

How Large the Direct Rebound Effect for Residential Electricity Consumption When the Artificial Neural Network Takes on the Role? A Taiwan Case Study of Household Electricity Consumption

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ABSTRACT

Amid the energy reform efforts by the Taiwan government, residential energy demand continues to face an escalating trend every year. This indicates the phenomenon of the energy efficiency gap. One of the factors that control the energy efficiency gap is the rebound effect. The rebound effect is related to the increase in energy consumption through efforts to reduce the use of energy itself. This can be due to the low cost of usage that causes a person to be encouraged to use more energy. This study aims to estimate the magnitude of the direct rebound effect of household electricity consumption in Taiwan using monthly time series data from January 1998 to December 2018 and to implement the artificial neural network (ANN) as an alternative approach to measure the direct rebound effect. Based on the simulation results, the direct rebound effect magnitude for household electricity consumption in Taiwan is in the range of 11.17% to 21.95%. GDP growth is the most important input in the model. Additionally, population growth and climate change are also critical factors and have significant implications in the model.

Keywords: Energy Efficiency Gap, Direct Rebound Effect, Artificial Neural Network

JEL Classifications: Q43, C63, E7

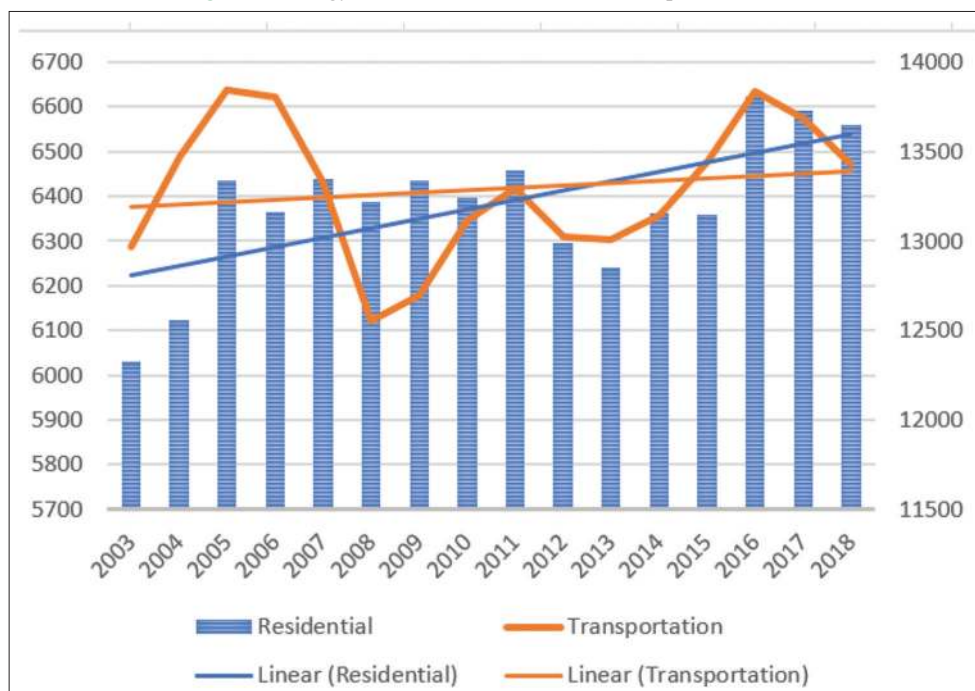
1. INTRODUCTION

In recent years Taiwan's economic growth has been faced with increasing uncertainty, especially related to the condition of the manufacturing industry caused by soaring energy prices because of the limited availability of natural energy in Taiwan, which has led to high energy import figures (Hong and Tsai, 2018). If we look at the data over the past few years, total domestic consumption has a rapid increase from 72,186 103KLOE in 2003 to 87,318 103KLOE in 2018 or an increase of 21%. This increase can also be seen by the sector, where energy consumption for transportation and residential continues to increase. More clearly can be seen in Figure 1.

Figure 1 shows the increasing trend of energy demand for the residential and transportation sectors from 2003 to 2018. If we attract a linear line between the two curves then we will find something interesting, energy demand for households grows faster each year compared to energy demand for transportation, causing a crossing between the two linear lines in 2013. On one hand, in those years, the Taiwanese government approved a mega smart grid system project, one of which aims to control people's consumption of energy use, including electricity consumption. Regardless, as the picture above shows, there is an indication of an energy-efficiency gap in Taiwan.

The discussion of the energy-efficiency gap has broadly evolved since the Hausman literature (1979) about consumer failures in

Figure 1: Energy demand for residential and transportation sector



investing income for energy efficiency. Moving forward, Greene (2011) believes that uncertainty around the net value of future savings and loss aversion of consumers causing under-investment of consumers. Besides, Allcott and Greenstone (2012) assessed that imperfect information and inattention makes under-investment in energy efficiency. Gillingham and Palmer (2014) have a more interesting discussion, which is about the size of the gap that has not been solved, but several factors can force its size, one of the factors is the rebound effect.

According to Gillingham and Palmer (2014), the rebound effect frequently gets less attention as part of the factors that affect the energy-efficiency gap. That is because the technical approach assumes energy service demand is constant before and after the efficiency of investment. However, consumers are using more energy services because of lower usage costs, this phenomenon known as the energy rebound effect. From the mechanism of occurrence, the rebound effect is divided into direct rebound effects, indirect rebound effects and economy-wide (Greening et al., 2000; Wang et al., 2018). The difference lies in the effects of the rebound effect. The direct rebound effect is when the price changes that occur because of energy efficiency will encourage energy consumption itself, which can directly cause a direct rebound in energy consumption. Then, the mechanism in the indirect rebound will affect the increase of real income of consumers so it will encourage other energy services consumption if we assume the price of goods and services has not changed (Sorrell et al., 2009; Wang et al., 2018). The direct rebound effect is the most familiar, and broadly studied compared to the others (Sorrell, 2014; Sorrell et al., 2009).

Furthermore, the results of research conducted by many researchers show the magnitude of the rebound effect varies depending on the location of the study and the estimation technique used. In the

US, Greene et al. (1999) with econometric estimates found a 23% rebound effect for household vehicle travel, then Bentzen (2004) using time series data from the US manufacturing sector and applying dynamic ordinary least square (DOLS), found the magnitude of the rebound effect around 24%. Small and Dender (2005) with aggregate cross-sectional time-series data from 1966 to 2001 on all US states, finding a direct rebound effect of 5.3% for short runs and 26% for long runs. Another study conducted by Thomas and Azevedo (2013) with their input-output approach simulates direct and indirect rebound effects, they find an indirect rebound of 5-15% for primary energy and CO₂ emission, assuming a rebound effect of 10%.

In addition to the US, studies in several EU countries also show different results for each country. Berkhout et al.(2000) found the value of rebound effects in the Netherlands is probably small, ranging between 0% and 15%. Another study, using panel data, Frondel et al. (2008) estimated the rebound effect in Germany where the results show a range ranging from 57% to 67%. De Borger et al. (2016) estimated the rebound effect on car transportation in Denmark by using micro-data, the result they found a rebound effect ranging from 7.5% to 10%. Besides studies conducted in each EU country, Freire-González (2017) conducted studies in EU-27 countries, he used a combination of econometric estimation methods and environmental extended input-output, by weighting individual estimates by GDP, and the average value for the overall EU-27 economy has been found between 73.62% and 81.16%. The results of a comprehensive review of Sorrell et al. (2009) concluded that for households in OECD countries, the direct rebound effect should be <30%.

Further, the results of studies in several Asian countries such as China showed a fairly high estimated rebound effect. A study conducted by Zhang and Peng (2016), using the panel threshold

model, they found the magnitude of the rebound effect of China's residential electricity consumption is 71.53% on average. The amount is slightly lower with the national average energy efficiency rebound effect of 74.18% (Li and Yonglei, 2012). The study result from Wang et al. (2018) shows the magnitude of the rebound effect is very high, ranging from 6.56% to 990.54%. Based on the spatial spillover effect, using panel data from China's urban population electricity consumption, found a direct rebound effect of 37% (Han et al., 2019). Besides in China, research conducted by Alvi et al. (2018) for residential electricity consumption in Pakistan shows the amount of direct rebound effect is 69.5% for the long run and 42.9% for the short run.

In the case of Taiwan, the results of a study conducted by Wu et al. (2016), by applying supply-driven input-output to find the magnitude rebound effect in the industrial sector, the results of their study show the amount of total rebound effect is no more from 10% for the industrial sector. In addition, for the household sector, a study conducted by Su (2019) conducted a survey of 7677 households, showing a total rebound effect of 33%. However, the two studies conducted in Taiwan did not clearly distinguish whether the amount came from direct or indirect rebound effects. Globally, a study from Wei and Liu (2017) using the CGE model shows that the estimated global rebound effect is very high at 70%.

The energy rebound effect has been studied extensively using various approaches, the most approach is to use econometrics with OLS, FGLS, 2SLS, 3SLS estimation techniques, fixed effects, random effects, and error correction models (Sorrell et al., 2009). In its advancement, studies of the rebound effect applying quasi-experimental, Computable General Equilibrium (CGE) models, input-output models, LMDI decomposition models, Cobb-Douglas function models have been used to analyze the energy rebound effect. However, not several estimates used are far from ideal. It can be seen from the many estimation results that have very high or even very low output, causing a bias in the size of the rebound effect and overestimated (Sorrell et al., 2009). Therefore, this study wants to reduce the bias obtained from the estimation results using the Artificial Neural Network or ANN approach.

ANN is a mathematical model that consists of an interconnected group of neurons and processes information using a computing-based connection. ANN changes the structure based on internal and external information that enters the network during the learning process. The advantage of using ANN is that they can represent both linear and non-linear relationships and learning the data flow directly (Haykin, 1998; Tsakiri et al., 2018). ANN has become popularly used for prediction and modeling for various cases (Rajurkar et al., 2002; Şahin et al., 2013; Tsakiri et al., 2018). Moreover, ANN has been used to be an alternative to several statistical methods and empirical methods to evaluate different physical phenomena. When compared with multiple linear regression (MLR), ANN presents a computational path to measure a non-linear relationship between several inputs and one or more outputs. ANN has been applied for modeling, identifying, and predicting complex systems (Li and Jiang, 2010). Comparing estimates using regression and ANN has shown that the performance value of the ANN model is better than the regression

model. Besides that, the mean absolute percentage error (MAPE) value of the ANN model is lower than the regression model, with the R values of ANN also higher (Kumar et al., 2015).

Furthermore, from the explanation of the advantages possessed by the neural network, it is felicitous if ANN is an alternative to estimate the rebound effect. Besides, the results of the study of the rebound effect using ANN as far as the researchers know has never been done. ANN accurately matches the non-linear variable which is the advantage compared to multivariate linear analysis based on linear variables (Goyal and Goyal, 2012; Stangierski et al., 2019). Therefore, this study measures the magnitude of the direct rebound effect of household electricity consumption using an artificial neural network approach and its implications for energy policy in Taiwan.

This study is organized as follows; section 2 presents the literature review to more understand the direct rebound effect and artificial neural network, section 3 describes the data used and simulation of the model, section 4 discussing the empirical results, and section 5 concludes and gives some implications.

2. LITERATURE REVIEW

2.1. Direct Rebound Effect

In general, the direct rebound effect is the tendency of consumers to use more energy because of lower usage costs. As Sorrell et al. (2009), an increase in energy efficiency results in lower prices for energy services and then drives consumption and services to increase. For example, consumers might choose a space heater that is energy efficient so that it can be used to heat the room for a longer period of time because of the costs incurred for cheaper electricity consumption.

Formally, to estimate the rebound effect, elasticity is the path most frequently used. Quoted from Freire-González (2017) and Sorrell et al. (2009) direct rebound effect can be explained as follows:

$$\vartheta_{\alpha}(x_E) = \vartheta_{\alpha}(S_E) - 1 \quad (1)$$

Where $\vartheta_{\alpha}(x_E)$ is the efficiency elasticity for energy demand and $\vartheta_{\alpha}(S_E)$ is the energy efficiency elasticity of an energy service demand. When the energy efficiency elasticity of the demand for useful work for an energy service is equal to zero, there is no direct rebound effect (Freire-González, 2017). This definition is the most natural of the direct rebound effect (Berkhout et al., 2000; Frondel and Vance, 2013) as described previously, the response to service demand for changes in energy efficiency is explained by the elasticity of service demand with respect to efficiency. However, according to Sorrell et al. (2009) due to the likely endogeneity of energy efficiency, Frondel and Vance (2013) argue that the elaboration will be difficult to calculate.

Additionally, the rebound effect is not only measured by the elasticity of energy efficiency but can also be measured by the price elasticity of energy demand (Berkhout et al., 2000; Freire-González, 2017; Saunders, 2013; Sorrell, 2014; Sorrell et al., 2009):

$$\vartheta_{\alpha}(x_E) = -\vartheta_{PE}(x_E) - 1 \quad (2)$$

Where $\vartheta_{PE}(x_E)$ is the price elasticity of energy demand. This model assumes that the response to decreasing energy prices is consistent with a response to energy efficiency.

However, using these assumptions does not completely describe the actual situation because energy prices do not always decline, and even always experience fluctuations continuously. To capture the phenomenon of price fluctuations, we conducted price decomposition using an approach such as that carried out by (Dargay and Gately, 1995, 1997). They decompose the price of P_t into three series of components, where each of them is monotonic: maximum historical price $P_{max,t}$, cumulating series of price cuts $P_{cut,t}$, and the cumulating series of price recoveries $P_{rec,t}$:

$$P_t = P_{max,t} + P_{cut,t} + P_{rec,t} \quad (3)$$

$$P_{max,t} \equiv \max(P_0, P_1, P_2, \dots, P_t) \quad (4)$$

$$P_{cut,t} \equiv \sum_{i=0}^t \min(0, (P_{max,i-1} - P_{i-1}) - (P_{max,i} - P_i)) \quad (5)$$

$$P_{rec,t} \equiv \sum_{i=0}^t \max(0, (P_{max,i-1} - P_{i-1}) - (P_{max,i} - P_i)) \quad (6)$$

Wherefrom the three decomposition series, the negative value shown by the price cut $P_{cut,t}$ indicates the existence of a rebound effect as well as showing the magnitude of the rebound effect itself (Ai et al., 2020; Alvi et al., 2018; Bentzen, 2004; Frondel and Vance, 2013; Han et al., 2019). For the notes, the sigma notation above will be changed to pi notation (product notation) when measuring direct rebound effect using the LRM approach with the logarithmic transformation of variables.

2.2. Artificial Neural Network

The basic inspiration of an artificial neural network or ANN is a highly complex human brain, capable of processing both linear and non-linear data (Haykin, 1998). ANN is a system that processes information just as it does in the human brain and represents general mathematics of human reasoning based on the assumptions that include: (1) Information is processed in neurons; (2) Signals are connected between neurons through established links; (3) Each connection between neurons relates to a weight that is the signal transmitted between neurons multiplied by the weights; (4) each neuron in the network implements the activation function for input so that it can regulate its output (Chiroma et al., 2017).

ANN is a method for classifying time series data that can provide solutions to non-linear problems using their inner-parallel architecture (Stangierski et al., 2019; Tsakiri et al., 2018). The application of ANN can be the right solution, but the problem is the network architecture and the selection of appropriate training methods. Normally, multilayer networks are used with the Feed Forward Neural Networks (FFNN) model. In FFNN, neurons are arranged in layers and signals flow from the input to the first layer, then to the second layer (Caraka et al., 2019; Caraka et al., 2019).

ANN comprises at least input, hidden layer, and output. The number of input layer nodes depends on the number of tested variables. The number of hidden layers and neurons counts on the complexity of the command and the amount of training data. Apart from the input-layer neurons that externally receive the input, each neuron in the hidden and output layer gets information from many other neurons. The weights determine the strength of the interconnection between two neurons. Each input of neurons in the hidden and the output layers are multiplied by the weight, input from other neurons added and the addition is an application of the activation function. The results of the calculations serve as input to other neurons and the optimum value of the weight is obtained through training (Chiroma et al., 2017; Malik and Nasereddin, 2006). For more details can be seen in Figure 2.

This study using a multilayer perceptron, also known as MLP, a network consisting of a set of sensor units (source nodes), where there are input layers, one or more hidden layers of computation nodes, and an output layer. This study also adopts MLP trained with back-propagation algorithm (BPA), the most commonly used neural network method (Pradhan and Lee, 2010). The back-propagation training algorithm is usually used to minimize the following cost function associated with weights and neurons thresholds (Fayed et al., 2019). According to Haykin (1998) and Tsakiri et al. (2018), MLP training identifies the weight, ω_{ji} for each layer based on network learning.

Figure 2 shows the MLP structure with inputs shown as x_1, x_2, \dots, x_n , weights with $\omega_{j1}, \omega_{j2}, \dots, \omega_{jn}$, b is the bias and ϕ is the transfer function, v is the weighted sum of the inputs. Next, the neuron j being fed by a set of signal functions produced by a layer of neurons on its left. The induced local field v_j is produced at the input of the activation or transfer function associated with neurons j (Haykin, 1998).

$$v_{jn} = \sum_{n=1}^m \omega_{jn} x_n \quad (7)$$

Where m is the total number of inputs (except bias) used by neurons j . the synaptic weight w_j equals with bias b applied to neuron j . As explained earlier, this study uses back-propagation to improve the weights of each neuron while minimizing errors (Haykin, 1998). Errors can be explained using the following equation:

$$e_{jn} = d_{jn} - y_{jn} \quad (9)$$

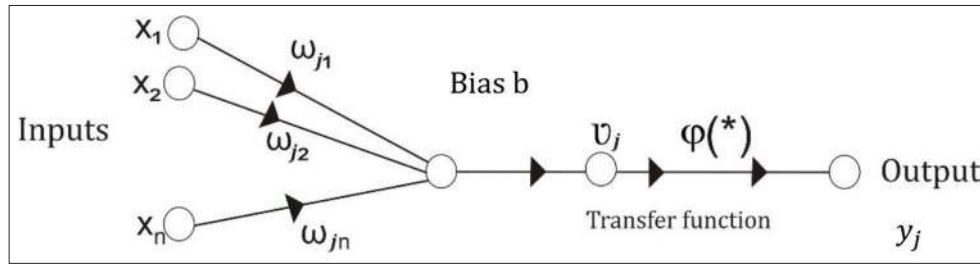
Where j is the output node, d is the target value, and y is the MLP produced value. The error in the output node j is given by the following equation:

$$\varepsilon_n = \frac{1}{2} \sum_j e_{jn}^2 \quad (10)$$

To minimize the error of each weight, we applying gradient descent:

$$\Delta \omega_{jn} = -\eta \frac{\partial \varepsilon_n}{\partial v_{jn}} y_{jn} \quad (11)$$

Figure 2: The multilayer perceptron (MLP) neural networks



In the equation above, η is the learning rate, y_j is the output of the previous neuron.

3. DATA AND SIMULATION

3.1. The Data

This study using monthly time series data, from January 1998 to December 2018, so that we obtain 252 data series. Data were acquired from the Bureau of Energy, the Ministry of Economic Affairs of Taiwan, the National Statistics Bureau of Taiwan, and the Central Weather Bureau of Taiwan.

According to Pradhan and Lee (2010), the ANN approach has many benefits compared to other statistical methods. ANN is not contingent on a statistical distribution of the data and also does not require specific statistical variables. We adopt electricity consumption data as a response variable to 6 input data (variable input), where electricity consumption is the amount of kWh consumed by households every month. Furthermore, to determine the existence and magnitude of the rebound effect, perceived from the $P_{cut,t}$ value as presented in formula number 5 (Ai et al., 2020; Alvi et al., 2018; Bentzen, 2004; Han et al., 2019). We can examine the decomposition results from formulas number 4 to 6 in Figures 3.

The following input is the degree days (DD). The degree days is a simple description of the temperature conditions that endure outdoors. DD is regularly used to estimate the impact of outdoor temperatures on indoor energy use. To measure DD, we use the formula:

$$HDD = \sum_{i=1}^n (T_{base} - T_n) M \quad (12)$$

$$CDD = \sum_{i=1}^n (T_n - T_{base}) M \quad (13)$$

Where HDD is heating degree days and CDD is cooling degree days. T_{base} refers to the basic temperature of the degree day. T_n is the average daily temperature, where it is a sum of the maximum and the minimum daily temperatures divided by two. Thus, the DD value denotes the sum of the HDD and CDD. The next input is the population (Pop). In our study, it is the number of Taiwan population growth every month from January 1998 to December 2018. The last input is Taiwan economic growth which is Gross Domestic Product (GDP) growth (Table 1).

Table 1: Variable and descriptive statistics

Variable definition	Variable name	Mean	SD
Monthly electricity consumption (kWh)	<i>ElectCons</i>	18458.85	3229.21
Maximum historical price	P_{max}	2.51	0.38
Cumulating series of price cuts	P_{cut}	-0.09	0.09
Cumulating series of price recoveries	P_{rec}	0.03	0.02
Monthly degree days	<i>DD</i>	353.88	181.99
Monthly population growth	<i>Pop</i>	0.04	0.01
Monthly GDP growth	<i>GDP</i>	3.76	3.64

3.2. Simulation

When developing a neural network, data construction is first split into two stages, first is data pre-processing which is to normalize data with min-max normalization into the specific range of 0.0 to 1.0. Second, dividing the data into two parts, particularly training data and testing data. This section proposes to test the performance and recognize the accuracy of the network using training data.

First, data normalization, the reason for producing data normalization is to make it more accessible to manage training data. Avoiding data normalization will provide useless results. The most common methods for data normalization are the z-normalization and the min-max scale. In this study, data normalization was completed with the min-max method which is the most commonly used method for data processing. With this method the data is transformed to a value between 0 and 1 (Pradhan and Lee, 2010), following the formula below, if y_i ($i = 1, 2, 3, \dots, n$):

$$Y_i = \frac{y_i - y_{min}}{y_{max} - y_{min}} \quad (14)$$

Y_i is the normalized value of y_i , y_{min} , and y_{max} is the minimum and maximum values of y_i respectively.

Second, separate the data into training and testing data. This step for the training stage of the model built and to update the weights of the network. The main purpose of this step is to verify the performance of the network using un-trained data and provide confirmation of its level of accuracy. There are no mathematical rules for determining the minimum size of each component (Nefeslioglu et al., 2010). In this study, the size of the training data is 80% or 202 data, and the testing data is 20% or 50 data.

The neural network applied in this study consists of four layers; an input layer; two hidden layers; and an output layer, and the

activation function used is linear. The ascertainment of architecture and activation function in this study is based on the lowest MSE value after conducting a series of experiments with different combinations of architectures and activation functions (Figure 4).

Where I is input, H is hidden layers, B is bias and O is output.

After taking the weight value of each neuron, the next step is to discover the variable importance relative between the inputs. This is to recognize the relationship between the input and the output. Variable importance or relative importance of input factors can be assessed by calculating the connection weights of neurons. This involves partitioning the hidden output connection weights into the components that are connected with each input neurons (Garson, 1991; Goh, 1995). Nevertheless, in assessing this relative importance, the Garson algorithm only calculates relative importance for a hidden layer and only examine absolute values. Thus, to generate output that is more under our craved, we modify the algorithm with backward examination because our neural network architecture has two hidden layers and no longer uses absolute values.

The calculation starts from the second hidden layer to find the output of the first hidden layer. If the hidden layer n we notify with h_m and our input is notified i_n and our output is o , then:

$$Ph_m = i_n \cdot o_m \tag{15}$$

$$Qh_m = \frac{Ph_m}{\sum_{n=1}^n Pi_n} \tag{16}$$

$$Ri_n = \sum_{m=1}^m Qh_m \tag{17}$$

The formula above is applied again to calculate the first hidden layer, using the results of the second hidden layer calculation. To resolve the relative importance of each variable, the above process continues with:

$$Si_n = \frac{Ri_n}{\sum Ri} \tag{18}$$

Figure 3: Price decomposition

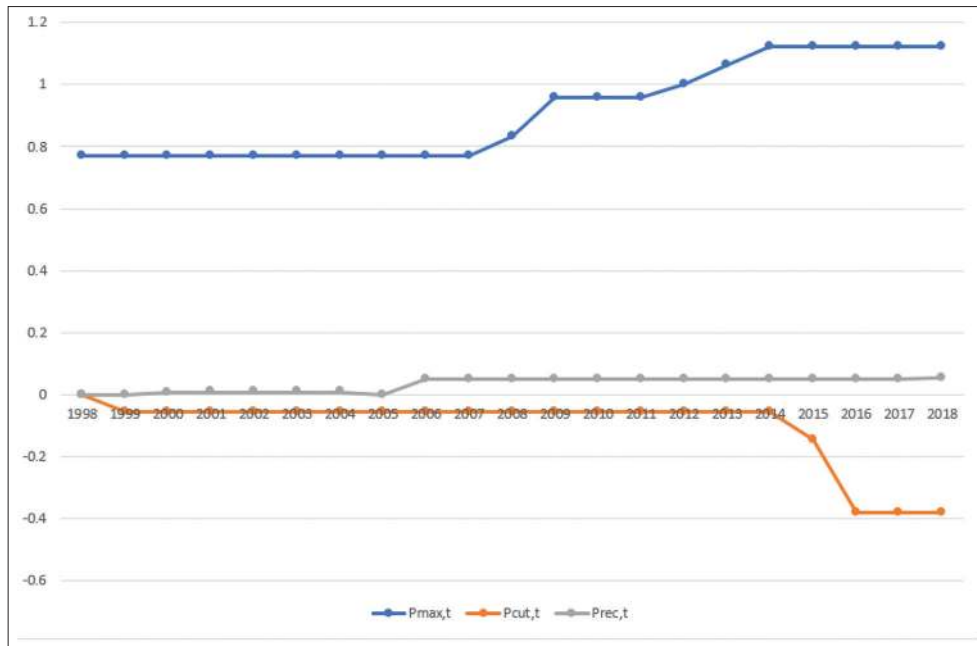
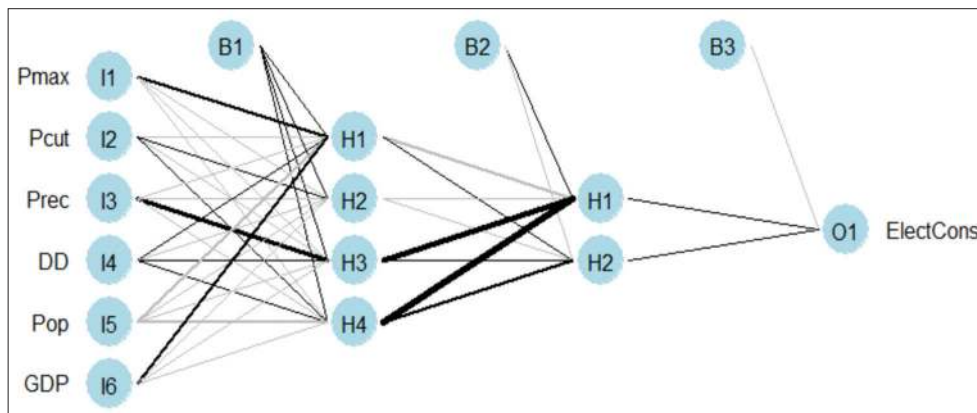


Figure 4: ANN architecture



The results of the estimation of relative importance will determine how much magnitude of the direct rebound effect examined from the relative importance value indicated by the P_{cut} input. The negative value of P_{cut} input confirms the amount of direct rebound effect.

Additionally, to compare the results of neural network computations, we calculate a Linear Regression Model (LRM), so that we can analyze the magnitude of the rebound effect of the two models. The general econometric model below shows the relationship between the variables in this study:

$$\ln EC_t = \alpha + \beta_1 \ln P_{max,t} + \beta_2 \ln P_{cut,t} + \beta_3 \ln P_{rec,t} + \beta_4 \ln DD_t + \beta_5 \ln Pop_t + \beta_6 \ln GDP_t + u_t \quad (19)$$

The ANN and regressions model were verified based on the amount of Mean Square Error (MSE), Root-Mean Square Error (RMSE) and coefficient of determination (R^2).

4. EMPIRICAL RESULTS AND DISCUSSION

To begin with, the selection of the neural network model is one of the important stages before deciding to continue to the next step. The selection of this model can be provided in various ways, in this study the determination of the model is prepared by testing on several models to find the minimum MSE value of each of the models tested previously. From Figure 5 we can notice the difference in MSE of each model based on the number of hidden layers and activation functions. In the first model, it uses two hidden layers and a linear activation function, the second model applies one hidden layer and a linear activation function, the third model applies two hidden layers and a sigmoid or logistic activation function, and the fourth model uses one hidden layer and a logistic activation function.

From the bar chart above it can be seen that the MSE value in the first model is the lowest when compared to the others. So, in this study applying the first model, which uses two hidden layers and a linear activation function.

After determining the best model based on the lowest MSE value, we move to the next step. The neural network plot displayed in the Appendix exposes the graphical representation of the model built with weights in each connection. The black lines show the connections between layers and weights for each connection, while the blue lines present the bias that exists at each step. Further, before calculating the weights of each connection to determine the relative variable importance that is applied to see the magnitude of the direct rebound effect, we will calculate the performance of the selected model. In this case, the performance of the first neural network model (Figure 5) will be compared with the linear regression model (LRM) using the predicted value generated by the two models.

From Figure 6 we can observe the performance of both models, these are neural networks and linear regression models. The plot illustrates the two models are fit to line or close to the ideal line. However, when we observe the distribution of the plots, the neural network looks better than the regression. That is because the predicted values generated by the neural network are more concentrated in the ideal line. This indicates that the neural network has a more satisfying predictive value.

Table 2 presents the estimation results using two approaches, the artificial neural network (ANN) and a linear regression model (LRM). The negative value is shown in the price cut parameter, both in the relative importance of the neural network and the regression coefficient proves the magnitude of the direct rebound effect. In ANN, the estimated rebound effect value is shown by the P_{cut} value of 11.17% and 21.95% for the train and test data. The amount is not too different from the estimation provided by LRM using min-max normalization data, which is 15.25% and 11.15% for the train and test data. However, using the LRM approach with the method most frequently used (logarithmic transformations of variables) gives a larger estimate of 32.4%.

Furthermore, the neural network value is quite consistent with the LRM, it confers that ANN can be an alternative to measure the magnitude of the rebound effect. The MSE value of ANN is 0.00444 and 0.00228, still lower than the MSE value indicated

Figure 5: Comparison of SME Values

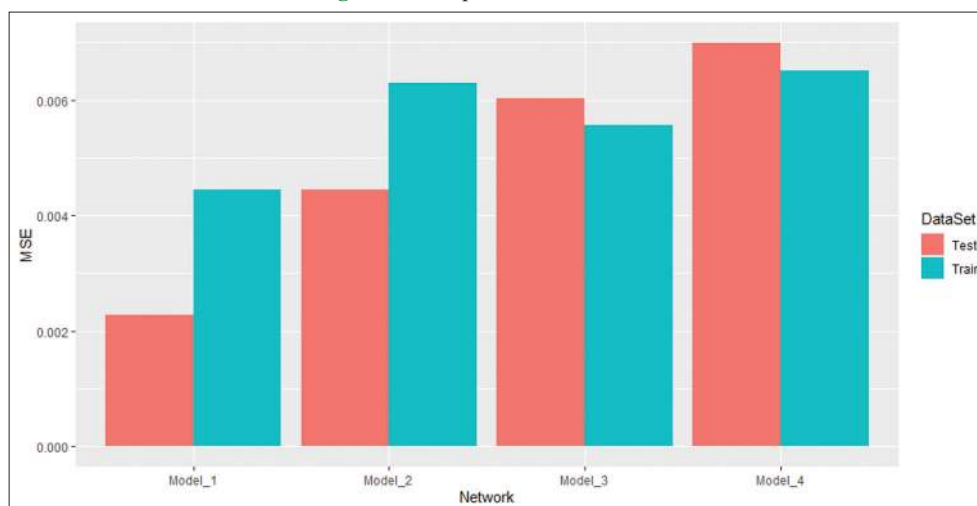
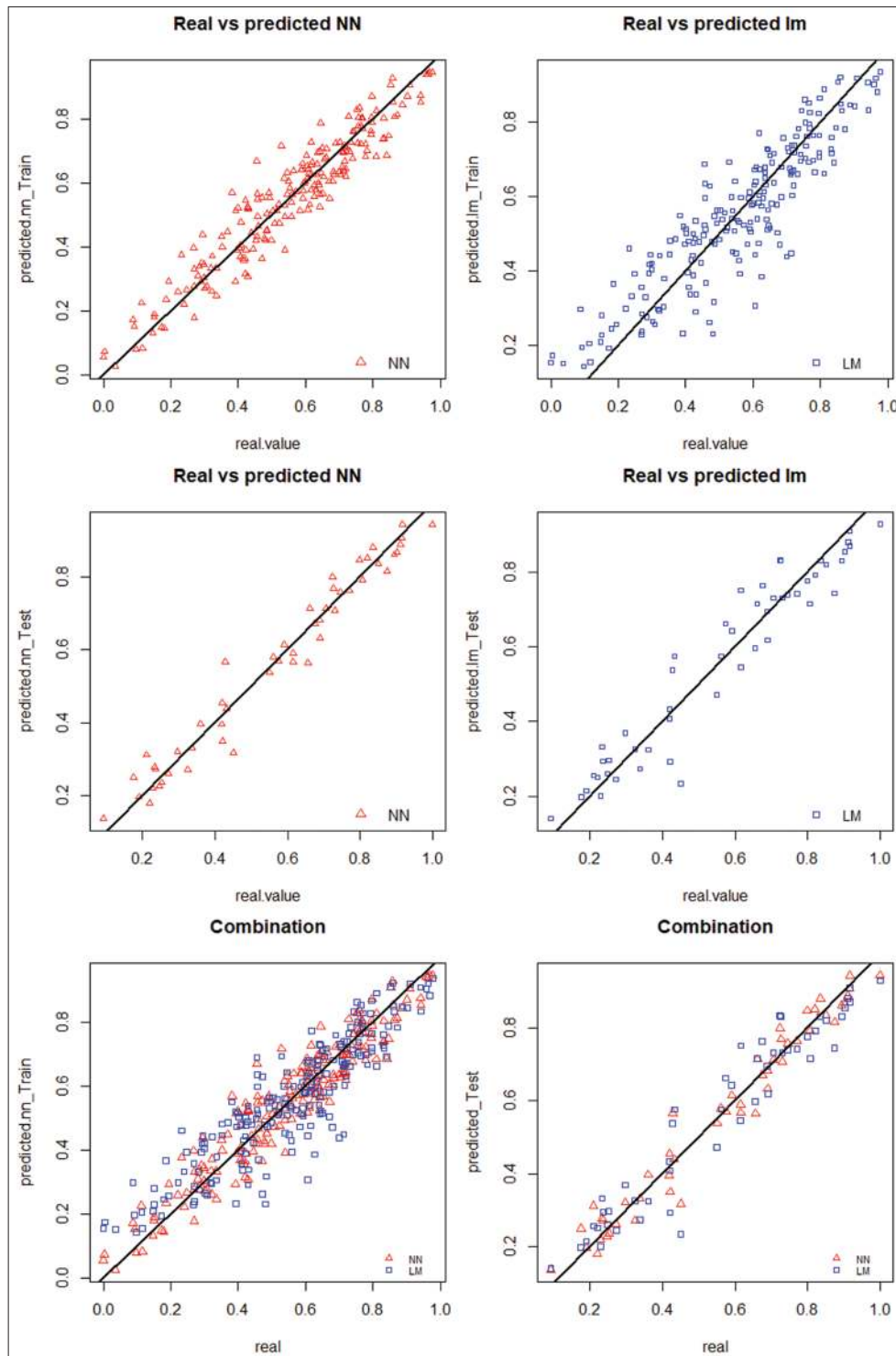


Figure 6: Model performance



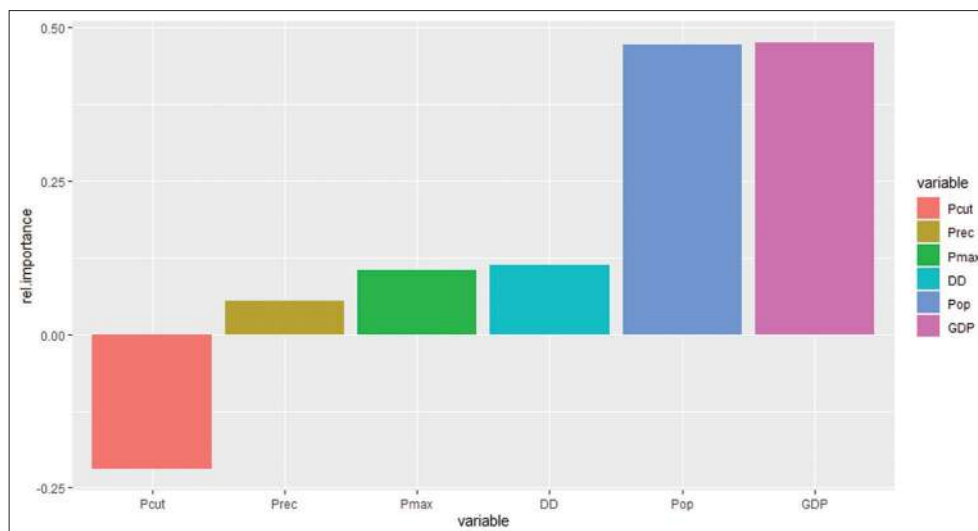
from the LRM with 0.03749, 0.00510 and 0.00712. This value affects the RMSE value of ANN which is also lower than the LRM. Besides, the value of R^2 (the coefficient of determination) in the ANN model is 0.90 and 0.96 or better than the value of R^2 presented in the LRM. Therefore, in this study, the estimation results produced by ANN are better than the LRM recognized from the MSE, RMSE and R^2 parameters. Figure 7 gives a view of the relative importance values from the test data as the best results in the model built.

From Figure 7 it can be seen that the GDP growth variable has the highest relative value of 47.56%, or in other words GDP growth is the most important input in the model developed, then followed by population growth with a value of 47.16% and degree days with a value of 11.31%. In addition to the three inputs, the maximum price and price recovery also have positive values in the model, particularly 10.52% and 5.4%, respectively. Furthermore, only the cumulative price cut variable is negative, which is 21.95%, while this negative value indicates the amount of direct rebound effect.

Table 2: ANN and LRM results

Variables		ANN		LRM		
		Relative importance		Coefficient		
		Train	Test	Train	Test	ln
P_{max}	$\ln P_{max,t}$	0.31495	0.10522	0.11681 (0.003)**	0.31314 (0.000)***	0.51435 (0.000)***
P_{cut}	$\ln P_{cut,t}$	-0.11168	-0.21949	-0.15254 (0.000)***	-0.11155 (0.046)*	-0.32402 (0.000)***
P_{rec}	$\ln P_{rec,t}$	0.15591	0.05390	0.39384 (0.000)***	0.46543 (0.000)***	7.36113 (0.000)***
DD	$\ln DD_t$	0.15033	0.11313	0.34673 (0.000)***	0.23730 (0.000)***	0.12787 (0.000)***
Pop	$\ln Pop_t$	0.03949	0.47162	0.20139 (0.007)**	0.36657 (0.012)*	0.26925 (0.000)***
GDP	$\ln GDP_t$	0.45098	0.47560	0.10465 (0.005)**	0.09652 (0.211)	-0.00463 (0.581)
Constanta				0.05454 (0.43)	-0.10695 (0.44)	9.2543 (0.000)***
MSE		0.00444	0.00228	0.03749	0.00510	0.00712
RMSE		0.06663	0.04774	0.19362	0.07141	0.08438
R ²		0.90325	0.96386	0.7918	0.9081	0.8012

Figure 7: Relative importance variable



The magnitude of the direct rebound effect is 11.17-21.95% for household electricity consumption, higher than the rebound effect for the industrial sector in Taiwan as the results of a study conducted by Wu et al. (2016). The study carried by Wu et al. (2016) showed a magnitude of rebound effect around 10% for Taiwan’s industries. Though, this number is still smaller than the results of a study conducted by Su (2019), where the results of his study showed a magnitude of the rebound effect around 33% for the residential sector in Taiwan.

Moreover, when compared with other Asian countries such as China, the magnitude of direct rebound effects is between 37% and 71.53%, even for the national average of 74.18% (Han et al., 2019; Li and Yonglei, 2012; Zhang and Peng, 2016), the magnitude of the direct rebound effect in Taiwan tends to be smaller. Likewise, when compared with Pakistan, studied from Alvi et al. (2018), the value of the rebound effect in Taiwan is still smaller because of the magnitude of the direct rebound effect in Pakistan which is 69.5% for the long-run and 42.9% for the short-run.

5. CONCLUSIONS AND IMPLICATIONS

To conclude, concerning the increase in household energy demand, the Taiwan government makes an important step by reforming the energy sector. Expecting changes quickly and easily is naive while the mega project is being pursued by the Government. Because any major policy change may bring huge obstacles to the interests of the other party. However, they need to give attention to some important issues correlated to the energy sector policy. One point to note is the rebound effect which is one factor causing the energy efficiency gap.

Studies on rebound effects have been provided in many countries using various approaches and the values obtained are also very diverse. Among the many approaches applied, as far as we know, no one has used an artificial neural network as an alternative to estimating rebound effects. ANN is a mathematical model that consists of an interconnected group of neurons and processes information using a computing-based connection.

From the calculation results, the magnitude of the direct rebound effect for residential electricity consumption in Taiwan is in the range of 11.17-21.95%. Additionally, to confirm the calculations result from ANN, we are using a linear regression model to compare. The LRM calculation results using min-max normalization data found the value of the direct rebound effect around 11.15-15.25%, and if using logarithmic transformations of variables, the rebound effect value increased to 32.4%.

Furthermore, modelling with ANN found that the GDP growth variable with a value of 47.56% was the most important input in the model built. GDP growth has direct implications for increasing household electricity consumption, as well as population growth, which has a role similar to GDP. Additionally, with a value of 11.31%, the degree days which also indicate climate change, reveal that the effect of climate change is crucial in the use of household energy. Degree days must be one of the indicators judged by the government in assigning energy policies.

From the estimation results with the ANN approaches, it looks better than LRM, both from the MSE, RMSE and R² values, so that ANN can be one of the alternative approaches in estimating the magnitude of the rebound effect. However, for further research, we recommend using a larger amount of data and more varied inputs to produce a better estimate value. The greater amount of data will largely determine the quality of the estimates produced by ANN. Besides, a very diverse model variation from ANN can be applied as another alternative in estimating rebound effects, particularly by using different types of data, so that a more comprehensive model will be found compared to other models that already exist. In the future analysis of Taiwan's electricity consumption's rebound effect, the impact of technological innovation cannot be ignored, which will be the author's future research topic.

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