ANN–GA Smart Appliance Scheduling for Optimized Energy Management in the Domestic Sector

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Abstract

Smart scheduling of energy consuming devices in the domestic sector should factor in clean energy generation potential, electricity tariffs, and occupants' behaviour (i.e. interactions with their appliances). The paper presents an ANN–GA (Artificial Neural Network / Genetic Algorithm) smart appliance scheduling approach for optimized energy management in the domestic sector. The proposed approach reduces energy demand in "peak" periods, maximizes use of renewable sources (PV and wind turbine), while reducing reliance on grid energy. Comprehensive parameter optimization has been carried out for both ANN and GA to find the best combinations, resulting in optimum weekly schedules. The proposed artificial intelligence techniques involve a holistic understanding of (near) real-time energy demand and supply within a domestic context to deliver optimized energy usage with minimum computational needs. The solution is stress-tested and demonstrated in a four bedroom house with grid energy usage reduction by 10%, 25%, and 40%, respectively.

Keywords: ANN; Optimisation, Genetic Algorithm, Scheduling, Energy Management; Parameter Tuning; PMV; Domestic Building.

1. Introduction

It is widely acknowledged that our built environment is responsible for some of the most serious global and local environmental change [1, 2, 3]. Creation and operation of the built environment account for at least 50% of all energy consumption in Europe [1-4]. The EU is promoting conservation and rational use of energy in buildings as part of the Energy Performance Building Directive [5].

There is an increasing regulatory demand to rely on clean energy generation sources. However, some of these technologies, such as PV (Photovoltaic), are weather dependent and generated energy is often available at times when occupants are either not at home or not using electricity. In this context,

Buildings, including houses, are becoming small scale "power plants" whereby occupants are becoming active energy prosumers (i.e. consumers and active producers of energy). Hence, electricity grids now have to accommodate a two-way system whereby electricity can flow both ways from the grid to consumers, varying in magnitude and direction based on a number of factors, including environmental and occupancy conditions [6]. Therefore smart grids are expected to facilitate better integration of fluctuating renewable energy and local distributed generation [7]. However, the fluctuation of energy generation from renewable sources requires smarter integration with the grid [8] which forms a form a grand challenge for Artificial Intelligence [6].

Feed in tariffs (FiT) are a form of government subsidy to encourage the update of Renewable Energy. Due to the way FiT tariffs are funded, it is more beneficial for owners of domestic renewable energy solutions to use the generated energy on site as opposed to selling it to the grid. Hence the need to rely on smart scheduling techniques to maximize renewable energy use and minimize the reliance on the grid [9-10]. Several studies have been conducted on scheduling of energy usage as elaborated below.

Majumdar et al., [11] explored changing schedules of meeting room use in an office building using various algorithms. The energy use is optimized based on room usage (length of time a room is occupied), capacity size difference (difference between room capacity and meeting size), time gap (interval between meetings when a room is unoccupied), and the number of occupied rooms (more occupied rooms require more energy). They have applied several optimisation algorithms with different methodologies, including backtracking, non-heuristic and greedy heuristics. These algorithms utilise an EnergyPlus simulation model to simulate energy consumption. Although the proposed methodology is efficient to reduce energy consumption, simulation tools such as EnergyPlus and TRNSYS are very time consuming when carrying out simulation and optimisation processes. They normally require tens or hundreds of repeating simulations. Options to speed up the calculation include simplifying the model or using high throughput computing techniques. A preferred option however is to use artificial intelligence methods such as neural network with historical or simulated data sets [12-13].

Kang et al., [14] consider using scheduling and real time control to operate a BEMS (Building Energy Management System) which involves distributed energy resources and energy storage systems. The BEMS collects information such as recent status of all the components of a building, prediction of the current pricing, and weather information to optimize energy use. In that respect, a linear optimisation model is proposed to reduce reliance on the grid. The prediction techniques utilised in this study are based on autoregressive integrated moving average (ARIMA) regression and transfer function models. Although they have used a linear model in the optimisation process, the proposed model has to rely on the prediction model which requires generating highly accurate results. If the modelling of

the optimisation problem is based on a non-linear function, then the linear programming technique will not perform well to generate an optimum solution. Therefore stochastic search algorithms such as Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Bees Algorithm (BA), and Ant Colony Optimisation (ACO) are better suited to solving non-linear energy management problems.

Haniff et al., [9] reviewed a number of scheduling techniques for HVAC systems, including Basic, Conventional, and advanced scheduling techniques. They conclude that all of the techniques work to some degree and generally the more advanced techniques work better and can achieve an energy saving of 42% as evidenced by their case study. They recommend to have pre-determined set-points based on weather forecasts to make the scheduling more efficient while maximising occupants' comfort, measured via predicted mean vote (PMV) index.

Setlhaolo et al., [10] proposed a method for scheduling domestic appliances to minimize electricity costs by using as much off peak energy as possible. The method involves a trade-off between incentive and inconvenience, converted into mathematical functions. The appliances have various rules applied to them such as runtime and order (e.g. dryer must run after washing machine). The inconvenience is calculated through the difference between the baseline and optimal schedule. The formulated model is then solved with AIMMS software which utilises CPLEX and CONOPT as mixed integer programming [15]. They have suggested that this model might allow users to fine tune their specific problem. In this model, they have achieved about 25% energy reduction. However, the results are dependent on the difference between peak and off peak prices and how much inconvenience occupants are willing to put up with.

Further studies have been completed combining domestic appliance schedules with renewable energy generation. Gruber et al., [16] proposed a probabilistic method of adjusting the schedules of a range of domestic appliances to lower energy usage cost. This was done by utilizing lower off peak tariffs and reliance on renewable energy. The proposed model is based on the determination of the required number, types and running periods of appliances. They have utilised binomial discrete distributions to predict the exact running time of each appliance. They demonstrated that using this technique with a demand optimisation tool, as well as the flexibility to modify the time of use and control of appliances, would allow considerable cost savings.

Given the above weaknesses and strengths of related research, an ANN-GA based domestic home scheduling technique is proposed to schedule the usage of domestic appliances factoring in renewable energy generation and grid energy usage. The paper involves the use of EnergyPlus simulation tool for generating the dataset – to enable the training process of ANN in order to learn the highly complex patterns in energy management, based on environmental (including climate) and occupancy factors. Furthermore, a GA based optimisation process is implemented to find optimum appliance schedules based on minimum grid energy usage to automatically control energy consuming devices.

Following this introduction, the advantages of the application of ANN (section two) and GA (section three) for energy management are discussed. Next, the proposed underpinning energy management methodology is explained in detail. Section five introduces the case study used to validate the research. In section six, a detailed description of our experiments is defined with three sub sections including, determination of the best performed ANN topology, a Taguchi based sensitivity analysis to identify the optimum GA parameters, and finally the experiments for the three energy reduction levels using weekly optimised schedules. The final section provides concluding remarks and directions for future work.

2. Artificial Neural Network for Building Energy Management

Artificial Neural Network (ANN) is one of the most popular techniques to make prediction and control in the area of robotics, control, mathematics, physics, and medicine [17-18]. ANN mimics the biological neural system and contains a number of parallel layers of neurons, all connected by weighted links. The neuron will receive an input from each of its weighted links and will combine the inputs by performing a normally non-linear calculation and then sends the output through each of the weighted links on its output side. The ANN therefore establishes relationships between known inputs and known outputs. ANNs involve high performance, fast and non-linear analytics. They start with no prior knowledge of any relationship between the inputs and outputs but use one of many different learning techniques to map to correct relationship. The learning process involves changing the weight of the links to direct the information down the correct path to the correct output [13].

ANN-based control and management systems can cope with non-linear and complex problems with less parameter, fast and accurately, with an adaptive training and learning process [13]. The literature reveals a wide use of ANN for the control and management of building environments [19-20].

ANN based solutions can also be utilised instead of simulation tools to generate a fast and rapid solution for prediction and control problems [13]. In fact, simulation environments require longer processing time. Moreover, a simulation system-based solution requires continuous calibration processes and long processing times to achieve energy saving objectives. An ANN-based energy management system is more efficient compared to a simulation based system and can easily reflect and factor in changes through an adequate learning process [12-13].

3. Genetic Algorithm Based Optimisation

Genetic Algorithm is a stochastic population-based optimisation algorithm, which is inspired from biological evolution in nature [21]. Genetic Algorithm is one of the most popular algorithms to search the optimum solution for linear and non-linear problems [21-22]. The algorithm utilises crossover, mutation and regeneration operators mimicking nature.

The GA starts with the initial population generation; this initial population then will be evaluated with a performance measurement function called fitness function. The fitness function is the objective function of the optimisation problem. According to the evolutionary theory the fittest solution will survive and the others will be removed. According to the evaluation process, if the termination condition is met, then the process will stop. Otherwise the GA operators will be implemented one by one as crossover and mutation operators until the termination condition is met [12 and 23]. The overall process of the GA is given Figure 1.

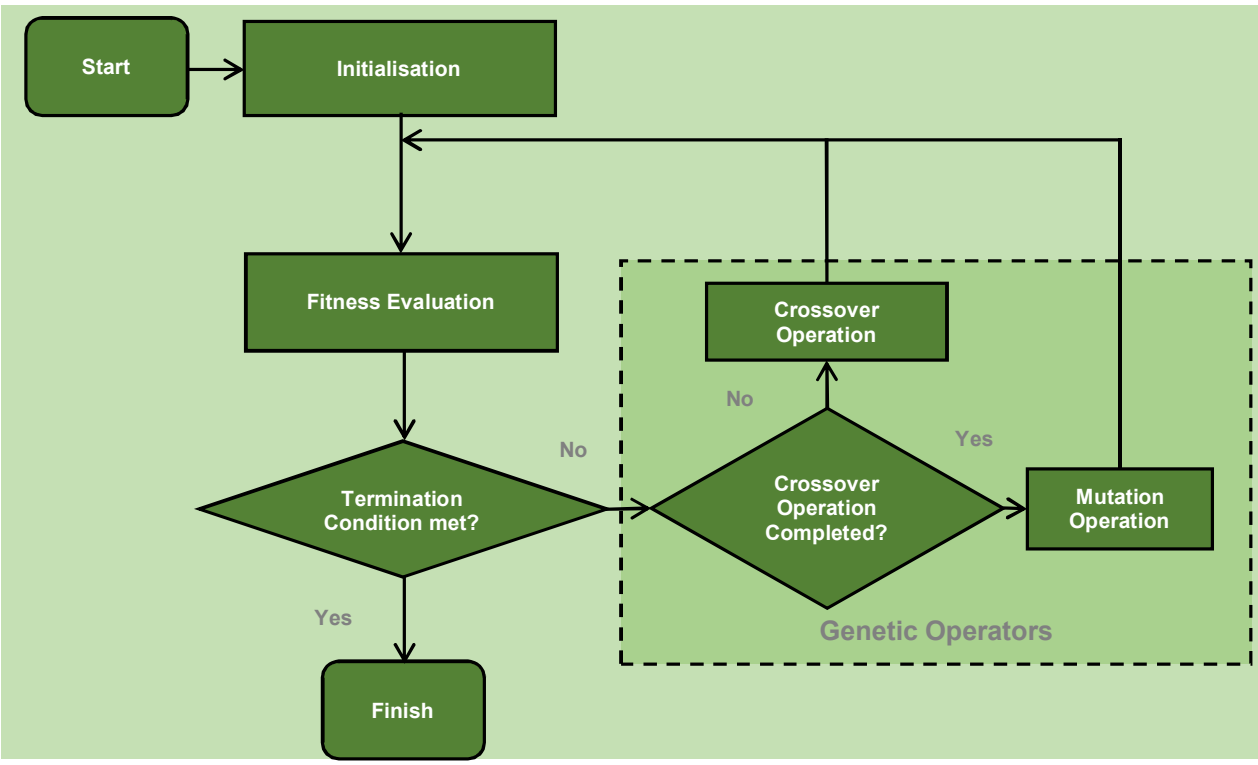


Figure 1. The flowchart of Genetic Algorithm.

4. Methodology

This section gives an overview of the optimized scheduling process and the underpinning framework for home appliances with the objective to implement negotiable energy saving plans that maximize the use of renewable energy.

The proposed study is aimed to reduce grid energy usage by 10%, 25% and 40% through intelligent scheduling of domestic appliances. These different levels of reduction are achieved through a negotiation process with the occupants. The latter can decide whether to allow switching off momentarily, or delaying the operation of existing domestic appliance(s) to reduce grid energy consumption.

The proposed method involves (a) thermal energy modelling of the pilot house and data generation, (b) ANN training, and (c) GA-ANN based optimization. To develop the thermal model for the pilot building, DesignBuilder software is utilised. This thermal model contains the details of the pilot building such as geometrical information, occupancy schedules, HVAC schedules and building materials details. DesignBuilder combines fast modelling with advanced energy simulation [24]. The model is then exported into EnergyPlus (a thermal load simulation environment) and further detailed with domestic appliances schedules and renewable energy generation solutions [25].

The next step involves the definition of a comprehensive scenario to contextualise the developed thermal energy model. In this paper, a comprehensive scenario is defined to minimise reliance on grid energy and maximise renewable energy usage by acting on the state of the appliances, through the selected control variables for this scenario. The state of each appliance has a binary value with desired running period: 0 or 1 (switch off or on).

Since the forecasting of energy consumption and generation are highly complex, stochastic and non-linear problems, it is hard to generate a generalised analytical model to define the relationship among these variables. Moreover, the user behaviour for the energy consumption is highly complex and stochastic. Therefore, an effective prediction engine needs to be developed to predict energy consumption and other desired objectives. Simulation is a popular approach for the delivery of a prediction engine. However, a simulation tool needs more parameters to set up and requires longer processing time. Thus, a well-trained ANN is a good replacement in place of the simulation tool [13]. This trained ANN can predict results with lower processing time compared to a simulation tool. Therefore, ANN is selected as a prediction engine to learn the appliance operation patterns and make prediction for the energy consumption and renewable energy generation. To generate a well-trained ANN model, a representative data set is required which covers the most possible combinations between inputs and outputs. Therefore, data generation is a very crucial step for complex problems to implement ANN. In this paper, data generation is carried out using a simulation of the thermal model. This involved several combinations of appliances' schedules set up weekly with a fifteen minutes

time steps whereby each simulation is run for a year. These schedules illustrate the weekly states of the appliances. Our considered thermal model involves nine appliances to set their schedule state as binary (on or off). Moreover, eight of the appliances start times are updated daily, whereas one of the appliance start time and day is updated weekly, as elaborated in the case study section. To cover all possible appliance start time combinations, the daily schedule is updated 15 minutes further every day. For example; if start time for an appliance is selected as 5:00 o'clock, the next day start time will be 5:15, to cover all possible combinations. This is generated for ten years worth of data. In each consequent simulation, the weekly schedule of appliances is updated to cover all possible appliance schedules with respect to the appliance constraints such as minimum run period for a day, minimum run period for a week and duration time. This process is carried out using a python script. EnergyPlus software is utilised to develop the thermal model with a focus on the period between 1st January and 31st December. Moreover, parameters for the wind towers and PV arrays are also included to generate the wind power and PV generation for a year with fifteen minutes time step. 68 outputs have thus been generated from simulation. Training an ANN with this huge number of variables is a complex task. Therefore, a stepwise sensitivity analysis is also utilised to determine the most effective variables (which has absolute coefficient value greater than 50) for each objectives which are total energy consumptions, PV energy generation and Wind Power generation. According to the stepwise sensitivity analysis, the most sensitive environmental variables for the objectives are found as outdoor temperature, wind speed, diffuse solar radiation and occupancy, given in equation 1-3.Moreover, the appliance states and time information will also utilised alongside with these variables as inputs of the ANN to train the model.

$$F_{EC}(\vec{X}) = -24937 + 148.7X_1 - 63.5X_2 + 74.4X_3 - 59.2X_4 \quad (1)$$

$$F_{PV}(\vec{X}) = 51738 + 93.6X_1 + 72.5X_2 + 82.5X_3 + 102.4X_4 \quad (2)$$

$$F_{WP}(\vec{X}) = 120921 + 61.3X_1 + 321.1X_2 - 54.4X_3 + 82X_4 \quad (3)$$

where $F_{EC}(\vec{X})$ is the total building energy consumption, $F_{PV}(\vec{X})$ and $F_{WP}(\vec{X})$ are the energy generation by PV systems and wind power, respectively. X_1, X_2, X_3 and $X_4$are outdoor temperature, wind speed, diffuse solar radiation, occupancy.

Finally, GA is utilised to find the best schedule to achieve the desired level of energy reduction. GA utilises ANN as prediction engine to evaluate the fitness of the solutions. The overall process is illustrated in the block diagram given in Figure 2.

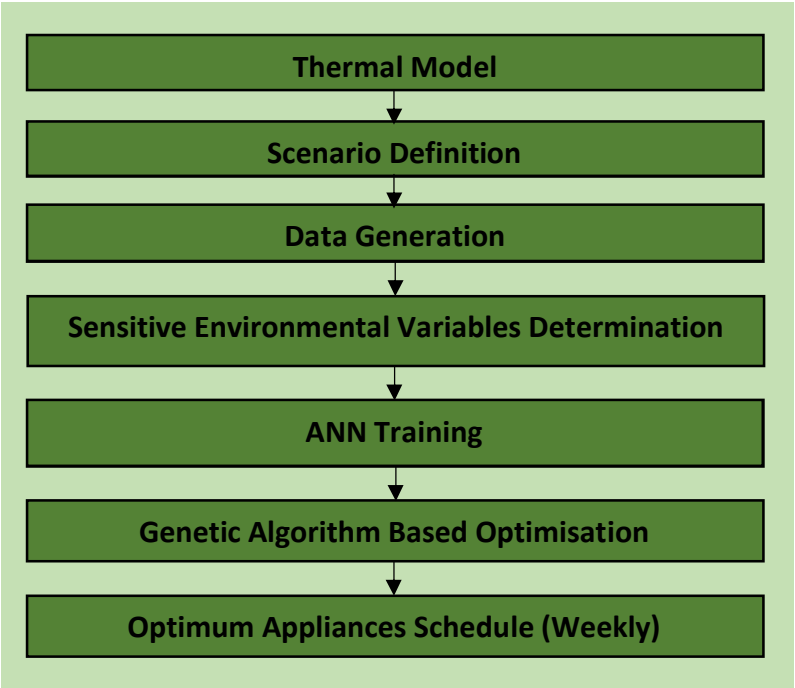


Figure 2. Appliance scheduling methodology.

5. Case Study

To demonstrate reduction in grid energy use, a domestic pilot building was selected. The latter is one of the cottages within the Little White Alice holiday resort in Cornwall (UK). Little White Alice is a collection of eco-friendly holiday houses. The selected house is the Oak House, a typical four bedroom house. The DesignBuilder model of the house is given in Figure 3. The building is a two floors building with four bedrooms, one bathroom, one dining room, one living room, one kitchen, a laundry room and a shower.

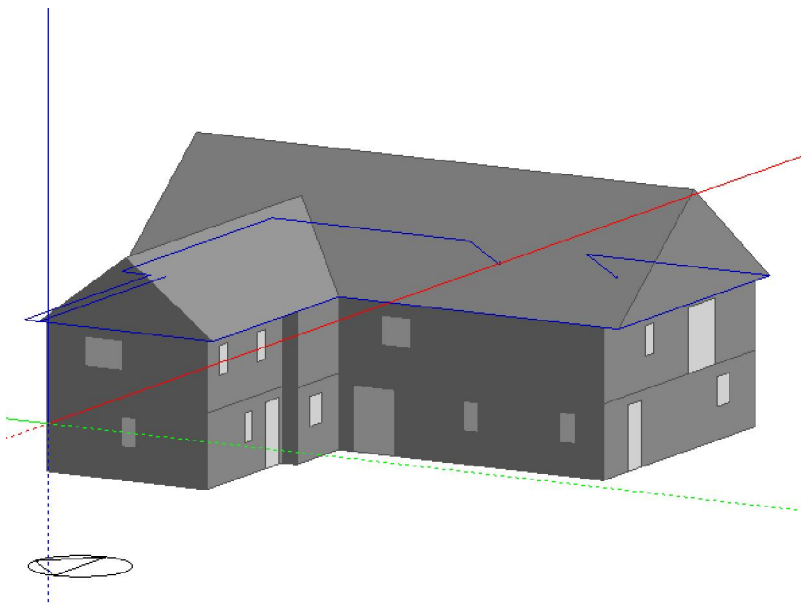


Figure 3. DesignBuilder Model of the Oak House.

The case study involves a domestic pilot house, the Oak House, in the Little White Alice holiday resort in Cornwall (UK). It is a typical four bedroom house with two floors, one bathroom, one dining room, one living room, one kitchen, a laundry room and a shower. This pilot building has a range of renewable energy solutions including both renewable electrical and thermal sources. The following renewable electrical energy sources exist in the pilot: (a) 18 kW capacity Photovoltaic (PV) systems and (b) 6 kW capacity wind turbine. The PV system consists of 72 poly crystalline modules and each module has 60 (6x10) cells and generates 0.25kW. The available wind turbine is a 15m tower turbine and has three blades with 5.5m diameter size. The expected annual energy production with the wind turbine is 11500KWh/year. In this study, the following appliances and schedules are selected for testing purposes as illustrated in Table1.

Table 1. The appliance list usage in the pilot.

No	Appliance	Power Rating (kW)	Minimum Running Time (minutes)	Interruption of Appliance	Required Usage Frequency	Required Start Time
1	Washing Machine	1.500	120	Not possible	Twice a day	Between (00:00-23:45)
2	Dishwasher	1.100	60	Not possible	Twice a day	Between (00:00-23:45)
3	Tumble Dryer	3.000	180	Not possible	Once a day	Between (06:00-23:45)
4	Iron	2.000	45	Not possible	Once a day	Between (06:00-23:45)
5	Cooker	7.000	45	Not possible	Twice a day	Morning (05:00-09:00) Evening (17:00-22:00)
6	Microwave	2.000	15	Not possible	Twice a day	Morning (05:00-09:00) Evening (17:00-22:00)
7	Vacuum Cleaner	2.000	60	Not possible	Twice a day	Between (07:00-23:45)
8	Phone Charger	0.015	180	Not possible	Twice a day	Between (00:00-23:45)
9	Car Charger	5.200	180	Not possible	Twice a week	Between (00:00-23:45)

As highlighted in the previous section, the thermal model is developed using Designbuilder for the pilot and contains all above information. Then the model is converted to an EnergyPlus model to generate the data set by changing the schedule of the selected appliances. The data generated with EnergyPlus simulation is then analysed with a stepwise sensitivity analysis approach to determine most sensitive environmental variables for the total energy consumption, and energy generations for the solar PV and wind power installed for this pilot house. Thus, the proposed ANN model has date and time info, outdoor temperature, wind speed, diffuse solar radiation, occupancy, appliances on/off state for the selected time frame, and the remaining duration time for each appliance as inputs. Wind power generation, PV electricity generation and total energy consumption and individual energy consumption for each appliance are used as outputs. The topology of the proposed ANN model is given in Figure 4.

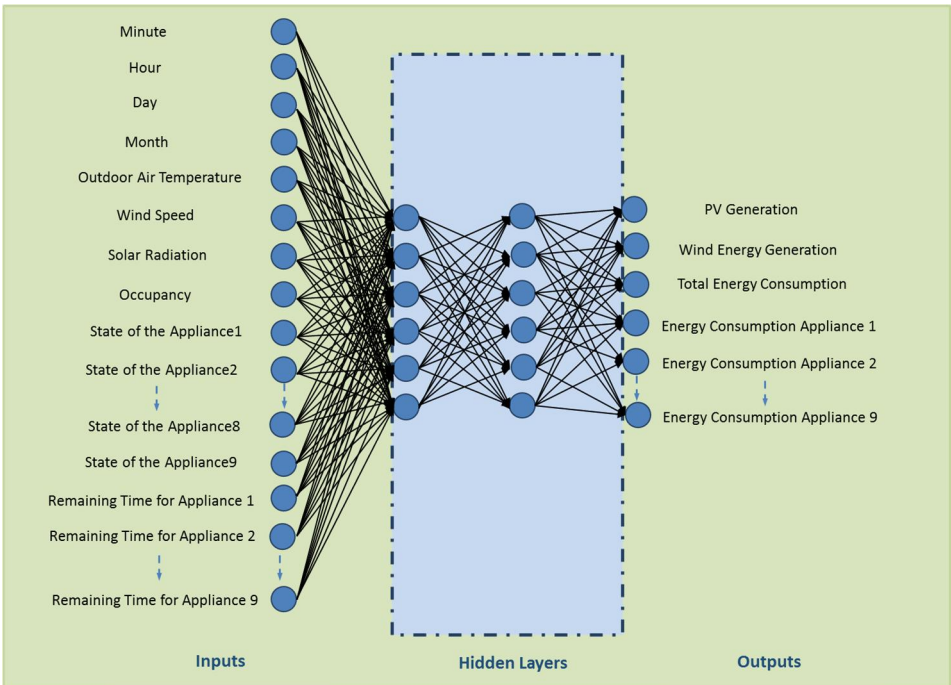


Figure 4.The proposed topology of ANN.

The next stage is then train the proposed ANN model using the generated data set to develop a prediction engine. As mentioned in the previous section, this trained ANN will then be utilised in a GA based optimisation as a prediction engine.

The optimization process for this case study uses the control variables and seeks for the optimum combination of set points for all nine appliances to achieve the desired grid energy reduction level. The control variables of this optimization model are determined based on the appliance types. For instance, once a device is activated it will be run until the duration time is completed. Some appliances have to be operated twice in a day, the second run can be started straight after the completion of the first run if this helps reduce grid energy consumption and maximise renewable

energy usage. Appliance nine runs twice in a week, which requires another parameter for its control i.e. “start day number” and “start time of a day”. To create a weekly schedule, a chromosome with 102 dimensional variable set has been generated: 100 for start times (daily) and 2 for week day numbers. The formation of start time is denoted as $X1(n, ID, d)$.

where “n” is the current running cycle number of the device (n= 2 for appliances ID number 1, 2,5,6,7,8; and n=1 for ID 3 and ID 4 given in Table 1); “d” is week day number (d=1..7); and ID is the appliance number (ID=1..9). Although the daily start time is one parameter for the device ID 9, the day number is another parameter for this appliance, denoted as, $X2(n, 9)$, where “n” is the current running cycle number of device. The daily time information is converted into fifteen minutes timescale. Thus, one day consists of 96 time frames, and a week has 672 time frames. The control variables of the nine appliances will be the parameters of the optimization model given in equation 4 which represents one chromosome of the GA process.

$$X = \{X1(1,1,1),\ X1(2,1,1),\ X1(1,2,1),\ X1(2,2,1),\ X1(1,3,1),\ X1(1,4,1),\ X1(1,5,1),\ X1(2,5,1),\ X1(1,6,1),\ X1(2,6,1),\ X1(1,7,1),\ X1(2,7,1),\ X1(1,8,1),\ X1(2,8,1),\ \ldots,\ X1(1,1,7),\ X1(2,1,7),\ X1(1,2,7),\ X1(2,2,7),\ X1(1,3,7),\ X1(1,4,7),\ X1(1,5,7),\ X1(2,5,7),\ X1(1,6,7),\ X1(2,6,7),\ X1(1,7,7),\ X1(2,7,7),\ X1(1,8,7),\ X1(2,8,7),\ X2(9,1),\ X2(9,2),\ X1(1,9,X2(9,1)),\ X1(2,9,X2(9,2))\} \quad (4)$$

Although the control variables are the main parameters for the optimization process, other variables such as weather data, occupancy, and time information, for each appliance are also utilised to feed the ANN prediction engine. Each control variable is a gene on the chromosome. Based on the start hour of day and start day of the week, the state of each device in each fifteen minutes time step will be either on or off, an example of weekly schedules is given in Figure 5. When $X1(n, ID, d)$ is generated the state of device during the device duration period will be 1, $\{ST(X1(n, ID, d)) = 1, \ldots, ST(X1(n, ID, d) + duration) = 1\}$, where $ST(X1(n, ID, d))$ is the state of device ID on the day d and on the running cycle “n” with start time frame $X1(n, ID, d)$; and the duration is the duration time length for the device based on a 15 minute time frame.

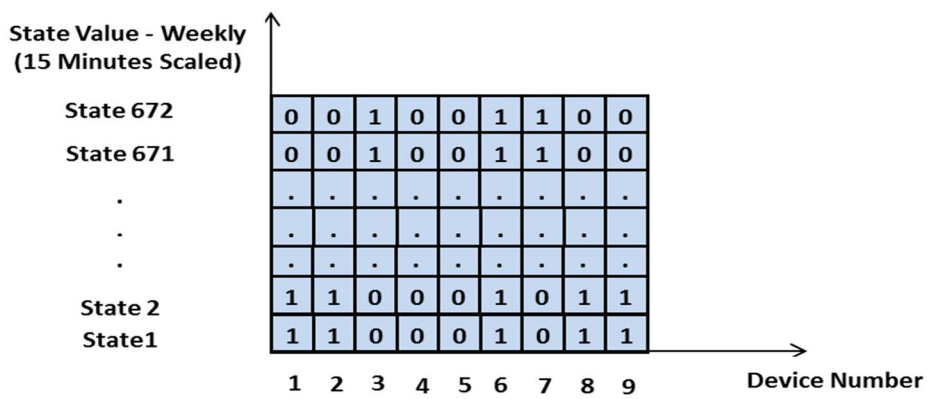


Figure 5. The sample weekly schedule of all appliances.

To evaluate the fitness of the solution, a cost function given in equations 5 is utilized under constraints given in equations 6-16. The aim is to maximise renewable energy usage thus the grid energy usage will be minimised for a desired reduction level. Thus, this is a maximisation problem for renewable energy usage which is equal to targeted reduction level with grid energy usage level denoted as $\mathrm{T_{TGEU}}$ in equation 5.

$$\boldsymbol{Max}\ \mathrm{T_{TREU}} = \mathrm{T^1_{REU}} + \mathrm{T^2_{REU}} + \mathrm{T^3_{REU}} \tag{5}$$

Subject to:

$$\mathrm{T^1_{REU}} = \begin{cases} \sum_{\mathrm{d}=1}^{\mathrm{d}=7} \sum_{ID=1}^{ID=8} \sum_{j=1}^{j=UF_k} \sum_{i=X1(j,ID,d)}^{i=X1(j,ID,d)+dur_{ID}+1} \mathrm{ST(i,j,ID,d)EC(i,j,ID,d)} - TRE(i,d) & \text{if } TRE(i,d) < \mathrm{ST(i,j,ID,d)EC(i,j,ID,d)} \\ 0 & \text{else} \end{cases} \tag{6}$$

$$\mathrm{T^2_{REU}} = \begin{cases} \sum_{i=X1(1,9,X2(9,1))}^{i=X1(1,9,X2(9,1))+dur_9+1} \mathrm{ST(i,1,9,X2(9,1))EC(i,1,9,X2(9,1))} - TRE(i,l) & \text{if } TRE(i,l) < \mathrm{ST(i,1,9,X2(9,1))EC(i,1,9,X2(9,1))} \\ 0 & else \end{cases} \tag{7}$$

$$\mathrm{T^3_{REU}} = \begin{cases} \sum_{i=X1(2,9,X2(9,2))}^{i=X1(2,9,X2(9,2))+dur_9+1} \mathrm{ST(i,2,9,X2(9,2))EC(i,2,9,X2(9,2))} - TRE(i,l) & \text{if } TRE(i,l) < \mathrm{ST(i,2,9,X2(9,2))EC(i,2,9,X2(9,2))} \\ 0 & else \end{cases} \tag{8}$$

$$TRE(i,d) = TWP(i,d) + TPV(i,d) \tag{9}$$

$$X1(j,ID,d) + dur_{ID} + 1 \leq X1(j+1,ID,d) \tag{10}$$

$$4 * \mathrm{DST}_{ID} \leq X1(j,ID,d) \leq 4 * DFT_{ID} \tag{11}$$

$$TPV(i,d) \geq 0 \tag{12}$$

$$TWP(i,d) \geq 0 \tag{13}$$

$$\mathrm{ST(i,j,ID,d)} = \{0,1\} \tag{14}$$

$$\text{if } \mathrm{ST(i,j,ID,d)} = 1 \quad then \sum_{i=X1(j,ID,d)}^{i=X1(j,ID,d)+dur_{ID}+1} \mathrm{ST(i+1,j,k,l)} = dur_{ID} \tag{15}$$

$$dur_{ID} = \frac{time_{ID}}{15} \tag{16}$$

where $\mathrm{T^1_{REU}}$ denotes weekly renewable energy consumption for device {1, 2, ..7, 8}; $\mathrm{T^2_{GEU}}$ and $\mathrm{T^3_{GEU}}$ denote weekly renewable energy consumption for device 9; d denotes the index number for the weekday (day1, day 2, …, day7); ID is the index number for the device number; j is the index number for the device cycle in a day (given table 1); $\mathrm{ST(i,j,ID,d)}$ denotes the state of the i.th device on day "d", time frame "i" and on the j.th cycle; $\mathrm{EC(i,j,ID,d)}$ denotes the state of the i.th device on the day "d", time frame "i" and on the j.th. cycle; $\mathrm{dur_{ID}}$ is the number time frame to run for the device ID; $\mathrm{time_{ID}}$ denotes the running time (minutes based) for the device ID given in table 1; The total renewable energy generation is denoted as $\mathrm{TRE(i,d)}$ on the time frame "i" in the day "d"; $\mathrm{TWP(i,d)}$ and $\mathrm{TPV(i,d)}$ denote wind power and PV generation on the time frame "i" of day "d", respectively. $\mathrm{DST_{ID}}$ and $\mathrm{DFT_{ID}}$ denote the lower and upper time range for device ID, given in Table 1. As stated

earlier, the energy generation and consumption values in each frame step "i" is equal to energy generation and consumption of each fifteen minutes time step. The start point value will be converted back to original time scale for ANN to make the prediction every 15 minutes. Thus the ANN will be used to predict the output for each fifteen minutes time steps data until one week results are generated. This is then factored into the cost function to compute the fitness value of each solution. The overall process of the proposed ANN–GA based solution is illustrated in Figure 6.

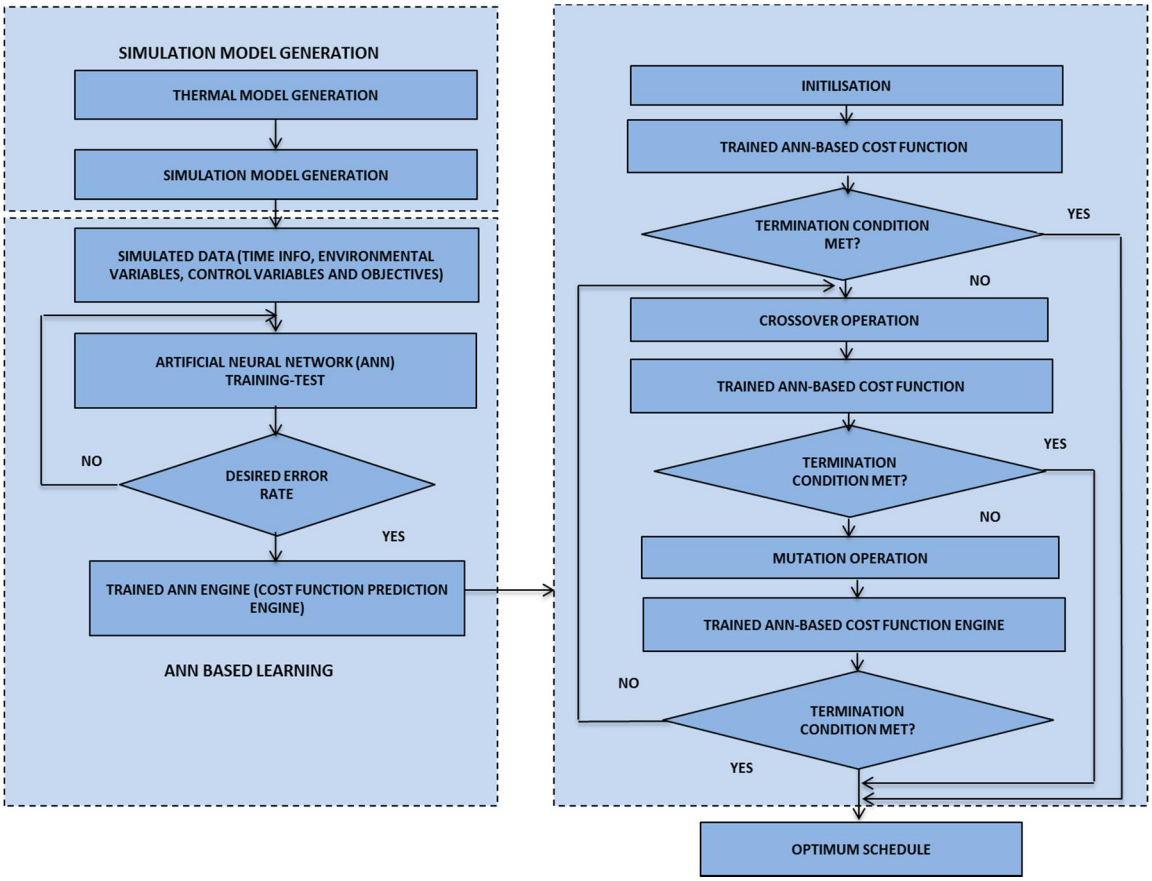


Figure 6. The flow chart of the proposed GA-ANN based optimisation process.

6. Experiments

In this section, the experiments for ANN and ANN-GA are presented. The first experiments were carried out to find the best performing ANN which then later were utilised as a prediction engine in GA. A well-trained ANN can make a good approximation to simulation results. The GA based optimisation algorithm needs to generate hundreds of results to find the global optimum solution. In this context, simulation tools are not effective as they require high power computing and parallelisation for the optimisation algorithm [23]. Hence, the aim is to generate the best performing ANN to be utilised instead of a simulation tool.

6.1 Determining the best configuration for the ANN

To find the best performing ANN, the topology which generates the best performance is required. In this topology, type of learning functions, number of hidden layers, number of process elements in each layer, and types of transfer functions need to be found experimentally. The experiments involve (a) a computer with the following specs: Intel Core (TM) I5CPU processor 2.27 -2.27 GHz speed and 4GB memory, and (b) MATLAB software.

The first experiment is to find the best performing learning algorithm. Several ANN learning algorithms were utilised to find the best performing one as given in Table 2. To find the best performing ANN, the other parameters were selected as follows for each configuration; 1, 15, Logarithmic sigmoid function (Logsig), Logsig, 0.01 and 0.9 for number of hidden layer, number of process elements in hidden layer, transfer function in hidden layer, transfer function in output layer, learning rate and momentum coefficient respectively. The results for these experiments are illustrated in Table 3.

Table 2. The utilized ANN learning algorithms in this paper.

No	Abbreviation	Learning Algorithm
1	Trainbfg	Broyden, Fletcher, Goldfarb, and Shanno (BFGS) quasi-Newton Backpropagation,
2	Traincgb	Conjugate Gradient Backpropagation with Powell-Beale restarts,
3	Traincgf	Conjugate Gradient Backpropagation with Fletcher-Reeves updates,
4	Traincgp	Conjugate Gradient Backpropagation with Polak-Ribiere updates,
5	Traingd	Gradient Descent Backpropagation,
6	Traingda	Gradient Descent with Adaptive Learning Rate Backpropagation,
7	Traingdm	Gradient Descent with Momentum Backpropagation,
8	Traingdx	Gradient Descent with Momentum and Adaptive Learning Rate,
9	Trainlm	Levenberg-Marquardt Backpropagation,
10	Trainscg	The Scaled Conjugate Gradient Algorithm Based on Conjugate Directions.

Table 3. Results of ANN training based on training functions.

Training Algorithm	Expected Error Level	Error Level of Algorithm	Number of Epoch
Trainbfg	0.005	0.0090	1000
Traincgb	0.005	0.0285	1000
Traincgf	0.005	0.0153	1000
Traincgp	0.005	0.0109	1000
Traingd	0.005	0.5471	1000
Traingda	0.005	0.0937	1000
Traingdm	0.005	0.0224	1000
Traingdx	0.005	0.0130	1000
Trainlm	**0.005**	**0.0087**	**1000**
Trainscg	0.005	0.0089	1000

According to Table 3, the best performance was found with Levenberg-Marquardt based learning algorithm. For the following experiments, trainlm is selected as the learning function.

The next experiments are conducted to find the number of hidden layers. To find the optimum number of hidden layers, the following topology is used: Trainlm, 15, Logsig, Logsig, 0.01 and 0.9 for the learning function, number process elements in each hidden layer, transfer function for each hidden layer, transfer function for output layer, learning rate and momentum coefficient, respectively. The results are given in Table 4.

Table 4. Results of ANN training based on training functions.

Number of Hidden Layer	Expected Error Level	Error Level of Algorithm	Number of Epoch
1	0.005	0.0089	1000
2	0.005	0.0089	1000

According to results given in Table 4, the number of hidden layer didn't make any change in the results. Thus, the number of hidden layer is selected as 1 for the following experiments.

The next experiments were to find the best combination of the transfer functions for hidden layer and output layer. In these experiments, different combinations of Tangent sigmoid (Tansig), logarithmic sigmoid (Logsig), Pure linear (Purelin) functions were tested as transfer function in hidden layer and output layer. To measure the performance of each combination, the following topology were utilised; Trainlm, 15, 1, 0.01 and 0.9 for the learning function, number of hidden layer, number process

elements in hidden layer, learning rate and momentum coefficient respectively. The results for each combination are given Table 5.

Table 5. The training performance of different combinations of transfer functions in hidden and output layers.

Function type in hidden and output layer	Expected Error Level	Error Level of Algorithm	Number of Epoch
[Tansig-Tangsig]	0.005	0.0378	1000
[Tansig-Logsig]	0.005	0.0093	1000
[Tansig-Purelin]	0.005	0.1604	1000
[Logsig-Tansig]	0.005	0.0098	1000
[Logsig-Logsig]	0.005	0.0090	1000
[Logsig-Purelin]	0.005	0.1031	1000
[Purelin-Tansig]	0.005	0.0159	1000
[Purelin-Logsig]	0.005	0.0174	1000
[Purelin-Purelin]	0.005	0.3571	1000

According to the results illustrated in Table 5, usage of the logarithmic sigmoid function in both hidden and output layer generates the best performance. This transfer function was selected for the following experiments.

The final experiment was carried out to find the required number of process elements. To find the number of process elements which produce the best performance, the following topology was utilised; Trainlm. 1, Logsig, Logsig, 0.01 and 0.9 for the learning function, number of hidden layer, transfer function in hidden layer, transfer function in output layer, learning rate and momentum coefficient respectively. The results for each combination are given Table 6.

Table 6. The training performance of ANN for different process elements in hidden layer.

Number of Process element in Hidden Layer	Expected Error Level	Error Level of Algorithm	Number of Epoch	Learning Time (Minute)
5	0.005	0.0139	1000	66
10	0.005	0.0133	1000	86
15	0.005	0.0097	1000	101
20	0.005	0.0089	1000	123
25	0.005	0.0086	1000	143
30	0.005	0.0086	1000	178
50	0.005	0.0088	1000	192

According to the results given above (Table 6), the performance of both 25 and 30 process elements in hidden layer are the best and exhibit the same level of error. However, the training time with 25 process elements are shorter than with 30 process elements. Therefore, the number of process elements in hidden layer was selected as 25 for the prediction stage. The performance of the best configuration is illustrated in Figure 7.

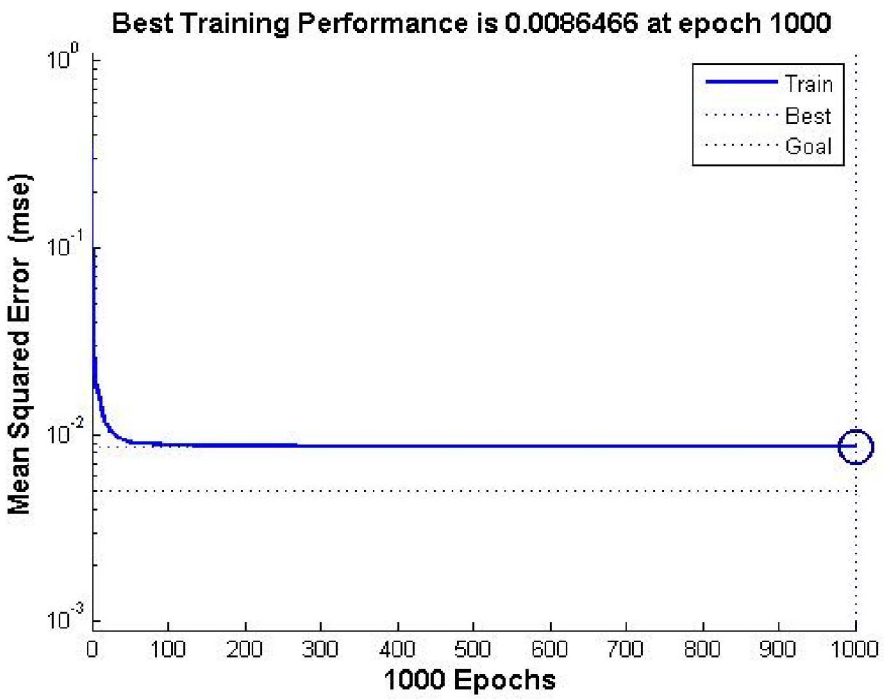


Figure 7. The training performance of the best performing topology of ANN.

The next stage uses the best performing ANN as a prediction engine in GA to find the optimum results for grid energy reduction with different reduction levels. The use of GA involves varying the state of the appliances with different time step to find the desired grid energy reduction level as defined in equation 5 by maximising the renewable energy usage. The test was run for 10%, 25% and 40% grid energy usage reduction levels. To achieve this reduction levels, the weekly schedule of the appliances was generated for a month with 15 minutes incremental size. As highlighted above, apart from phone charger, if any appliance is activated it will be run until the duration time. Further, some appliances should only be activated in specific time periods. For instance the oven and microwave should be active between 5am-9am (morning) and 5pm-10pm (evening).

6.2Taguchi-based GA Parameter tuning

This section presents the determination of the best parameter sets for the GA Algorithm. Initially, the parameters given in Table 7 are used for optimization process which has been coded under MATLAB framework. These parameters then were tuned using the Taguchi method.

Table 7. The parameters of GA.

Parameter name	Parameter Value
Population Size	12
Mutation Rate	0.5
Number of Bits	16
Cross Over Rate	0.5

Several configurations of the GA parameters are utilised to improve the performance of the optimisation process. Taguchi Method uses an orthogonal design to elicit the interaction between parameters and the performance of the optimisation process. This involves using the signal-to-noise ratio to analyse the experimental data and find the optimal parameter combinations [26]. Four main parameters of GA (i.e. population size, mutation rate, chromosome length and crossover rate), with three levels were investigated. L9 orthogonal design [27] is selected to carry out the experiments and to calculate the factor effects, as shown in Table 8. To implement the Taguchi analysis, Minitab software was used to carry out the analysis and provide a signal-to-noise ratio for each of the factors. The signal-to-noise ratio, according to the criteria 'Larger is better', is expressed with equation 17 [28].

$$\frac{S}{N} = -10log_{10}\left[\frac{1}{N}\sum\frac{1}{\gamma^2}\right] \tag{17}$$

Once the most important factor is known, further experiments will be carried out keeping all variables constant except the factor found using Taguchi Analysis.

Table 8. The selected L9 Taguchi orthogonal array for analysis of GA parameters.

Experiment No	Design Set				Design Level			
	Population Size	Mutation Rate	Chromosome Length	Crossover Rate	Population Size	Mutation Rate	Chromosome Length	Crossover Rate
1	16	0.750	64	0.750	1	1	1	1
2	16	0.500	32	0.625	1	2	2	2
3	16	0.250	16	0.500	1	3	3	3
4	12	0.750	32	0.500	2	1	2	3
5	12	0.500	16	0.750	2	2	3	1
6	12	0.250	64	0.625	2	3	1	2
7	8	0.750	16	0.625	3	1	3	2
8	8	0.500	64	0.500	3	2	1	3
9	8	0.250	32	0.750	3	3	2	1

Based on Taguchi analysis, the factor which has the biggest impact on the optimum solution with minimum time and error, based on the delta value, was found as 9.822 (as illustrated in Table 9). Crossover rate, mutation rate and chromosome length were found as second, third and fourth

important factors, respectively, for the optimisation process (Table 9). Moreover, the best interaction level for each factor was found as 16, 0.500, 16, 0.625 for the population size, mutation rate, chromosome length and crossover rate, respectively, as shown in Figure 8 and Figure 9a-d.

Table 9. Taguchi Results Table – (Response Table for Signal to Noise Ratios Larger is better)

Factors / Design Level	Population Size	Mutation Rate	Chromosome Length	Crossover Rate
1	19.544	17.395	17.517	17.122
2	13.980	19.863	18.045	21.141
3	9.722	18.880	19.843	19.512
Delta Values	**9.822**	**2.468**	**2.326**	**4.018**
Rank	1	3	4	2

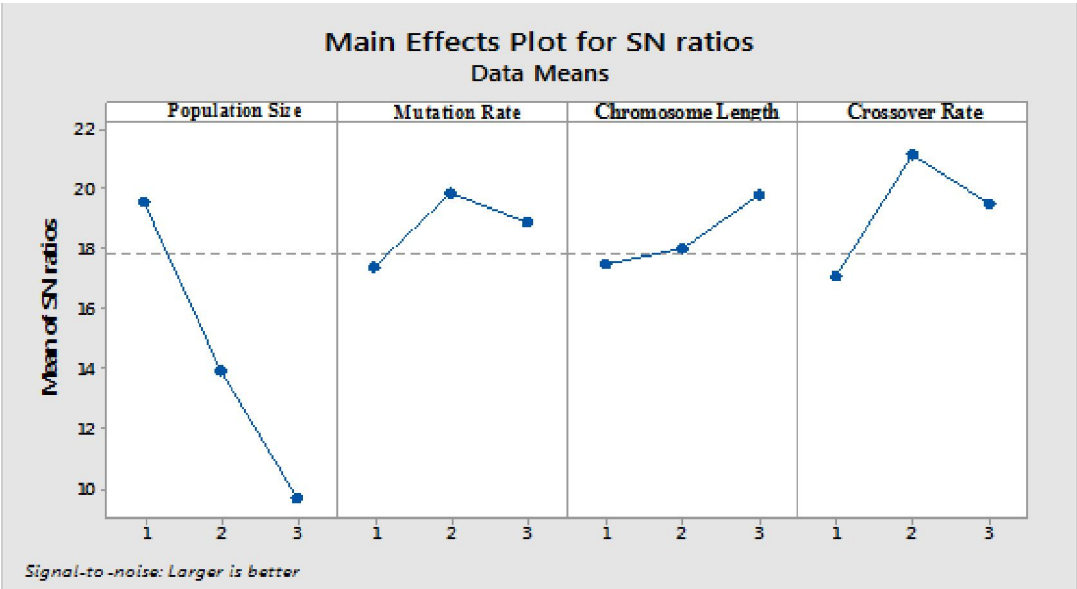
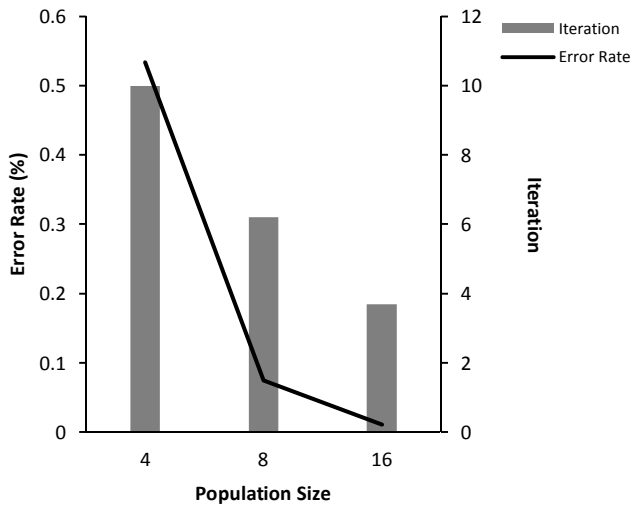
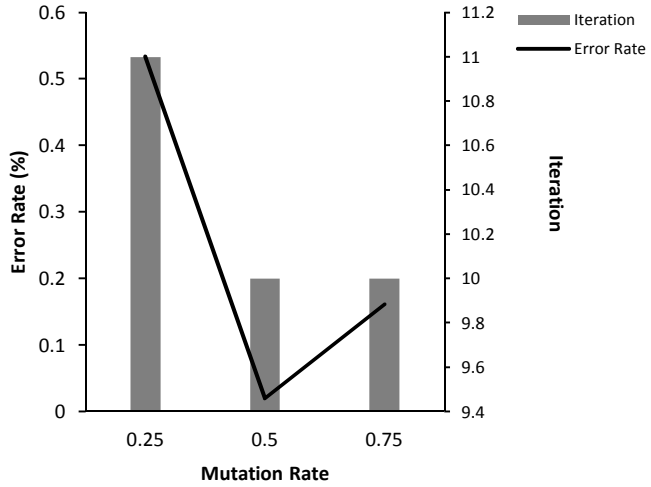


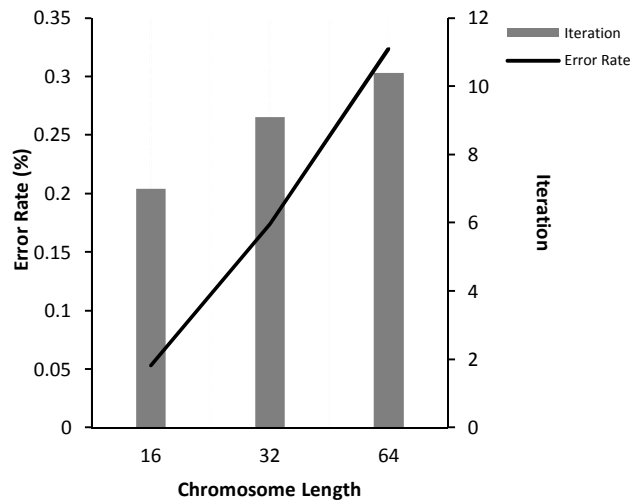
Figure 8. The results of Taguchi analysis for each factor and its levels.



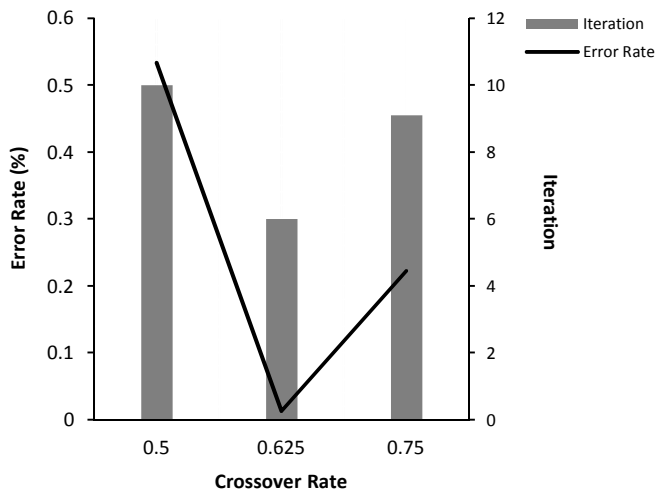
a) Experiments based on population size.



b) Experiments based on mutation rate.



c) Experiments based on chromosome length.



d) Experiments based on crossover rate.

Figure 9. The experimental results for changing; a) population size, b) mutation rate, c) chromosome length and d) crossover rate.

As highlighted above, the most important effect on the optimum solution with lower iteration time is the population size. The effects of others are illustrated in Figure 9a-d. These best parameters are then utilised to run GA with ANN to find the best weekly schedule for the appliance schedule.

6.3 Grid energy reduction using ANN-GA based optimised scheduling

The experimental results for ANN-GA based optimization for all 10%, 25% and 40% reduction levels are carried out using the best parameter of both ANN and GA. The experiments were carried out to find the best state combination of the appliances for a week and this is repeated for one month. The initial device states are illustrated in Figure 10.

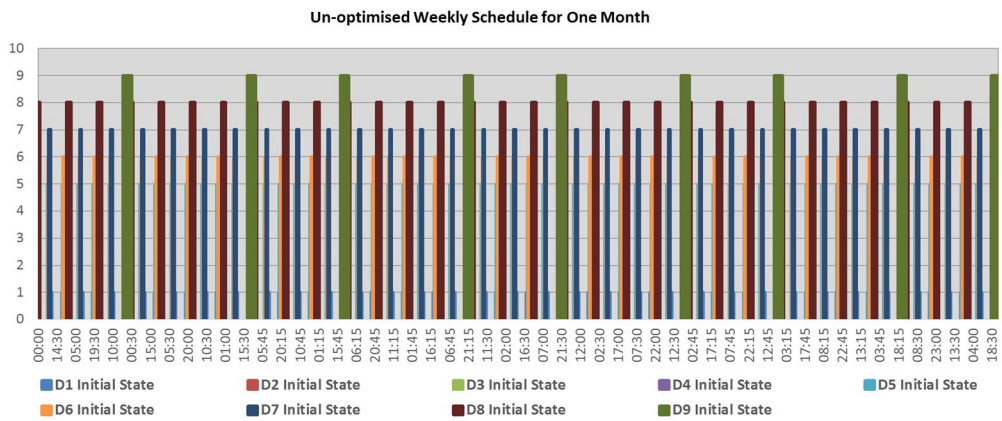


Figure 10. The initial schedule of the nine appliances for a month.

*D1=Washing Machine, D2= Dishwasher, D3= Tumble Dryer, D4= Iron, D5=Cooker, D6=Microwave, D7=Vacuum Cleaner, D8=Phone Charger and D9= Car Charger

Further, the total renewable energy generation, initial grid energy usage and initial surplus (idle) renewable energy are presented in Figure 11-13.

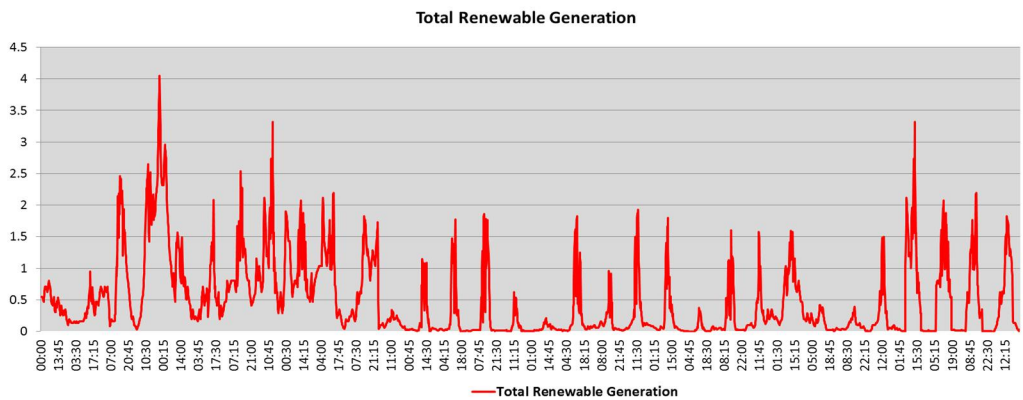


Figure 11. The total renewable energy generation.

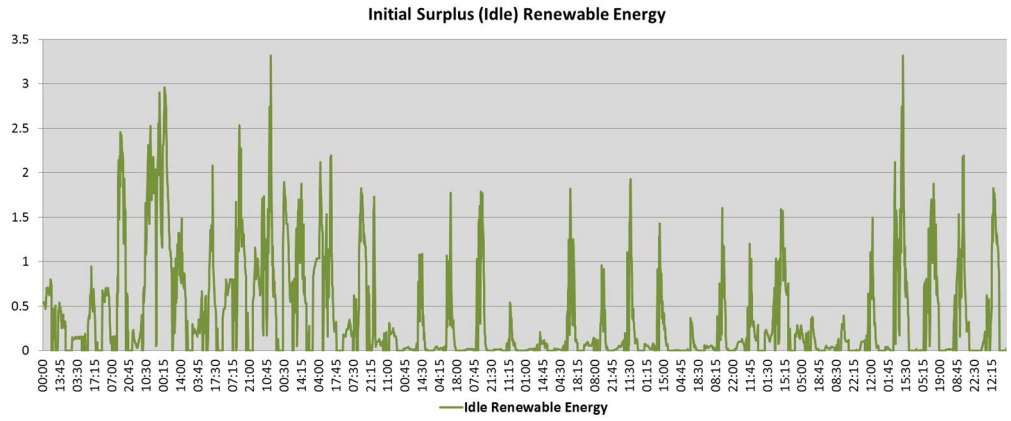


Figure 12. The initial surplus renewable energy (before scheduling).

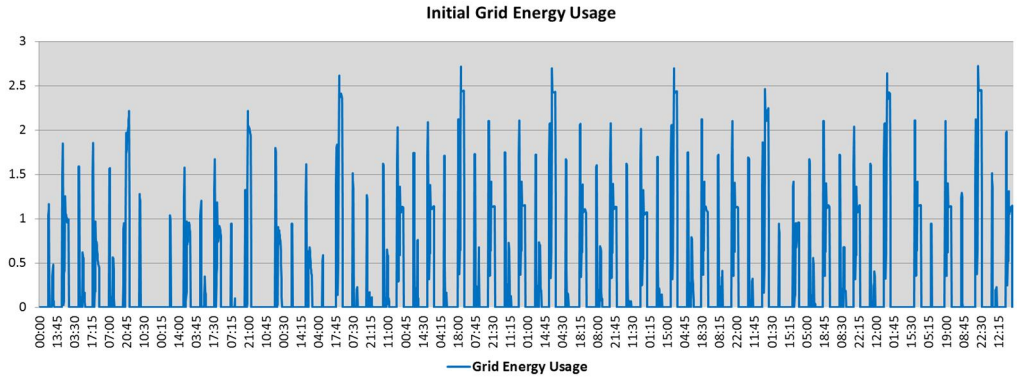


Figure 13. The initial grid energy usage (before scheduling).

The total grid energy usage for a month was 816.4311KWh for the pilot house before proposed model. The optimization process was utilized to find the optimum weekly schedule with constraints given in Table 1. The optimum schedule for the reduction level for 10%, 25% and 40% were successfully implemented and total energy consumption was found as 734.7881 KWh, 612.3234 KWh and 489.8587KWh, respectively. The optimized schedules are illustrated in Figure 14-16. Further, the surplus renewable energy and grid energy usage are illustrated for these three reduction level in Figure 17-22, respectively.

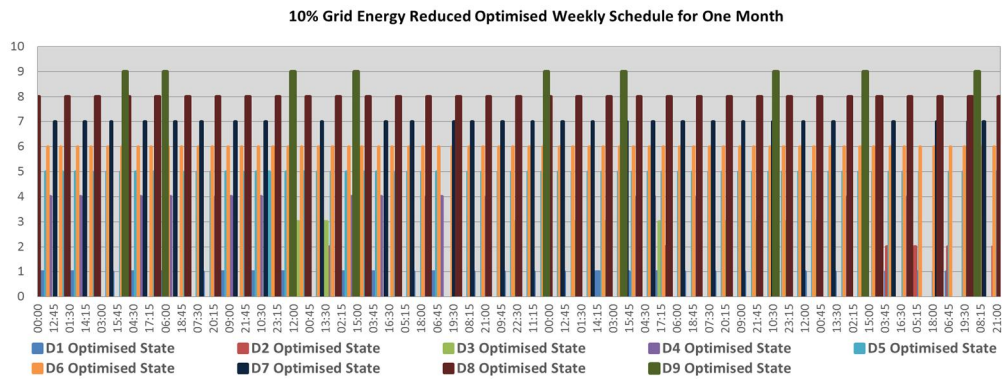


Figure 14. The optimized weekly schedules of appliances for 10% less grid energy usage.

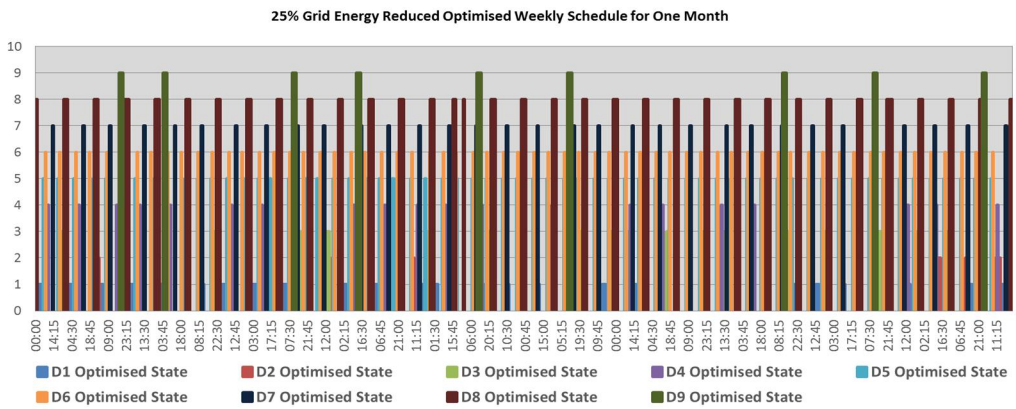


Figure 15. The optimized weekly schedules of appliances for 25% less grid energy usage.

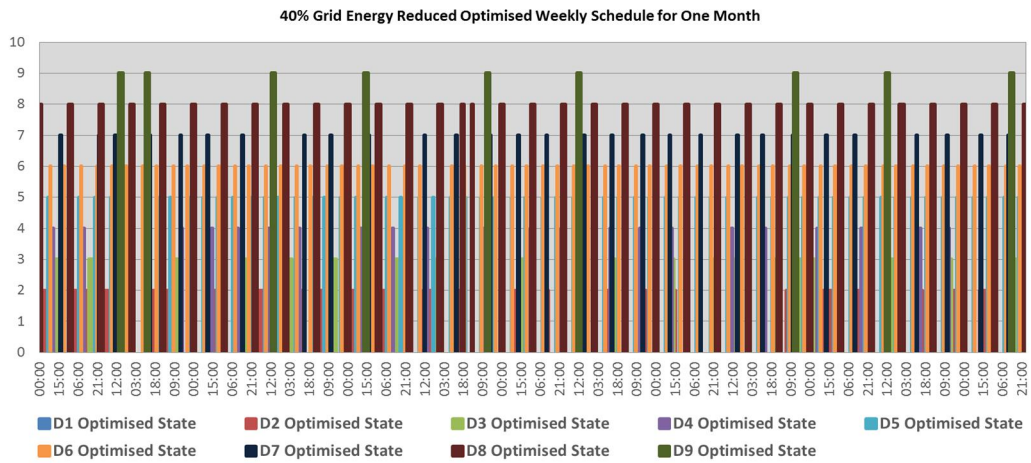


Figure 16. The optimized weekly schedules of appliances for 40% less grid energy usage.

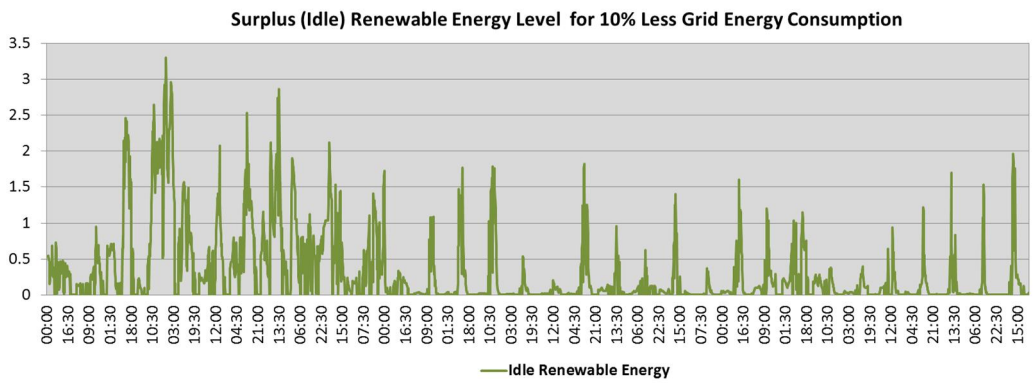


Figure 17. The surplus renewable energy amount after the optimised schedule for 10% less grid energy consumption level for one month (weekly).

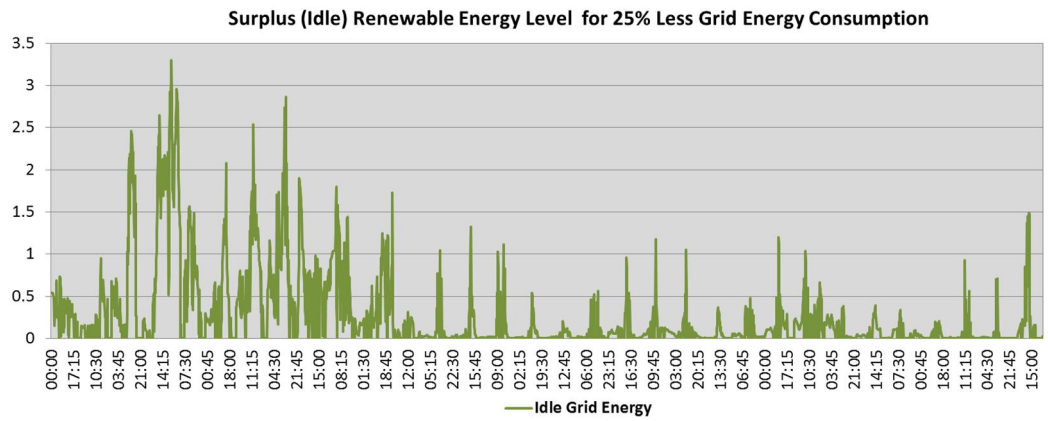


Figure 18. The surplus renewable energy amount after the optimised schedule for 25% less grid energy consumption level for one month (weekly0.

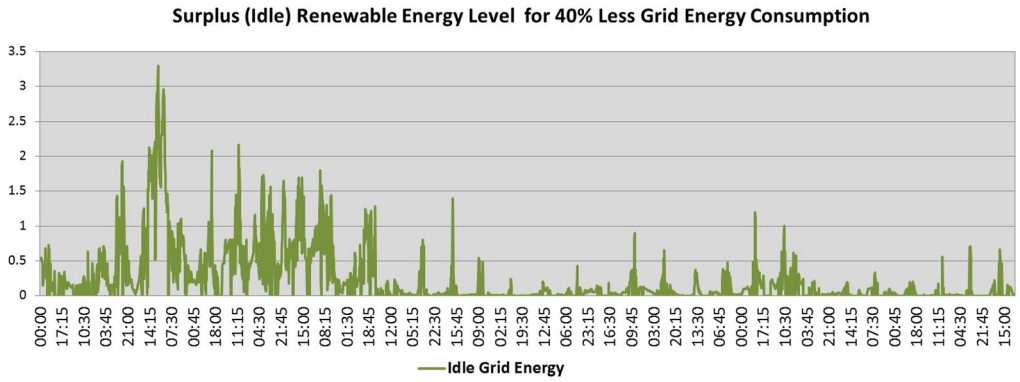


Figure 19. The surplus renewable energy amount after the optimised schedule for 40% less grid energy consumption level for one month (weekly).

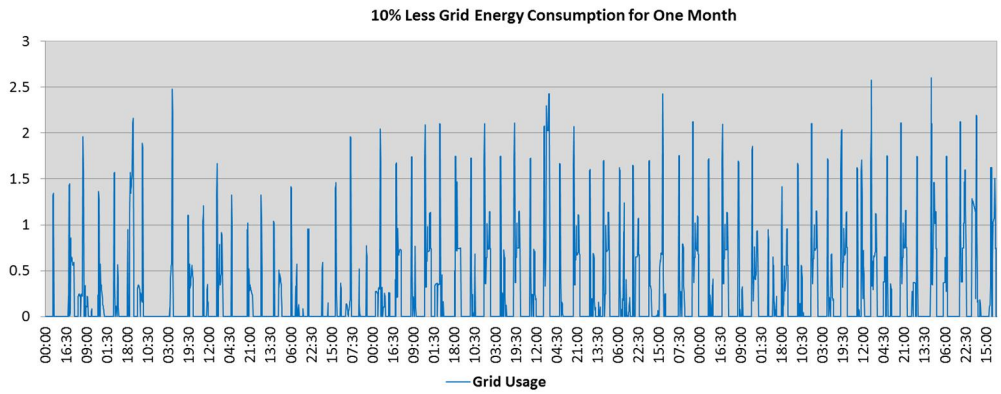


Figure 20. The amount of the grid energy consumption after the optimised schedule for 10% reduction level for 1 month.

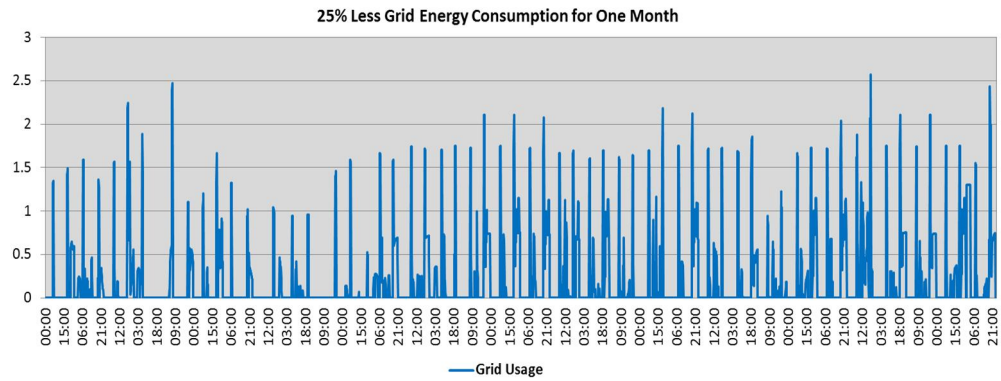


Figure 21. The amount of the grid energy consumption after the optimised schedule for 25% reduction level for 1 month.

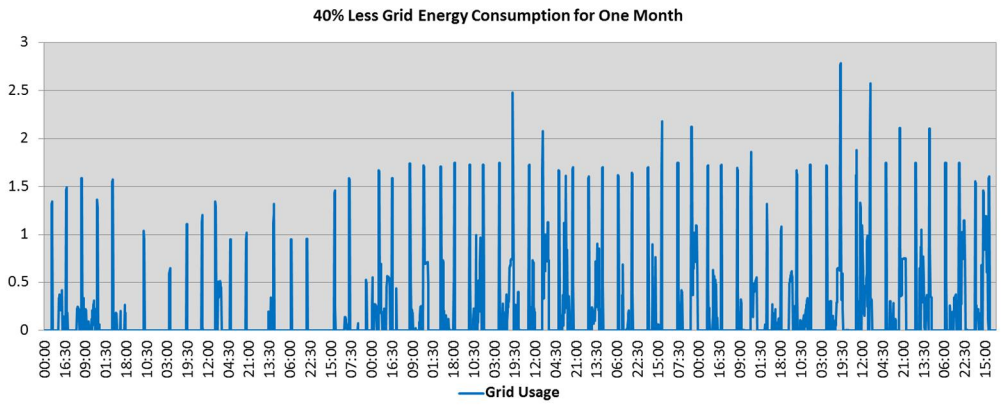


Figure 22. The amount of the grid energy consumption after the optimised schedule for 40% reduction level for 1 month.

The simulation program was run for one month, between 1- 30 September 2014. The grid energy reductions for all three reduction levels have successfully been found using the proposed methods. The process time for optimum reduction levels were 7.2, 19.5 and 58.5 minutes for 10%, 25% and 40% grid energy reduction levels, respectively.

7. Conclusion

In this a paper, an intelligent scheduling algorithm is proposed using Artificial Neural Network and Genetic Algorithm. The proposed scheduling methodology is aimed to reduce grid energy usage by 10%, 25% and 40% respectively, based on weekly generated schedules of appliances on a 15 minutes time increment.

The methodology involves a thermal model of a four bedroom house developed using DesignBuilder. Data set generation was then carried out using EnergyPlus simulation environment. The data set was

used to train an ANN to generate a prediction engine. This prediction engine was then coupled with a GA-based optimization system to find the desired reduction level of grid energy usage.

During the experimentation stage, the best topology of ANN was found after several tests; a Levenberg-Marquardt based learning algorithm with a single hidden layer and 25 neurons was found as the best performing network. The latter was embedded into GA as a prediction engine to compute the fitness function inputs, including renewable energy generation and total demands for each individual appliance, using the states of appliances and weather data information. GA then seeks for the global optimum value of reduced grid usage level using current state of each appliance. All four reduction levels were achieved successfully.

Finally, a Taguchi based sensitivity analysis was conducted to find the most important parameters for GA to reduce the computational time. According to the analysis, the population size is the most important parameter (to reduce the computational time).

There is still room to further stress-test and possibly enhance the proposed methodology by deploying the solution in different building types involving a higher number of appliances, with different computational systems and algorithms. In that respect, future work involves implementing the proposed methodology in an office building. This will require a high computational system to perform the scheduling of a much larger number of appliances [29]. This will be reported in a follow on publication.

The proposed solution is timely as it has the potential to reduce energy demand in "peak" periods while contributing to reducing energy consumption and reliance on grid energy. Building on previous work [30], the authors are in the process of delivering a commercial implementation of the proposed system through a domestic Raspberry Pi controller that embeds the proposed algorithms, enabled by a simple and easy-to-use interface that can be activated from a smart phone.

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