DETERMINING THE BEST LOAD SCHEDULING ALGORITHM FOR A HOME WITH ELECTRICITY SUPPLY FROM GRID AND SOLAR

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Abstract

Improving energy efficiency is becoming increasingly critical to reduce energy consumption and to solve the environmental crisis. The following paper describes a mixed-integer linear programming optimization algorithm to minimize the peak demand at the micro-grid level and to reduce the cost function in a smart home environment. The optimization methods take into account the time-varying electricity price and the varying energy demand peaks to determine the most suitable time to use home appliances. The algorithms are further used to compare the energy cost reduction results with and without the use of renewable resources and more precisely photovoltaic modules. Also, the sizing of a photovoltaic system is implemented to achieve further efficient energy optimization and appliance scheduling. Finally, a cost-benefit analysis is performed on all the scheduling algorithms to determine which is the most cost-effective.

Keywords:

Mixed Integer Linear Programming (MILP), Artificial Neural Networks (ANN), Scheduling, Load Profile, Electricity Company of Ghana (ECG)

1. Introduction

The ever-increasing world population produce exceedingly high energy demand. With issues of global warming and pollution from fossil-based energy supplies at the forefront of public debates and concerns, [1] solar energy –amongst other renewable energy sources – have been well embraced and integrated into society. Residential photovoltaic (PV) installations have helped reduce the number of grid-energy dependents over the past years. However, unutilized excess solar energy produced at peak hours raise a cause for alarm for energy wastage [2].

Successful residential solar-grid energy sharing relies significantly on the effective use of energy in homes and management of constraints associated with pushing power unto the grid through master planning and short-term look-ahead scheduling. The primary focus of this research interest is to investigate how homes can most effectively maximize solar consumption from their residential PV installations; reducing the amount of excess solar energy fed unto the grid and reducing the dependency on much battery storage. The second part of the project would analyze the electricity tariffs trends for the day, to determine the time of the day with the cheapest electricity. Finally, the MILP and ANN algorithms would be used to schedule loads for home consumption and the best in terms of highest reduction in electricity tariffs would be determined.

Background

For a third-world country like Ghana where the utilities provided by the government are not enough for the populace, it is essential that residential PV installations are embraced to reduce the number of grid energy dependents and hence reduce the cost of electricity for homeowners. However, for homeowners, allowing energy produced from PV installations to be pushed unto the grid without generating any revenue from it [3] represents a loss. Therefore, the maximum energy consumption of solar energy in a home would enable homeowners to maximize the benefits of their solar installations while reducing the cost of electricity.

Objectives

The long-term goal of the research is to develop a formalized energy selling structure from PV installation in homes to the grid at high tariff-hours so that households can maximize profit. The objective of the current study is to investigate and analyze the best scheduling algorithm for home appliances between Mixed Integer Linear Programming and Artificial Neural Networks. Significantly, the study has the following sub-objectives:

1. The first part of the research would investigate load consumption patterns of household appliances and classify them into schedulable and "unschedulable" loads.
2. The second part would schedule the loads using MILP and ANN and a comprehensive cost-benefit analysis, which is done to determine the best scheduling algorithm between the two.

Research Methodology

The primary research method for this study is a literature review and modelling with MATLAB. MATLAB is a programming language that has mathematical modelling APIs for creating the ANN and MILP models. In sequence, this study will follow these technical steps:

a. Following the literature review, it will first model a typical household with energy-consuming loads in MATLAB. Also, based on solar irradiation graphs and peak hours of sunlight, a structured load-scheduling system would be implemented.
b. In the second stage of the study, existing tariff rates at different times of the day would be modelled against energy production in the form of the PV home installation.
c. Then, the load in the house would be scheduled to operate at different times of the day. Graphs of scheduled loads with ANN and MILP would be produced.
d. Finally, a cost-benefit analysis of all scheduling algorithms would be done to determine the best scheduling algorithm.

2. Literature Study

This section introduces the concepts of literature on the subject of optimizing solar consumption in PV residential solar installations, using load scheduling. It describes the idea of solar energy optimization, load scheduling, household loads and related studies of electricity tariff variations across different times of the day. It will show the concept of energy maximization and attempt to explain the integration of load scheduling, both against the unscheduled load in a standalone residential PV installation

Solar Energy Optimization

Self-consumption is one of the most effective ways to target the maximum benefit of a residential photovoltaic (PV) installation. When a residential entity consumes his/her generated PV electricity instantaneously, grid-related energy bills decline. By acting as both the producer and the consumer, the "prosumer" can move toward greater future independence from the grid and electricity rate variations.

Of course, achieving the largest drop in demand for electricity from the grid requires coordinating household energy use with the periods of most outstanding availability of PV-generated electricity. Yet, because residential energy use is typically highest in the mornings and evenings, whiles energy availability peaks at midday, load-management is required.

The difference in solar irradiation, across different times of the day, would be reflected in differences in the output of the residential PV module. As a result, wattage-heavy loads can be scheduled to perform at peak hours of sunshine [10]. This scheduling can be achieved by considering the load profiles and load priorities. In the Ghanaian context, an air-conditioner is of high priority at peak sunlight hours, while the lamp may not be needed because of natural light in the home.

Load Scheduling

Load scheduling is a way of managing household loads that enables homeowners to conserve electricity while reducing the cost of electricity bills [11]. One can achieve an efficient load schedule operation when a load profile of all household appliances is created. This profile helps to identify the high wattage loads and allows for appropriate scheduling to reduce the cost of electricity. It enables loads to be classified as schedulable and "unschedulable" based on consumer-behaviour.

Purpose of Load Scheduling

The objective of household load scheduling is to improve its energy and cost-efficiency in line with consumers comfort and constraints. Towards this end, experts consider renewable source availability prediction and day-ahead electricity market price forecasting. Furthermore, they propose dynamic priority allocation and scheduling for appliances aligned with consumers comfort and constraints[12]. Also, to effectively schedule appliances according to real-time weather and electricity market price changes, an algorithm for real-time household load scheduling is required.

Classification and 'Schedulability' of Household Loads

According to the article, '*Real-time Household Load Priority Scheduling Algorithm based on Prediction of Renewable Source Availability*', written by Xin Liu, the loads in a home can be classified as [11]:

A. Real-time energy consumption loads
B. Periodic nonreal-time energy consumption loads
C. Nonperiodic nonreal-time energy consumption loads

These three categories work as follows:

A. Real-time energy consumption loads

The real-time energy consumption loads are directly related to human behaviour. Thus, when a user switches such an appliance on, energy will be consumed instantaneously and continuously until the user turns it off. This behaviour implies that the electricity cost of a real-time energy consuming load is directly related to the duration of its usage [11].

B. Periodic nonreal-time energy consumption loads

The periodic non-real-time energy consumption load is intermittent and fluctuant when it is in use. A typical example of such a load is the air-conditioner. The air-conditioner periodically consumes energy to maintain a desired temperature. The upper and lower bounds practically define the desired temperature, and the air-conditioner begins energy consumption when its temperature is higher than the upper bound. Note that this type of appliance is also related to consumer behaviour because the air-conditioner consumes more energy when the user opens the door in contrast to when it is kept shut [11].

C. Nonperiodic nonreal-time energy consumption loads

Nonperiodic non-real-time energy consumption loads consume energy consistently and may have an operational limit. However, the load may have a deadline to finish running. The pool pump, washing machine and dishwasher belong to the category of devices that are deemed as nonperiodic nonreal-time energy consumptions loads [11].

3. Design and System Requirements

The model should offer a real-time priority scheduling algorithm based on predictions of renewable source availability without compromising the home user's comfort. Home appliances are classified into three categories, according to the Demand Response categorization for load-management. The model should dynamically allocate scheduling slots based on their different energy consumption modes, and the cost of electricity at particular times in the day. Finally, an algorithm for real-time household load scheduling would be proposed.

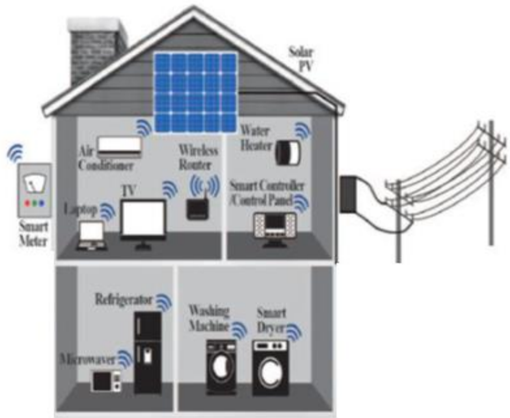


Figure 1 Model Home with home appliances

A model green home is a house with solar panels, which ideally provides energy for all the home appliances during the day. In the evening, the household relies on the national grid for power.

On days with little sunshine, the grid acts as a backup for the home. The load scheduling aims to ensure that

$$consumption - production = 0$$

However, on any rare occasion where there is excess energy produced that cannot be consumed by the home appliances, the excess energy is fed into the grid.

Load Profile for Major Household Appliances

In this paper, for load profiles of appliances, a mid-size home is considered with the following significant electricity consuming appliances: a dishwasher, washing machine with dryer, refrigerators, and air-conditioners. These appliances are considered in this model to study their demand response and optimize their operation over a period of time to minimize the total energy cost and level the load curve.

The Dishwasher

The dishwasher washes rinses and dries in individual cycle sequences, and it takes approximately an hour and 25 minutes to complete all the cycles on average. The dishwasher is classified in the category of a *schedulable load* because its usage does not directly depend on user's comfort.

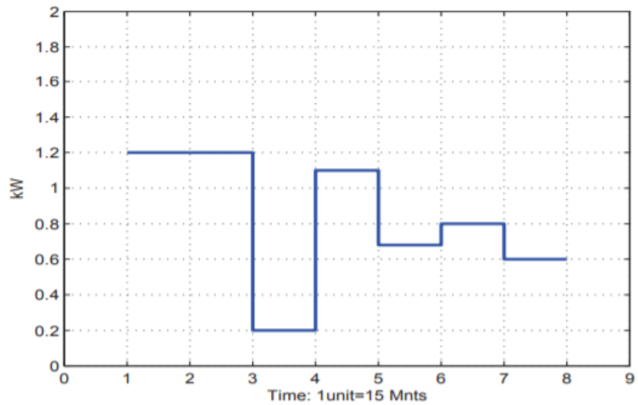


Figure 2 Load profile for dishwasher

Laundry

The laundry machine represents the case of two appliances – washing machine and drying machine – working consequentially. The washing machine, similarly to the dishwasher, has three cycles of operation: wash, rinse, spin, and dry. It takes about two hours to complete all the cycles. Laundry is classified in the category of a *schedulable load*.

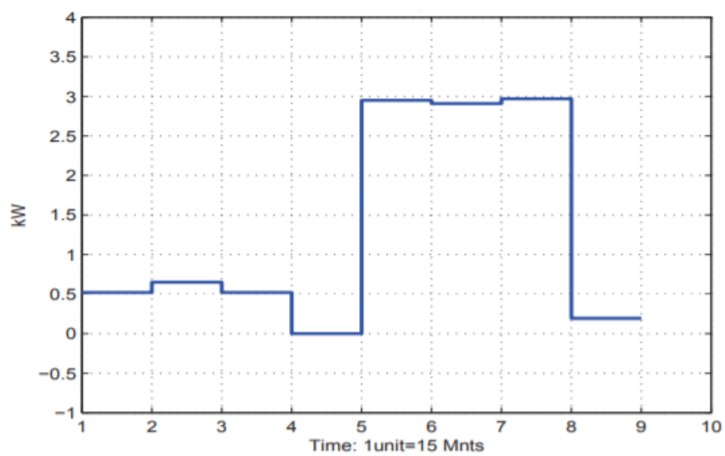


Figure 3 Load Profile for Laundry

Air-conditioner (AC)

The load consumption pattern of the air-conditioner is shown below, represented by a series of square wave trains. When the AC compressor is working, it consumes 0.25 kW. The peaks in Figure 4. show that the AC compressor is working, usually at 0.25kW, and the troughs depict the momentary compressor off-time. AC is classified as a continuous non-shiftable load with a sub-classification as weather-based load.

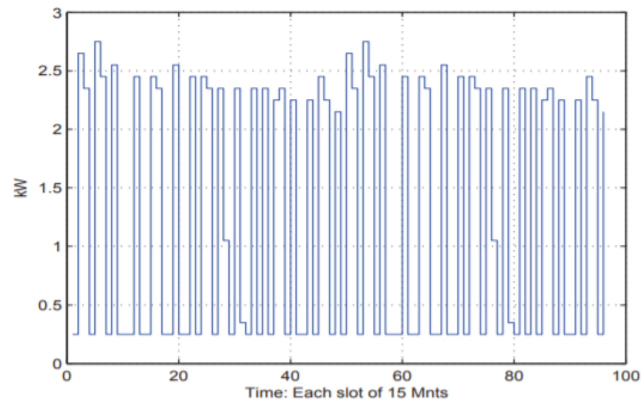


Figure 4 Load profile of air conditioner

Oven

The load profile of the oven is shown in Figure 5. The oven is used both in the morning and evening. For this scenario, the two different times of use show the same energy consumption pattern. The spike represents the energy needed to heat the oven, and the fall is the energy required to maintain the already heated oven in operation. Its electricity consumption is approximately 0.53 kWh. The oven is considered an “unschedulable” load.

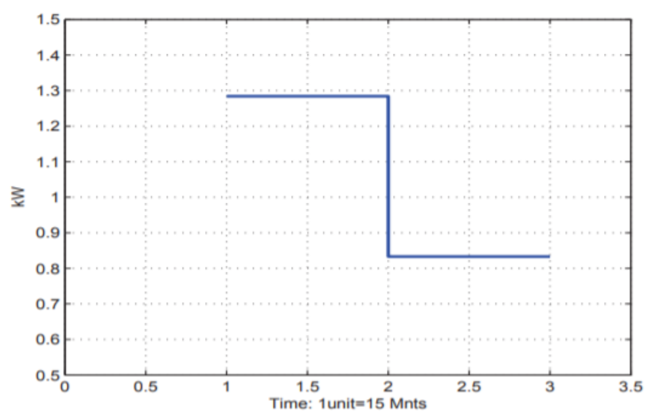


Figure 5 Load Profile for Oven

Solar Power Supply as Micro-Grid

In the model home understudy, there is a solar installation which is conceptualized as a micro-grid of 3kW. The photovoltaic (PV) system is connected to the grid in which the direct current produced by PV panels is converted to alternating current (as per national AC standards) by smart inverters.

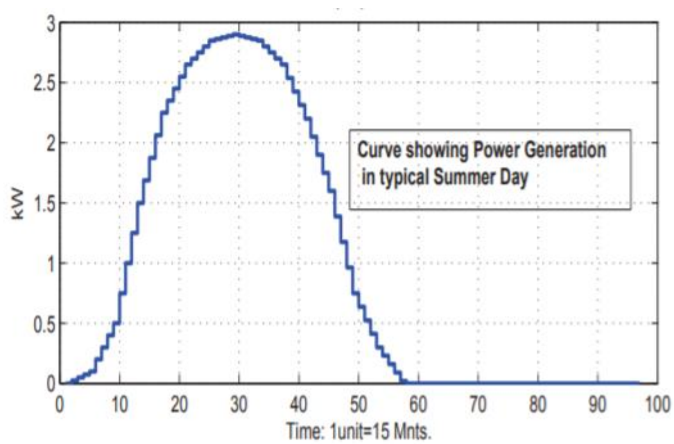


Figure 6 Photovoltaic (PV) Generation Profile

Flowchart of Scheduling Algorithm

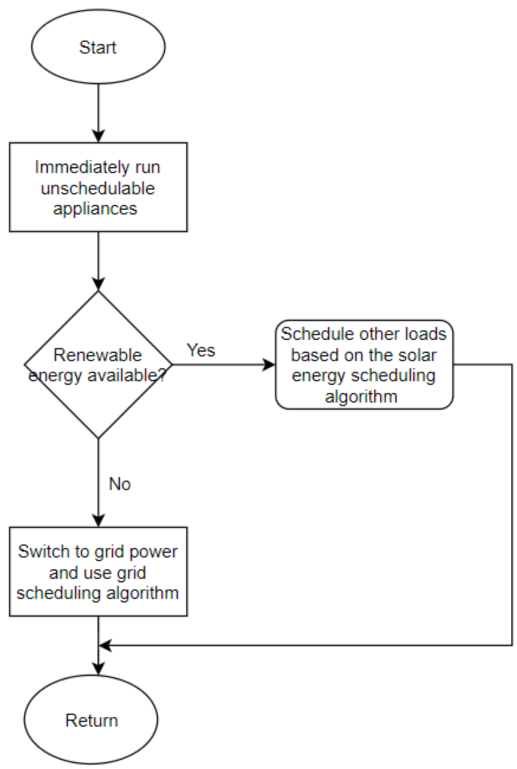


Figure 7 Flow chart illustrating the logic for load scheduling

Duration of Operation

The 24 hours in a day is divided into 24-time slots. Thus, each time slot represents 1 hour. The appliances can be set to start at any time within this time frame and end its cycle of operation before or during the 24th time

Execution Window of each Operation

The home appliances would commence operation at a user-specified time frame. More precisely, for each device, there is a time before the appliance cannot start and an ending time, by which it should have finished running. The following rules apply to each slot; surely not later than the assigned 24 hours. For illustration, results on graphs will show the time slots for each hour of the day given the following constraints:

1. Should an appliance run more than once, then other appliances with non-colliding execution windows could run at the same time with it.

2. If an appliance would not be used at all in a day, then its duration of use should be set to zero.

4. Optimal Load Scheduling Without Solar Energy

To be able to make a better conclusion on the load scheduling with solar energy, a control load scheduling with grid energy only would be modelled in this section. The electricity price fluctuation for every hour is also considered. The optimization scheduling required the use of the MILP in the MATLAB simulation and the addition of scheduling constraints.

Method 1: Mixed Integer Linear Programming

Linear optimization techniques are widely used to solve engineering problems by minimizing or maximizing an objective function. Indeed, many concrete problems can be expressed as a linear program and be efficiently solved by an algorithm. For instance, optimizing the time it takes to go from Ashesi to Accra can be accomplished using linear programming methods. In linear programming, all functions and constraints are related to a variable x with the form

$$a^t x + b$$

There are three main types of linear optimization techniques; namely continuous, integer and mixed-integer. The continuous optimization method deals with real number variables. Algorithms are used to solve this type of optimization to generate iterated values of the variables until a solution is found [12]. The second integer programming optimization is similar to the previous. This is the last mixed-integer linear programming technique that would be used in this paper. The mixed-integer technique uses both discrete and continuous variables while minimizing or maximizing an objective function under a set of constraints [13]. The MILP mathematical equation is given by:

$$max, \min c^T x$$

Let an appliance set G be defined as $G = \{1,2,3, \dots , n\}$, where n represents the total number of time-shiftable appliances, and let a vector pi,j – which represents the power consumption of the ith appliance in a time slot j $\in H = \{1, \dots ,24\}$ – be defined by the equation below.

$$pi.j = (pi, 1, pi, 2 \dots \dots \dots ., pi, 24) \in R24, for\ i \in G \ \& \ J \in H$$

The power consumption formula pi,j has to be included within a specific range defined by the standby power α and the maximum working power β. The standby power, also called vampire power, refers to the small amount of electric power consumed by the appliances while they are switched off. The maximum working power defines the maximum energy that an appliance can consume over a period of time. The consumption constraint is formulated in the equation below:

$$\alpha i,j \leq pi,j \leq \beta i,j \ \ \forall j \ \& \ i \in G$$

The electricity price (tariff) changes over a time of 24 hours according to the Electricity Company of Ghana's index on tariffs for residential usage. The defined electricity cost is given by a $1 * 24$ matrix such as:
[0.9,0.8,0.8,0.9,1,1,0.8,1,0.1,0.1,0.1,0.1,0.1,0.1,0.9,0.1,0.2,0.1,0.2,0.1,0.2,0.1,0.2,0.1]

Let the summation denoted as $\sum_{i \in G} p_{i,j}$ represent the non-negative required power of all five appliances for a time slot j, where $n = 5$ and $G = \{1,2,3,4,5\}$, since only five appliances are considered. The objective function, which represents the residential electricity bill for a day in our case, is given by multiplying the electricity cost that varies according to the fluctuation method used by the appliances' power consumption as seen in equation below.

$$\sum_{j \in H} cost_{j,s} \sum_{i \in G} p_{i,j} = \sum_{i \in G} cost_{j,s}{}^T p_i$$

Where the value of $s = \{1,2,3\}$ represents which method of electric price fluctuation is used. The optimization objective based on the MILP method can be formulated as follow:

$\sum_{iEG} cost_{j.s^T}\, pi$. The optimization function is given by a 5*24 matrix as seen in the equation below.

$$\sum\nolimits_{iEG} cost_{j.3^T} * pi = \begin{matrix} cost_{1.3} \\ cost_{2.3} \\ . \\ . \\ . \\ cost_{24.3} \end{matrix} * \begin{bmatrix} p_{1,1} & p_{1,2} & p_{1,3} & . & . & p_{1,24} \\ p_{2,1} & p_{2,2} & p_{2,3} & . & . & p_{2,24} \\ p_{3,1} & p_{2,3} & p_{3,3} & . & . & p_{3,24} \\ p_{4,1} & p_{2,4} & p_{4,3} & . & . & p_{4,24} \\ p_{5,1} & p_{2,5} & p_{5,3} & . & . & p_{5,24} \end{bmatrix}$$

$$= \begin{bmatrix} cost_{1,3} * p_{1,1} & cost_{2,3} * p_{1,2} & cost_{3,3} * p_{1,3} & . & . & cost_{24,3} * p_{1,24} \\ cost_{1,3} * p_{2,1} & cost_{2,3} * p_{2,2} & cost_{3,3} * p_{2,3} & . & . & cost_{24,3} * p_{2,24} \\ cost_{1,3} * p_{3,1} & cost_{2,3} * p_{3,2} & cost_{3,3} * p_{3,3} & . & . & cost_{24,3} * p_{3,24} \\ cost_{1,3} * p_{4,1} & cost_{2,3} * p_{4,2} & cost_{3,3} * p_{4,3} & . & . & cost_{24,3} * p_{4,24} \\ cost_{1,3} * p_{5,1} & cost_{2,3} * p_{5,2} & cost_{3,3} * p_{5,3} & . & . & cost_{24,3} * p_{5,24} \end{bmatrix}$$

To implement the MILP model in MATLAB, the solver "intlinprog" is used and is based on the following arguments: f, intcon,A, b, Aeq, beq, lb, ub) [14]. The vector f represents the coefficient vector, intcon refers to the vector of integer constraints, A is the linear inequality matrix, Aeq is the linear equality constraint matrix, beq is the linear equality constraint vector and lb and ub refers to the lower and upper bounds.

Below is the general form of the MILP method in Matlab.

$$min f^T x \text{ subject to } \begin{cases} x(intcon) are\ integers \\ A.x \leq b \\ Aeq.x = beq \\ lb \leq x \leq ub \end{cases}$$

Table 1 Home appliances and their corresponding scheduling time

Appliances	**Type**	**Daily Power**	**Energy consumption Patterns**
Oven	Time and power shiftable	1100 W	Preferred hours: 7am-9am: 300Wh,10am: 200Wh
Washing Machine	Time and power shiftable	500 W	Preferred hours: 12pm: 500Wh
Iron	Time and power shiftable	400 W	Preferred hours: 9am: 500Wh, 1pm: 300Wh
Dishwasher	Time and power shiftable	400 W	Preferred hour: 12pm-2pm: 400W

Heater	Time and power shiftable	800 W	Preferred hour: 9am: 500Wh, 2pm: 300Wh

Based on the power consumption pattern given in the table, the following scheduling graph in Figure 8 was obtained using Matlab.

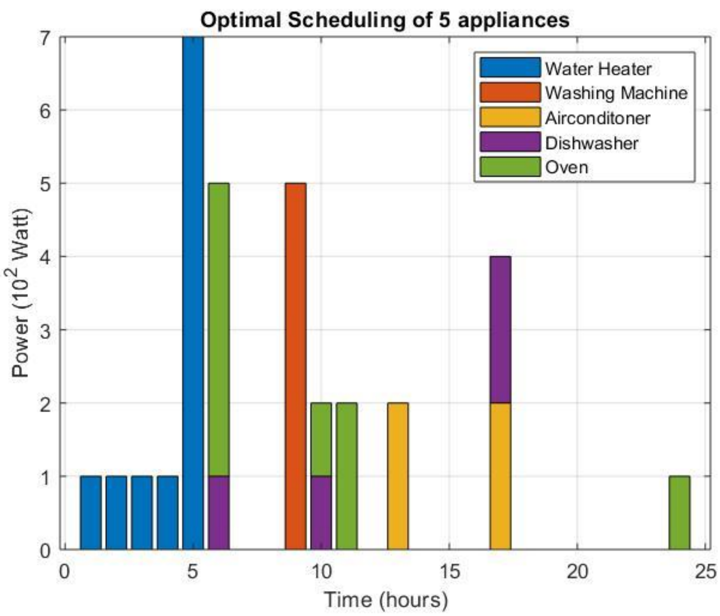


Figure 8 MILP scheduled loads without solar

Method 2: Artificial Neural Networks

From Figure 9, the inputs are the availability of grid supply, the rating of the device, and the user's want. The user's want is an arbitrary value between 0 and 5, with five being the highest. If the user's want is 3 and above, the load would be scheduled for grid consumption. If the user's want of the device at a time is less than 3, then the load is not scheduled at all.

Contrarily, the ANN outputs are the signals determining consumption from the grid, or consumption from the solar system or no consumption at all. The ANN parameters are shown in the table below.

Table 2 ANN Parameters

Parameters	**Value**
Number of inputs	5
Number of outputs	5
Number of hidden layer	2

Number of neurons in hidden layer N1	18
Number of neurons in hidden layer N2	20
Number of iterations	1000
Learning rate	0.6175
Regression Coefficient	0.99518

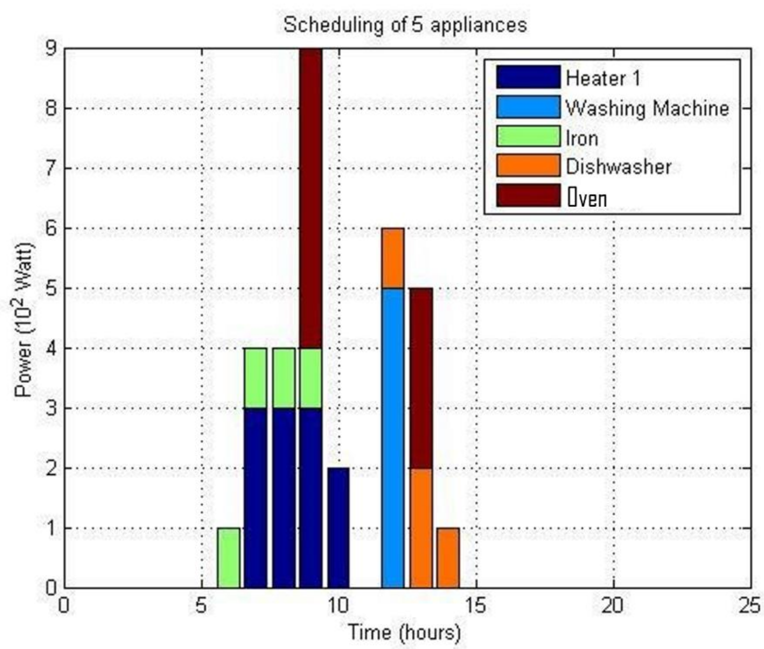


Figure 9 ANN scheduled loads without solar

5. Optimal Load Scheduling with Solar Energy

Method 1: Mixed Integer Linear Programming

This section focuses on the ultimate scheduling of household loads, which involves the consumption of solar energy and the grid. The same approach from section 4 was used; however, here the solar energy produced was considered. Data of solar irradiance for Ghana was downloaded from NASA's website for an average day in May. The factors of my MILP model depend on:

1. User Want,
2. Power Rating of the device,
3. Sunshine availability

The user want is an arbitrary number between 0 and 5, with 5 being the highest. If sunshine is available, with a user want of 3 and above, and the Power Rating of the device is less than the solar energy produced, the load would be scheduled for the solar energy to be consumed. If all conditions remain constant, however, the power rating of the device is higher than the solar energy produced.

Under these conditions, the load is scheduled for grid. If the user want of the device is less than 3, then the load is not scheduled at all.

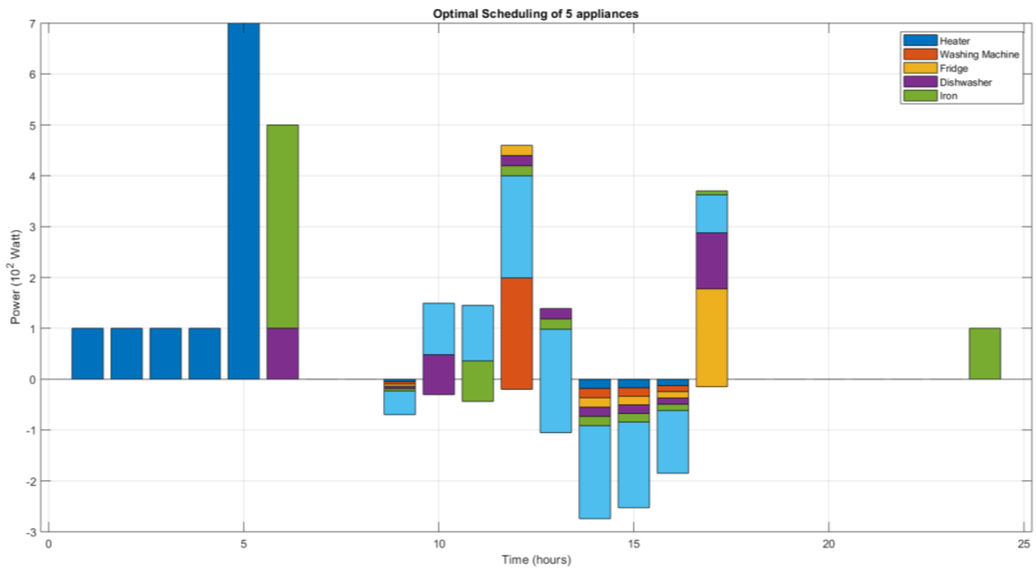


Figure 10 MILP scheduled loads with solar

Method 2: Artificial Neural Networks

This section focuses on the ultimate load scheduling of household loads, which involves the consumption of solar energy and the grid, using Artificial Neural Networks. The same approach from section 4; here, however, the solar energy produced was considered. Data of solar irradiance data for Ghana was downloaded from NASA's website for an average day in May. This makes the factors for my ANN network change from four to five, with the availability of solar energy included. Household loads were scheduled according to Table 1 in Section 4.

The parameters are Sunshine Intensity, User Want, and Power Rating of the device

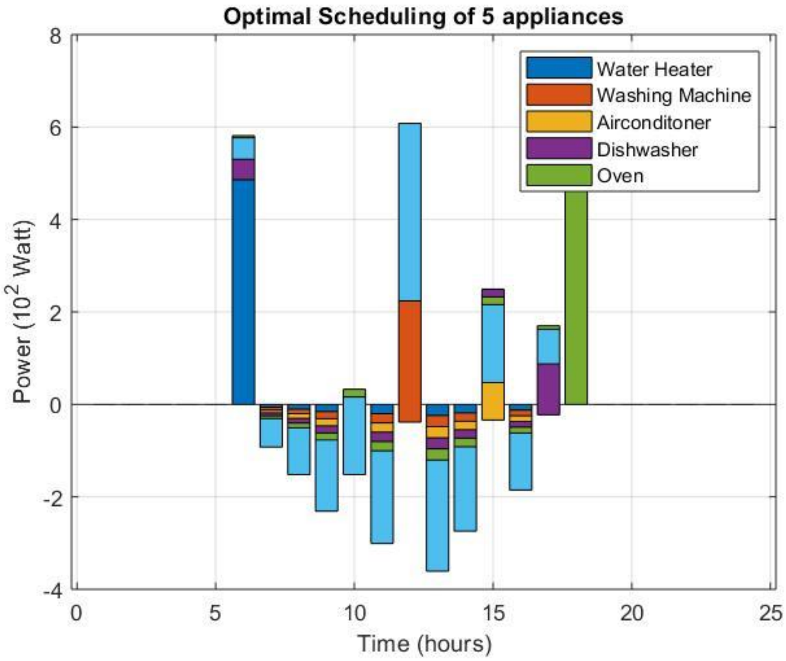


Figure 11 ANN scheduled loads without solar

Section 6 Load Consumption Without Optimization

A control of the load consumption in a home without any form of scheduling is illustrated below with the normal energy consumption patterns in a home.

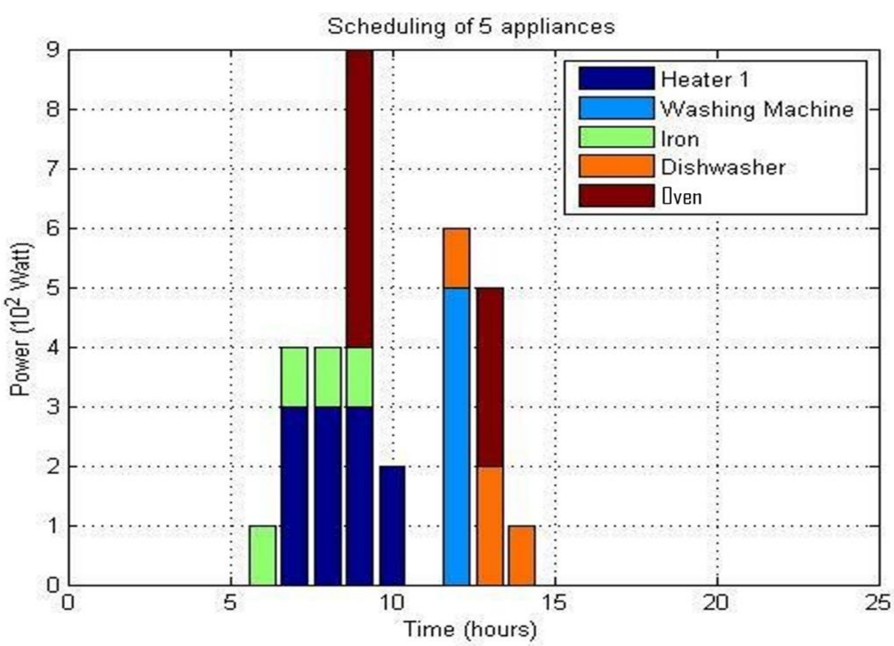


Figure 12 Load consumption without scheduling

1. Cost Benefit Analysis for the Best Optimization Algorithm

After having compared the different pricing methods and their relative cost, it is important to compare the costs associated with the different optimization methods. Three different approaches are compared, namely: optimal scheduling, PV optimal scheduling and optimization, which are based on the assumption that the surplus of solar energy can be sold back to the grid. The percentage reduction of the daily cost is formulated for each method with respect to the scheduling plan without optimization. We assume that the selling price of the solar energy back to the grid is equal to the electricity cost value for a constant pricing method. A summary of the different costs with respect to each pricing and optimization method is given in the tables below.

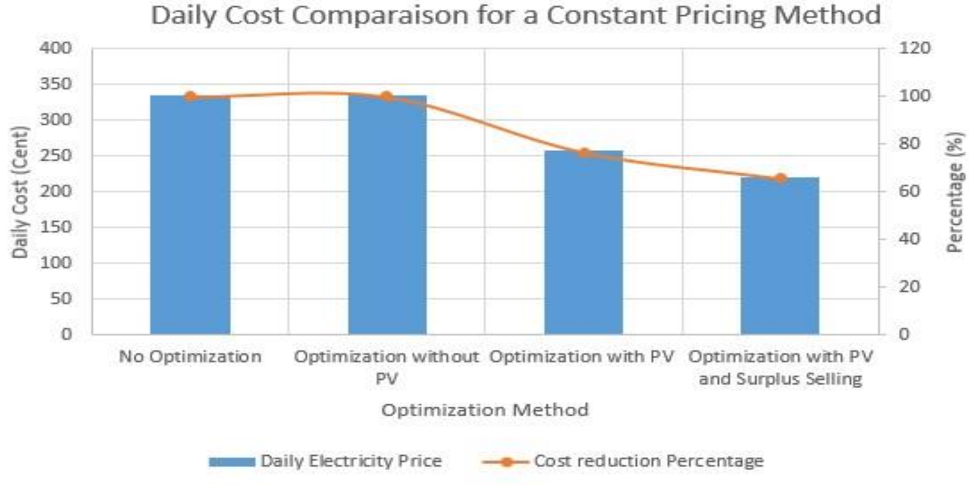
The percentage change of the cost from one optimization approach to another and with respect to each billing method can be calculated using equation (15).

$$percentage\ change = \frac{cost_{i+1} - cost_i}{cost_i}$$

The percentage change can then be derived and gives an idea about the most cost-effective pricing method.

Scheduling With Solar Energy		
Appliances	**Cost without Optimization ($)**	**Cost with PV Optimization ($)**
Heater	0.099	0.069
Washing Machine	0.055	0.049
Iron	0.032	0.03
Dishwasher	0.048	0.048
Oven	0.064	0.045
Total	0.298	0.24

Daily Electricity Cost of the Appliances ($)				
Pricing / Optimization Method	No Optimization	Optimization without PV	Optimization with PV	Optimization with PV and Energy selling
Daily Electricity Cost	0.336	0.336	0.257	0.221



The cost analysis shows that the optimal scheduling of electric appliances reduces the cost and proves to be effective. It can be concluded that the most cost-effective method is the bi-daily pricing method because the savings can reach 47.1%, even if its initial cost without optimization is higher.

2. Conclusion and Future Works

Reducing the environmental impact of energy generation and responding effectively to the energy demand is crucial toward achieving sustainability. The purpose of this capstone project was to identify the best algorithm for household load scheduling to reduce the cost of electricity bills in the home. Two optimization method – the Mixed Integer Linear Programming and Artificial Neural Networks – were considered. The scheduling optimizations were implemented respectively according to the availability of solar energy. Moreover, the optimization part was divided into two main sections, namely optimizing without solar energy resources and optimizing in conjunction with solar energy. The simulation results showed that optimizing the scheduling of the electric appliances could reduce the bill by up to 38%, when no renewable energy is considered and by up to 47% when it is considered with renewable energy.

Finally, the results obtained demonstrated the efficiency of the ANN to achieve the appliances optimal scheduling, as against the efficiency of the MILP. In this project, the utility function, which represent the satisfaction level of the consumer, was not considered. The algorithm and optimization method could be enhanced by taking into account the user's time of preference to use a particular appliance.

Acknowledgments

I would like to express my deepest gratitude and special thanks to Mr. Richard Akparigbo for his excellent supervision. My sincere thanks are also expressed to Mr. Kofi Adu-Larbi for his input and for encouraging me to work on the ANN algorithm for this project. I extend my gratitude to Ashesi University and the Electrical and Electronics Engineering Department for giving me the opportunity to work on this project.

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