs PSO cost for price scheme 1

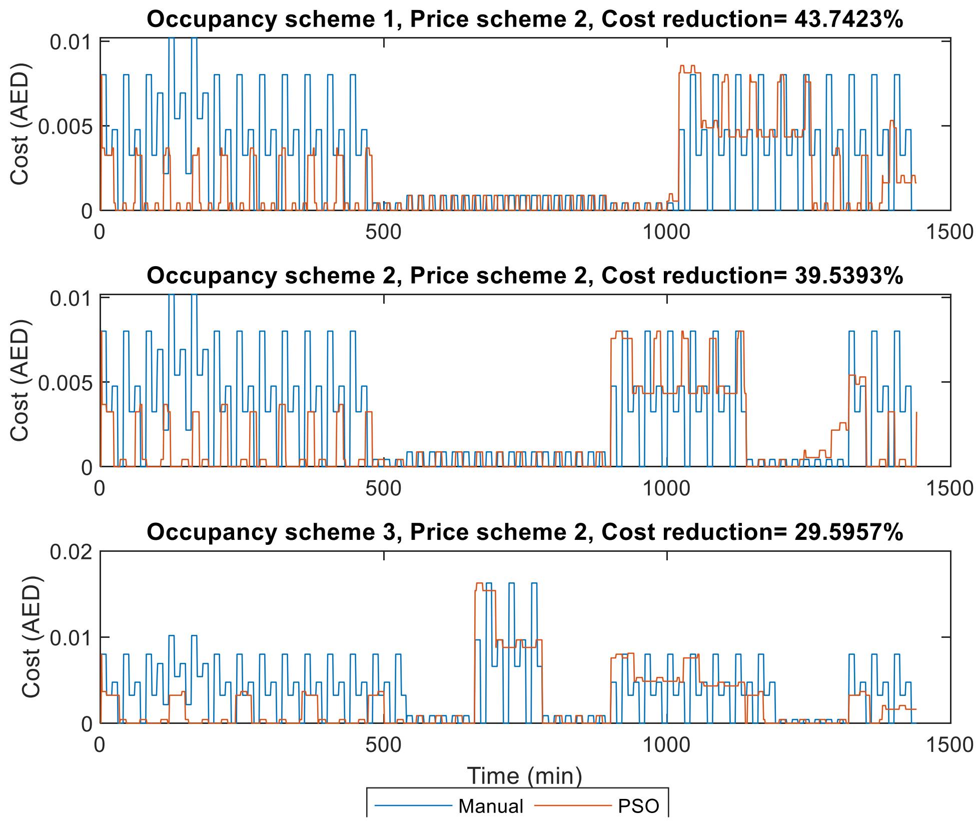

Figure 20: Manual controller cost vs PSO cost for price scheme 2

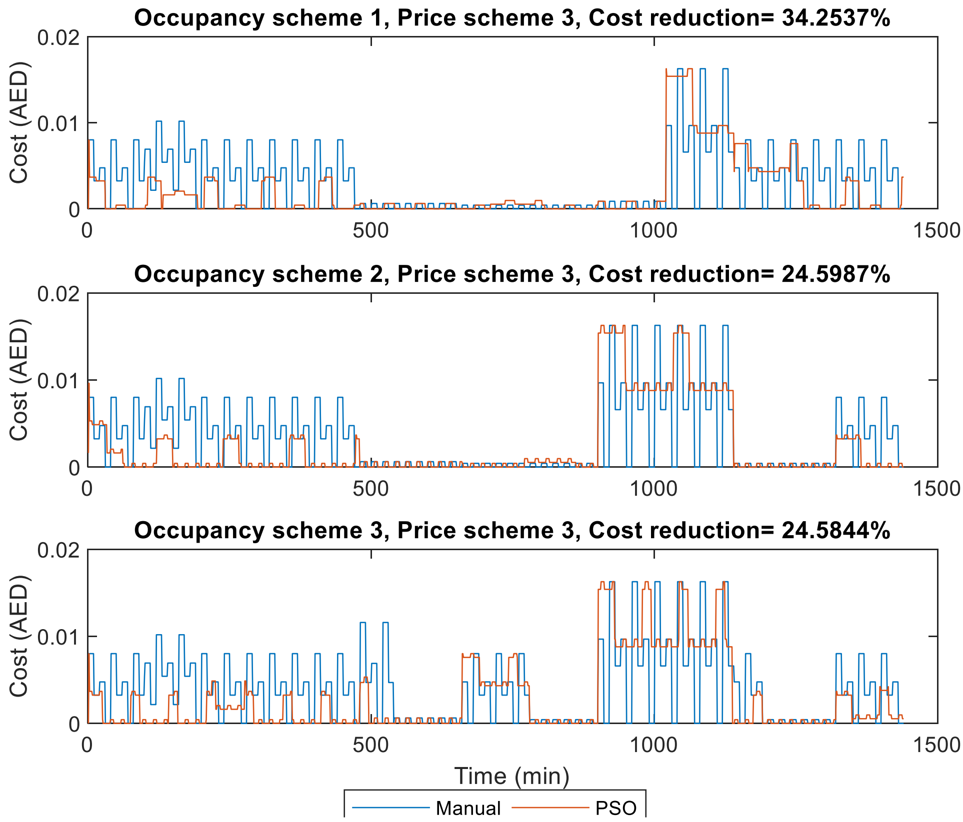

Figure 21: Manual controller cost vs PSO cost for price scheme 3

In every price scheme, it was noticed that the first occupancy scheme gave the most cost reduction, while the third occupancy scheme gave the least reduction. This is because having multiple no occupancy slots puts more restrictions on the system to find the optimum profile considering the multiple in-occupancy slots. Comparing the three price schemes, price scheme 2 gave the most reduction on the three occupancy levels. For a single price scheme, we cannot compare the reduction for multiple occupancy levels because they are completely different scenario where the optimizer's output is compared to the corresponding output of the manual controller.

4.2.2.2 WOA

The same was applied using the WOA, the cost was calculated under the 9 different scenarios and the cost reduction was calculated. Figures 21-23 show the results of the comparison.

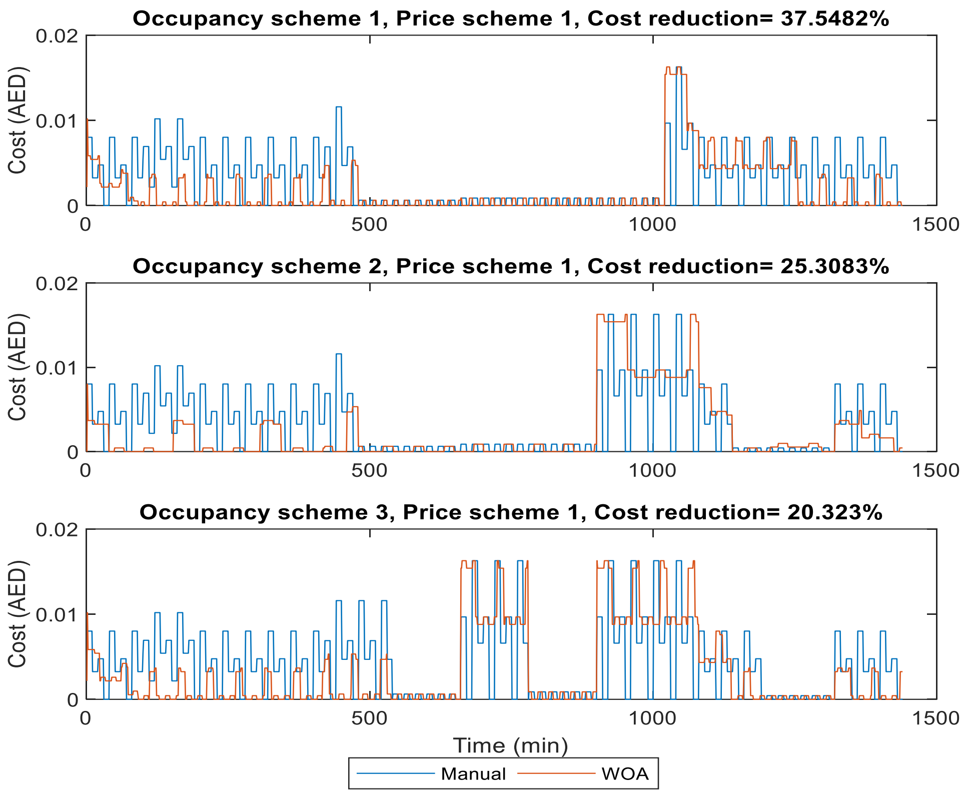

Figure 22: Manual controller cost vs WOA cost for price scheme 1

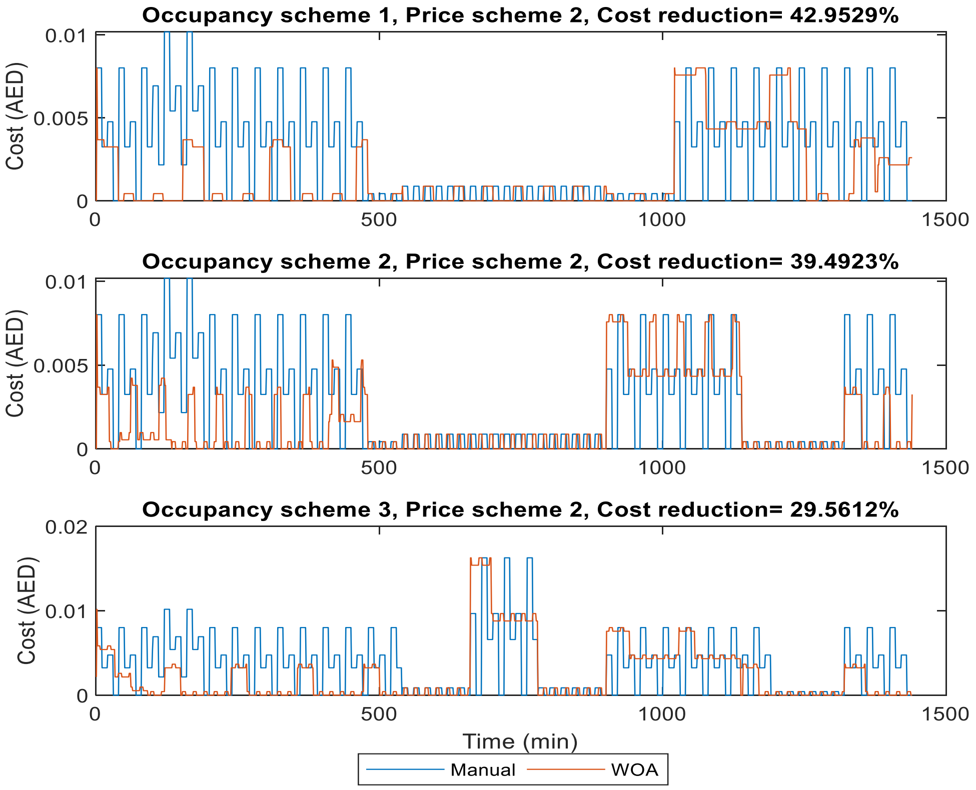

Figure 23: Manual controller cost vs WOA cost for price scheme 2

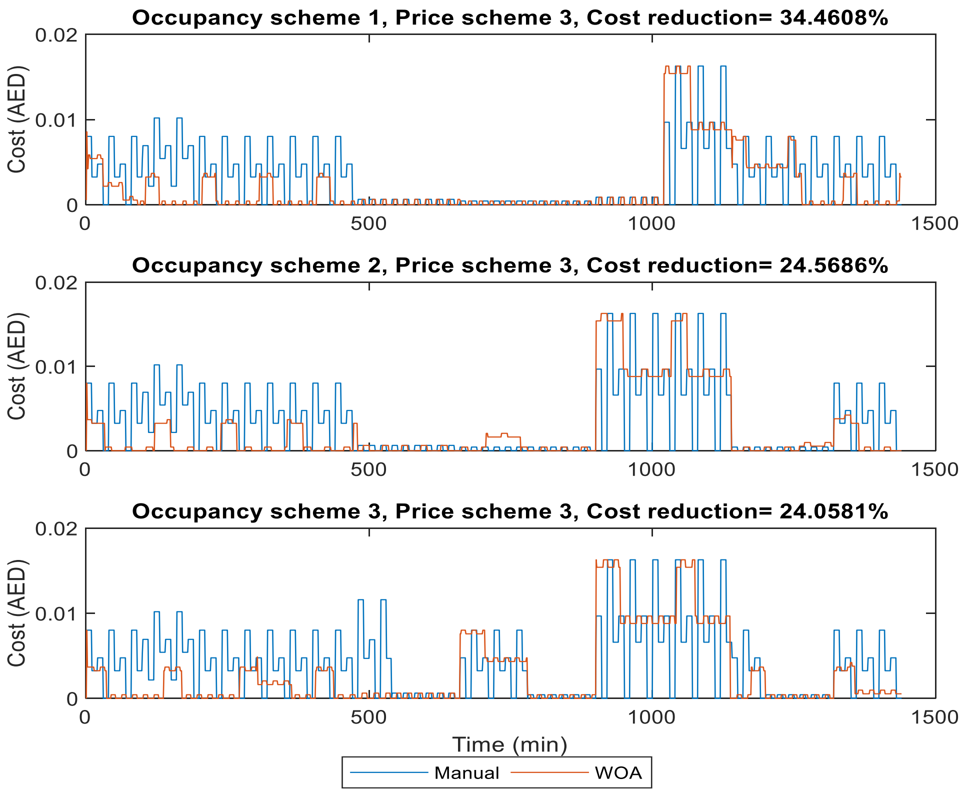

Figure 24: Manual controller cost vs WOA cost for price scheme 3

Just like the PSO, occupancy scheme 1 gave the most reduction and on the price schemes levels, price scheme 2 gave the most reduction across the 3 occupancy levels. Occupancy level 3 gave minimum reduction just like in using PSO.

4.2.2.3 GWO

The final algorithm to be tested is the GWO, again the same testing procedure was applied, and the results are shown in Figures 25-27.

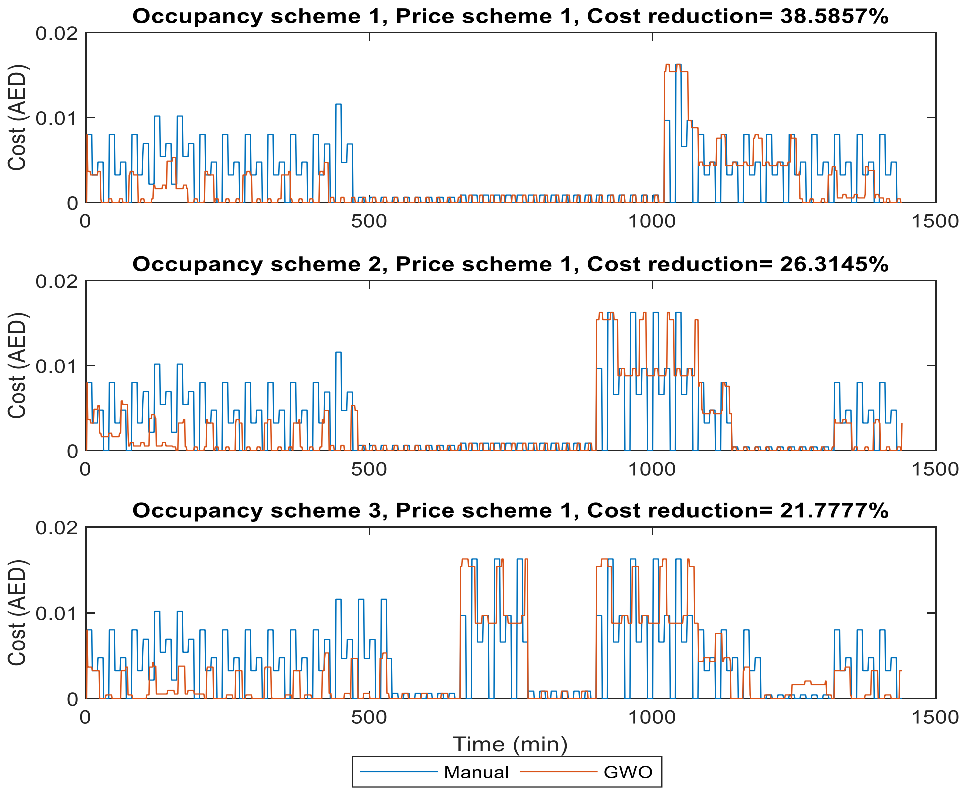

Figure 25: Manual controller cost vs GWO cost for price scheme 1

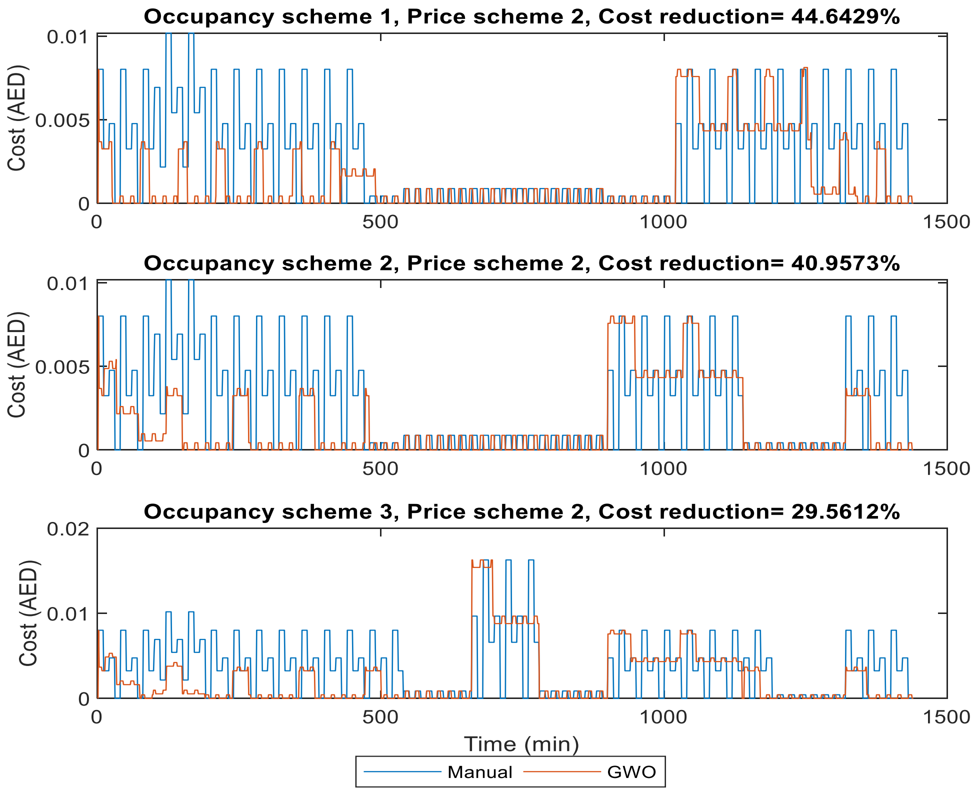

Figure 26: Manual controller cost vs GWO cost for price scheme 2

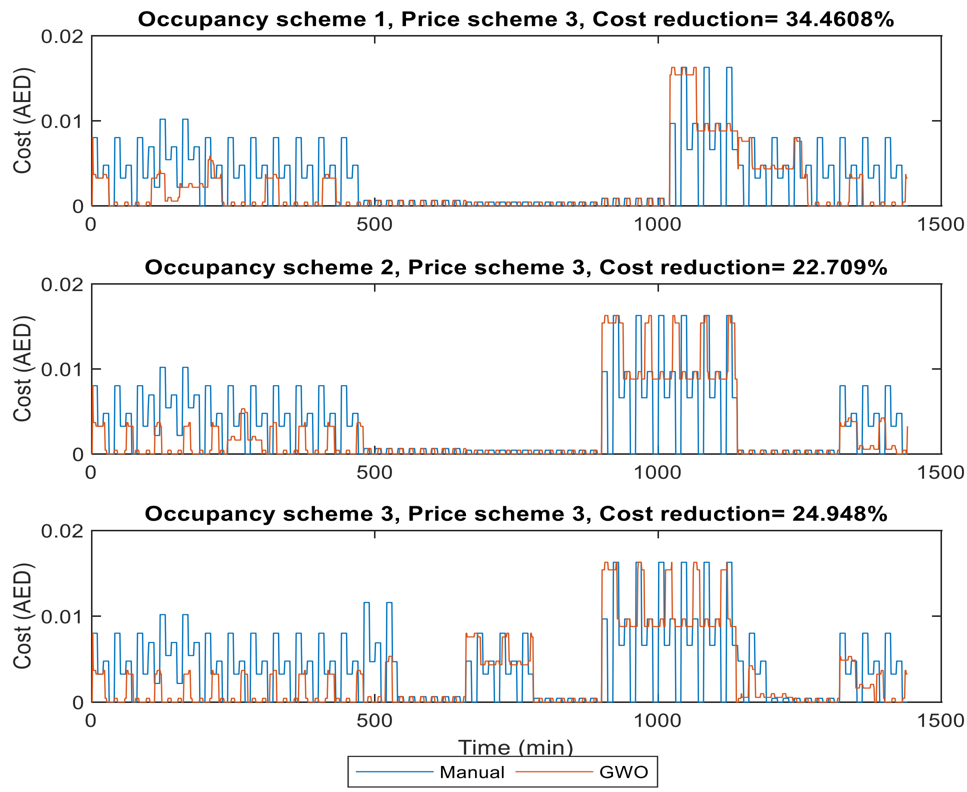

Figure 27: Manual controller cost vs GWO cost for price scheme 3

confirming the results of the PSO and the WOA, the GWO gave similar results where the reduction is the most in occupancy scheme 1 and the overall reduction between the three price schemes was in price scheme 2.

Due to the large variety of the test scenarios, the load profile of a sample of each algorithm is plotted in Figures 28-30. The profiles were for occupancy scheme 1 and price scheme 1, and as noticed in the figures, the water heater and the AC were off during the time slots where the user is out, the shiftable loads were shifted to the off peak periods (beginning and end of day). Table 4 shows the corresponding input parameters and the cost for the selected scenarios.

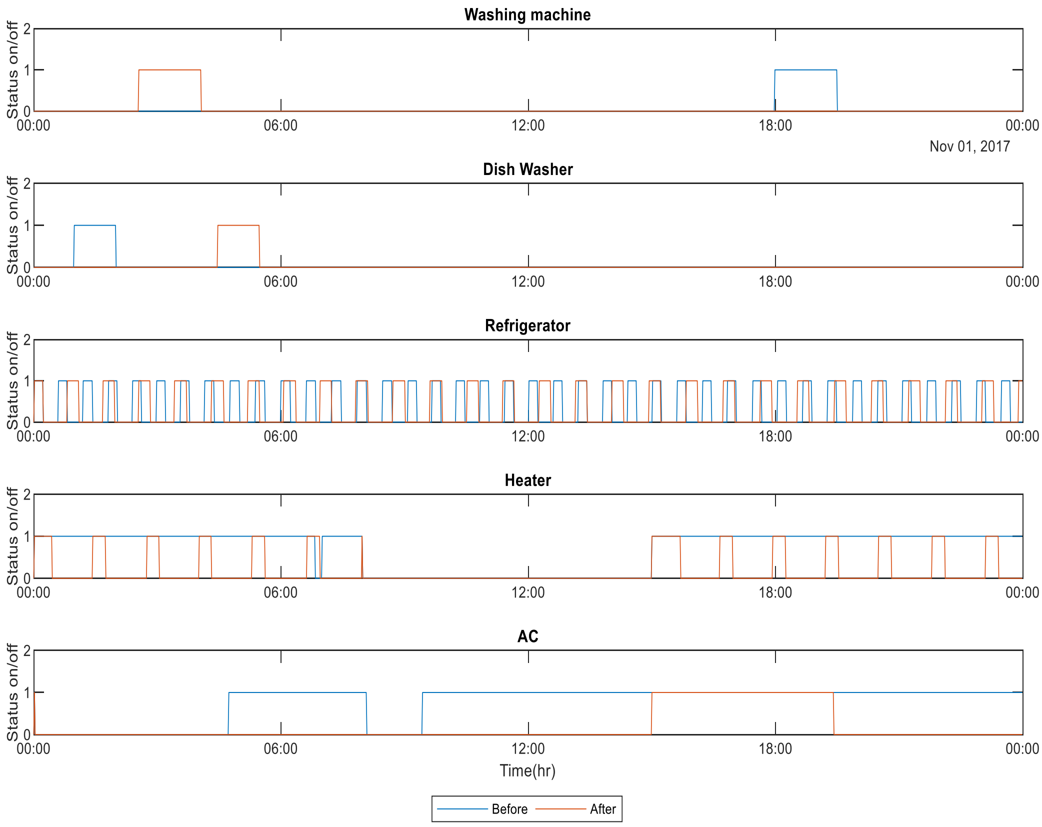

Figure 28: PSO full house profile before and after scheduling

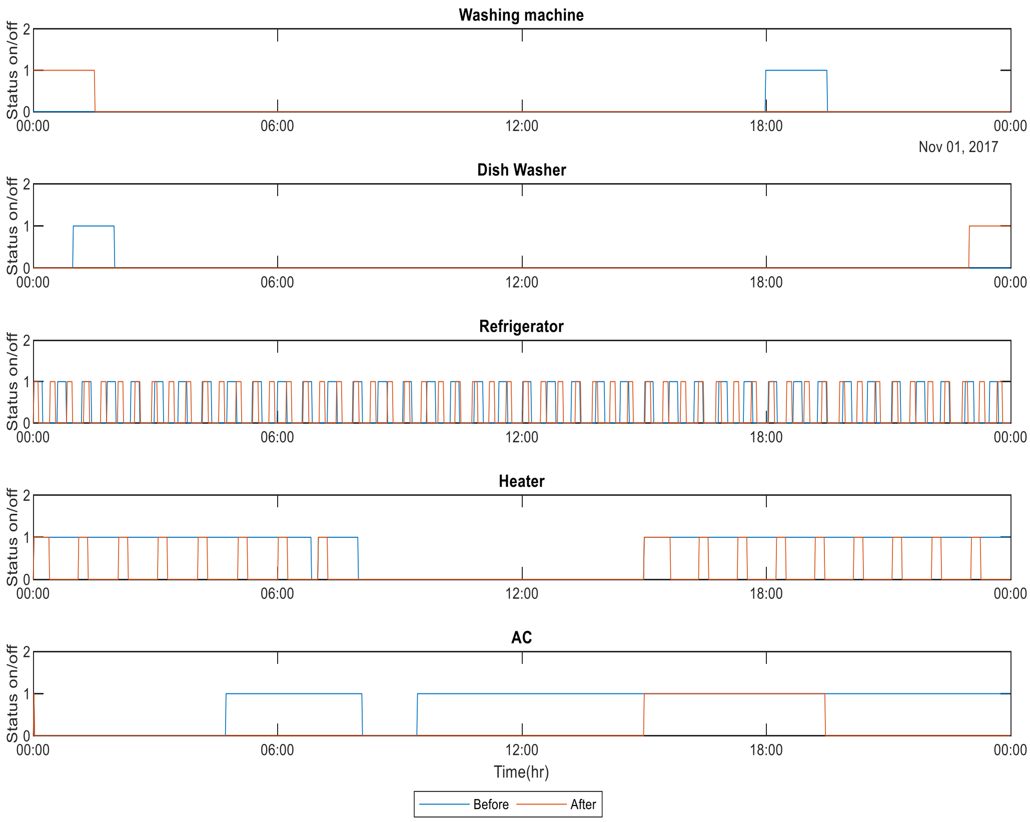

Figure 29: WOA full house profile before and after scheduling

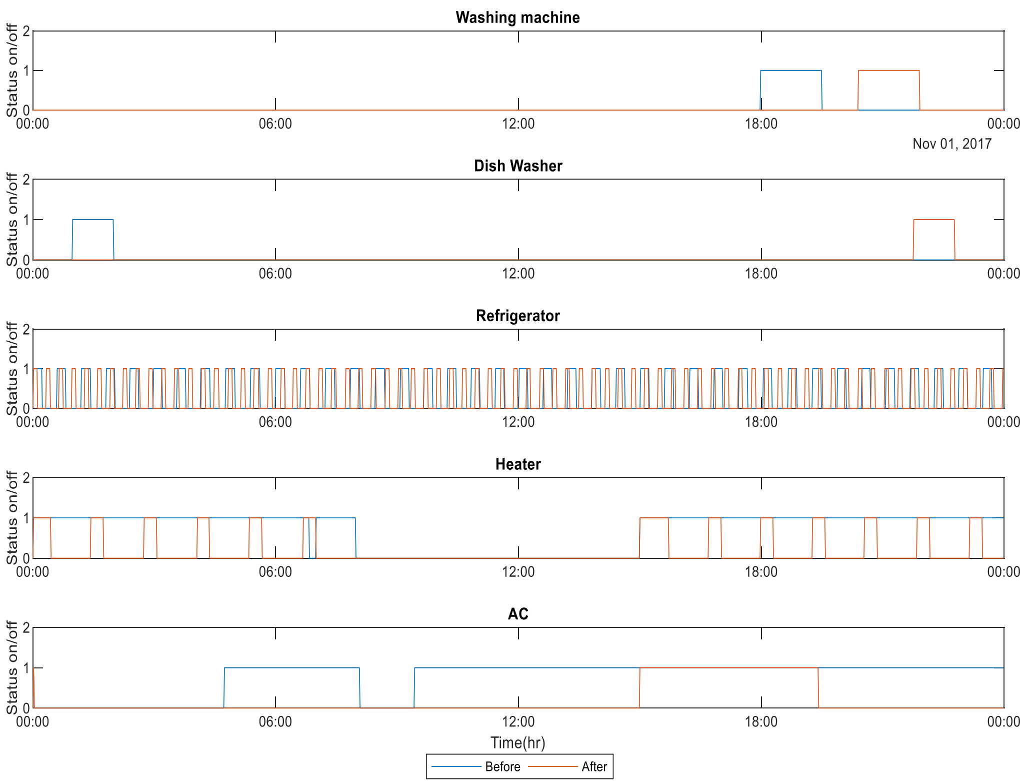

Figure 30: GWO Full load profile before and after scheduling

Table 4: Optimum input parameters for selected scenarios using PSO, WOA, and GWO

Algorithm	**Xbest (appliances setpoints)** **[WM, DW, Ref_set, Ref_tol, Heater_set, Heater_tol, AC_set, AC_tol]**	**Ybest (cost)**	**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%

Comparing the best input parameters, they were similar in almost all the algorithms for the thermal loads (x(3) - x(8)). The first two elements from the input vector represent the starting point of the shiftable loads' cycle, they are usually discrete, representing the time sample when the shiftable load cycle will start. Their values were either very small (beginning of the day) or very high (end of the day), which are both low peak price periods. Table 5 summarizes all the results from the three algorithms.

Table 5: Cost reduction percentages for all the scenarios

Algorithm		**Occupancy scheme 1**	**Occupancy scheme 2**	**Occupancy scheme 3**
PSO Cost reduction %	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 Cost reduction %	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 Cost reduction %	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

As noticed from the table, the reduction was consistent in all three algorithms, where price scheme 2 gave the largest reduction. Comparing the same scenarios across the three algorithms, it is noticed that the GWO gave the largest reduction in almost all scenarios with a slight difference with the PSO. The WOA on the other hand gave the lowest reduction compared to the other two algorithms. Across all the scenarios and algorithms, the largest reduction was using price scheme 2 and occupancy scheme 1 where it reached 44.64%, whereas the lowest was at the 3^{rd} occupancy scheme and the first rice scheme using the WOA.

Overall, although there was a slight difference in the result, they are still consistent and close to each other's using different algorithms, proving the reliability of the system and the house controller model. To further test the consistency of the system, convergence test was done as will be shown in the next section.

4.2.3 Consistency

To check for scheduling consistency when a single algorithm is applied, all the 3 algorithms were run multiple time and the minimum is recorded at every time. It is important for the system to be stable, giving the same expected minimum for the same input parameters. Figures 31-33 show the convergence curves for every algorithm repeated multiple times with the same initial values.

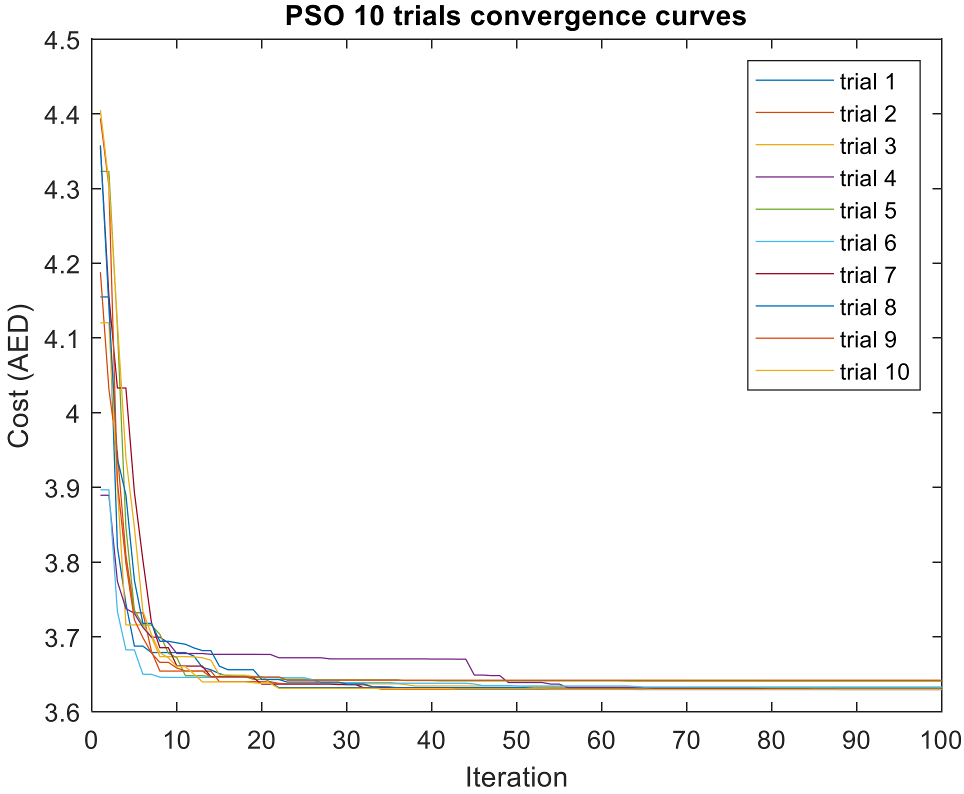

Figure 32: PSO consistency test

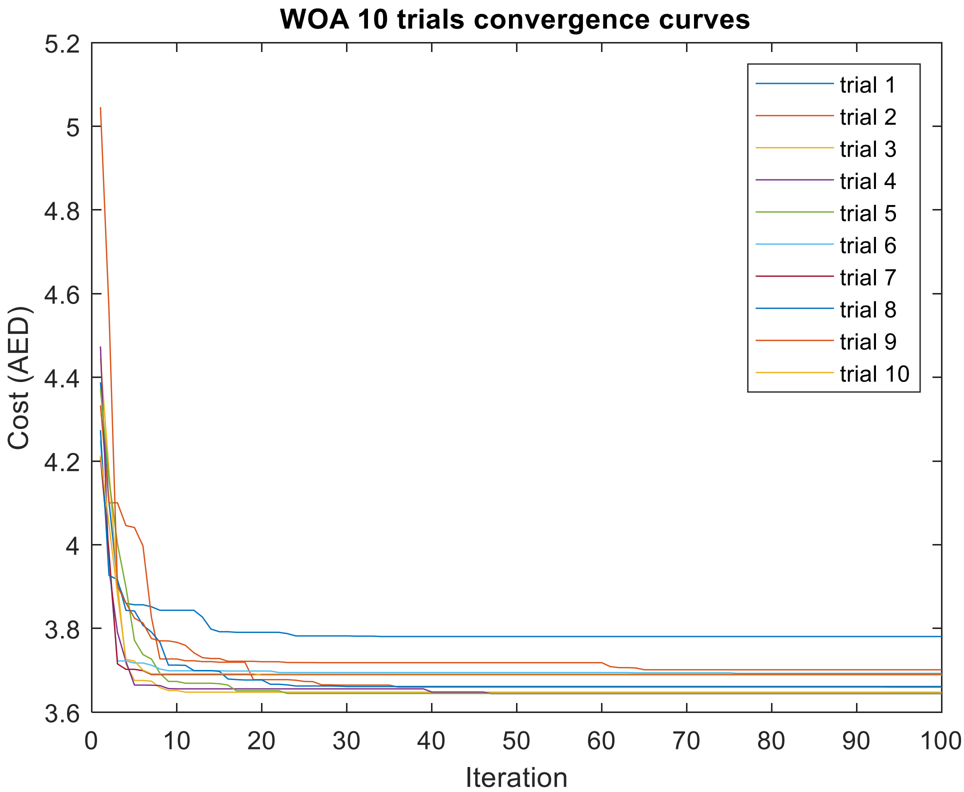

Figure 31: WOA consistency test

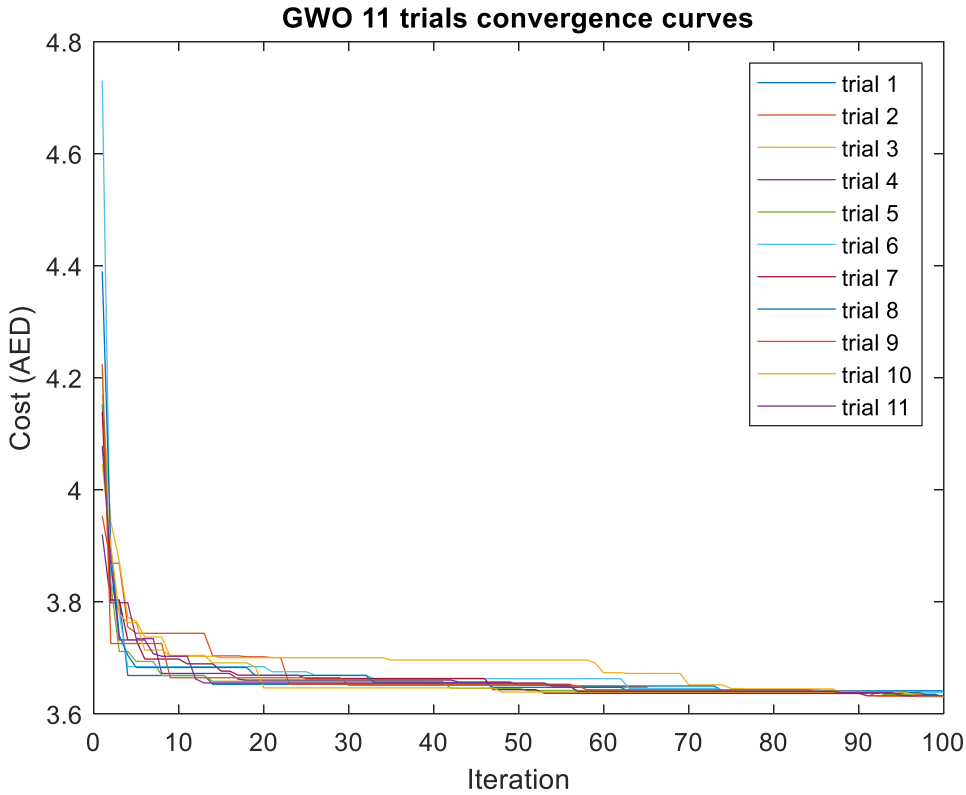

Figure 33: GWO consistency test

As noticed in the figures, the PSO and GWO were very consistent, whereas the WOA was inconsistent. Even though WOA was tested on many multimodal systems and proved to be very powerful, it wasn't as powerful with this system. Selecting the constants for an algorithm can affect the results in a great manner, the WOA has many constants which are randomly generated or randomly changing with time. Tuning them could improve the results. Overall, the GWO agreed with the PSO which is a well-known reliable algorithm, they both gave almost identical results in both best fitness and best input parameters.

Chapter 5: Conclusion

5.1 Overview and Findings

This research was aimed at implementing a full HEMS for load scheduling in DR applications. The main objectives were, firstly, to create accurate empirical models for home appliances, mainly thermal loads to produce accurate minutely load profiles of appliances considering many input parameters. Secondly, to create a full house controller that contains both shiftable and thermal loads where the user can easily see the load profile of the house and the expected cost for the day according to the input's settings. Finally, to create a simple interactive HEMS which can schedule the loads away from the peak hours by controlling their settings in response to a certain ToU DR signal, thus reducing power consumption. The scheduling is to be done using multiple metaheuristic algorithms.

All the objectives were fulfilled, the house appliances models were accurately created, and their response agreed with basic logic when operating thermal loads. The house controller managed to create a full house load profile and produce the total cost for that house at a single day.

The scheduling was implemented using different metaheuristic algorithms and their performance was compared. Even with all the algorithms agreeing on the minimum cost and input parameters, the PSO and GWO gave the most consistent results, scoring the minimum value at every iteration.

More tuning of the algorithm's constants could help improving the performance, especially for the WOA.

5.2 Potential Contributions and Limitations of the Study

The main contributions of this research are in the full house controller where each appliance is modelled to take into consideration many significant factors such as setpoints, outer temperatures, physical structure of the medium, user's comfort, and the room occupancy. All these factors will play a significant role in the accuracy of the load profile produced by the house model, hence providing better cost reduction once the scheduler is applied.

Moreover, the full house controller which was developed can give the user a clear understanding of how his/her settings for each appliance can affect the load profile of the house and the total power consumption.

The scheduler developed in this research is very accurate in determining the optimum input parameters to give the lowest power consumption for the day. Many similar systems optimize consumption by controlling the status of the appliances turning them on and off as needed to reduce the consumption, while the proposed HEMS controls the settings of every appliance to achieve the minimum cost. Also, most schedulers use hourly based information to calculate load profiles and cost, while this system optimizes the load for every minute achieving a high accuracy and more control over shiftable loads.

5.3 Limitations and Future Work

The proposed system can be improved in two aspects, firstly, the range of appliances to be included can be expanded to include more appliances such as renewable energy sources. This will help the user further reduce the cost and possibly get an incentive when the renewable sources contribute to the grid. Another limitation for the proposed system was the long run time for the simulation. Because of the nature of the input parameters and the minutely sampling time, the scheduler could be slightly slow when generating the final schedule, with this trade off of course comes the accuracy, as a minutely schedule can achieve more accurate and immediate responses than hourly ones.

As for future work, an important improvement to this system would be smaller time windows, this will speed up the processing time and give a more dynamic output. Also, having more options for DR signals will make the system more flexible, where the user can participate in any desired plan depending on their house appliances and their daily routines. Finally, expanding the models to include more types of appliances, especially power generation appliances will reduce cost even further where the users can help feeding the grid and getting incentives for it.

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List of Publications

I. Haroun, H.Shareef, "Home Appliance Modelling and Control for Demand Response Applications," presented at the International Conference on Electrical and Computing Technologies and Applications, AURAK, 2019.