Neural Network Based Home Energy Management for Modelling and Controlling Home Appliances under Demand Response

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Abstract. Nowadays, the consumption of homes is around 40% of the total world consumption. Furthermore, 21% of the total greenhouse gas emissions are produced by homes. The emergence of smart grids has presented new opportunities for home energy management (HEM) systems for the purpose of reducing energy in the residential sector. Demand response (DR) tool that curtails and shifts demand to enhance the consumption of energy at home. It usually creates optimal schedules for energy consumption by considering load profiles, the cost of energy, level of comfort people, and environmental concerns. The deployment of smart meters, it is possible to control the load by using HEM system with demand response (DR) enabled appliances. Without a proper system, it is difficult to efficiently control the energy in houses. In this work, a Neural Network technique as a controller to control the energy in the building with DR strategy is developed to control and reduce peak demand load. Reduce the electricity cost and power consumption for the appliances while maintaining customer comfort is the motivation of this work. The electrical appliance such as air conditioning (AC), electric water heater (WH), washing machine (WM), and refrigerator (RF) were modeled using the Matlab program. The designed model can make an accurate decision in scheduling and shifting the operation of the electrical appliance at the peak time by scheduling the s domestic household at a specific time with no affecting the customer's preference.

Keywords: HEMS, Demand Response (DR), Power consumption, ANN, Smart meters.

1. Introduction

The power consumption of the residential sector is around 30–40% of the total world consumption [1]. In the domestic areas, the home energy management system (HEMS) has been getting a lot of attention because of the global warming and power storage. Consequently, the home energy management system (HEMS) controller essential to reduce the power demand at peak time [2]. HEMS can help to minimize the energy consumption by utilize the perfect system to schedule the household energy and achieving different goals by curtailing and shifting the energy consumption to reach the optimal residential load scheduling [3]. Therefore, Energy management system is required to cover customer’s preferences and get the benefits of decrease loads consumptions and to get an efficient to all electrical aspects [4]. HEMS inventions can achieve a general fulfilment between consumers by assisting energy sparing techniques and comprehension in their comfort level and the utility [5]. HEMS provide a common understanding between residents by comprehension their comfort...
tendencies and utility through the aid of energy saving methods [6]. The controlling of the domestic home appliances such as air conditioning (AC), electric water heater (WH), washing machine (WM) and refrigerator (RF) needs different efforts to create numerous HEMS controllers. HEMS can be implemented in residential homes to manage energy supplies. This can be accomplished by controlling energy consumption, interacting with building and utility loads, and acquiring data. Hence using HEMS reduces power consumption by scheduling the building appliances [7]. In peak hours, demand response (DR) plays a major and important role in reducing power consumption. Furthermore, it also helps in improving the efficiency and reliability of the operation [8]. At peak times the need to use electrical energy increases, therefore, the DR program is a process to motivate homeowners to reduce energy consumption, especially at peak times. DR is the control by the source to convert normal use into a type of use urging the user to use energy less to reduce payments or to reduce energy demand during the wholesale market prices rising [9]. Therefore, the use of DR technology allows users participating in this program to reduce energy usages by converting peak times into off-peak times. Reducing energy consumption can be implemented by HEMS, which schedules household appliances to obtain many favorable functions in homes [10].

The installation of smart meters in a smart grid helps us to manage load using innovative HEM with DR-enabled appliances. The smart energy meter establishes dual communication between the utility companies and the users which enables DR signals to encourage users to adopt appropriate decisions that reduce electrical energy consumption [11]. In the literature, numerous studies have been discussed the HEMS and their properties. For instance, the HEMS has been proposed in [12] to design the rule-based algorithm. In this study, reducing the energy consumption has been achieved based on shift and schedule the appliances of the home considering residential DR technology. However, traditional HEMS has been used without mentioning the using of smart methods. In [13], four domestic home appliances have been proposed which are water heater, clothes dryer, air-conditioner and electric vehicle. Comfort levels and priority have been used as factors to control these appliances which lead to reduce the power consumption. However, the outputs of this study focusing on the reduction in the cost without taking into consideration the occupancies’ comfort. In [14], the authors introduced a steady to control the power sockets and lighting using an efficient HEMS. The proposed HEMS has been used the infrared remote control (IRD). However, the IRD suffers from a coverage problem as it is unable to cover the distance between the center controller and the ports.

Recently, artificial intelligence (AI) has been utilized in different applications including controlling with high effective efficiency. Different techniques, as random forest [15], fuzzy logic [16], and adaptive neuro-fuzzy inference (ANFI) controllers [17], have been mentioned in the literature. Therefore, artificial neural network (ANN) based home energy controlling has been used in this work. Four household appliances were modelled and analyzed based on mathematical and measurement empirical models using the Matlab program namely, water heater (WH), washing machine (WM), air conditioner (AC), and refrigerator (RF). The key contribution of this study is focusing on the modelling of home appliances and introducing a proposed HEMS controller to achieve power saving based on artificial neural network (ANN) controller and DR events and scheduled operation of appliances at specific time according to priority of appliances and customer lifestyle.

2. Load model enabled demand response

To design an algorithm for residential customers with DR strategy, it's important to understand the characteristics of the loads and their preferences. In this work, only controllable loads that consume high power such as: AC, WH, WM, and REF are considered to be controlled according customer preferences and priority of appliances. These home appliances are selected for executing DR at residential building because they have consumed high energy compared to other appliances and are most utilized on a daily basis. The architecture of HEMS with AC, WH, WM, and REF as in figure 1.
2.1. Air Condition

To determine the appropriate AC load model, the mathematical expression should be obtained at first. The mathematical expression has been used to find all parameters that can be utilized with a physical-based AC model. The aforementioned parameters of AC have been grouped to three parts which are the temperatures set points, the building structures, and the characteristics of AC model. The input parameters are outside temperature $T_{out,t}$, the occupant heat gain $H_p$, set point temperature $T_s$, room temperature at time $t$, $T_{r,t}$, and the signal of demand response. The output room temperature has been utilized as an input to the proposed model at the following step of time and power consumption. The load characteristics of AC is shown in Table 1.

| Parameter                      | Value                                      |
|--------------------------------|--------------------------------------------|
| Model                          | AC-LG                                      |
| Rated power (Watt)              | 1200 W                                     |
| The capacity of the cooling     | 10000 Btu                                  |
| The volume of the Air flow      | 420 m3/h                                   |
| The number of the people        | 5                                          |
| House area                      | 110 (m$^2$)                                |
| $A_{fl}$, $A_{wall}$, $A_{ce}$, and $A_{win}$ | 110, 150, 110, 7 (m$^2$)                  |
| Window area facing south $A_{win_s}$ | 6.4 (m$^2$)                               |
| $R_{fl}$, $R_{wall}$, $R_{ce}$ and $R_{win}$ | 10, 12, 32.49 (°C. m2. h/Btu)             |
| Occupant heat gain $m_p$        | 392.38 (Btu /h)                            |
| Solar heat gain coefficient $S_{HGC}$ | 0.67                                      |

The temperature of the room should be computed in the initial condition at time $t$ based on cooling load factor and it is given by the equation (1),

$$T_{r,t+1} = T_{r,t} + dt \left( m_{hvact} \frac{j_{hvac}}{dc} + \frac{y_t}{dc} \right)$$  

(1)

where $T_{r,t}$ is the temperature of the room at time $t$, $dt$ is the time slot length, $m_{hvact}$ is AC status in the time slot, $j_{hvac}$ is the capacity of the cooling load, $y_t$ is the heat gain rate, and $dc$ is the required energy that modify the temperature of the air in the room by 1 °C.
At the following time step, the output temperature of the room has been used as input temperature in the proposed AC model. The house heat gain rate, $Q_t$, can be defined as [13]:

$$y_t = S_{HGC} + (m_p \times N_p) + \left(\frac{A_{fl}}{R_{fl}} + \frac{A_{wal}}{R_{wal}} + \frac{A_{ce}}{R_{ce}} + \frac{A_{win}}{R_{win}}\right) \times \left(T_{out,t} - T_{r,t}\right) + \ A_{win} \times H_{SOLAR}$$  \hspace{1cm} (2)

where $m_p$ is the occupant heat gain (Btu/h); $N_p$ is the number of the people, $z$ is the change in room air at any time slot, $x$ is the air heat factor (Btu/°C m$^3$); $R_{fl}, R_{wal}, R_{ce}$ and $R_{win}$ are the average thermal resistance of the floor, wall, ceiling, and window in (°C·m$^2$/Btu), $A_{fl}, A_{wal}, A_{ce}$ and $A_{win}$ are the areas of floor, wall, ceiling, and window of the dwelling in (m$^2$), respectively; $S_{HGC}$ is the solar heat gain coefficient of a window respectively; $T_{out,t}$ is the outside temperature (°C); $H_{SOLAR}$ is the solar radiation heat power (W/m$^2$) and $A_{win}$ is the window area facing south (m$^2$).

The amount of power consumed in Watt with an OFF and ON thermostat mode and running at its rated power when switched on at a given interval, $P_{acr,t}$ as in equation (3):

$$P_{acr,t} = m_{ac} \times P_{acr}$$  \hspace{1cm} (3)

where $m_{ac}$ is the device status; the value of the $m_{ac}$ is equal to 1 or 0 which means the appliance is turned on or off, respectively. $P_{acr}$ is the AC rated power in Watt.

If the device turned on means that $m_{hvac} = 1$ and If is turned off means that $m_{hvac} = 0$. The set point temperature of AC and the difference between the upper or lower limit are called dead band of the temperatures, $\Delta T$. The AC is turned ON, If the temperature inside room reaches its maximum set point plus the dead band temperature. The AC unit is turned OFF, If the room temperature decreases below a set point minus the dead band temperature, while, the AC keeps the same status if the room temperature is within its tolerable band. These AC statuses are expressed mathematically as,

$$m_{hvac,t} = \begin{cases} 0, & T_{hvac,t} < (T_{s,t} - \Delta T) \\ 1, & T_{hvac,t} > (T_{s,t} + \Delta T) \\ m_{hvac,t-1}, & T_{s,t} - \Delta T \leq T_{hvac,t} \leq T_{s,t} + \Delta T \end{cases} \times Dn_{hvac,t}$$  \hspace{1cm} (4)

The power consumption of the AC model can be calculated according to DR signal $\Delta T$ at (±2 °C). $Dn_{hvac}$ this signal, which creates from the revised thermostat set point, and $T_{s,t}$ is the temperature set point.

2.2. Water Heater

Two categories and parameters of WH, namely, the characteristics of device and the set point temperature. From Table 2 the load characteristics of electric water heater at 4 kW rated power with rated voltage 220–230 V.

**Table 2:** characteristics Load of WH

| Parameter          | Value                  |
|--------------------|------------------------|
| Power rated $P_{ewh}$ (kWatt) | 4 kW                  |
| Tank size          | 25 litter              |
| Volume of the tank, $Vol_{tank}$   | 0.0502 m$^3$          |
| Ambient temperature, $T_{amp}$     | As room temperature   |
| Heat resistance $R_{tank}$        | 10 (°C·m$^3\cdot$h/ Btu) |
| Base area of Tank, $A_{tank}$     | 2.5 m$^2$             |

The water temperature in the initial state (t) must be determined according to flow rate usage pattern and outlet temperature of water is mathematically expressed as in Eq (5):

Where, the input parameters are $T_{amp}$, ambient temperature , $T_{set}$ set point temperature, $Flr$, it hot water flow rate temperature of inlet water temperature , $T_{inl}$ the temperature of water tank, $T_{out,t}$ and
DR signal, $D_{n_{ewh,t}}$. The output temperature of the WH tank is also used as input in the design of model at the next step of time and power consumption. Many factors can contribute to the design of model such as the tank size, volume, storage tank, the surface area. In addition, other parameter such as tank volume $V_{ol_{tank}}$, surface area $A_{tank}$, $R_{tank}$ is the heat resistance and time duration the time slot $t \ dt$ [13]. In the proposed system, the WH would turn OFF if the water tank temperature exceeded the preset upper limit. The operation of the WH is depending on the condition of the device $m_{ewh}$. The mathematical expression of the $m_{ewh}$ is defined as:

$$m_{ewh} = \begin{cases} 
0, & T_{ewh,t} > T_{set,t} + \Delta T \\
1, & T_{ewh,t} < T_{set,t} - \Delta T \\
&m_{ewh,t-1}, & T_{set,t} - \Delta T \leq T_{ewh,t} \leq T_{set,t} + \Delta T
\end{cases} \ast D_{n_{ewh,t}} \quad (5)$$

where $T_{set,t}$ is the set point temperature, $D_{n_{ewh,t}}$ is the demand response status, and the dead band temperature, $\Delta T$ change between ($\pm 2$ °C). The power of the WH calculated depends on the status of DR $D_{n_{ewh,t}}$. When WH thermostat switched OFF/ON states and runs at its rated power that mean WH consume power in Watt and can determined according to the Eq(6)

$$P_{ewh,t} = m_{ewh} \ast P_{ewh} \quad (6)$$

Where, the device status is $m_{ewh}$, if the device turned ON means; $m_{ewh}=1$, if turned OFF means; $m_{ewh}=0$ and rated power of WH is, $P_{ewh}$.

### 2.3. Washing Machine and Refrigerator Empirical Models

WM is one of home appliance work by induction motor. The WM can be divided to two categories which are vertical axis and horizontal axis. Whereas, the refrigerator is the compressor, which is an induction motor. The WM and REF have been modeled using different approaches. In this work, real data was collected by a power quality analyzer. This data has been used to model WM and REF. The Matlab environment has been used to develop the WM and REF modeling by resistors and reactances. The working stages of the WM including the three stages (washing, rinsing, spinning) depends on the temperature as shown in Table 3.

| Table 3: Load priority and power ratings characteristics. |
|---------------------------------|-----------------|-----------------|
| Home Appliance                  | Load priority   | Customer lifestyle. | Power         |
| Air conditioner (AC)            | 1               | Temperature of room 22–26 °C | 1.25 kW       |
| Water heater (WH)               | 2               | Temperature of water 40–48 °C | 4 kW          |
| Washing machine (WM)            | 3               | Different intervals | 0.3 kW        |
| Refrigerator (REF)              | 4               | 24 hours          | 0.16 kW       |

### 4. Artificial Neural Network for HEMC

The artificial neural network (ANN) mimics the way the brain works. ANN is a distributed processing system consists of neurons which are simple connected elements. The ANN have different benefits such as solves problems with the complex nonlinear that would prove impossible or difficult by human or statistical standards through training and learning system [18]. Using the Levenberg-Marquardt back propagation algorithm, the ANN is trained with the training data to define the mapping between the inputs (and the output. The training of a network using the back-propagation algorithm involves three phases which are the feedforward of the input training pattern, the calculation and backpropagation of the associated error, and the adjustment of the weights.
The ANN structure as shown in Figure 2 has four inputs \((T_{ac}, T_{wh}, Tot, DR_{signal})\), and four output with the sigmoid activation function and two hidden layers as well, the training data for the ANN collected from experiment and actual data.

![Figure 2: Architecture of the ANN.](image)

Where \(Tot\) is the total power, \(T_{ac}\) denotes the room temperature (°C), and \(T_{wh}\) is the WH temperature and DR signal is the signal that come from utility. The outputs of the ANN controller in binary numbers (1,0) are the signals to turn the four home appliances ON or OFF according to customer preferences, comfort level, and priority of appliances. All sudden changes in power consumption of appliances can be forecasted by using ANN. The ANN parameter that include the number of inputs, number of outputs, number of hidden layer, Number of neurons in each hidden layer \((N1,N2)\), and the Learning rate with number of iterations are shown in Table 4.

| ANN Parameters          | Value |
|------------------------|-------|
| Outputs Number         | 4     |
| Inputs Number          | 4     |
| Total of hidden layer  | 2     |
| Number of neurons in hidden layer \(N1\)| 20 |
| Number of neurons in hidden layer \(N2\)| 20 |
| Learning rate          | 0.721 |
| Iterations Number      | 1000  |

5. Results and discussion

In this research, the temperature of room for air condition is assumed to be set between 26.5 °C and 22.5 °C, and these values can be changed by the home owner in the model according comfort level. The air conditioner is turned on if the room temperature is more than the installed value, which is 26.5, while the air conditioner is turned off if the room temperature is less than the installed value, which is 22.5, in order to achieve the desired comfort. If the room temperature between 22.5 and 26.5 °C, in this case the appliance will keep the switch status on or off depend on the previous device state. Figure 3 show the status of AC at various setting.
To illustrate the performance of the electric WH model, there is need to show the hot water usage at various times as in figure 4 (a). Its assumed to choose a setting temperature of WH between 48 - 42 °C and these values can be altered according to the preference of customers as shown in figure 4 (b). To keep the water temperature within its comfortable range the WH is turned ON, when the customer uses the hot water at 7:00 am and the temperature of WH reaches its set point of 42 °C. In addition, if the hot water used between 4:15 pm and 6:15 pm, the water heater will turn on to keep the temperature of water in the tank till reach to set point of 48 °C and the WH is turned off. When the temperature is between 42–48 °C, in this case the appliance will keep the switch status on or off depend on the previous device state.

**Figure 3:** Energy consumption of AC with temperatures set between 26.5°C and 22.5°C.

Power quality analyzer has been used to measure the real data and the data are used to get accurate REF and WM models based on resistors and reactances. The simulation results for WM and RF load models that have been designed based on measurement empirical models using the Matlab program are as shown in figure 5 and figure 6, respectively.
The neural network is used to as a controller for HEMS. four inputs ($T_{ac}$, $T_{wh}$, $Tot$, $DR_{signal}$), and four output with the sigmoid activation function and two hidden layers and four outputs(AC, WH, WM, RF). For the ANN training the regression coefficient (R) is 0.99518 and it is close to unity as in figure 7.

The result of total power consumption by using ANN controller to predict the power consumption and control the home appliances and reduce the power consumption is shown in figure 8.
The case study is considered to prove the performance of the ANN in minimize the energy consumption and save the power at residential area. From figure 8, it's assumed that the utility send the signal to the home to reduce the power consumption with demand limit 4kw at time 5:00 pm to 11:00 pm. At this value of the demand limit, the RF, WM and AC should be shut and only WH on to maintain the power consumption lower than the value of 4kw by considering the priority of home appliances and shifting other home appliances to other time after the period of time.

The results show that the performance of the controller in maintaining the total power consumption for all devices under the value of demand limit. Furthermore, the proposed controller can save the energy per 5 hours to 2.991 % from the total power without any effect on the customer preference.

6. Conclusion
In this study, the HEM system which designed by using ANN as a controller has been presented. ANN type feed-forward neural network type and the Levenberg–Marquardt training algorithm used for training and learning the ANN. Four residential loads were modelled using Matlab program according to the characteristics operation of each device and that include AC, WH, WM, and REF to control the consumption at residential area depending on the utility signal. The designed model shows a high response in controlling the devices. Furthermore, the total power can save the energy by using the ANN as a controller about 2.991 % per 7 h. The designed system of HEM never allows the total power consumption to exceed the selected value of demand limit.

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