

Application of a Modified Perceptron Learning Algorithm to Monitoring and Control

Mathews Chibuluma
School of Graduate Studies
Copperbelt University
Kitwe, Zambia
mathews421@gmail.com

Josephat Kalezhi
School of Mathematics and Natural Sciences
Copperbelt University
Kitwe, Zambia
kalezhi@cbu.ac.zm

Abstract—Zambia has faced economic challenges since the beginning of 2015. The economy has come under strain in 2015 due to climate change. As a result, the water levels in the main source of electricity, the Kariba Dam, have dropped. This has caused a critical power deficit. This problem has negatively affected the economy and has further resulted in reduced GDP for the country. Solar energy is a possible alternative to mitigate this crisis. Despite government efforts in embracing renewable solar energy, the current photovoltaic (PV) systems require additional mechanisms to monitor and control individual appliances. In this paper, we propose a system that uses a modified perceptron-learning algorithm to control and monitor individual appliances. The proposed system is capable of finding the best combination of household appliances that optimizes user priorities and limits the power consumed from the grid. The algorithm has also been shown to be computationally efficient.

Keywords—Control; Monitoring; Perceptron; Photovoltaics; Information and Communications Technology (ICT)

I. INTRODUCTION

Zambia faces its toughest economic challenges in at least a decade. The economy has come under strain in 2015 as external factors and domestic pressures have intensified [1]. A report by World Bank indicates that growth of the economy has dropped beneath 4% from 2015 onwards for the first time since 2000 [1]. According to the report [1], external factors that affect the economy include slower regional and global growth. This is caused mainly by a reduction of China's purchasing power from 40%. There are a number of domestic pressures that have affected the economy [1]. Firstly, a power crisis has affected almost all sectors of the economy. Secondly, repeat fiscal deficits have led to a reduction in investor confidence. Thirdly, low and unpredictable rainfall patterns have reduced the agricultural incomes of 62% of the population.

The majority of Zambia's electricity is hydro generated [2]. The energy generated was enough for more than 30 years [2]. However, in May 2015, Southern Africa experienced a severe drought resulting in low water levels in the Kariba Dam, the main source of electricity. This necessitated the national power utility company to introduce loadshedding. Due to the high-energy demand, the country has considered investing in alternative sources of clean energy. Solar energy is a possible alternative [2].

In this paper, a system that applies a modified perceptron-learning algorithm to monitor and control appliances is proposed. The system then determines an optimum combination of the appliances that allows for the maximum and efficient usage of the photovoltaic (PV) system.

The concept behind this approach is to enable the user manage their own load. This is in line with the concept of a nano-grid where loads in a building are managed using controllers and gateways [3]. One purpose of a controller is to manage the power supply to loads. The gateway receives power consumption of the loads from the power meters.

This paper is organized as follows: Section II reviews smart monitoring and control systems in place. Section III gives the model description of the proposed approach. Section IV gives a load analysis of an average household. The modified perceptron-learning algorithm is described in Section V. In Section VI, the details on how appliances are monitored and controlled are provided. The results of the work are provided in Section VII. The cost benefits of the system are given in Section VIII. Lastly but not the least is the conclusion in Section IX.

II. REVIEW OF SMART MONITORING AND CONTROL SYSTEMS

There are a number of approaches for addressing energy shortage. Barbato et al. [4] proposed a home energy management system for individual residential units and small communities of domestic users. The functionalities of the system included profiling, electricity generation forecast, energy load, and storage optimization. In their work, they used a linear regression model to predict the photovoltaic (PV) panel production. They also used a stochastic method to forecast home appliances usage. An optimization model was used to optimize management of electricity for residential users in order to minimize bills.

In a similar approach Kashale et al. [5] applied the Best First Search algorithm to demand control in PV systems. They developed a model that uses heuristic search methods to determine the best combination of household appliances that optimizes user priorities and aims to limit the power consumed from the national grid.

In another related research, Nathangashree et al. [6] proposed a system that monitors the status of PV panels using

Global System for Mobile Communication (GSM) technology. The status of the PV system, whether normal or abnormal, was obtained using a Parallel Line Communication Module (PLC). This was achieved using GSM messaging technology.

Paulauskaite et al. [7] proposed a system that implements the use of Artificial Neural Networks in an intelligent control based system. The system was capable of learning and adapting to the user's behavior and thereby providing intelligent lighting.

Bai and Hung [8] introduced a remote power control and current measurement system for electric outlets. The system was based on an embedded board and a Zigbee communication network. In this system, the measurement circuit sensed the current of appliances and then sent these to a server module through Zigbee. The embedded board analyzed the current and voltage readings of appliances. In a case where the readings caused an overload, the circuit breaker was informed of this.

From the above literature, application of ICT to monitor and control energy consumption is of vital essence to address the current energy deficit. In comparison to the reviewed systems the proposed system uses a new algorithm to monitor and control individual appliances based on power coming from a PV system. The system is able to learn using a modified perceptron-learning algorithm, and optimize a PV system.

III. METHOD DESCRIPTION OF THE PROPOSED APPROACH

In this work, the problem of monitoring and controlling appliances based on demand is addressed. The system monitors power supply levels from the PV system and the power consumption of each appliance connected to the PV system. Based on the available power supply level and demand, the system controls appliances by identifying appliances to be switched on and alerts the user.

The identification of appliances to be switched on is carried out using a modified perceptron-learning algorithm. The original perceptron-learning algorithm, used in Artificial Intelligence, appears in [9]. The perceptron is an artificial neuron that can be found in neural networks. The inputs to the algorithm are appliance power ratings and power supply level from the PV system. The algorithm then selects the optimum combination of appliances that can be powered by the PV system. It is possible for the user to set preferences for required appliances that should not be switched off. Though the time constraint was not included, it is possible to incorporate this feature in the system.

Figure 1 shows the architecture of the overall system. Each appliance is connected to a wireless power meter that reads the appliance power consumption. The wireless power meter then sends the power readings to an embedded server in a wireless energy gateway. This embedded server then sends the readings to a server in the computing node via a WIFI link. The communication between the two servers is achieved using TCP sockets. The server in the computing node sends the readings to the modified perceptron-learning algorithm. The power supply readings from the PV system are also read and supplied to the algorithm. The PV system comprises the inverter, battery

bank and the PV array. The algorithm then runs and identifies appliances to be switched on.

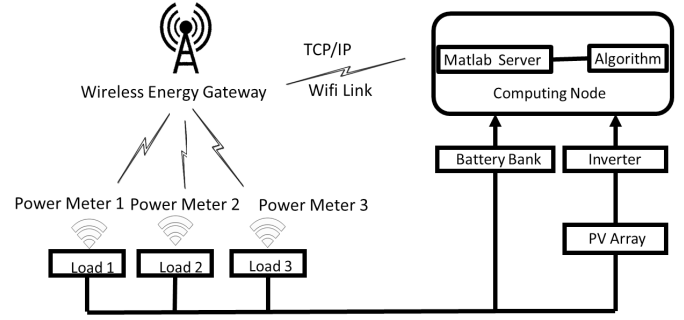


Fig. 1. System architecture showing how the components are connected. Each wireless power meter communicates with a wireless energy gateway which in turn communicates with server in a computing node. The server communicates with the modified perceptron algorithm. The computing node also reads power supply levels from the PV system.

IV. LOAD ANALYSIS FOR AN AVERAGE HOUSEHOLD

Before implementing a renewable system, load analysis is firstly carried out [10]. In this task, appliances that are to be connected to the PV system are identified. In this study, appliances used in an average household were considered as shown in Table I [5,10].

TABLE I. LOW POWER APPLIANCES AND THEIR RATINGS [5,10]

Appliance	Quantity	Power Ratings (W)	Hours of Use/Day
Laptop	1	100	6
Flood Light	1	100	6
Television	1	300	10
Ceiling Fan	1	100	5
Home Lighting	1	14	5
Modem	1	40	6
Cell phone Charger	1	8	2
Doorbell	1	5	0.16

V. MODIFIED PERCEPTRON-LEARNING ALGORITHM

A perceptron forms the basis of artificial neural networks [9]. These networks are employed in Artificial Intelligence to solve a number of problems [9]. A perceptron is an artificial neuron and has the following components [9]:

- Input signals. These comprise data that comes from the environment or from other neurons. In this work, input signals represented power ratings of appliances.
- Set of real valued weights. The weights determine the strengths of connections. In this work, weights were either 0 or 1, which indicates whether an appliance was to be switched on or off.
- Activation level. This quantity is obtained by computing the weighted sum of inputs. The activation level in this work represented the total power consumption of appliances.

- iv. Threshold function. This function determines the output state of the neuron. In this work, the threshold function represented the power supply from the PV system.

There are several learning algorithms that can be used by artificial neural networks and one of these is a perceptron-learning algorithm [9]. This algorithm was modified in this work so that it can be used to monitor and control household appliances. Figure 2 illustrates the modified perceptron-learning algorithm.

```

1. Begin
2. Inputs: Appliances1, Appliances2, ... % initialize
3. Weights: Set everything to 1 since we want to connect all
4. Assume threshold is given
5. calculate activation function,  $\sum \text{power}[i] \times \text{weight}[i]$ 
6. if activation function <= threshold
7.     switch all appliances.
8.     stop
9. else
10.    sort appliance power consumption in ascending order
11.    set all weights, weight[] to zero
12.    set first weight, weight[1] = 1
13.    start = true
14.    i = 1
15.    while (start = true) and (i <= length(weight[])) do
16.        begin
17.            calculate activation function,  $\sum \text{power}[i] \times \text{weight}[i]$ 
18.            if activation function <= threshold
19.                i = i + 1
20.                weight[i] = 1
21.            else
22.                start = false
23.                weight[i] = 0
24.            end
25.        end
26.    end
    output weight[]

```

Fig. 2. The modified perceptron-learning algorithm.

The aim of the algorithm is to adjust the weights such that the total power consumption of appliances to be connected to the PV system does not exceed the power supply.

In this algorithm, the weights of all household appliances to be connected are initially set to 1. The activation level is then computed. Following this, the activation level is compared to the threshold function. If the threshold function is greater than the activation level, the artificial neuron fires and the inputs reported. On the other hand, if the activation level is greater than the threshold, the following steps are taken. Inputs are reordered according to the power consumption and all weights are set to 0. The weight of the appliance with the smallest power consumption is set to 1. The activation level is computed and compared to the threshold function. If the activation level is less, the weight of the next appliance with the smallest power consumption is set to 1. This process continues provided the activation level is less than the threshold function and there are more appliances to be connected.

It is possible that certain appliances are preferred compared to others. In this case, these appliances are examined

individually in order of priority. If the total power consumption of these priority appliances is less than the threshold, the new threshold on remaining appliances is computed. The new threshold is obtained by subtracting the sum of the power consumption of these priority appliances from the initial threshold. The algorithm then selects the remaining appliances as described before.

If the total power consumption of the combined priority appliances is greater than the threshold, only priority appliances whose total power consumption does not exceed the power supply are chosen.

VI. MONITORING AND CONTROL OF APPLIANCES

A function was written in MATLAB to implement the modified perceptron-learning algorithm. Another MATLAB function was written to communicate with the wireless energy gateway. This second function, referred to as a MATLAB server, used sockets to communicate with the embedded server in the wireless energy gateway over a TCP/IP link. Wireless power meters and the wireless energy gateway were obtained from Sailwider [11]. The embedded server understood commands in Extensible Markup Language (XML) format [11]. The Application Programming Interface (API) document of the wireless energy gateway provided an extensive list of commands to monitor and control appliances connected to wireless power meters [11].

To communicate with the embedded server, the MATLAB server first creates a socket. This is followed by accepting the next connection request coming from the embedded server. In the next step, the MATLAB server sends a command to the embedded server. The embedded server then interacts with wireless power meters and sends a response to the MATLAB server. The socket is then closed.

A script was written in MATLAB that calls the MATLAB server requesting for information from the embedded server in the wireless energy gateway. After obtaining all the needed information, this script calls the modified perceptron-learning function. The output of the modified perceptron-learning function is used to control appliances.

VII. RESULTS

To demonstrate how this algorithm works, the appliances given in Table 1 were considered. A MATLAB script captured appliance details obtained from the wireless power meters. The details relevant to the research were appliance name, power ratings and total power coming from the PV system. This script was used to call the function that runs the algorithm. The modified perceptron-learning algorithm returned a vector of weights. From this vector of weights, the corresponding optimal combination of appliances that make maximum use of the PV system was identified. In addition, the script alerts the user by providing more information as regards to appliances that need to be switched off.

For demonstration purposes, the PV array was assumed to consist of two solar modules each rated at 170 Watts [5,10], giving a total power output in this case also called threshold of 340 Watts.

The power consumption of the gateway when it was switched on and sending data was measured using a wireless power meter. The reading from the wireless power meter was negligible which meant that the power consumption of the gateway could be neglected. Similarly, the power consumption of a wireless power meter when sending data was also measured and was negligible. Therefore the power consumption of the WIFI network was not an issue.

Table II shows possible combinations as given by the algorithm. The cross symbol (X) denotes an appliance that the algorithm has selected and is ready to be turned on.

Combination 1, 2 or 3 are generated when there is no user preference given. The system sorts the appliances in ascending order and finds the maximum combination of the appliances less than the threshold or total PV array output. This gives a total of 267W. Combinations 4-8 in Table II are also possible, but these can arise if a user sets priorities. Results shown in Table II are similar to those obtained by Kashale et al. [5].

TABLE II. POSSIBLE COMBINATIONS OF HOUSEHOLD APPLIANCES IN TABLE I BASED ON PRIORITY

2 x 170 Watts PV modules = 340 W	Appliance ^a							
	A 5W	B 8W	C 14W	D 40 W	E 100W	F 100W	G 100 W	H 300W
Combination 1	X	X	X	X	X	X		
Combination 2	X	X	X	X	X		X	
Combination 3	X	X	X	X		X	X	
Combination 4	X	X	X					X
Combination 5				X				X
Combination 6	X	X	X			X	X	
Combination 7	X	X	X		X	X	X	
Combination 8				X	X	X	X	

a. Appliances are labeled as follows: A=Doorbell, B=Cell phone charger, C=Home lighting, D=Modem, E=Laptop, F=Flood light, G=Ceiling fan and H= Television.

The performance of the algorithm was evaluated against two other methods, the Best First Search Algorithm and the Breadth First Search algorithm [5]. Figure 3 compares the performance of these algorithms. The modified perceptron learning-algorithm performs much better than the others.

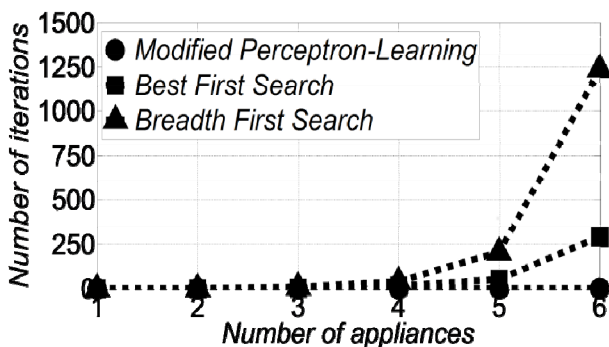


Fig. 3. Number of iterations required to find optimum appliance combinations for several appliances using Best First Search, Breadth First Search [5] and modified perceptron-learning algorithm.

VIII. COST BENEFITS OF THE SYSTEM

The system provides a number of benefits to both the consumers and the utility companies in that grid dependency by domestic consumers will be kept at a minimum and the power that will be generated from the utility companies can be channeled to more energy demanding sectors of the economy such as manufacturing and mining. The remaining small power percentage can be channeled to domestic consumers, as most of them will be dependent on solar energy.

Other cost benefits of the system include:

1. Increased savings on the part of domestic consumers as this will reduce on the bills paid to utility companies and ensure a continuous supply of power.
2. The system will derive from the use of clean, pure energy from the sun hence combating on a global challenge of dependency of fossil fuels that emit harmful gases in the atmosphere.
3. The system will reduce on the effects of load shedding, as most consumers will be dependent on solar energy.
4. The system will provide energy independence to the consumers, as they will be able to manage their own energy produced from the PV system.

The cost of the WIFI network may be a limiting factor for a large population. However, ICT access is growing and the prices of ICT equipment are falling. Some solutions involve providing support for building local ICT equipment and making more affordable devices such as gateways and wireless power meters available.

IX. CONCLUSION

A system has been implemented that uses a modified perceptron-learning algorithm to monitor and control appliances. The algorithm is able to learn the components of a PV system and be able to find the optimum combination of appliances. The system is better than both the Best First search and Breadth First search algorithm in terms of performance at finding the optimum combination of the appliances.

The system is able to monitor and give more control of their PV system and limit the dependency on the grid. The other benefits are increased savings on the part of the user, slowing the effects of global warming by diversifying into renewable energy resources. Lastly, the system helps reducing the effects of load shedding by providing a continuous supply of power.

ACKNOWLEDGMENT

The authors would like to express sincere gratitude to the Computer Science Department at Copperbelt University for acquiring the necessary tools needed to test the algorithm on.

REFERENCES

- [1] Smith, Gregory, Chinzara, Zivanemoyo, Kapika, J Mwelwa, Elahi and Raihan, "Powering the Zambian Economy," vol 1(101704), pp. 1-2, December 2015

- [2] SolarAid. (2015, Sept.). Solar is the solution to Zambia's energy shortage. [Online]. Available: <https://solar-aid.org/solar-is-the-solution-to-zambia-s-energy-shortage/>
- [3] B. Nordman, Nanogrids: Evolving our electricity systems from the bottom up. In Darnell Green Building Power Forum, May 2010
- [4] A Barbato, A Capone, G Carello, M Delfanti, D Falabretti, M Merlo, "A framework for home energy management and its experimental validation," . *Energy Efficiency* (2014) 7: 1013. doi:10.1007/s12053-014-9269-3
- [5] K. Chimanga, P. Mumba, J. Kalezhi, "Application of Best First Search Algorithm to Demand Control" in Proc. 2016 IEEE Power and Energy Society Conference, 2016, pp. 51-55.
- [6] D. Nathangashree, L. Ramachandran, S. SenthilKumar, R.LakshmiRekha, "PLC Based Smart Monitoring System for Photovoltaic Panel Using GSM Technology" in Proc. 2016 IJARECE, vol 5, No. 2
- [7] A. Paulauskaite-Taraseviciene, N. Morkevicius, A. Janaviciute, A. Liutkevicius, A. Vrubliauskas, E. Kazanavicius, "The Usage of Artificial Neural Networks for Intelligent Lighting Control Based on Resident's Behavioural Pattern" in Proc. 2015 ELEKTRONIKA IR ELEKTROTECHNIKA, vol. 21, No. 2
- [8] Y. Bai, C. Hung, "Remote Power On/Off Control and Current Measurement for Home Electric Outlets Based on a Low-Power Embedded Board and ZigBee Communication," unpublished. [Online]. Available: https://www.researchgate.net/profile/Nerijus_Morkevicius/publication/275260765_The_Usage_of_Artificial_Neural_Networks_for_Intelligent_Lighting_Control_Based_on_Resident's_Behavioural_Pattern/links/561756de08ae839f3c7d853c.pdf?origin=publication_list
- [9] G. F. Luger, "Artificial Intelligence: Structures and Strategies for Complex problem solving" 5th ed, Addison Wesley, 2005, pp. 456-459
- [10] Mwinga Cheelo, "Zambia's Sole Source of Alternative Energy Information," *Alternative Energy Magazine*, Vol 1, No.2, Published by Alternative Energy Limited, Lusaka-Zambia.
- [11] SailWider. Manufacturer of Smart Electricity Energy Saving Monitor and Control System. [Online]. Available: <http://www.sailwider-smartpower.com/>