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Using Artificial Neural Network Models to Analyse Diesel Prices in Selected Regions in Tanzania

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A B S T R A C T

In the current study, artificial neural network (ANN) models are applied to estimate monthly diesel cap prices for the three selected Regions; Mbeya, Ruvuma and Katavi, utilizing data obtained in Mbeya City, Songea and Mpanda Municipalities respectively. The study proposed 5-12-10-1, 5-10-10-1 and 5-12-8-1 architectures for the Mbeya City ANN model, Songea Municipal ANN model and Mpanda Municipal ANN model, respectively, due to their exceptional estimation capabilities. The performance forecast of the ANN models was assessed with that of the historical monthly diesel cap price published by the EWURA. The results demonstrated that the suggested ANN models achieved R^2 and MAE values of 1.0000, 1.0000, 1.000 and 1.31×10^{-12}, 1.08×10^{-12}, 1.23×10^{-12} for ANN models for Mbeya City, Songea and Mpanda Municipalities, respectively, historical monthly diesel cap prices. Additionally, the study analysed the trends of the monthly diesel cap price variations, utilising outputs of the ANN models. Based on the analysis it shows that from July 2015 to February 2016, the monthly diesel price decreased by an average of 3.41%. Whereas, starting from March 2016 to December 2018, the monthly diesel price increased by an average of 1.56%. The analysis results demonstrate that the suggested ANN models exhibited superior performance in predicting monthly diesel cap prices in the study areas. Therefore, it can be deduced that the proposed ANN model is a reliable and effective tool for analysing monthly diesel cap prices in the selected regions. Based on the results, it can be concluded that the proposed ANN models are accurate and useful tools for analysing monthly diesel prices in Mbeya, Ruvuma and Katavi.

1. Introduction

In today's era of development and industrialisation, energy has emerged as a crucial driving force behind every economic sector globally. For instance, in Tanzania, petrol and diesel are the primary energy sources utilised to sustain various sectors including agriculture, transport, health industry, commerce, education, and home activities. Moreover, 82% of Tanzania's energy utilised is attributed to diesel and petrol energy products. However, the price per litre of these energy products varies significantly across different regions. Furthermore, the diesel and petrol markets are characterised by significant price fluctuation. The fluctuation in pricing can be ascribed to various reasons, such as import costs, product prices, distribution and transportation costs, marketing expenditures, and government taxes.

The volatility and fluctuation in monthly prices of diesel have significant repercussions on financial markets and economies, as well as amplifying the impact on consumers' household expenses (Taghizadeh-Hesary et al., 2016; Abdelsalam et al., 2020; Saari et al., 2016). For instance, Sun et al. (2022) conducted a study on the effect of price variation on consumption products and investment in the Chinese industrial sector. The study revealed that oil price variations most affect crude oil and gas extraction goods, refined products, and fuel products of processed nuclear.

In the petroleum industry, the estimation of diesel prices can be carried out by using a range of conventional techniques, such as time series, financial models, structural models, supply and demand models, and

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inventory models, among others. Although traditional methods are extensively used for predicting diesel and gasoline prices, they still have some drawbacks. Among them is the fact that these techniques fail to incorporate external variables such as geopolitical developments, natural disasters, abrupt regulatory modifications, market speculation, exchange rates, and other such elements. The impact of these external disturbances can have a substantial effect on the costs of gasoline and diesel, making it difficult for any technique to generate reliable predictions.

Therefore, recently, the petroleum industry has shifted its focus towards the utilisation of machine learning algorithms (MLAs) to address the limitations uncounted by conventional techniques in estimating diesel prices. Several researchers are now utilising artificial neural networks (ANN) approaches to estimate diesel prices. These techniques are preferred for their capacity to quickly and efficiently analyse and assess predicted outcomes (Azad et al., 2022; Mamudu et al., 2020; Rahimi et al., 2023; Davoodi et al., 2023). A study conducted by Shafique et al. (2018), pointed out that these methods provide a dynamic view of analysing input datasets and may effectively identify outlier values.

Using ANN techniques, several scholars obtained reliable results when predicting the prices of various petroleum products including asphalt base, petrol, diesel, kerosene, liquefied petroleum gas (LPG), liquefied natural gas (LNG), and heating oil. For example, Qiu et al. (2017) introduced an ANN ensemble deep-learning model for predicting the price of crude oil. A study employed six input signals in a feedforward network, and the findings demonstrated that the proposed technique exhibited superior performance. Similarly, Mirmirani (2004) and Cheng et al. (2003) utilised a vector autoregression (VAR) methodology to ascertain oil prices, employing petroleum consumption and oil supply as input variables. Then, the parameters were also utilised in the application of a back-propagation neural network (BPNN) with a genetic algorithm (GA) to analyse 275 observations of monthly oil price data over 17 years. The comparative results indicate that the suggested ANN with the GA model outperforms the Vector Autoregression technique in terms of realisation.

In addition, Mafinezhad et al. (2010) utilised the ANN technique to estimate the monthly price of crude oil. The study utilised several input variables, including refinery capacity, nominal effective exchange rate, total liquid capacity, gross domestic product growth (GDPG), crude oil output ceiling allocation, and petrol ending stocks. The results revealed that the proposed technique produces reliable results. Moreover, Haider et al. (2008) proposed ANN models for the crude oil commodities prices prediction. The study utilised a total of 2705 datasets encompassing five inputs. The data collection period spanned from September 1996 to August 2007. The inputs included light sweet crude oil spot price, West Texas Intermediate (WTI), and NYMEX futures contracts. The study demonstrated that the suggested approach yielded dependable outcomes with an accuracy of 78%.

Furthermore, ANN and wavelet approaches were suggested by Jammazi et al. (2012) to forecast the short-term price of crude oil for 12 years. The bipolar sigmoid, sigmoid, and hyperbolic tangents are the three types of transfer functions that were employed in a study utilising various neural network designs. The results demonstrate that experimental data from ANN and wavelet decomposition techniques were fared in predicting the price of crude oil. Also, Glorot et al. (2010) predicted the volatility of oil prices using the ANN-GARCH hybrid model. The findings revealed that the proposed model improved volatility forecasting precision over earlier models by 30%. Similarly, Moner et al. (2016) used eight years' worth of daily data to examine correlations between the price behaviour of gold, crude oil, and the euro exchange rate using ANN models. It was determined that the price of oil is a key factor in predicting the price of gold and the value of the euro. Moreover, Wang et al. (2020) used a bivariate ANN and the copula function to assess changes in oil prices. The findings demonstrated that the proposed model forecasts quite well and that the exchange rate is greatly impacted by changes in oil prices.

The previous discussion highlighted that oil price fluctuations are influenced by various factors. However, most of the existing literature focuses on studying oil price variations in countries that produce crude oil. There is a lack of studies on predicting oil prices in countries that import refined crude oil products, such as Tanzania. Therefore, the current study employs the ANN model to estimate the imported and distributed diesel in three specific regions of mainland Tanzania: Ruvuma, Mbeya, and Katavi. Tanzania is comprised of 31 regions that are distributed over a land area of 945,087 square kilometres. As a result of the substantial distances between these regions, 80% of them are more than 200 km apart, which greatly influences the fluctuations in oil prices. Hence, it is imperative to ascertain the shared elements that dictate pricing in every location and create a predictive instrument that will aid decision-makers in creating a fundamental benchmark for oil prices.

Diesel is imported into Tanzania via the ports of Tanga, Mtwara, and Dar es Salaam. These ports are situated along the Indian Ocean and are known for their considerable distance from other sections of the country, requiring truck road transit over thousands of kilometres. Off-road diesel vehicles are more rugged, with a gradient of up to 16%. The distinct circumstances surrounding the distribution of diesel lead to divergent price patterns. According to a report by Citizen News in 2019, there are significant variations in the pricing of fuel and petrol throughout different zones in Tanzania, including the southern highlands, western, and lake zones. These price disparities are particularly notable when contrasted with the eastern and southern districts, where ports are situated. Hence, it is crucial to analyse the impact of input variables, such as distance from the region's centre to consumers, inflation rate, gold world market price and Europe Brent spot price on the forecasting of energy prices to mitigate the volatility of diesel prices. The assessment of price volatility using ANN models is based on a decade of data on diesel prices obtained from the Energy and Water Utilities Regulatory Authority (EWURA).

2. Theory

2.1 Artificial Neural Network (ANN)

ANN is a sophisticated network composed of interconnected processing units known as neurons, capable of performing simultaneous calculations to process information. The ANN design is based on the structure of the human central nervous system. ANN is created to imitate the information-processing abilities of the human brain. Artificial neural networks can process several variables that are both independent and dependent concurrently without requiring a previous understanding of the intrinsic interrelationship. Likewise, an ANN can acquire knowledge about the underlying connections between the input and output variables. Additionally, ANN is capable and efficient at representing complex, non-linear, and linear interactions between dependent and independent variables. ANN exhibit some fundamental differences compared to traditional computational approaches. ANN operates in an iterative computational manner without adhering to a rigid set of rules or algorithms. In contrast, conventional approaches are characterised by a sequential set of rules and a logical nature. For instance, traditional approaches are capable of learning through rules and logic, whereas ANN learns by extracting correlation from examples. Therefore, ANN is recognised to be a general function approximator and aims to offer a means of independently acquiring knowledge and skills from the given data (Peterson et al., 2004).

The current investigation employed feed-forward backpropagation (FFB) ANN with the Levenberg-Marquardt algorithm (LMA) technique to facilitate the learning process. The output layer utilised a linear transfer function, while the hidden layers employed a tan-sigmoid transfer function, as indicated in Fig. 1. This approach was proposed because of its frequent status as the most accurate backpropagation supervised algorithm (Karlik and Olgac, 2011; Karsoliya, 2012; Sibi et al., 2013). The data were inputted into the input neurons, processed, and subsequently transmitted to the hidden layer neurons at the specified level. During this process, the input signal was subjected to multiplication by weight, as described in Eq. 1, to ascertain the magnitude of the input. According to Eq. 2, the hidden layer neurons added up the weighted input from each neuron and correlated it with a bias before sending the result to the following level via a transfer function. The main objective of the proposed FFB-ANN technique was to determine the optimal architecture and its weight matrixes that would generate an output vector with high accuracy and a minimal root mean square error (RMSE), closely resembling the target values of the trained vector, as indicated in Eq. 3.

$$\mathrm{sum} = \sum_{i=1}^{n} x_i w_i + b \tag{1}$$

$$\mathrm{Output: f(sum)} = \frac{1}{1+e^{-\mathrm{sum}}} \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{K}\sum_{n=1}^{Z}\left(y_n^i - y_n^{ai}\right)^2}{KZ}} \tag{3}$$

Equations 1 and 3 are described as follows:

In Eq. 1, *Wi (i = 1, n)* represents connection weights, b represents bias, and Xi represents input. While in Eq. 2, Z represents the number of patterns utilised in the training process, K represents the number of output nodes; i specifies the index of the input pattern (vector), whereas y_n^i and y_n^{ai} represent the desired (target) and anticipated outputs of the nth output node, respectively.

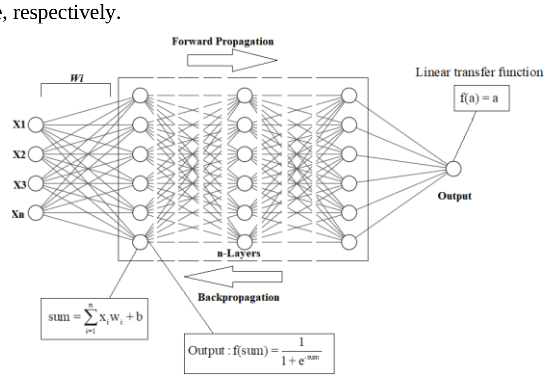


Fig. 1. Feed Forward Backpropagation–ANN

2.2 *Evaluation metrics for ANN models*

The performance of ANN models was evaluated using three parameters: root mean square error (RMSE), coefficient of determination (R^2), and mean absolute error (MAE). The R^2 statistics are utilized to assess the strength of the correlations between the performance of the models and the historical data. On the other hand, the RMSE metric is employed to measure the average divergence between the predicted values of the models and the actual values. RMSE measures the extent to which the accuracy of the models can properly predict the target value. The MAE is a metric used to quantify the average difference between the predicted and actual values in a dataset, regardless of their direction. Model architecture is deemed valid when the estimated R^2 value approaches 1 and the RMSE and MAE values approach 0. Eqs (4), (5), and (6) represent the calculation of the RMSE, R^2, and MAE as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(p_i^s - p_i^h\right)^2} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(p_i^s - p_i^{as}\right)^2}{\sum_{i=1}^{N}\left(p_i^h - p_i^{ah}\right)^2} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|p_i^s - p_i^h\right| \tag{6}$$

The variable p_i^s and p_i^h represent the model results and desired historical dataset, respectively. On the other hand, p_i^{as} and p_i^{ah} present the average model result and historical dataset, respectively and N represents the total quantity of datasets.

3. Material and Methods

3.1 *Input and output datasets*

The ANN model was constructed using the datasets specified in Tables 1-3. The study utilised monthly diesel prices from January 2009 to March 2019, spanning a total of 123 months. The data was collected from the headquarters of three selected regions: monthly diesel price in Mpanda Municipal in the Katavi region (MDPK in TZS/Litre), monthly diesel price in Songea Municipal in the Ruvuma region (MDPS in TZS/Litre), and monthly diesel price in Mbeya City in the Mbeya region (MDPM in TZS/Litre). These datasets were the diesel monthly cap prices published by EWURA, a government institution mandated for economic and technical regulation of petroleum, natural gas, electricity, and water resources on the Tanzanian mainland. Also, among the input datasets, such as the Tanzanian current exchange rate (TZSER in TZS/USD), world gold market price (WGMP in USD/ounce), Europe Brent spot price (EBSP in USD/bbl) and West Texas Intermediate Crude Oil Spot Price (WTIP in USD/bbl) were downloaded from the online through *https://prosperitydata360.worldbank.org/en/indicator/IMF+WEO+PCPIE*; *https://www.gold.org/goldhub/data/gold-prices*a and *https://fred.stlouisfed.org/series/WCOILWTICO* links, respectively on the 20th of May 2024. The distances from Dar es Salaam port to the three selected regions were collected from the Tanzania National Roads Agency (TANROADS). These include the distance from Dar es Salaam to Mbeya Municipal in the Mbeya region (DDM in km), the distance from Dar es Salaam to Songea Municipal Council in the Ruvuma region (DDS in km), and the distance from Dar es Salaam to Mpanda Municipal Council in the Katavi region (DDK in km). About 6 multiplications of dataset regularisation were performed to mitigate overfitting problems, resulting in a total of 738 datasets.

Table 1. Input and output data sets for the ANN Model for Mbeya City

Category	Parameters	Symbol	Data Sets	After regularization	SI Unit
Inputs	World Gold Market price	WGMP	123	738	USD/Ounce
	Tanzania current exchange rate	TZSER	123	738	TZS/USD
	Europe Brent spot price	EBSP	123	738	USD/bbl
	West Texas Intermediate Price	WTIP	123	738	USD/bbl
	Distances from Dar to Mbeya	DDM	123	738	km
Output	Monthly Diesel Price Mbeya	MDPM	123	738	TZS/Litre

Table 2. Input and output data sets for ANN Model for Songea Municipal

Category	Parameters	Symbol	Data Sets	After regularization	SI Unit
Inputs	World Gold Market price	WGMP	123	738	USD/Ounce
	Tanzania current exchange rate	TZSER	123	738	TZS/USD
	Europe Brent spot price	EBSP	123	738	USD/bbl
	West Texas Intermediate Price	WTIP	123	738	USD/bbl
	Distance from Dar to Songea	DDS	123	738	km
Output	Monthly Diesel Price Songea	MDPS	123	738	TZS/Litre

Table 3. Input and output data set for ANN Model for Mpanda Municipal

Category	Parameters	Symbol	Data Sets	After regularization	SI Unit
Inputs	World Gold Market price	WGMP	123	738	USD/Ounce
	Tanzania current exchange rate	TZSER	123	738	TZS/USD
	Europe Brent spot price	EBSP	123	738	USD/bbl
	West Texas Intermediate Price	WTIP	123	738	USD/bbl
	Distance from Dar to Katavi	DDK	123	738	km
Output	Monthly Diesel Price Katavi	MDPK	123	738	TZS/Litre

3.2 Training of the ANN models

The goal of training ANN models was to determine the best training parameters, such as the number of hidden layers, number of neurons, and transfer function. The aim was to generate model output that closely matched the actual target values, and monthly diesel cap prices recorded at the headquarters of the three selected regions. During the training process, the ANN models for the selected three regions were equitably handled by dividing the data into three proportions: testing, training, and validation. The network's weights in the suggested models were adjusted using a training dataset, and the performance of the models was evaluated using a testing dataset. The validation subset was utilised to assess the suggested models' capacity for generalization.

Currently, there are no established scientific standards for determining the appropriate amounts of data needed for training, testing, and validation. For example, a study conducted by Saritas et al. (2019), recommended dividing the data in the following manner: 65% for training, 10% for validation, and 25% for testing. Additionally, Trivedi et al. (2015) proposed dividing the data sample into three segments: 40% for training, 40% for testing, and 20% for validation. In contrast, Maxwell et al. (2018) allocated 25% of the data for training purposes and reserved 75% for validation.

The reviewed literature demonstrates that the datasets are divided into training, testing, and validation sets randomly. Nevertheless, it is feasible to derive general inferences by analysing the findings through statistical regression. Therefore, in the current study, the ANN models were trained using a trial-and-error approach, with a maximum of 36 trials at a fixed 1000 number of epochs. The data sets were portioned as follows: 10% of the data samples were used for testing, 10% were used for validation, and the remaining 80% were used for training, as depicted in Table 4. The modelling and training of the ANN models were conducted using coding developed by researchers in the MATLAB R2021a software. The error gradients were assessed in each epoch. Subsequently, the models' performances were assessed by adjusting the number of hidden layers, neurons, and sample data set for training, validation, and testing. All training processes were carried out using a ThinkPad Lenovo personal computer with a 2.71 GHz Core (TM) i7-6820HQ processor and 32 GB installed random access memory.

Table 4. Training Parameter sets for ANN Models

Category	Total	Training [80%]	Testing [10%]	Validation [10%]
Input data sets	**738**	**590**	**74**	**74**
Epochs			**1000**	
Number of trials			**36**	

3.3 Choosing the Architecture for ANN models

This refers to the procedure of determining the optimal number of hidden layers, neurons, and input parameters in the ANN models by utilising the validation, training, and testing subsets. The technique assesses the efficacy of models by employing proposed statistical parameters, namely R^2, RMSE, and MAE, to compare and differentiate the accuracy of the models' estimations. The estimation performance outcomes of the suggested ANN models are greatly influenced by several aspects, such as the number of hidden layers, neurons, and input parameters. Hence, in the current investigation, the structures of the ANN models were altered by manipulating the quantities of neurons and hidden layers. Ultimately, the model designs were chosen according to the evaluation outcomes of the validation and training datasets. To reduce over-fitting, it is crucial to minimise the number of parameters when determining the number of hidden layers and neurons in each architecture. The reason for this is that overfitted models are incapable of effectively predicting outcomes as they only capture a fraction of the residual variability. Therefore, the number of hidden layers and neurons was reduced to decrease the possibility of overfitting. To determine the required model architectures, numerous experiments were performed on both the validation and training datasets.

The study investigated ANN models with several configurations, including different numbers of hidden layers, ranging from one to two, and varied numbers of neurons, from 2 to 12, with increments of 2 neurons. Fig. 2 depicts the arrangement of the ANN model architectures. To ensure reliable and accurate outcomes, and to avoid any erroneous associations caused by arbitrary biases and weight allocations, the setdemorandstream (491218382) codes were incorporated into every topology. The outputs of the ANN models were compared to the historical data sets, and the conclusions of the models were then evaluated. The ANN model generated the simulated diesel monthly price for Mbeya City was termed SDPM in TZS/Litre, Songea Municipal as SDPS in TZS/Litre, and Mpanda Municipal as SDPK. The R^2, RMSE, and MAE matrices were calculated by comparing the historical data sets with the outputs of ANN models, SDPM, SDPS, and SDPK. The architectures of ANN models are considered valid when the calculated R^2 values approach 1, and the RMSE and MAE values approach 0.

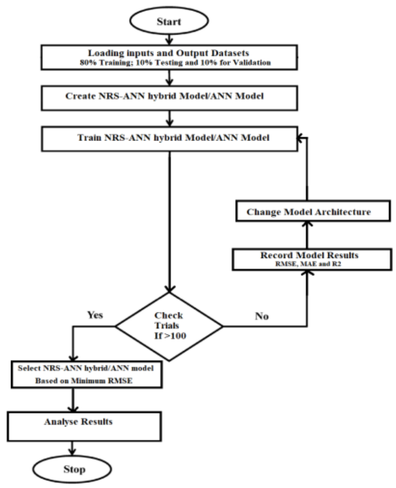
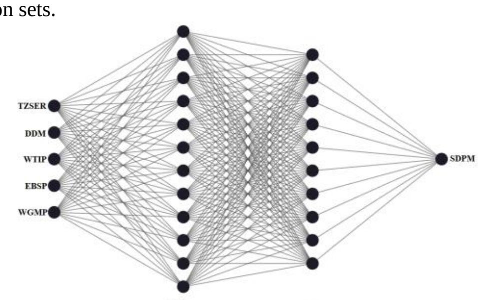
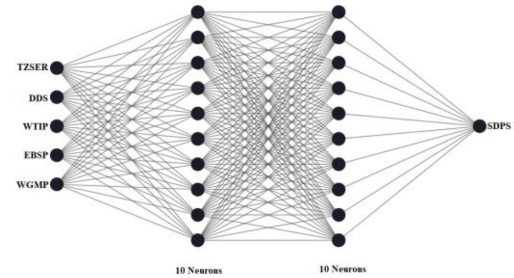


Fig. 2. Formulation of ANN model Architectures from 1st to 36th Trials.

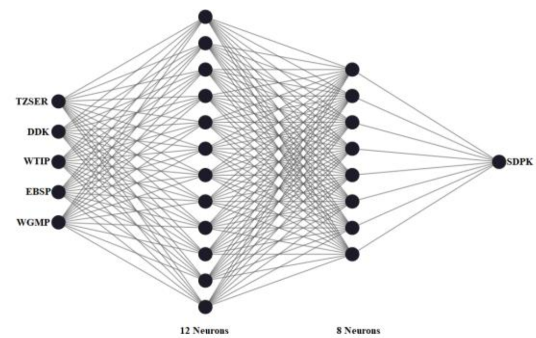
The analysis of the model results revealed that the Mbeya City ANN model outperformed on the 35th trial, Songea Municipal's ANN model excelled on the 29th trial, and Mpanda Municipal's ANN model achieved its peak performance on the 34th trial. The ANN model for Mbeya City had a network structure with twelve neurons in the first hidden layer and ten neurons in the second hidden layer. The ANN model for Songea Municipal had a network structure consisting of ten neurons in the first hidden layer and ten neurons in the second hidden layer. The ANN model for Mpanda Municipal had a network structure with twelve neurons in the first hidden layer and eight neurons in the second hidden layer. Therefore, the study selected the 5-12-10-1 ANN model architecture for Mbeya City, the 5-10-10-1 ANN model architecture for Songea Municipal, and the 5-12-8-1 ANN model architecture for Mpanda Municipal to estimate diesel prices in the headquarters of the selected regions. Fig. 3 (a), (b), and (c) depict the configurations for the selected ANN models for Mbeya City, Songea Municipal, and Mpanda Municipal, respectively. Tables 5 (a), (b), and (c) display the MAE, RMSE, and R^2 values. These values demonstrate the degree of similarity between the outputs of the selected model designs and the values observed in the testing, training, and validation sets.



(a) A 5-12-10-1 Selected ANN model Architecture for Mbeya City.



(b) A 5-10-10-1 Selected ANN model Architecture for Songea Municipal



(c) A 5-12-8-1 Selected ANN model Architecture for Mpanda Municipal

Fig. 3. (a) (b) and (c) Optimal ANN models for the three headquarters of selected regions.

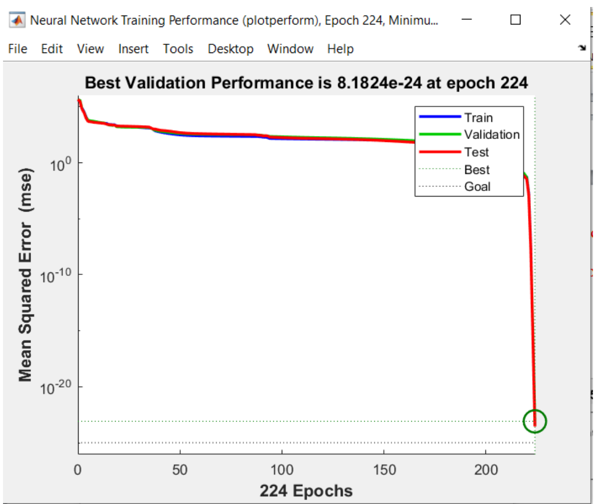
4. Results and Discussion

4.1 ANN models Inputs and Output datasets

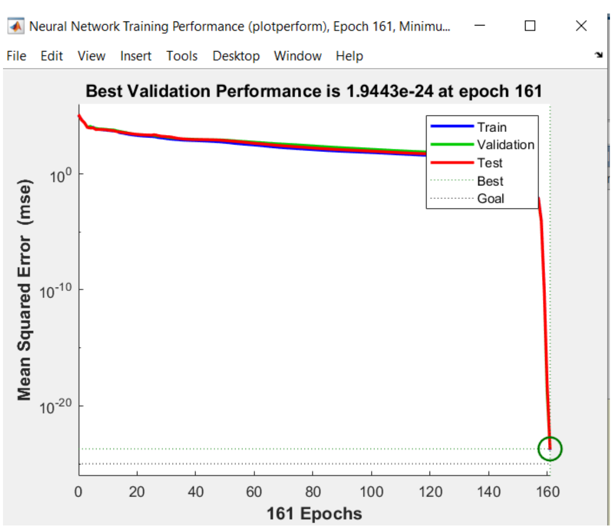
The proposed ANN models utilised 123 historical datasets gathered from various sources. A suggested ANN model for Mbeya City utilised TZSER in TZS/USD, DDM in km, WTIP in USD/bbl, EBSP in USD/bbl, and WGMP in USD/ounce as input datasets. The model output presented the MDPM in TZS/Litre, the monthly diesel cap price as published by EWURA for the Mbeya City Council. The proposed ANN model for Songea Municipal used 123 historical datasets, including TZSER in TZS/USD, DDS in km, WTIP in USD/bbl, EBSP in USD/bbl, and WGMP in USD/ounce as input variables. The model output represented the MDPS in TZS/Litre, the recorded monthly diesel cap price published by EWURA for Songea Municipal. The suggested ANN models for Mpanda Municipal used 123 historical datasets, including TZSER in TZS/USD, DDK in km, WTIP in USD/bbl, EBSP in USD/bbl, and WGMP in USD/ounce as input variables. The model output presented the DMPK in TZS/Litre, which was the monthly diesel cap price for Mpanda Municipal, as published by EWURA. Table 6 shows the inputs and outputs of the data sets used to train the ANN models.

4.2 Assessing ANN Models Performance Prediction Capabilities

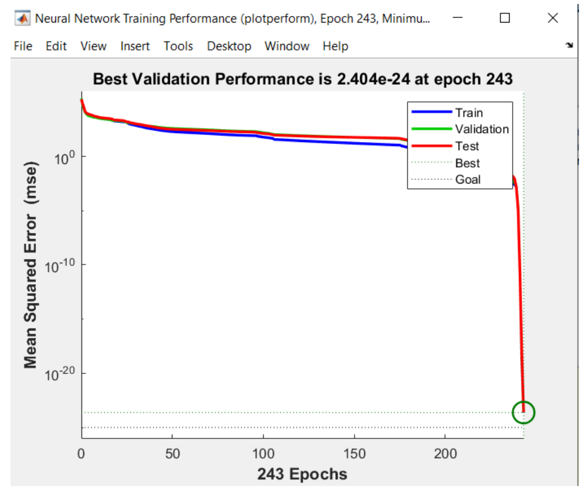
The efficacy of the trained ANN models in assessing the diesel prices in Mbeya City, Songea and Mpanda Municipalities was evaluated by computing the MAE, R^2, and RMSE matrices based on the models' outputs, which were simulated diesel prices. In addition, numerous validation tests were conducted during the training of the ANN models to achieve optimal values for MAE, R^2, and RMSE matrices, to determine when to terminate the training process. The validation checks were conducted by identifying the moment at which the models' performances in the validation phase ceased to decrease in subsequent iterations. During training, at the 35th epoch, the ANN model for Mbeya City showed a significant enhancement in performance. This improvement is illustrated in Fig. 4 (a), where the RMSE in the validation dataset was measured at 2.49 x 10^{-12} values. In addition, as depicted in Fig. 4 (b), the Songea Municipal ANN model was effectively trained and demonstrated exceptional performance at the 29th epoch, achieving an RMSE of 1.40 x 10^{-12} values in the validation dataset. Similarly, in Fig. 4 (c), an ANN model for Mpanda Municipal was trained successfully. The model demonstrated outstanding performance at the 34th epoch, achieving a RMSE of 1.60 x 10^{-12} values in the validation dataset.



(a) ANN Model Performance for Mbeya City.



(b) ANN Model Performance for Songea Municipal.

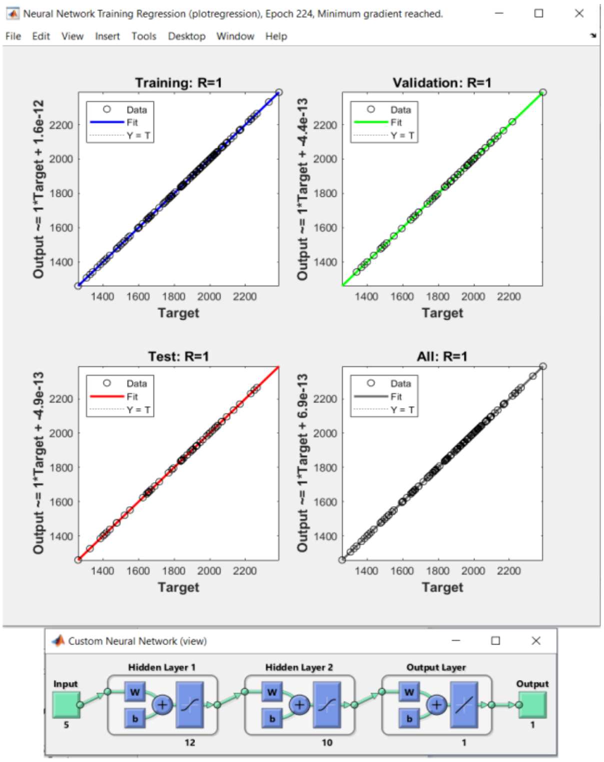


(c) ANN Model Performance for Mpanda Municipal.

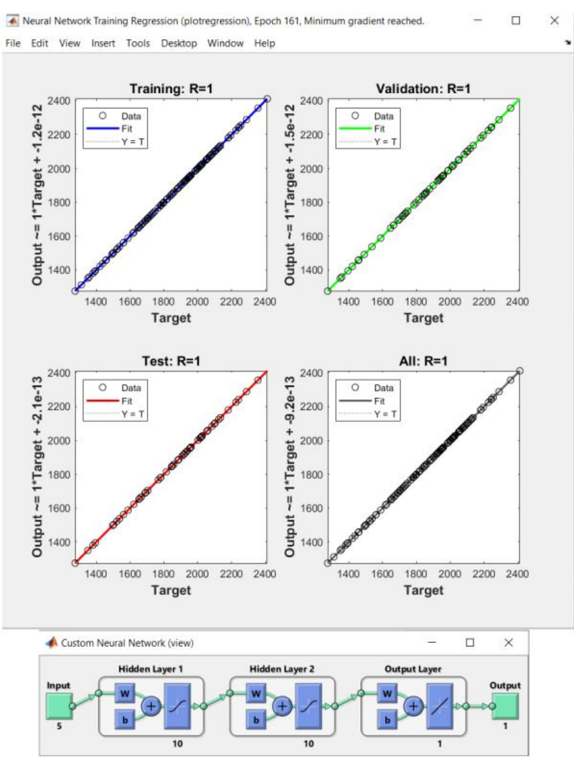
Fig.4. (a), (b) and (c) depict the performance of the suggested ANN Models for Mbeya City, Songea and Mpanda Municipalities.

The results are considered good because of the following reasons: First, the extremely low RMSE values of 2.49 x 10^{-12}, 1.40 x 10^{-12}, and 1.60 x 10^{-12} were achieved by the proposed ANN models for Mbeya City, Songea Municipal, and Mpanda Municipal, respectively, in the validation datasets. Secondly, the R^2 and MAE matrices for the testing values of 1.0, 1.0, 1.0, and 1.88 x 10^{-12}, 1.12 x 10^{-12}, as shown in Table 5, demonstrate the highest and lowest values, respectively. Finally, we observed no significant overfitting during the training of ANN models in the 1st to 35th, 1st to 29th, and 1st to 34th iterations, respectively. Fig. 5 (a), (b), and (c) display the regression graphs and architecture that illustrate the relationship between the outputs of the ANN models and the training, validation, and test data sets for Mbeya City, Songea Municipal, and Mpanda Municipal, respectively. The R^2 values for the three suggested ANN models exceed 0.99999, as evidenced by the graphs. According to the results, it appears that the proposed ANN models' output replicates the historical monthly diesel cap prices published by EWURA for Mbeya City, Songea, and Mpanda Municipalities.

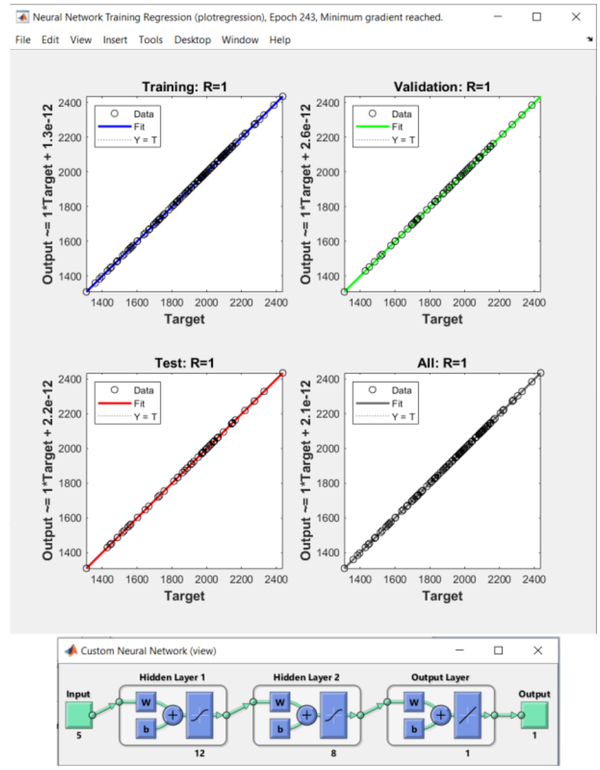
Table 7 displays the evaluated outcomes of the chosen three ANN models for examining the monthly diesel prices in Mbeya City, Songea and Mpanda Municipalities. The results exhibit strong concordance with the historical monthly diesel ceiling prices given by EWURA for the proposed study area. The proposed ANN model for Mbeya City achieved minimal RMSE values of 2.37 x 10^{-12} and 1.69 x 10^{-12} in the testing and training datasets, respectively. Similarly, the suggested ANN model for Songea Municipal achieved minimal RMSE values of 1.12 x 10^{-12} and 1.23 x 10^{-12}, while the selected ANN model for Mpanda Municipal achieved minimal RMSE values of 1.51 x 10^{-12} and 1.65 x 10^{-12} in the testing and training datasets, respectively. The study shows that the proposed ANN models are valuable and reliable tools for assessing monthly diesel prices in Mbeya City, Songea, and Mpanda Municipalities.



(a) Regression Graph and Architecture for ANN Model for Mbeya City



(b) Regression Graph and Architecture of ANN Model for Songea Municipal.

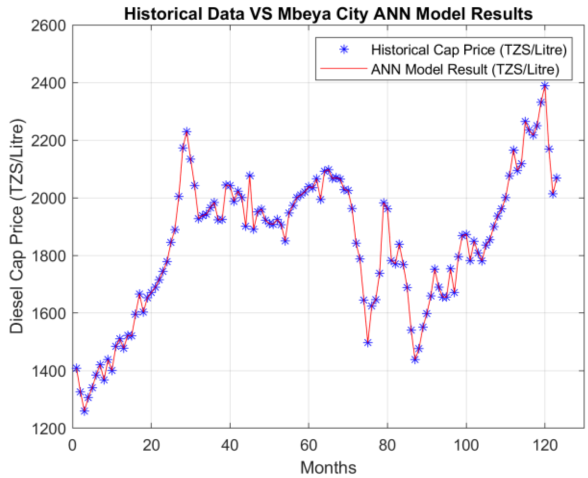


(c) Regression Graph and Architecture of ANN Model for Mpanda Municipal.

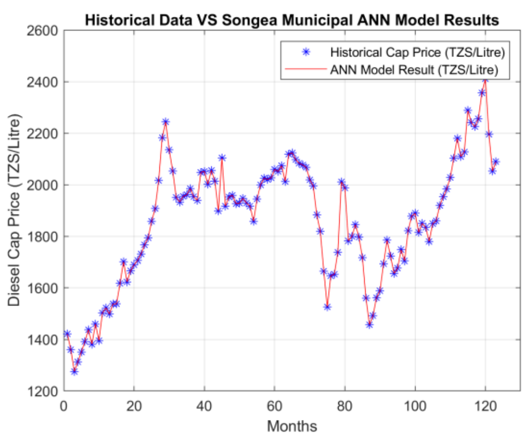
Fig. 5. (a), (b) and (c) Regression Graph and Architecture for proposed ANN models.

Performance Analysis of Selected ANN Models

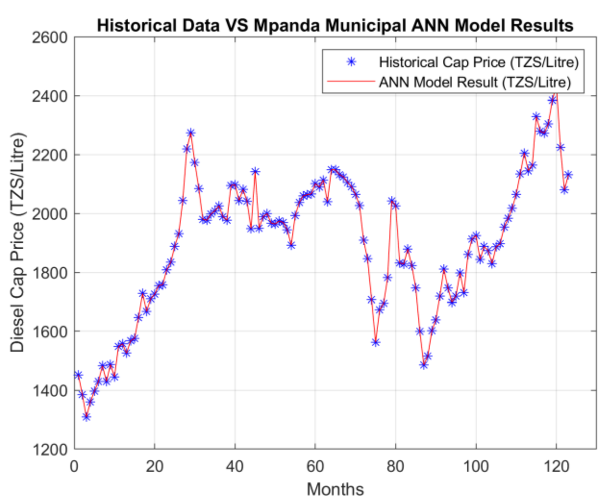
The current study investigated the performance of the proposed ANN models for the Mbeya City, Songea, and Mpanda municipalities. The study conducted a comparison between the outputs of the ANN models, namely SDPM, SDPS, and SDPK, and the recorded monthly diesel cap prices posted by EWURA for the headquarters of the selected regions, namely MDPM, MDPS, and MDPK. Fig. 6 (a), (b), and (c) show comparisons using two different colours: blue represents the actual monthly diesel cap prices as reported by EWURA while red represents the simulated monthly diesel prices using ANN models for Mbeya City, Songea, and Mpanda Municipalities, respectively. All y-axis and x-axis datasets are presented in TZS/Litre and month, respectively. There is a strong association between the SDPM, SDPS, SDPK, MDPM, MDPS, and MDPK, respectively. The results indicate that the predicted performance of the selected ANN models for Mbeya City, Songea Municipal, and Mpanda Municipal, SDPM, SDPS, and SDPK, respectively, mimics the monthly diesel cap prices reported by EWURA for the study areas. Therefore, the study suggests that the proposed ANN models are resilient and important as predictive instruments for analysing monthly diesel prices in Mbeya City, Songea Municipal, and Mpanda Municipal.



(a) Comparison of Mbeya City ANN model results against historical data.



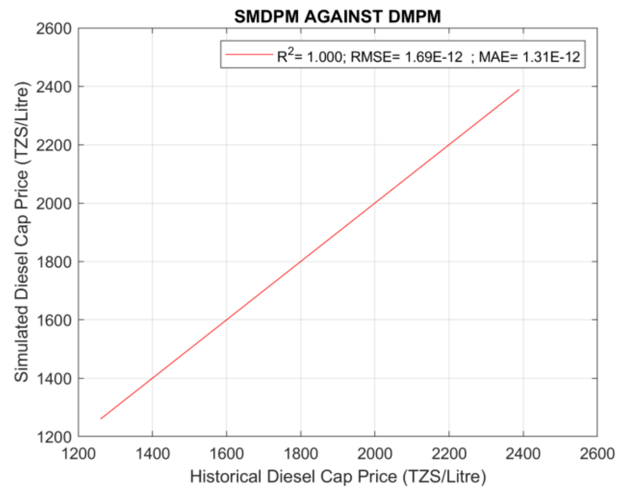
(b) Comparison of Songea Municipal ANN model results against historical data



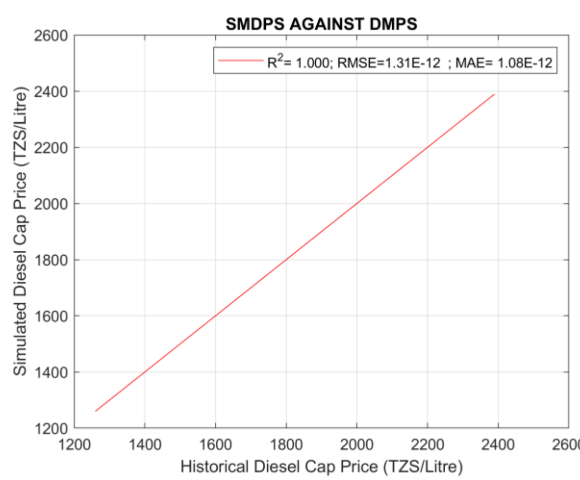
(c) Comparison of Mpanda Municipal ANN model results against historical data

Fig. 6. (a), (b) and (c) Historical diesel cap prices against ANN modes results

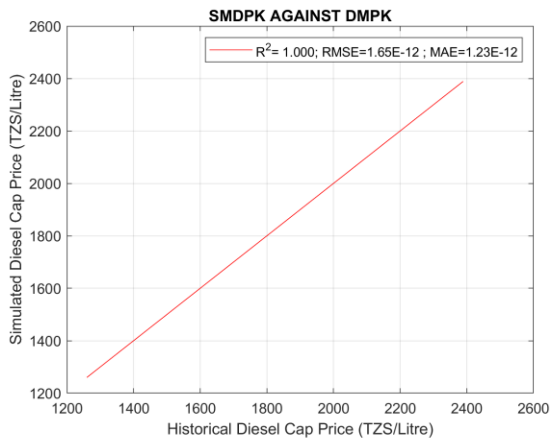
Additionally, Fig. 7 (a), (b), and (c) provide regression plots and statistical measures, including R^2 and MAE, that are employed to assess the effectiveness of the ANN models in forecasting diesel prices. The ANN model for Mbeya City, as shown in Fig. 7 (a), demonstrated R^2 and MAE values of 1.0000 and 1.31 x 10^{-12}, respectively. The ANN model for Songea Municipal, as shown in Fig. 7 (b), achieved outstanding prediction results. This was evident from the high values of R2 of 1.0000 and MAE of 1.08 x 10^{-12}, indicating a remarkable level of performance. The ANN model for Mpanda Municipal, as shown in Fig. 7 (c), achieved outstanding prediction results. This is evident from the high R^2 value of 1.0000 and the very low MAE value of 2.12 x 10^{-12}, indicating a remarkable level of performance.



(a)



(b)



(c)

Fig. 7. (a), (b), and (c) regression plots for ANN models trapping indices R^2, RMSE and MAE.

In addition, the figures present the RMSE to the historical diesel prices published by EWURA in study areas, Mbeya, Ruvuma and Katavi Regions. Upon analysis, it is evident that the forecast produced by the ANN models, SMDPM, SMDPS, and SDMPK, closely aligns with the recorded diesel prices published by EWURA, DMPM, DMPS and MDPK, respectively. This is demonstrated by a minimal RMSE of x 10^{-12} values. The performance analysis of the proposed ANN models demonstrates a significant level of accuracy in predicting monthly diesel cap prices for the selected regions' headquarters, Mbeya City, Songea, and Mpanda Municipalities. Therefore, it can be deduced that the suggested ANN models exhibit resilience and importance as a prognostic instrument for examining diesel prices in specified areas of Tanzania.

4.3 Analysis of the Input and Output Variables

The study analysed the connections between the five input variables and the simulated diesel monthly cap price for each ANN model. The study utilised two segments from the diesel monthly price profile of the optimised ANN models' dataset, as depicted in Fig. 8. The graph displays the simulated monthly cap price for diesel, showing the average trends in segments **A** and **B**. In segment **A**, from July 2015 to February 2016, the monthly diesel price decreased by an average of 3.41%. Whereas, in segment B, starting from March 2016 to December 2018, the monthly diesel price increased by an average of 1.56%. At the start of each segment, a single simulated monthly diesel cap price was selected together with its corresponding input variables. The adjustment of each input variable was based on the proportion of output in a specific segment, while the other four input variables remained constant.

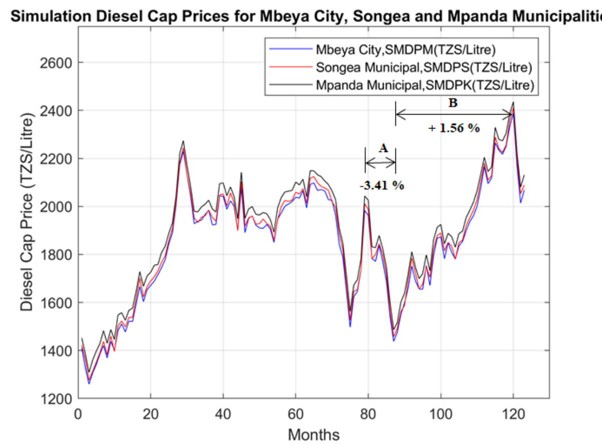


Fig. 8. Simulated monthly cap prices for diesel ANN Models.

5. Conclusion

A current study examined monthly diesel costs in three regions of Tanzania: Mbeya, Ruvuma, and Katavi, deploying data from Mbeya City, Songea, and Mpanda Municipalities, respectively. The ANN models were trained, assessed, and checked with code generated by researchers in the MATLAB R2021a software. Three models were developed using five input variables comprising 123 datasets namely: WGMP, TZSER, EBSP, WTIP and DDM Mbeya City; WGMP, TZSER, EBSP, WTIP and DDS Songea Municipal and WGMP, TZSER, EBSP, WTIP and DDK for Mpanda Municipal. The SMDPM, SMDPS and SMDPK were utilised as output data for the proposed ANN models for Mbeya City, Songea and Mpanda Municipalities, respectively. In addition, the models were trained, tested and validated using a trial-and-error approach, with a maximum of 36 iterations and a fixed number of 100 epochs. The RMSE, R^2, and MAE were parameters employed to evaluate the performance of the proposed ANN models. The architecture of the models was determined based on the minimum value of the RMSE of the validation data set. The study selected 5-12-10-1, 5-10-10-1 and 5-12-8-1 architectures for the Mbeya City ANN model, Songea Municipal ANN model and Mpanda Municipal ANN model, respectively, due to their exceptional estimation capabilities. The performance forecast of the ANN models was assessed with that of the historical monthly diesel cap price published by the EWURA. The results demonstrated that the suggested ANN models achieved R^2 and MAE values of 1.0000, 1.0000, 1.000 and 1.31 x 10^{-12}, 1.08 x 10^{-12}, 1.23 x 10^{-12} for ANN models for Mbeya City, Songea and Mpanda Municipalities, respectively, historical monthly diesel cap prices. Additionally, the study analysed the trends of the monthly diesel cap price variations, utilising outputs of the ANN models. Based on the analysis it shows that from July 2015 to February 2016, the monthly diesel price decreased by an average of 3.41%. Whereas, starting from March 2016 to December 2018, the monthly diesel price increased by an average of 1.56%. The analysis results demonstrate that the suggested ANN models exhibited superior performance in predicting monthly diesel cap prices in the study areas. Therefore, it can be concluded that the proposed ANN model is a reliable and effective tool for analysing monthly diesel cap prices in Mbeya, Ruvuma and Katavi Regions.

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Declaration of competing interest
The authors affirm that the research conducted in this study was not impacted by any identifiable conflicting financial interests or personal relationships.

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Table 5 (a). Statistical Parameters for Mbeya City ANN Model Architectures.

Trials	Architecture	MAE			RMSE			R^2		
		Test	Train	Val	Test	Train	Val	Test	Train	Val
1	5-2-2-1	2.03E+02	2.01E+02	2.22E+02	2.40E+02	2.34E+02	2.55E+02	2.80E-02	4.36E-02	1.49E-02
2	5-2-4-1	6.85E+01	7.82E+01	7.52E+01	8.92E+01	9.57E+01	9.32E+01	8.69E-01	8.05E-01	8.57E-01
3	5-2-6-1	6.20E+01	6.69E+01	5.91E+01	8.23E+01	9.32E+01	8.04E+01	8.87E-01	8.52E-01	8.83E-01
4	5-2-8-1	1.01E+02	9.03E+01	1.17E+02	1.54E+02	1.32E+02	1.77E+02	5.99E-01	7.18E-01	4.61E-01
5	5-2-10-1	7.57E+01	6.95E+01	7.12E+01	1.02E+02	9.86E+01	9.54E+01	8.28E-01	8.40E-01	8.21E-01
6	5-2-12-1	5.29E+01	5.77E+01	4.91E+01	6.79E+01	7.07E+01	6.42E+01	9.22E-01	9.29E-01	9.16E-01
7	5-4-2-1	4.28E+01	4.63E+01	4.76E+01	5.53E+01	5.92E+01	6.07E+01	9.49E-01	9.40E-01	9.34E-01
8	5-4-4-1	7.99E+01	6.82E+01	8.52E+01	1.05E+02	8.87E+01	1.02E+02	8.12E-01	8.71E-01	8.19E-01
9	5-4-6-1	3.75E+01	3.74E+01	4.00E+01	4.97E+01	5.07E+01	5.76E+01	9.59E-01	9.60E-01	9.36E-01
10	5-4-8-1	2.46E+01	2.63E+01	2.37E+01	3.39E+01	3.33E+01	3.10E+01	9.80E-01	9.84E-01	9.85E-01
11	5-4-10-1	3.81E+01	4.31E+01	3.86E+01	5.15E+01	6.18E+01	5.05E+01	9.56E-01	9.25E-01	9.57E-01
12	5-4-12-1	1.39E+01	1.50E+01	1.52E+01	2.31E+01	2.60E+01	2.38E+01	9.91E-01	9.87E-01	9.90E-01
13	5-6-2-1	3.45E+01	4.08E+01	3.27E+01	4.54E+01	5.21E+01	4.40E+01	9.66E-01	9.55E-01	9.62E-01
14	5-6-4-1	3.27E+01	2.96E+01	4.26E+01	4.38E+01	4.39E+01	6.02E+01	9.67E-01	9.74E-01	9.38E-01
15	5-6-6-1	2.98E+01	2.99E+01	3.29E+01	3.88E+01	3.61E+01	4.38E+01	9.75E-01	9.75E-01	9.68E-01
16	5-6-8-1	3.19E+01	3.07E+01	2.58E+01	4.18E+01	4.19E+01	3.35E+01	9.71E-01	9.70E-01	9.79E-01
17	5-6-10-1	1.79E+01	2.01E+01	1.94E+01	2.65E+01	2.77E+01	2.68E+01	9.88E-01	9.86E-01	9.87E-01
18	5-6-12-1	4.24E+00	4.61E+00	4.72E+00	7.61E+00	8.00E+00	8.07E+00	9.99E-01	9.99E-01	9.99E-01
19	5-8-2-1	1.20E+02	1.21E+02	9.44E+01	1.67E+02	1.74E+02	1.37E+02	5.30E-01	5.52E-01	6.15E-01
20	5-8-4-1	3.06E+01	3.85E+01	3.40E+01	4.43E+01	5.43E+01	4.34E+01	9.67E-01	9.47E-01	9.72E-01
21	5-8-6-1	1.95E+01	2.12E+01	2.02E+01	2.77E+01	3.19E+01	2.81E+01	9.87E-01	9.83E-01	9.85E-01
22	5-8-8-1	6.10E-01	6.75E-01	9.73E-01	1.20E+00	1.18E+00	1.91E+00	1.00E+00	1.00E+00	1.00E+00
23	5-8-10-1	3.80E+00	4.34E+00	5.38E+00	6.87E+00	7.60E+00	9.68E+00	9.99E-01	9.99E-01	9.99E-01
24	5-8-12-1	1.86E-12	2.16E-12	2.17E-12	2.57E-12	3.11E-12	3.08E-12	1.00E+00	1.00E+00	1.00E+00
25	5-10-2-1	1.88E+02	1.73E+02	2.15E+02	2.34E+02	2.24E+02	2.62E+02	5.86E-02	4.93E-02	3.96E-02
26	5-10-4-1	1.23E+01	1.31E+01	1.39E+01	1.91E+01	1.99E+01	2.10E+01	9.94E-01	9.94E-01	9.91E-01
27	5-10-6-1	1.56E+00	3.14E+00	1.57E+00	3.95E+00	6.99E+00	4.32E+00	1.00E+00	9.99E-01	1.00E+00
28	5-10-8-1	2.20E-12	1.76E-12	2.22E-12	2.94E-12	2.31E-12	2.90E-12	1.00E+00	1.00E+00	1.00E+00
29	5-10-10-1	1.86E-12	1.92E-12	1.88E-12	2.42E-12	2.49E-12	2.49E-12	1.00E+00	1.00E+00	1.00E+00
30	5-10-12-1	9.72E-11	1.08E-10	1.27E-10	2.48E-10	2.69E-10	2.65E-10	1.00E+00	1.00E+00	1.00E+00
31	5-12-2-1	4.73E+01	5.39E+01	6.20E+01	7.55E+01	8.69E+01	9.27E+01	9.04E-01	8.65E-01	8.57E-01
32	5-12-4-1	5.69E+00	7.31E+00	4.84E+00	1.32E+01	1.70E+01	1.10E+01	9.97E-01	9.95E-01	9.98E-01
33	5-12-6-1	2.55E-02	3.85E-02	2.87E-02	6.44E-02	9.70E-02	7.45E-02	1.00E+00	1.00E+00	1.00E+00
34	5-12-8-1	1.81E-12	2.06E-12	1.99E-12	2.37E-12	2.69E-12	2.59E-12	1.00E+00	1.00E+00	1.00E+00
35	**5-12-10-1**	**1.80E-12**	**1.31E-12**	**1.88E-12**	**2.37E-12**	**1.69E-12**	**2.49E-12**	**1.00E+00**	**1.00E+00**	**1.00E+00**
36	5-12-12-1	5.43E-11	7.10E-11	8.89E-11	1.60E-10	2.23E-10	2.55E-10	1.00E+00	1.00E+00	1.00E+00

Table 5 (b). Statistical Parameters for Songea Municipal ANN Model Architectures.

Trials	Architecture	MAE			RMSE			R^2		
		Test	Train	Val	Test	Train	Val	Test	Train	Val
1	5-2-2-1	1.79E+02	1.45E+02	1.94E+02	2.31E+02	2.01E+02	2.43E+02	1.02E-01	2.35E-01	8.79E-02
2	5-2-4-1	7.08E+01	7.86E+01	7.73E+01	9.02E+01	9.58E+01	9.45E+01	8.66E-01	8.08E-01	8.55E-01
3	5-2-6-1	7.65E+01	8.18E+01	7.07E+01	1.03E+02	1.17E+02	9.77E+01	8.23E-01	7.63E-01	8.27E-01
4	5-2-8-1	6.96E+01	6.06E+01	7.79E+01	8.87E+01	7.47E+01	1.00E+02	8.67E-01	9.09E-01	8.29E-01
5	5-2-10-1	5.29E+01	5.34E+01	6.20E+01	6.98E+01	7.66E+01	8.07E+01	9.19E-01	9.04E-01	8.73E-01
6	5-2-12-1	4.01E+01	4.22E+01	3.74E+01	5.20E+01	5.63E+01	5.03E+01	9.54E-01	9.55E-01	9.48E-01
7	5-4-2-1	4.80E+01	5.17E+01	5.26E+01	6.29E+01	7.02E+01	6.74E+01	9.34E-01	9.14E-01	9.18E-01
8	5-4-4-1	4.97E+01	5.32E+01	5.26E+01	6.62E+01	7.42E+01	6.96E+01	9.26E-01	9.10E-01	9.16E-01
9	5-4-6-1	5.30E+01	4.88E+01	5.30E+01	7.33E+01	6.27E+01	7.05E+01	9.10E-01	9.38E-01	9.04E-01
11	5-4-10-1	2.10E+01	2.57E+01	1.93E+01	3.38E+01	4.17E+01	3.16E+01	9.81E-01	9.67E-01	9.83E-01
12	5-4-12-1	1.48E+01	1.58E+01	1.68E+01	2.33E+01	2.75E+01	2.41E+01	9.91E-01	9.85E-01	9.90E-01
13	5-6-2-1	9.95E+01	1.13E+02	1.09E+02	1.28E+02	1.43E+02	1.37E+02	7.29E-01	6.64E-01	6.36E-01
14	5-6-4-1	2.69E+01	2.69E+01	3.01E+01	3.85E+01	3.79E+01	4.21E+01	9.74E-01	9.81E-01	9.70E-01
15	5-6-6-1	1.67E+01	1.93E+01	2.01E+01	2.38E+01	2.55E+01	2.75E+01	9.91E-01	9.88E-01	9.87E-01
16	5-6-8-1	4.81E+01	4.97E+01	4.33E+01	6.03E+01	6.09E+01	5.31E+01	9.40E-01	9.36E-01	9.47E-01
17	5-6-10-1	1.04E+01	1.36E+01	1.05E+01	1.76E+01	2.32E+01	1.50E+01	9.95E-01	9.90E-01	9.96E-01
18	5-6-12-1	1.27E+00	1.54E+00	1.07E+00	2.52E+00	2.90E+00	1.96E+00	1.00E+00	1.00E+00	1.00E+00
19	5-8-2-1	1.76E+02	1.87E+02	1.42E+02	2.32E+02	2.39E+02	1.84E+02	1.01E-01	1.59E-01	2.98E-01
20	5-8-4-1	1.60E+01	1.94E+01	1.79E+01	2.55E+01	2.75E+01	2.36E+01	9.89E-01	9.86E-01	9.92E-01
21	5-8-6-1	2.33E+01	2.94E+01	2.28E+01	3.02E+01	3.70E+01	2.88E+01	9.85E-01	9.77E-01	9.85E-01
22	5-8-8-1	1.07E+00	1.26E+00	9.85E-01	2.68E+00	3.15E+00	2.72E+00	1.00E+00	1.00E+00	1.00E+00
23	5-8-10-1	6.56E-02	2.78E-02	7.91E-02	2.92E-01	5.74E-02	3.55E-01	1.00E+00	1.00E+00	1.00E+00
24	5-8-12-1	3.13E+00	4.11E+00	4.15E+00	6.41E+00	8.53E+00	8.67E+00	9.99E-01	9.99E-01	9.99E-01
25	5-10-2-1	1.80E+02	1.70E+02	2.25E+02	2.17E+02	2.04E+02	2.69E+02	1.92E-01	2.03E-01	-5.89E-03
26	5-10-4-1	8.26E+00	9.33E+00	8.60E+00	1.29E+01	1.46E+01	1.28E+01	9.97E-01	9.97E-01	9.97E-01
27	5-10-6-1	1.52E+00	1.96E+00	1.90E+00	3.07E+00	3.50E+00	3.93E+00	1.00E+00	1.00E+00	1.00E+00

28	5-10-8-1	5.62E+00	7.18E+00	6.94E+00	1.06E+01	1.40E+01	1.25E+01	9.98E-01	9.96E-01	9.98E-01
29	**5-10-10-1**	**9.70E-13**	**1.08E-12**	**1.12E-12**	**1.23E-12**	**1.31E-12**	**1.40E-12**	**1.00E+00**	**1.00E+00**	**1.00E+00**
30	5-10-12-1	1.52E-12	1.61E-12	2.12E-12	2.72E-12	2.17E-12	3.59E-12	1.00E+00	1.00E+00	1.00E+00
31	5-12-2-1	3.75E+01	4.29E+01	3.21E+01	5.19E+01	5.28E+01	4.33E+01	9.55E-01	9.50E-01	9.69E-01
32	5-12-4-1	2.12E+00	1.86E+00	1.86E+00	3.96E+00	3.50E+00	2.69E+00	1.00E+00	1.00E+00	1.00E+00
33	5-12-6-1	1.24E-10	1.75E-10	1.31E-10	2.62E-10	3.48E-10	2.23E-10	1.00E+00	1.00E+00	1.00E+00
34	5-12-8-1	9.46E-11	2.40E-10	1.70E-10	2.66E-10	7.43E-10	4.82E-10	1.00E+00	1.00E+00	1.00E+00
35	5-12-10-1	8.48E-11	8.25E-11	7.80E-11	2.31E-10	2.19E-10	1.92E-10	1.00E+00	1.00E+00	1.00E+00
36	5-12-12-1	1.69E-12	1.43E-12	1.55E-12	2.30E-12	2.17E-12	2.16E-12	1.00E+00	1.00E+00	1.00E+00

Table 5 (c). Statistical Parameters for Mpanda Municipal ANN Model Architectures.

Trials	Architecture	MAE			RMSE			R^2		
		Test	Train	Val	Test	Train	Val	Test	Train	Val
1	5-2-2-1	2.02E+02	2.01E+02	2.20E+02	2.40E+02	2.34E+02	2.53E+02	2.81E-02	4.23E-02	1.58E-02
2	5-2-4-1	6.94E+01	7.44E+01	7.26E+01	8.83E+01	8.77E+01	8.90E+01	8.71E-01	8.38E-01	8.70E-01
3	5-2-6-1	7.10E+01	7.47E+01	6.60E+01	9.95E+01	1.13E+02	9.67E+01	8.34E-01	7.80E-01	8.31E-01
4	5-2-8-1	6.78E+01	5.81E+01	7.59E+01	8.68E+01	7.24E+01	9.88E+01	8.72E-01	9.14E-01	8.31E-01
5	5-2-10-1	3.76E+01	3.42E+01	4.31E+01	5.10E+01	4.60E+01	6.00E+01	9.56E-01	9.65E-01	9.29E-01
6	5-2-12-1	5.15E+01	5.47E+01	5.13E+01	6.62E+01	6.92E+01	6.51E+01	9.26E-01	9.33E-01	9.12E-01
7	5-4-2-1	4.88E+01	5.22E+01	5.42E+01	6.41E+01	6.93E+01	6.87E+01	9.31E-01	9.17E-01	9.15E-01
8	5-4-4-1	4.55E+01	4.74E+01	5.19E+01	6.14E+01	6.06E+01	6.95E+01	9.36E-01	9.40E-01	9.16E-01
9	5-4-6-1	4.29E+01	4.65E+01	4.40E+01	6.11E+01	6.46E+01	6.44E+01	9.37E-01	9.34E-01	9.19E-01
10	5-4-8-1	1.82E+01	1.96E+01	2.14E+01	2.67E+01	2.62E+01	3.00E+01	9.87E-01	9.90E-01	9.86E-01
11	5-4-10-1	2.64E+01	2.89E+01	2.49E+01	4.06E+01	4.46E+01	3.86E+01	9.73E-01	9.61E-01	9.75E-01
12	5-4-12-1	1.00E+01	1.22E+01	1.36E+01	1.49E+01	1.88E+01	2.01E+01	9.96E-01	9.93E-01	9.93E-01
13	5-6-2-1	3.78E+01	3.16E+01	3.49E+01	5.20E+01	4.62E+01	5.03E+01	9.55E-01	9.65E-01	9.50E-01
14	5-6-4-1	2.31E+01	2.21E+01	2.60E+01	3.34E+01	3.13E+01	3.53E+01	9.80E-01	9.87E-01	9.79E-01
15	5-6-6-1	2.06E+01	2.18E+01	2.13E+01	2.76E+01	2.98E+01	2.85E+01	9.87E-01	9.83E-01	9.87E-01
16	5-6-8-1	3.29E+01	3.74E+01	3.11E+01	4.52E+01	5.11E+01	4.22E+01	9.66E-01	9.55E-01	9.67E-01
17	5-6-10-1	1.56E+01	1.99E+01	2.06E+01	2.31E+01	2.75E+01	2.99E+01	9.91E-01	9.86E-01	9.84E-01
18	5-6-12-1	1.51E+00	1.95E+00	1.47E+00	3.73E+00	4.70E+00	3.51E+00	1.00E+00	1.00E+00	1.00E+00
19	5-8-2-1	1.67E+02	1.73E+02	1.75E+02	2.07E+02	2.13E+02	2.16E+02	2.81E-01	3.23E-01	3.61E-02
20	5-8-4-1	2.08E+01	2.30E+01	2.33E+01	3.01E+01	3.28E+01	3.22E+01	9.84E-01	9.80E-01	9.85E-01
21	5-8-6-1	1.38E+01	1.79E+01	1.56E+01	2.05E+01	2.67E+01	2.13E+01	9.93E-01	9.88E-01	9.92E-01
22	5-8-8-1	1.31E+01	1.83E+01	1.29E+01	1.99E+01	2.68E+01	1.92E+01	9.93E-01	9.88E-01	9.94E-01
23	5-8-10-1	4.32E+00	4.33E+00	4.46E+00	8.16E+00	6.85E+00	7.50E+00	9.99E-01	9.99E-01	9.99E-01
24	5-8-12-1	8.75E-12	1.40E-11	9.98E-12	2.22E-11	3.28E-11	2.25E-11	1.00E+00	1.00E+00	1.00E+00
25	5-10-2-1	2.23E+01	3.02E+01	2.23E+01	3.76E+01	4.69E+01	3.77E+01	9.76E-01	9.58E-01	9.80E-01
26	5-10-4-1	1.29E+01	1.46E+01	1.29E+01	1.93E+01	2.12E+01	1.87E+01	9.94E-01	9.93E-01	9.93E-01
27	5-10-6-1	1.33E+01	1.65E+01	1.59E+01	2.10E+01	2.48E+01	2.39E+01	9.93E-01	9.88E-01	9.89E-01
28	5-10-8-1	2.38E+00	3.50E+00	2.77E+00	6.82E+00	1.08E+01	7.87E+00	9.99E-01	9.98E-01	9.99E-01
29	5-10-10-1	1.48E-12	1.73E-12	1.37E-12	1.95E-12	2.20E-12	1.73E-12	1.00E+00	1.00E+00	1.00E+00
30	5-10-12-1	3.51E-01	2.93E-01	4.42E-01	1.09E+00	1.20E+00	1.25E+00	1.00E+00	1.00E+00	1.00E+00
31	5-12-2-1	4.12E+01	4.12E+01	3.52E+01	5.73E+01	5.42E+01	4.40E+01	9.45E-01	9.47E-01	9.67E-01
32	5-12-4-1	2.00E+01	2.24E+01	1.92E+01	2.78E+01	3.10E+01	2.90E+01	9.87E-01	9.83E-01	9.87E-01
33	5-12-6-1	2.77E+00	3.96E+00	2.80E+00	6.66E+00	8.36E+00	4.65E+00	9.99E-01	9.99E-01	1.00E+00
34	**5-12-8-1**	**1.11E-12**	**1.23E-12**	**1.12E-12**	**1.51E-12**	**1.65E-12**	**1.60E-12**	**1.00E+00**	**1.00E+00**	**1.00E+00**
35	5-12-10-1	5.28E-12	6.28E-12	4.85E-12	1.18E-11	1.28E-11	9.12E-12	1.00E+00	1.00E+00	1.00E+00
36	5-12-12-1	4.61E+00	6.30E+00	3.83E+00	1.03E+01	1.34E+01	7.11E+00	9.98E-01	9.97E-01	9.99E-01

Table 6. Inputs and Output datasets utilised for ANN models.

Category	ANN Model for Mbeya City			ANN Model for Songea Municipal			ANN Model for Mpanda Municipal			SI Unit
	Parameters	Min	Max	Parameters	Min	Max	Parameters	Min	Max	
Inputs	TZSER	1307	2343	TZSER	1307	2343	TZSER	1307	2343	TZS/USD
	DDM	822	822	DDS	947	947	DDK	1383	1383	km
	WTIP	30	110	WTIP	30	110	WTIP	30	110	USD/bbl
	EBSP	31	125	EBSP	31	125	EBSP	31	125	USD/bbl
	WGMP	858	1781	WGMP	858	1781	WGMP	858	1781	USD/ounce
Output	MDPM	1260	2389	MDPS	1276	2411	MDPK	1306	2436	TZS/Litre

Table 7. The optimal Parameters of selected ANN Models for Mbeya City, Songea and Mpanda Municipals.

Parameter	ANN Model for Mbeya City			ANN Model for Songea Municipal			ANN Model for Mpanda Municipal		
	Testing	Training	Validation	Testing	Training	Validation	Testing	Training	Validation
R^2	1.00000	1.000000	1.00000	1.00000	1.0000	1.00000	1.00000	1.00000	1.00000
RMSE	2.37E-12	1.69E-12	2.49E-12	1.23E-12	1.31E-12	1.40E-12	1.51E-12	1.65E-12	1.60E-12
MAE	1.80E-12	1.31E-12	1.88E-12	9.70E-13	1.08E-12	1.12E-12	1.11E-12	1.23E-12	1.12E-12