HOUSEHOLD ENERGY MANAGEMENT BASED ON DYNAMIC PRICING USING EXTREME LEARNING MACHINE

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Abstract - The goal of energy management is to utilize energy effectively and efficiently without reducing energy quality. This application must have the ability to regularly record and evaluate, schedule, and can provide advice on the energy use required. In this paper, household loads are used to implement energy management applications. This energy management has a Load scheduling feature. This feature is used to implement Dynamic Pricing. Household electrical loads will be grouped based on energy consumption and loads, ie inelastic loads, flexible elastic loads, flexible running loads, and flexible elastic loads. After classifying the load, Extreme Learning Machine (ELM) is used to predict the upcoming electricity prices. From the simulation results, the accuracy and speed of ELM are better than artificial neural network (ANN) with a Mean Absolute Percentage Errors (MAPE) of 1.54% and learning speed with a maximum time of 0.1081 seconds. The price Prediction produced by ELM, as well as load scheduling, can help user to find out the electricity cost usage and the right time to use electrical loads.

Keywords - Energy Management, Dynamic Pricing, Extreme Learning Machine, Load Scheduling

I. INTRODUCTION

Various countries in the world are increasingly fond of sustainable energy development, so every country is competing to invest in creating the smart city. The core of the smart city is on the implemented technology that serves to support every activity of society and also regulate energy consumption. real-time information updates through communications networks so that consumers can schedule the activation of electrical loads based on price changes notified by the energy management automatically installed at home is the ability of smart grid that can overcome the problem of sustainability and reliability of the household consumers side called demand response (DR) [1]. The smart home in the smart city has the ability to communicate with homeowners, or between homes using communication networks to organize and inform all the circumstances that occur at home one of them is the use of electricity [2]. The smart grid is an electricity system in the smart city that can maintain power service providers communicate with consumers [3]. The smart grid can provide information to consumers about the price of electricity that occurs. consumers will be exposed to excessive bills when the power consumption not arranged in the system that has implemented dynamic pricing, so the need for energy management to keep the electricity bill paid by consumers to the electricity providers is not excessive [4]. In this paper, assumed that the household electrical system has only one source of electricity with a variety of residential consumers and each house has a smart meter [5], that can communicate two-way through a computer network and connect with the smart grid distribution system. [6-8].Household electronic loads will be classified based on the energy consumed and the time of use of the loads.Grouping for household electronic loads on [9] namely inelastic loads, flexible elastic loads, flexible running loads, and flexible elastic loads.Consumers do not understand the right time to consume electricity without the help of energy management, because they do not have the scheduling of the use of electrical loads based on the response by predicting the future electricity prices automatically.Dynamic Pricing is a pricing scheme that can vary based on demand response time. According to [10], there are various pricing schemes based on demand response times, such as time-of-use pricing (TOU), peak load pricing (PLP), Vickrey-Clarke-Groves (VCG), peak-day-rebates (PDR), critical peak pricing (CPP), flat pricing, and real-time pricing (RTP).IBR simulated in this paper, refers to [11].In the application of IBR, the price for using electricity will be higher according to the quantity of electricity consumption. [12]. In this paper, the RTP that will be simulated will use data from [13].Extreme Learning Machine is an artificial intelligence that will be used to forecast future electricity prices. The results of ELM will be compared with Artificial Neural Network using the values of Mean-Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) as parameters. The events that affect the electricity prices are during the afternoon, hot days in summer, cold days in winter, weekdays, weekend, and holidays [14]. The household loads scheduling will be done manually based on the future electricity prices prediction then compared with the price that obtained from the providers without the forecasting method.

In this paper, wireless communication is assumed using the ZigBee, created by the ZigBee Alliance [15]. Besides ZigBee, there is also a communication technology called HomePlug power-line created by HomePlug Powerline Alliance [16]. Another example of existing technology in [17].

II. DETAILS EXPERIMENTAL

The Flowchart of Price Prediction Methods and Loads Scheduling using ELM seen in Fig.1.

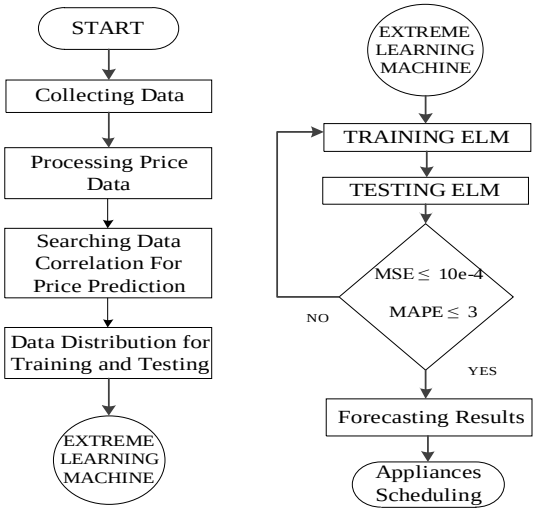


Fig.1. Research Flowchart

2.1. Collecting Data

The data used in this study is hourly real-time pricing data that has been applied by Ameren Illinois from 1 January 2016 to 31 December 2017 and inclining block rate data by British Columbia Hydro in 2017.

2.2. Price Data Processing

The RTP data are grouped based on the same month for 2 years. Then it will be sorted based on the same day so that it can be analyzed optimally.

In Fig.2 it is seen that the average annual for 2016 is higher than the average value in 2017. In Fig.3 there is a noticeable difference between months.

In general, the average price change pattern seen from 1 am to 12 pm for one year which can be observed to get a price change pattern. Creating price predictions based on the previous year can cause a significant error due to other factors such as rising oil prices, taxes, and inflation. So are the price predictions based on every month, because it has different patterns.

Fig.4. is the average price per day for 2 years. from the picture can be seen the pattern that has a striking difference between the weekend and the weekdays.

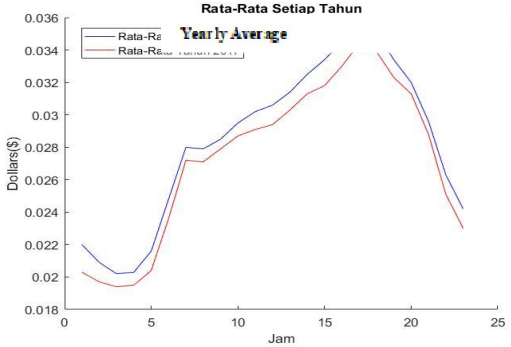


Fig. 2.The RTP graph yearly average

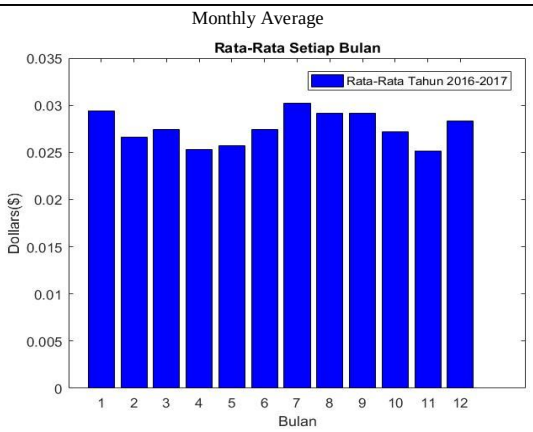


Fig.3.The RTP graph monthly average

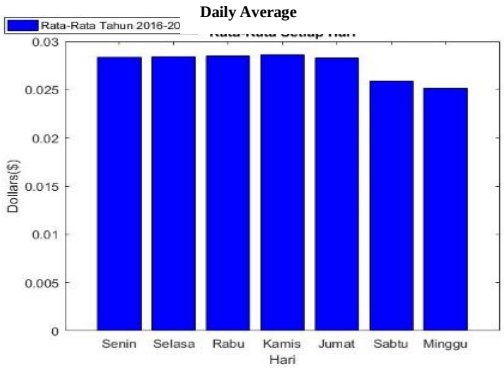


Fig.4.The RTP graph daily average

2.3. Data Correlation Searching For Price Forecasting

The processed data will then analyzed for getting the similar patterns before being set as input to the prediction process to be done by ELM. the analysis aims to make prediction from ELM has minimal errors and works according to needs.

In Fig.5, there is a high correlation between Monday, Monday last week, and Monday on the 2nd weeks ago. Monday on the 3rd and the 4th weeks ago also has a high correlation it is above 0.85. So are the correlation value for Monday the 5th and the 6th weeks ago, it is 0.8. so that Monday the 5th and the 6th weeks ago can be used as an alternate input in predicting prices.

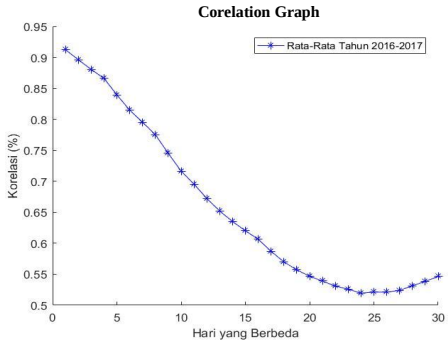


Fig.5.The corellation graph week ago

2.4. Data Distribution for Training and Testing

The training process aims to develop a model from ELM, while the testing process used to test ELM's

ability as a predictor tool. So, the processed data divided into training and testing data. In price prediction using The ELM, price prediction models based on training data are:

$$y_{t-1\ \text{training result}} = f(y_{t-2}, y_{t-3}, y_{t-4}, y_{t-5}) \quad (1)$$

While the prediction model based on testing data is:

$$y_{t\text{forecasting result}} = f(y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}) \quad (2)$$

2.5. Prediction with ELM Method

There are several steps to forecast with the ELM method, namely: data processing, training, testing, then analyzing prediction results before scheduling.

2.6. ELM Training

Before price prediction using ELM, training needs to be done to get input weight, bias, and output weight with a low error rate. There are several steps in this ELM training process, namely:

A. Training Data Normalization

The data that becomes input to ELM needs to be normalized to have a value in a certain range. Because the activation function is used to produce [0.1] or [-1,1] range output. The algorithm used for normalization as in [18], is:

$$x_n = 2\,x\left(\frac{x_p - \min\{x_p\}}{(\max\{x_p\} - \min\{x_p\}) - 1}\right) \quad (3)$$

Where x_n is the normalization result, x_p The value of the original data that not been normalized, $\max\{x_p\}$ maximum value in the data set, and $\min\{x_p\}$ minimum value in the data set.

B. The Activation Function Determination and Hidden Layer Number

the activation function and the number of hidden layers used in the ELM training process need to be determined. This paper using Logsig as the activation function. The number of hidden layers will be determined by trial and error so that the prediction results obtained with a small error rate. According to [19], ELM will produce a stable prediction output if using a hidden layer in the range 0-30. However, if the output generated from ELM is less than optimal, it will use another activation function or by changing the number of hidden layers to produce optimal values as needed.

C. Input Weight Calculation, Bias of Hidden layer, and Output Weight.

The ELM training process will get input weight, output weight and hidden layer bias with a small error rate measured by the MSE and MAPE parameters. Input weight and hidden layer bias are determined randomly, while output weight is the inverse result of the hidden layer matrix and output target. The equation is:

target. The equation is:

$$H\hat{\beta} = T \quad (4)$$

Where:

$$H(\omega_i, \dots, \omega_M, b_i, \dots, b_M, x_i, \dots, x_N) = \begin{bmatrix} g(\omega_1 x_1 + b_1) & \cdots & g(\omega_M x_1 + b_M) \\ \vdots & & \vdots \\ g(\omega_1 x_N + b_i) & \cdots & g(\omega_M x_N + b_M) \end{bmatrix}_{NxM} \quad (5)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_M^T \end{bmatrix}_{Mxn} \quad (6)$$

$$T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{Nxn} \quad (7)$$

$$\hat{\beta} = H^{-1}T \quad (8)$$

D. Training Output Denormalization

The output generated from the training process is denormalized so that prediction data obtained from the ELM training process.

The denormalization formula that used as in [20] is:

$$x_d = 0.5\,x(x_n + 1)x(\max\{x_p\} - \min\{x_p\}) + \min\{x_p\} \quad (9)$$

Where x_d is the data after deformalization, x_n is output before it is denormalized, $\min\{x_p\}$is the minimum value in the data set and $\max\{x_p\}$ maximum value in the data set.

2.7. ELM Testing

ELM testing executed after going through the training process that has the goal to be able to know the ELM capabilities as a prediction tool. This process using data testing, input weight, hidden layer bias, and output weight as input for testing that obtained from the training process. The input data will be normalized first so that it has a certain range, and the output will be denormalized as in the training process to produce the output value with the actual value.

2.8. Prediction Results Analysis

The training and testing process that has been carried out will result in ELM prediction. ELM forecast results will be analyzed to see whether the output from the forecast has a large or small error. If the error result is big, then it must be reevaluated starting from the training and testing process until the optimal results obtained. Error in ELM remarked through MSE and MAPE values produced in the testing process. The MSE and MAPE formula used to determine error value produced by ELM is:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - t_i)^2 \quad (10)$$

Where, N is data amount, y_i is forecast output, and t_i is actual load data.

While for MAPE are:

$$\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_{\text{forecast}} - Y_{\text{target}}}{Y_{\text{target}}}\right| . 100\% \quad (11)$$

Where n is processed data amount, Y_{forecast} is ELM forecast value, and Y_{target} is the actual price that occurred.

2.9. ELM with ANN Prediction Resultscomparison after training and testing, MSE and MAPE obtained from the results of ELM prediction. MSE and MAPE from ELM then compare to Artificial Neural Network backpropagation (ANN BP) that also used as a prediction method. Comparing between ELM and ANN BP will be able to see the accuracy of each method, both in terms of the magnitude of the error produced, the training and testing time required by each method. By comparing with ANN BP, you can also plot the results of the forecasts produced with actual data

2.10. Loads Grouping

A. Inelastic Loads
Inelastic Loads are loads that cannot be disturbed while it is running because this loads must continue. In this paper, power consumption by inelastic loads modeled and added from historical data usage by consumers. The smart switch will function as a regulator of the loads.

B. Elastic Loads with Time-Flexible
Elastic Loads with Time-Flexible are loads that can be controlled when the loads run, this type controlled by a smart switch. Not only as a controller but also get the data on the power consumed during the time the device is running.

C. Continous-Run Loads with Time-Flexible
Continous-Run Loads with Time-Flexible are loads that has special characteristics for its running time. When running, this type of loads cannot be disturbed or turned off. So that the smart switch will recommend the right time for this load to run.

D. Elastic Loads with Power-Flexible
Elastic Loads with Power-Flexible are loads that can be scheduled when running. When this loads are running, it consumes a lot of power, but when it doesn't run it will consume minimum power because it runs in the standby phase. The smart switch can control and provide recommendations when these loads run

III. RESULTS AND DISCUSSION

The overall price prediction from Monday to Sunday using ELM compared directly with ANN, indicating results of predicting by ELM has a value more accurate than the results of ANN prediction.

Tabel 1 Error comparison using ELM and ANN.

Perbandingan Error Hasil Peramalan (%)			
Day	Error	ELM	ANN
Monday	Maximum	0.1409	0.1163
	Minimum	0.0004	0.0004
	Mean	0.0254	0.0304
Thursday	Maximum	0.0393	0.0506
	Minimum	0.0000	0.0000
	Mean	0.0151	0.0216
Wednesday	Maximum	0.0737	0.0749
	Minimum	0.0008	0.0000
	Mean	0.0156	0.0214
Thursday	Maximum	0.0766	0.0574
	Minimum	0.0000	0.0000
	Mean	0.0190	0.0215
Friday	Maximum	0.0469	0.0547
	Minimum	0.0000	0.0000
	Mean	0.0184	0.0210
Saturday	Maximum	0.0481	0.0519
	Minimum	0.0053	0.0000
	Mean	0.0248	0.0264
Sunday	Maximum	0.0370	0.1448
	Minimum	0.0036	0.0000
	Mean	0.0162	0.0245

The following table presents the results of error comparison (%) predicting prices from Monday to Sunday. From table 1 it can be seen the magnitude of the error generated by the ELM and ANN methods for daily predicting from Monday to Sunday. The data plot results of the predicting electricity prices from Monday with the ELM method compared to the ANN method are presented in Fig.7 below.

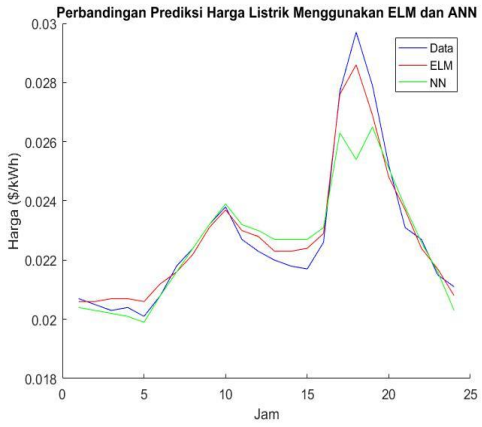


Fig.7. The actual data comparison graph, ELM and ANN price prediction data on Sunday, November 26, 2017.

Tabel 2 Comparison of ELM and ANN training and testing time

Prediction Time Comparision (Detik)			
Day	Time	ELM	ANN
Monday	Training	0.0950	3.3948
	Testing	0.0163	2.1563
Tuesday	Training	0.0951	3.2381
	Testing	0.0161	2.3731
Wednesday	Training	0.0854	3.2568
	Testing	0.0126	2.1803
Thursday	Training	0.0914	4.1157
	Testing	0.0154	2.4928
Friday	Training	0.0881	3.1786
	Testing	0.0165	2.1966
Saturday	Training	0.1081	3.2115

	Testing	0.0168	2.2323
Sunday	Training	0.0929	3.2914
	Testing	0.0177	2.2076

From table 2 the comparison above can be seen that ELM has faster learning speed than ANN.

Tabel 3 Comparative Benefits of Using Scheduling load on electricity prices of different models.

Model Pricing	Invoice without scheduling ($)	Invoice with scheduling ($)	Total Profit ($)
RTP	3.8945	3.6867	0.2078
ELM Predict	3.9350	3.7332	0.2018
ANN Predict	3.9268	3.7376	0.1892
IBR with RTP	8.7945	6.4657	2.3289

Table 3 shows a comparison of power consumption when users have predicting tools using the ELM and ANN methods compared to users without having predicting and comparison between users using equipment scheduling and the users without equipment scheduling features.

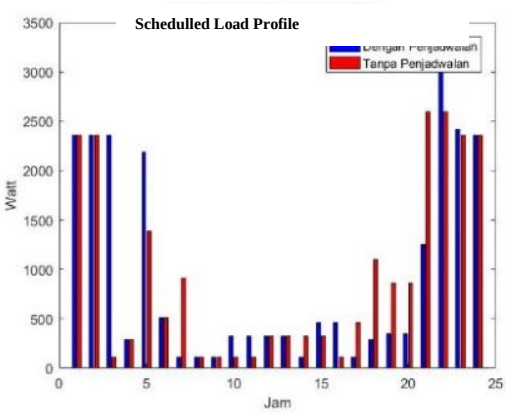


Fig.8.Comparative Graph of Scheduled Equipment Profile

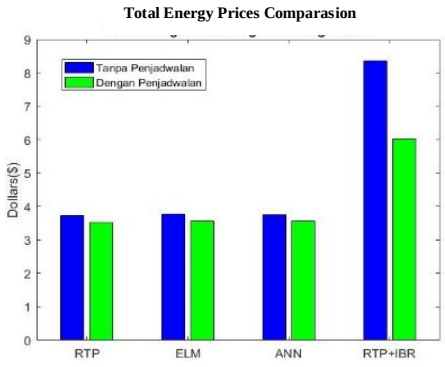


Fig.9. Comparative graph of amount electricity invoice.

In Fig.8 shows the comparison of graph between using scheduling and those not using scheduling in usage equipment.

In Fig.9 it can be seen the difference generated when the user uses scheduling in the usage of owned equipment then the difference is the profit that will be owned by the user.

CONCLUSIONS

In this paper, can be concluded:

1. The price prediction using the Extreme Learning Machine (ELM) is able to produce predictions with a minimum average error of 0.0015% with a maximum average error of 0.0661%.
2. ELM has fast learning speed with a minimum time of 0.0854 seconds and a maximum of 0.1081 seconds. While the learning speed of ANN has a minimum time of 3.1786 seconds and a maximum time of 4.1157 this highly profitable ELM because for predicting requires a fast learning speed.
3. The logsig activation function with a hidden layer most appropiate all days except Sunday is 15 hidden layers. This is because it can produce the smallest MSE and MAPE error values compared to the number of other hidden layers.
4. The ELM algorithm is simpler and tends to get a small error. The output of ELM is determined by the number of hidden layers and activation functions.
5. The real-time pricing model has many advantages for users on a household scale, but users must be prepared to have equipment for automatic scheduling and equipment for predicting future electricity prices. IBR and RTP can force users to use the scheduling equipment to be more profitable and more efficient.
6. By scheduling electricital energy consumption when the electricity provider applies the power market concept, it can benefit household users..

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