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LOAD SCHEDULING FOR SMART HOME USING DAY-AHEAD PREDICTION FROM ARTIFICIAL NEURAL NETWORK (ANN)

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ABSTRACT
This paper presents load scheduling for smart home application using day-ahead prediction from an artificial neural network (ANN). In this study, load forecasting using ANN approach is embedded in the load scheduling scheme that is modeled using mixed integer linear programming (MILP). The main objective of the scheduling is to reduce the electricity bill by shifting peak load to off-peak period. A day-ahead energy consumption is predicted based on a previous yearly data set of hourly resolution. The dataset is normalized and injected as input in ANN and the result is then fed to the load scheduling optimization process. The results show that the integration process affects the allocation of load consumption in the load profile as well as the electricity cost. From the comparative study between before and after ANN integration, the total cost saving achieved is $1.53/day with the cost reduction of 38.44%.

Key words: Artificial Neural Network, Load Forecasting, Load Scheduling, Mixed Integer Programming.

1. INTRODUCTION

The customary way of load scheduling of household appliances is presented in various research papers these past years. The sole problem of today's power generation and distribution system is the surge in energy demand during peak hours. Companies around the world are forced to put in additional generating units to achieve this peak demand [1]. Therefore, smart home system is a necessary component of the smart power grid, which permits active participation from residential end users in reducing peak demand. The changes from generation-follows-load to load-follows-generation has somewhat shaped a new improved dimension in issues in real world [2].

A well proposed new algorithm namely Genetic Algorithm Super-clustering (GASC) for scheduling appliances is done by using super clustering appliances and their working timing hours [3]. By scheduling the appliances of the smart home, the operation of these appliances can be shifted to off-peak hours and spread over a longer period of time that would in turn reduce the excessive energy consumed [4],[5]. Thus, optimizing the scheduling of appliances should greatly minimize the peak demand and electricity bills [6]. The authors in [2] implemented day-ahead prediction in their paper prior to load scheduling. Their proposed optimization model is to reduce the total electricity cost and their model is performed subjected to several constraints which are energy constraint, power safety constraint, production capacity constraint, consumer preference and also equipment flexibility. AMPL is used as the optimization tool to unravel larger scale optimization and scheduling have proceeded to solve the optimal scheduling problem using shift-able appliances where they have used a method that could perform real time scheduling of appliances [7]. All these aforementioned papers did not include load forecasting in their scheduling scheme. Load scheduling is vital in reducing load demand of a residential units and electricity price, all research papers strategize further to optimize load scheduling by implementing multiple load forecasting techniques to meet these needs [8].

Several methods of load forecasting have been studied in previous work [9]-[12]. Most research papers deal with 24-hour-ahead load forecasting or known as day-ahead load forecasting. These approaches forecast the demand power by using a forecasted temperature and other variables as forecast data. But in case of rapid fluctuations in temperature on the predicted day, load power changes abruptly and momentously and would eventually increase the error in forecast. Therefore, in this case, some researchers conducted a research of one-hour-ahead load forecasting which uses the temperature of a forecast day as prediction information. Neural networks that uses conventional methods practices all similar day's data to learn the trend of similarity [13]. Nevertheless, learning of all similar day's data is a complex task, and is not advisable in the study of ANN. For that reason, it is more essential to lessen the neural network structure and learning time.

In another research paper, load forecasting is studied using short-term electric load forecasting technique using a multi-layered feedforward Artificial Neural Network (ANN) and a Fuzzy set-based classification algorithm. The hourly data was classified into classes based on the fuzzy set representation of two weather variables; dry-bulb temperature and relative humidity [14]. The classification is based on the power system load that is profoundly subjective by the weather condition. The fuzzy set was used to assist the classification process in order to achieve the smooth transition between the classes of weather condition. The proposed technique was verified and its performance was evaluated by MAPE.

A research has been made on load forecasting technique to predict peak and valley loads. The paper proposed to use Artificial Neural Network (ANN) with multilayer feed-forward neural network and the neural net is first trained using historical weather and load data. These peak and valley loads, when combined 8 with the hourly load pattern, can yield the desired hourly loads [15]. This paper however uses the average of the hourly predicted load patterns of these days to estimate the desired hourly load pattern hence making the output less precise and accurate.

In addition, a team from University of North Dakota successfully managed to conduct deep learning or Deep Neural Network (DNN) to predict next day energy consumption of appliances. DNN-based forecasting system is design with backpropagation learning algorithm and feed-forward network to train a dataset for forecasting energy consumption. They constructed its neural network model using TensorFlow deep learning platform. This platform is an open source software library for numerical computation using data flow graphs which is known to be flexible and general enough to be applicable to other domains [16].

Some drawbacks in load forecasting methods were explained such as inaccurate prediction, difficulty in modelling processes, numerical instability, requirement of large historical database, and demand of high human expertise [14], [17],[18]. Henceforth, these works were made into a much complex process and not practical only to successfully achieve the optimum goals of the work. Also as mentioned in [14], the data collected for prediction is based on similar trend or average load consumption on similar days which means that the data used are just an estimation and not accurate. Therefore, more simplified algorithm has to be created including the implementation of load prediction of the next day using a real past yearly dataset. By having a true predicted value of load consumption of a home, and with the right algorithm, the process could be much easier and precise in optimizing load scheduling.

The main gap of the above aforementioned approaches is that the appliances are scheduled without considering forecasted energy consumption. Thus, this paper presents load scheduling for smart home using day- ahead prediction from artificial neural network (ANN). Load forecasting using ANN approach is embedded in the load scheduling scheme that is modeled using mixed integer linear programming (MILP). The advantage of integrating energy forecasting in load scheduling scheme is to ensure all the appliances are scheduled at the optimal time which contributing to electricity bill reduction. The results show that the cost saving achieved is \$1.53/day with the cost reduction of 38.44% when integrating with load forecasting scheme.

2. LOAD FORECASTING USING ANN APPROACH

A database of an energy consumption consists of 8,760 samples has been collected from a yearly dataset of a smart home in Little Rock, Arkansas, U.S. This data consists of 5 features or appliances of the home with its demand value every hour in a day. These data will be normalized prior to be fed into the ANN system. Some of the data will then be used as training data while the rest will be used as test data and this division were made randomly before it enters the system. While the classification process is based on a machine learning algorithm that has been constructed based on research, the method that is being used is an ANN as the classifier. Figure 1 explains the process of ANN in MATLAB in details.

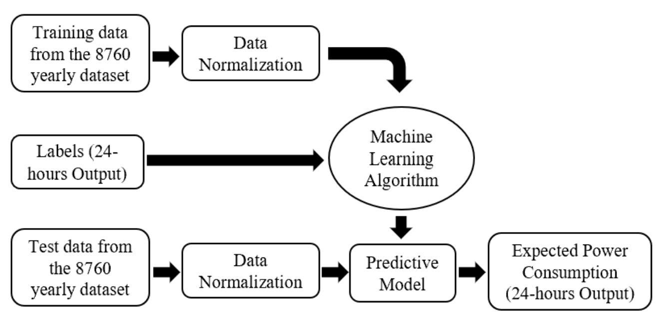

Figure 1: Artificial Neural Network Diagram

These 5 distinct features or appliances are chosen as they have the first few that have the highest load consumption of the smart home and the rundown is demonstrated as follows:

i. Space Heater
ii. Air Conditioner
iii. Personal Computer
iv. Dishwasher
v. Water Heater

The database is distributed unevenly in 24 hours classes in a day. In addition, the data from the smart home are extracted and described by 5 features or appliances as a preliminary separation before going through the proposed system to produce the predictive model of energy consumed the next day. The model that is created can be fed with another set of data of a day and it will predict the future energy consumption at the same time calculate the differences of predicted and expected energy consumed by each appliance. The value of the differences is the MAPE or the percentage error calculated by the ANN itself. These load profiles are studied and the patterns of appliances usage are taken into consideration and used later in load scheduling process.

Artificial neural network (ANN) is a processing system that is made up from a highly interconnected neural computing elements that is able to learn and acquire knowledge and make it accessible to use by others [17],[18].

The structure of a feed forward neural network and backpropagation is formed by an “input” layer, one or more “hidden” layers, and the “output” layer as shown in Figure 2. The number of neurons in a layer and the number of layers depends strongly on the complexity of the system studied [19],[20]. The primary goal of this backpropagation is to iteratively change the weights in the system to deliver the sought yield by minimizing the output error. The preparation will force the generated outputs spoke to by the vector to the chose target output vector by conforming the weights while moving in reverse. Therefore, the optimal network architecture must be determined by studying the change of hidden layer size.

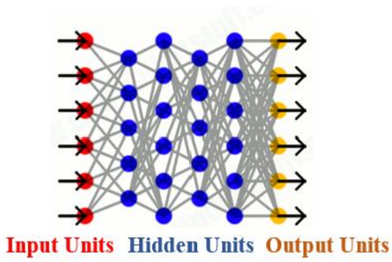

Figure 2: Feed Forward Network Structure

3. LOAD SCHEDULING USING MILP APPROACH

As for the load scheduling, the technique used is MILP and the objective functions is to reduce electricity bills under a 24 hours TOU electricity bill tariff as in Figure 3. The objective of the optimization process is to minimize the electricity cost as formulated in (1).

$$f_c = \min_{x} \sum_{k=1}^{m} C^k \left(\sum_{i=1}^{N} \sum_{j=1}^{n_i} P_{ij}^k X_{ij}^k \right) \quad (1)$$

f_c is the total cost of electricity consumption while C^k is the electricity tariff for time slot *k*. X is a vector whose entries is X_{ij}^k. The equivalent auxiliary binary variable $X_{ij}^k \in \{0,1\}$ is used with P_{ij}^k as ON or OFF switch to a degree the time slot k whilst the equipment the first phase starts until all of the load phases relinquish.

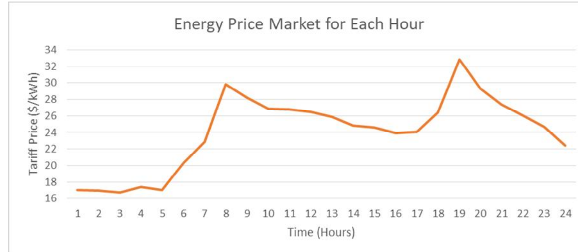

Figure 3: Energy Price Market.

As for the constraints, energy constraint and timing constraint were used in this proposed work.

3.1 Energy Constraint

For the load phases of each appliances to achieve their energy demand, as in (2). E_k represents the power demand for appliance i at each hour with load section j and k is the convenient time slots in a day.

$$\left(\sum_{i=1}^{n} P_{ij}^k \right) \le E_k \vee \{i, j\} \quad (2)$$

3.2 Timing Constraint

Operating hour and time preferences of appliances are the time constraints chosen for this work. As shown in Table 1, each one of the appliances has its own total hours of operating and the time preferences by the user. Appliances have to complete operation within the specified time and not to operate outside the time interval hence acting as a boundary of usage. Refer to (3), t_{st} as the starting time of the appliance operate and t_{end} as the finishing time of the appliance operate based on the consumer comfort or preference.

$$t_{st} - t_{end} \ge a \quad (3)$$

Table 1: Operating Hour and Time Preferences of Appliances

Appliance	Operating Hour (h)	Time Preferences
Space Heater	3	Cannot operate between 1-5
Air Conditioner	6	Can operate at any time
Personal Computer	4	Cannot operate at 17-21
Water Heater	3	Can operate at any time
Dishwasher	3	Cannot operate at 7-11

4. RESULT AND DISCUSSION

In this section, the results obtained from the investigations are presented. The results can be divided into three (3) parts:

A. The prediction of load consumption of appliances for the next day

Prediction of load consumption for the next day is shown in Figure 4. These are the outputs of the chosen 5 appliances that the ANN system has predicted using normalized data inputs of the last day of December in that year. These 8,760 data are normalized as part of data preparation for machine learning and the goal of normalization is to change the numeric values to a common scale without altering or distorting the difference values in the range of the dataset. Five appliances were considered in this proposed work which are space heater, air conditioner, personal computer, water heater and dishwasher. These 5 appliances are taken into consideration due to the amount of load consumption of the smart home which are the top most used in a year hence making it the best appliances to optimize.

It is shown that these appliances were predicted with values ranging from 0.9 kW to as low as 0.09 kW based on the usage of the home owner throughout December. Hence, these predictions are the forecasted load consumption for the day after which is in January for day one. These values would then be used for load scheduling through the MILP process for optimization. Figure 5 demonstrates the flow process of ANN model for load prediction by considering temperature, humidity, solar strength, and wind strength as input parameters. The hidden layer used is 13 as it has gained the lowest Mean Square Error (MSE) value, 0.8982. ANN model is trained to achieve its highest performance. The lower the value of the MSE, the better the performance or the prediction of the ANN model.

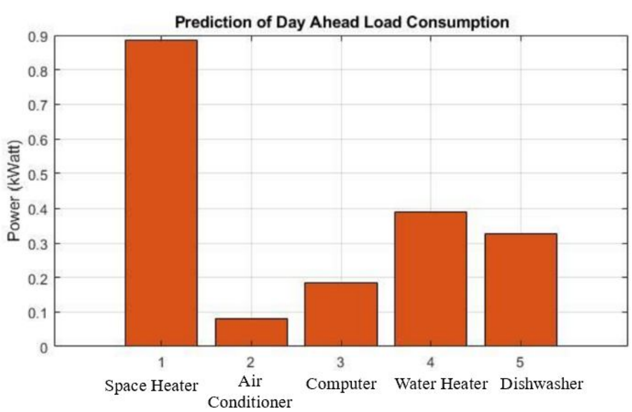

Figure 4: Prediction of Day-Ahead of 5 Appliances.

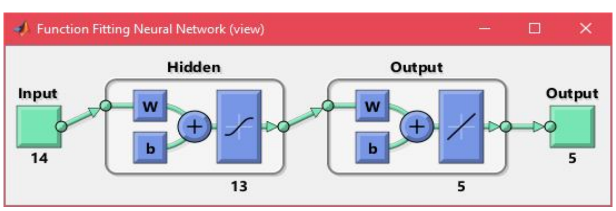

Figure 5: Process Flow Neural Network.

B. The Mean Square Error (MSE) performance of ANN with different hidden layer

MSE performance of the ANN is studied when the hidden layer is reduced. The hidden layer is part of the process which is between the input and output as it acts as an activation function by weighing the inputs and producing the information needed to produce an output of a desired scale. This method is to ensure the optimum prediction of the ANN model before the output undergoes the scheduling process thus, finding the right hidden layer size is vital. As the plot is shown in Figure 6, reducing the hidden layer size does not guarantee an improvement of the performance nor will it show any specific pattern but only to the extent where the MSE is reduced and at best which is at hidden layer 13 with MSE 0.898. Further reducing it will only increase the MSE and would disrupt the performance of ANN.

Other than that, the ANN model is also tested for multiple trials to study the effect of running the ANN model for few times towards the performance of the ANN model as shown in Table 2. The first trial of prediction which is the yellow line indicates that the best performance reached highest 0.903 at hidden layer 15 and least best performance at 0.993 at hidden layer 9. Running the ANN model, the second time, the performance improved when it is seen that the MSE is lower for most of the different number of the hidden layer compared to the first trial. The lowest MSE is as low as 0.8982 at hidden layer 13. The 3rd trial of the ANN was run and as presumed, the performance did not significantly improve but defers with different hidden layer and are usually high on MSE than the rest of the trials. Henceforth, progressing forward in this work, the ANN model and its output values are taken from the ANN model during its hidden layer at 13 on the second trial prediction as highlighted in green in Table 2.

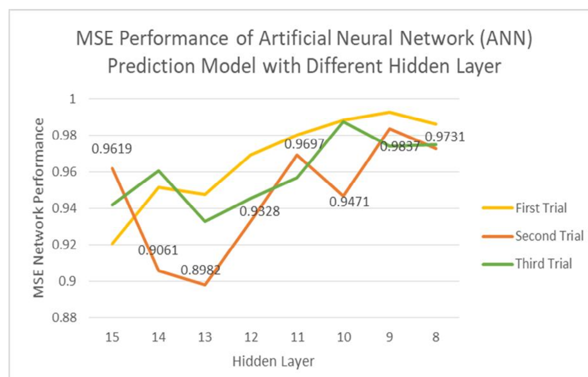

Figure 6: MSE Performance of ANN with Different Hidden Layer

Table 2: MSE for Different Hidden Layer and Trial

No of Hidden Layer	MSE			Lowest MSE
	1st Trial	2nd Trial	3rd Trial	
8	0.9863	0.9731	0.9753	0.9731
9	0.9929	0.9837	0.9742	0.9742
10	0.9877	0.9471	0.9877	0.9471
11	0.9805	0.9697	0.9568	0.9568
12	0.9697	0.9328	0.9458	0.9328
13	0.9478	0.8982	0.9329	0.8982
14	0.9517	0.9061	0.9610	0.9061
15	0.9207	0.9619	0.9422	0.9207

C. The total load and total cost of load scheduling with and without ANN integration.

All the appliances are scheduled based on a non-predicted load profiles as shown in Figure 7. It can be seen that the highest usage of these 5 appliances at the time slot 7, 19 and 20, due to the starting of the user's day and during user's free time at home. While its peak demand is at slot 20 which is at 8.00 PM, the highest power usage is seen to be the space heater which operates from 5.00 AM to 7.00 AM and at 7.00 PM to 8.00 PM. Other components to look into in Figure 7 is the TOU tariff curve. The highest price of the tariff is between 8.00 AM to 9.00 AM and also 7.00 PM to 8.00 PM. The load scheduling indicates that most of the appliances are scheduled within the region of on-peak and off-peak of the TOU tariff because the scheduling was not based on the tariff.

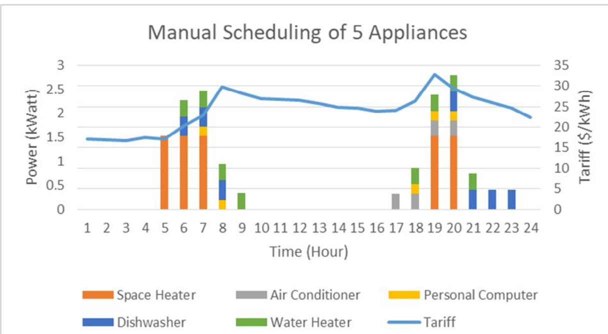

Figure 7: Load Scheduling without ANN Integration

In Figure 8 however, the chart represents the load scheduling of all 5 appliances with its MILP inputs based on the prediction load profile. This load profile is compared with the TOU tariff price and the appliances are seen to operate only at the off-peak region. When compared to previous scheduling, the load consumption in Figure 7 have been shifted to off peak in Figure 8 where this proved the optimization has occurred. The operating time of each appliance have changed and the peak demand is allocated at off-peak hour 6.00 PM. The space heater will be operated at 6.00 PM, 7.00 PM and 12.00 AM while the water heater will only be ON at 1.00 AM to 3.00 AM. The dishwasher is scheduled to be used either in the early morning or late night to reduce the electricity price. Personal computer also is shifted and can be used only in the morning before peak hour.

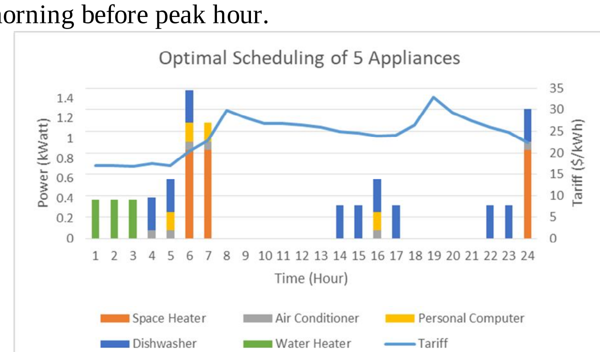

Figure 8: Load Scheduling with ANN integration

Table 3 summarizes the comparative study between with and without ANN integration where the proposed scheduling shifted the load curve for all appliances and have reduced the total load consumption by a substantial amount. Peak load was dropped from 2.79 kW without ANN integration to 1.48 kW after ANN integration whereas the total load consumption of appliances has reduced significantly for about 6.4 kW per day. Consequently, having the peak load and total load consumption reduced, it is reasonable that the total cost per day is also decreased by a huge amount and have caused a total cost saving of $1.53 per day. Other than that, it can be seen that the cost of electricity bills has been reduced about 38.44%.

Table 3: Total Load and Total Cost With and Without ANN Integration

Findings	With ANN Integration	Without ANN Integration
Peak Load (kW)	1.48	2.79
Total Load (kW/day)	44.84	51.24
Total Cost ($/day)	2.45	3.98
Cost Saving ($/day)	1.53	
Percentage of Deduction (%)	38.44	

5. CONCLUSION

This paper highlights the importance of having integration with load forecasting in the load scheduling optimization process. In this approach, ANN and MILP techniques are used for load forecasting and load scheduling processes, respectively. By having the right amount of dataset with the right hidden layer size of ANN, the prediction can be achieved with lower MSE thus leading to the optimized results of the load scheduling. From the comparative study, it shows that the cost reduction of about 38.44% is achieved when scheduling the load based on the ANN prediction. For future recommendation, the objective function and constraints that play an important role in load scheduling can be improved by considering more related functions and constraints such as uninterrupted operation, start-end time and user comfort preferences.

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