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Hybrid load forecasting considering energy efficiency and renewable energy using neural network

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ABSTRACT

In recent years, the relationship between a country's gross domestic product (GDP) and its electricity consumption has changed significantly due to increased energy efficiency (EE) and renewable energy (RE) adoption. This decoupling disrupts conventional load forecasting models, affecting utility companies. This study has developed an innovative solution using an artificial neural network (ANN) Hybrid method for load forecasting, resulting in a remarkably accurate model with 99.68% precision. Applying this model to Malaysia's electricity consumption from 2020 to 2040 reveals a significant 13% reduction when accounting for EE and RE trends. This method aids risk management, contingency planning, and decision-making by accurately reflecting changing energy usage dynamics influenced by EE and RE sources.

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1. INTRODUCTION

According to Malaysia's Economic Planning Unit, the energy sector contributes 28% of the gross domestic product (GDP) per annum, which is around RM 400 billion [1]. On the demand side, the sector needs to address issues such as increasing energy consumption and the burden of subsidies. On the supply side, it faces challenges like the depletion of non-renewable resources, rising supply costs, complex environmental issues, and fragmented governance. Internationally, future-proofing the industry involves tackling megatrends such as the energy transition and various regional and global socioeconomic, technological, and geopolitical changes that could reshape the energy landscape in implementing the 17 sustainable development goals (SDGs) [2].

A study by Chandran *et al.* [3] found a clear link between energy consumption and economic growth in Malaysia. Ozturk and Acaravci [4] identified four types of causality between these variables: no causality, unidirectional causality from energy consumption to economic growth and vice versa, and bidirectional causality. Liao *et al.* [5] discovered that a one percentage point increase in GDP per capita growth leads to a 0.15 percentage point increase in energy usage. In China, Guang *et al.* [6] observed that the electricity growth rate averaged 11.22% from 2000 to 2013 but dropped to 5.55% from 2014 to 2019. Rahman *et al.* [7] confirmed a bidirectional relationship between renewable energy (RE) use and economic growth in Malaysia. Zhang *et al.* [8] warned that differences in variables like industrial growth and foreign direct investment across countries could bias results unless properly accounted for. Tran *et al.* [9] suggested that analyses should consider GDP threshold effects to avoid biases. Mauleón [10] used a statistical approach to show that the relationship between GDP, population growth, and energy demand is increasingly non-linear over time.

The research identifies a gap in the accuracy of current load forecasting models, particularly regarding the impact of energy efficiency (EE) and RE factors. While existing studies explore the relationship between economic growth and energy consumption or investment factors, they do not specifically address how EE and RE significantly influence load forecasting. Various methods have been used for electrical load forecasting, including time series, statistical analysis, regression analysis, multiple linear regression, and artificial intelligence (AI). The rapid development of AI and deep learning, particularly neural networks (NN), has significantly impacted the electricity sector. However, traditional artificial neural networks (ANN) face challenges in medium and long-term load forecasting due to data collection and processing difficulties. To address these issues, Mauleón [10] proposed using radial basis function neural networks (RBFNN). Additionally, Ali *et al.* [11] suggested a fuzzy logic approach to account for the non-linear relationship between weather and peak monthly loads. In a more radical approach, Chen and Wang [12] formed a committee of experts to forecast annual energy consumption using principal component analysis and fuzzy feed-forward neural networks (PCA-FFNN), combined with partial-consensus fuzzy intersection and radial basis function network (PCFI-RBF) methods. Despite these advancements, ANNs remain one of the most widely used methods, modeling computationally the structure and behavior of biological brain networks.

While various load forecasting models based on NN approaches have been proposed in previous studies, to the best of our knowledge, none have considered including the impacts of RE and EE, especially in the context of Malaysia. Therefore, this study aims to address this gap by developing a new load forecasting method using a hybrid approach. Initially, a baseline econometric forecast was formulated to capture the relationship between parameters. Subsequently, the end-use forecast was calibrated to the econometric forecast to incorporate additional macro trends, along with several post-estimation adjustments to improve accuracy. In essence, the forecasted results obtained from the feed-forward back-propagation ANN modeling using MATLAB do not currently reflect the prevailing trends. Thus, adjusting the post-estimation model for RE and EE would enhance the accuracy of the forecasting results, thereby demonstrating the impact of the decoupling between GDP and population on electricity consumption. This method could enhance risk management, contingency planning, and decision-making by meticulously capturing the evolving dynamics of energy usage, which are intricately influenced by both EE measures and RE sources.

The paper is structured as follows: in section 2, the methodology process of the study is outlined, emphasizing the entire process starting from data collection, modeling of ANN econometrics, and tuning modeling parameters. Section 3 explains the ANN correlation analysis and presents the results of the following process, where regression analysis is performed to show the variables' correlation. Furthermore, EE and RE measures were used to design the end-use model prior to the model adjustment. Finally, conclusions are drawn in section 4.

2. RESEARCH METHOD

The research methodology can be summed up in three processes, namely, i) data gathering, ii) ANN modeling, and iii) hybrid load forecasting. To start, data gathering from reliable sources were performed. ANN econometric-based modeling was then constructed, and retraining of the network was done if the R-squared value was low, signifying that the result from the model was inaccurate. The load forecasting was established for the years 2020 to 2040. Furthermore, residual analysis was performed, and the results were compared with the regression analysis to further examine the accuracy of the resulting output. After the initial results had been acquired from the constructed network, the EE end-use model and RE post-estimation model using the data forecasted from the years 2019 to 2040 were utilized. After both models have been constructed, they will then be subtracted from the original ANN-modelling baseline econometric model. For EE, the assumption is that a 5% reduction in the total energy consumption will happen annually while in RE, an assumption of 10% in energy consumption will occur. Previously, the relationship between energy consumption and GDP can be explained by the econometric model. The econometric model obeys the neo-classical theory of growth proposed by Robert Solow and Trevor Swan in 1956 [13]. In this theory, energy is recognized for its role in relation to economic growth, acting as both an intermediate input in the production process and a tradable commodity in the market. However, the theory mainly focuses on how energy affects production and economic efficiency but fails to capture the intricate and multifaceted relationship between energy and the economy, or its broader implications for society and the environment as has been shown by Rochon and Rossi [14].

2.1. Data gathering

In this stage, the historical patterns of projected consumer demand that do not take EE and RE into account are introduced for the baseline electricity consumption forecast. The independent variable of this model is the population and GDP per capita while the dependent variable is the energy consumption in ktoe. The independent variables act as the input of the ANN modelling while the dependent variable is the target data. The data used in the ANN modeling are from the years 1980 to 2040 and were acquired through the National Energy Balance (NEB) and the Malaysian Energy Information Hub (MEIH) managed by the energy commission.

For the next part of data gathering, concrete data that measures the EE and RE are needed to construct both the end-use model and post-estimation model. In terms of EE, the study considers EE measures from appliances such as air conditioners, refrigerators, and fans, that are based on Malaysia's minimum energy standard (MEPS) [15]. The data used were from the years 2013 to 2015. On the other hand, all types of RE are considered, and the available data are from the years 2010 to 2019.

2.2. ANN-based econometric model

The general equation of the ANN model is shown in (1). ANN takes fewer instances than statistical techniques as it is nonlinear in characteristic, making it more efficient to solve more complex problems than most standard approaches. The NN was constructed by utilizing the tools available in MATLAB. The network was a three-layer feed-forward back-propagation where the basis of the network is a single hidden layer network with one input layer and one output layer. Network settings like the number of neurons and transfer function are heuristically computed and cross-validation methods are used to find the ideal network architecture. Furthermore, the three-layer feed-forward back-propagation was chosen due to its non-linearity handling that enables it to capture complex relationships and underlying patterns in data, a crucial feature for energy consumption estimation. Backpropagation also allows the model to iteratively adjust its weights to minimize error. This process helps the model to converge to a solution that can accurately represent the underlying patterns in the data.

$$Output_n = Activation(Weight_{S_{n-1}} \times Output_{S_{n-1}}) \tag{1}$$

Figure 1 is the visualization of the architecture of the network. The input data, x is the independent variables namely the population and the GDP per capita data, while the electricity consumption which is the dependent variable acts as the target data, y meaning that we put the y data to act as the benchmark for the forecasted output, Y to measure itself against. The target for the forecasted output, Y is the period from 2021 to 2040.

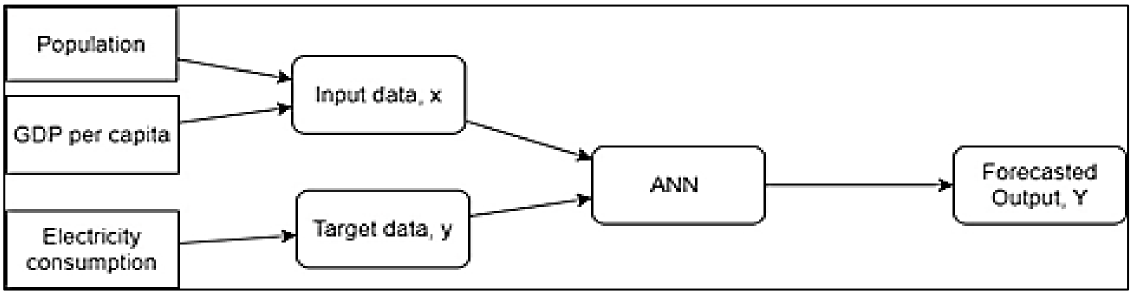


Figure 1. ANN architecture

2.2.1. Training the model

During the training process, the network underwent both forward and backward propagation. In the forward propagation process, the input data are passed through the 50 hidden networks. The input values propagate in the direction from left (input) to right (output). During this process, the activation function occurs when the pre-activation function calculates the weighted sums of the data, and when the activation function is eventually applied, it would be based on the weighted sum to ensure that the network flows non-linearly using bias. Furthermore, according to the study conducted in [16], the existence of the hidden layers enables the extraction of higher-order statistics for the network. The backpropagation meanwhile propagates the data in the opposite direction while comparing the actual output to the desired output and then each node is adjusted by changing the weighted sums to reduce the error in predicting the output.

As has been concurred, for this network there are two input data, which are the population and the Malaysian GDP per capita from the year 1980 to 2040. Meanwhile, the target data are also considered as input in the initial phase as the model learned to approximate the underlying mapping between the input and the target data by adjusting its internal weights and biases. Next, the output of the network is compared to the corresponding target data to compute the error or loss. By repeatedly presenting input data and target data pairs to the network and updating its parameters, the model aims to minimize the discrepancy between its predictions and the actual value as seen in the target value.

Figure 2 shows the NN training information. In this training, the Levenberg-Marquardt method is used, and the performance is evaluated using the mean squared error (MSE). The training epoch takes around 12 iterations for the dataset involved. The Levenberg-Marquardt algorithm adjusts the model's parameters during training to optimize the fit between the predicted energy consumption and the target data. In the 12 iterations done, minimization of error was done to help the ANN model learn the underlying relationship between the input variables, that is the GDP per capita and population, and the output variable, energy consumption. The ANN's performance value of 1.17e-23 also suggested an extremely low error or loss indicating that the ANN model has achieved a high level of accuracy and precision in predicting the target variable. The gradient of the ANN model being 4.05e-08 meant that the loss function is changing slowly with respect to the model parameters, indicating that the model is approaching a local minimum or is close to convergence.

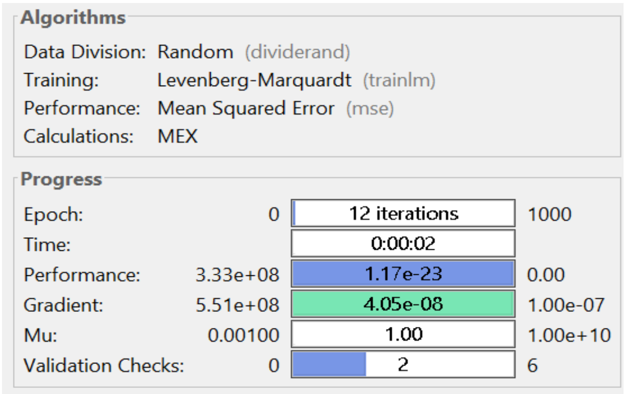


Figure 2. Network training information

2.2.2. Testing the model

The next step in this process is testing the model. Testing the model is crucial in assessing the trained network's performance by way of regression analysis that compares the network's output and the target data. Regression analysis can ensure that the resulting network output is cohesive and reflective of the target data. A significant association can be concluded when the resulting R-value between the output data and the target data is near 1. However, it must be noted that sometimes the model might not be accurate on the first try therefore, retraining should be done to make sure that the output aligns with the target data that is sought.

2.3. Hybrid load forecasting with EE and RE model

2.3.1. Energy efficiency end-use model

According to Bhattacharyya and Timilsina [17], the end-use model in terms of the engineering-economy approach refers to the disaggregation of the final consumption or the end-use of consumers at certain levels. In this model, the end-use approach is symbolized in the EE measures that can be counted in everyday appliances as more appliances comply with the MEPS. The standard econometric model does not accurately explain changes that are driven by the interconnecting additional factors such as the effect that MEPS appliances can have on future energy consumption. The end-use model meanwhile allows these factors to be considered and are deterministic in nature. By extrapolating the gathered EE measures data from the years 2013 to 2015, (2) was acquired, where y is the energy savings from the EE measures and x is the year where it provided a forecasted result up to 2040. The regression has an R-squared value of 0.9847, which indicates a good correlation. To add, the forecasted trend is a steady incline in the immediate future [18]–[20].

$$y = 253.23 + 1966.4 \tag{2}$$

2.3.2. Renewable energy post-estimation model

Post-estimation model is then implemented to ensure forecasted result would more accurately reflect the current situation. In this case, the post-estimation process consists of all RE projects implemented. An aggregation of all sources of RE data that was made available via the NEB and the MEIH was taken into consideration in constructing the post-estimation model. From these data, we can also surmise that the policy and regulations such as the net energy metering (NEM), feed-in tariff, and the self-consumption (SelCo) scheme are included [21]–[23]. Using the gathered data from 2010 to 2019, an exponential trend was observed as shown in (3), where y is the total of the RE generation in Malaysia and x is the year. From this, the approximation of the subsequent data from 2020 to 2040 was acquired using the equation. The fitted line also underwent an R-squared test, where it was seen that the results were 0.9746 indicating that the approximation was highly reliable.

$$y = 2 \times 10^{7} e^{0.0567x} \tag{3}$$

2.3.3. Adjusted load-forecasting model

The equation used for the adjusted load-forecasting model is shown in (4). The data involved in this process are the ANN forecasted output, EE, and RE measures from the years 2019 to 2040. Further adjustments are made to both the EE and RE measures, where each data from each year is multiplied with the factor 0.1 and 0.05 respectively. These multiplication factors symbolize the percentage of reduction in electricity consumption. In this case, an assumption was made that EE measures being implemented would reduce the overall electricity consumption by 10% while RE measures would yield a 5% reduction in overall electricity consumption. Studies in [24], and [25] have shown that both measures can yield a higher percentage of reduction in energy consumption, but this study chose to employ a more conservative estimation of 5 and 10% reduction by RE and EE measures respectively.

$$\begin{aligned} &Adjusted\ Consumption = \\ &Forecasted\ output - (EE\ measures\ \times 0.1) - (RE\ measures\ \times 0.05) \end{aligned} \tag{4}$$

3. RESULTS AND DISCUSSION

3.1. Artificial neural network-based econometric model

As has been shown in the previous section, the tests have shown that all the variables have strong correlations with each other. Therefore, in constructing the model, the data were separated into two categories, testing data and training data. Data from 1980 to 2020 acted as the training data while the data from 2021 to 2040 acted as the testing data.

By referring to Figure 3, it was seen that the overall value of R for training, testing, and validation tests is 0.99968. The correlation coefficient, R is very close to 1 therefore we can surmise a significant degree of correlation between the independent variables and the dependent variables. The testing data act as a benchmark to evaluate the network's performance. The R-squared value of the ANN model is then evaluated by comparing it with the R-squared value of the regression analysis done on the Excel ToolPak application. The R-squared value of the ANN model is 0.99968 while the R-squared value of the Excel ToolPak regression analysis is 0.9962. By these, it is indicated that the ANN's forecasted output shows a stronger correlation between the variables being analyzed, suggesting that perhaps it has a closer fit to the data points used for training and testing. It may also suggest that the ANN model may have utilized additional variables or employed a more sophisticated algorithm that enables it to uncover hidden patterns or nonlinear relationships that the Excel ToolPak application's regression analysis or the ANOVA test could not accurately capture.

Next, Figure 4 depicts the graph of the actual versus the forecasted value of the model. From it, one can see that the forecasted value follows along more or less a similar slope of the graph as the actual value. Meanwhile, after the training and testing of the data had been done, residual analysis was carried out to test the validity of the results. In Figure 5, which depicts the scatter plot of the results. Fit can be seen that the small dispersion trend of the graph means that the data points have a better fit to the horizontal straight line. This reinforces the hypothesis that variables have a strong linear relationship. The fact that there is no significant deviation to the plot also means that the data can be assumed to be accurate.

Next, Figure 6 shows the histogram plot of the result. By interpreting this data, the distribution is skewed to the left which indicates that most of the forecasted data are concentrated towards higher levels with a longer tail towards lower values. From this, an interpretation was made that there are relatively few instances of lower electricity although there is one outlier in the right that suggests the existence of a few data points with exceptionally high electricity consumption values that fall far outside the typical pattern of the distribution. This phenomenon might be attributed to extreme or outlier observations. Overall, the left-skewed distribution indicates that there is a tendency for a higher consumption level with a limited number of instances of lower consumption values with few exceptional instances of abnormally high electricity consumption as represented by the outlier that skewed to the right.

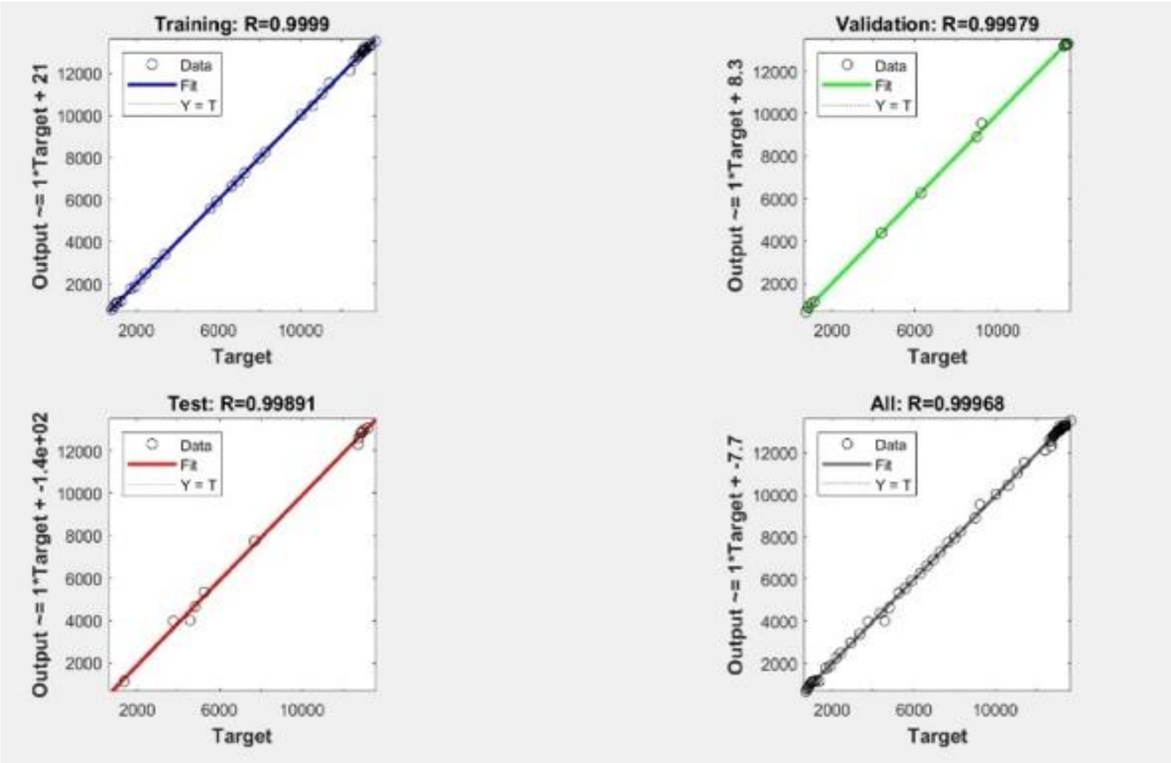


Figure 3. Network results

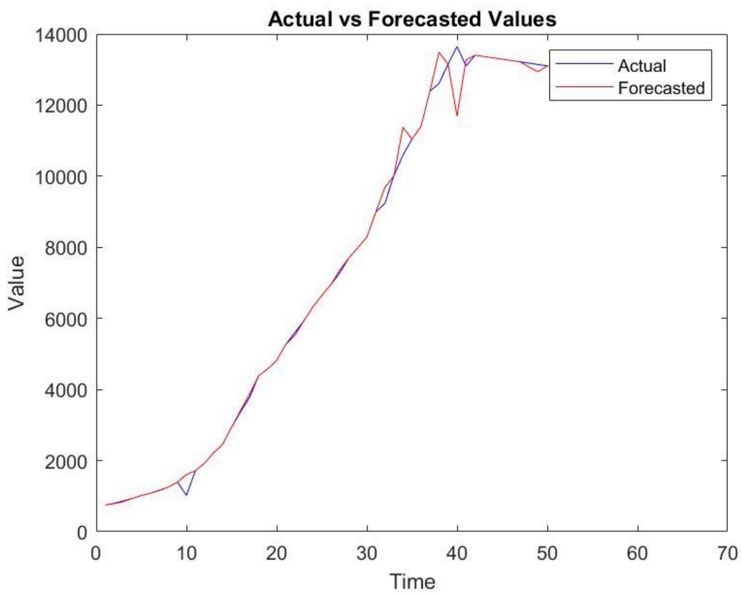


Figure 4. Actual versus forecasted value

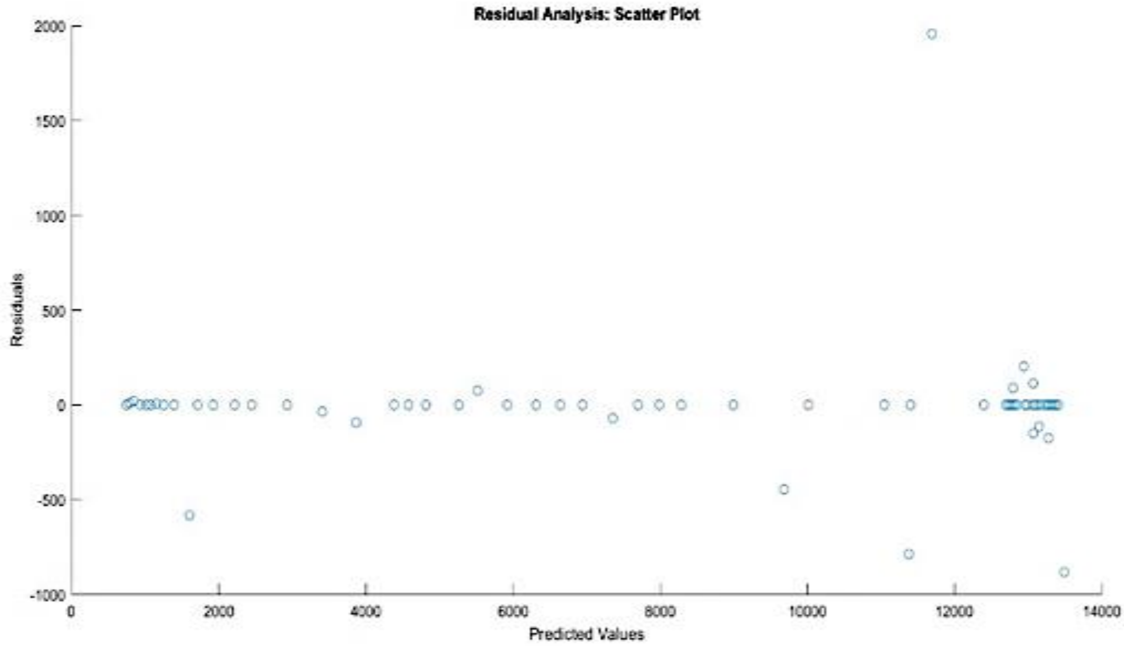


Figure 5. Scatter plot

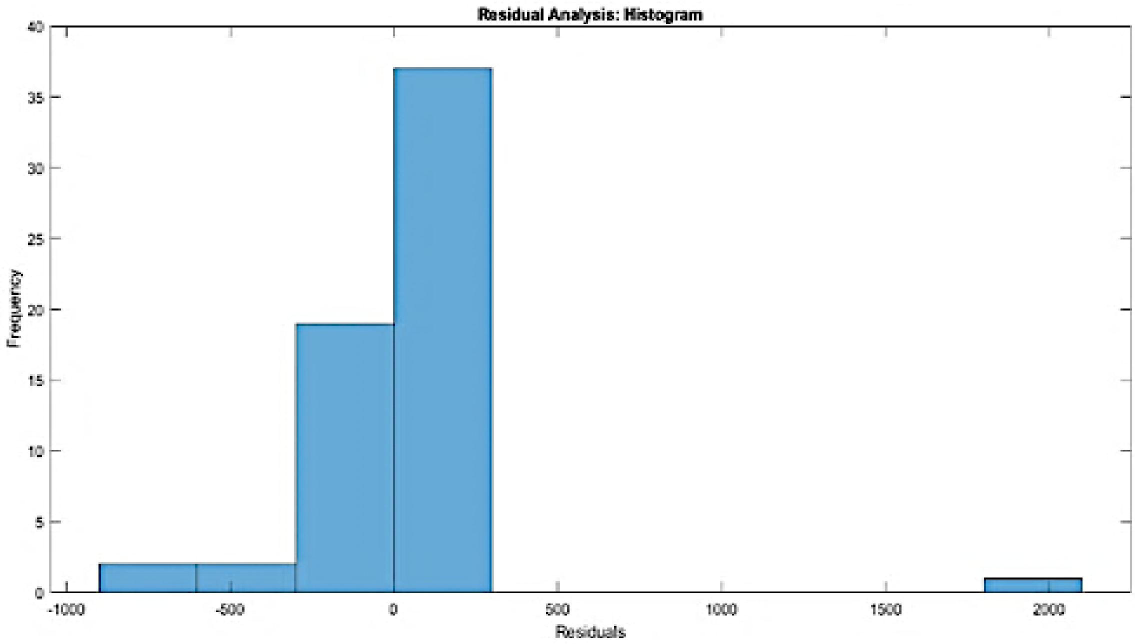
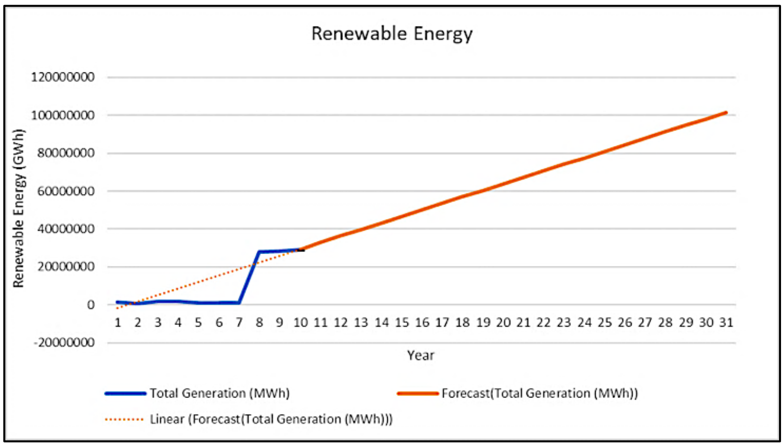


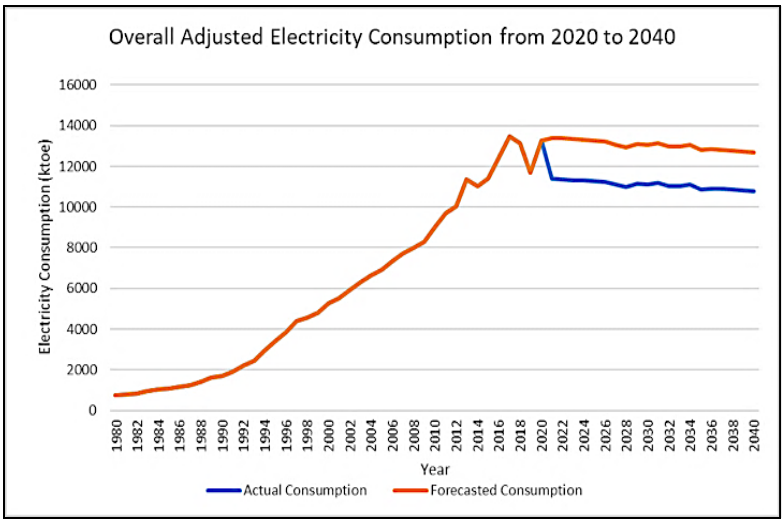
Figure 6. Histogram plot

3.2. Hybrid load forecasting model

Figure 7 shows the adjusted consumption based on the hybrid load forecasting system in MATLAB. From the figure, a reduction of 2,000 ktoe in energy consumption can be observed. The summation of forecasts from the econometric models has created the aggregation of the baseline forecast of the electricity consumption (Figure 7(a)). The line chart shows that a decline in electricity consumption started around 2019 and will continue to decline until 2040 based on our hybrid load forecasting technique (Figure 7(b)). Further calculations were done and the average for the adjusted consumption and actual consumption are 28,5796.46 and 24,6671.39 W respectively.



(a)



(b)

Figure 7. Electricity consumption based on a hybrid load forecasting system in (a) actual vs forecasted and (b) overall adjusted electricity consumption

4. CONCLUSION

The two main objectives of this study are to develop a model that predicts electricity consumption that considers the effect that EE and RE measure while analyzing the effect that both measures can have on electricity consumption. By analyzing the result of this study, it can be concluded that both measures influence electricity consumption by reducing the demand and thus proving that in the future there will be a wider trend of decoupling between economic growth that is symbolized by the GDP per capita and the overall electricity consumption. A further conclusion can be made that the dependent variable has some correlation with the independent variable by looking at the ANN model and the hybrid load forecasting model that precedes it. However, some recommendations can also be made. Since this study involves variables such as population and GDP per capita, in the future more variables should be considered as both variables have a wide breadth of factors that can influence them such as the flow of capital into the country, human capital, inflation or to give a recent example, the pandemic COVID-19. External and uncontrollable factors like these can sometimes have a domino effect on how we behave which can indirectly affect how we use and consume energy.

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