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Application of Artificial Neural Network Models for Predicting Diesel and Petrol Prices in the Geographically Sparsed Regions in Tanzania

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ABSTRACT

Fuel consumption in Tanzania, mainly diesel and petrol, accounts for 82 percent of the energy consumption in the country, with significant price volatility affecting market stability, availability of fuel, and investment decisions. This study uses an artificial neural network (ANN) with a backpropagating algorithm to predict fuel prices in four regions of Tanzania. Key input parameters include the currency inflation rate (CIR), the petrol fuel inventory (PFI), the diesel fuel inventory (DFI), and the fuel transport costs (FTC). The study selected the 6-10-10-2 ANN structures for Sumbawanga-Rukwa, Mpanda-Katavi, and Mbeya-Mbeya as well as 6-10-9-2 for the Songea-Ruvuma region. The results show that transit distances between 200 and 400 km have a significant effect on the price of fuel, with petrol ranging from 0.1199 to 0.1349 Tanzania shillings per litre and diesel from 0.1203 to 0.1502 Tanzania shillings per litre. Road conditions also have an impact on fuel costs, with average fuel consumption of 0.9685 l/km on gravel roads versus 0.1325 l/km on paved roads. This finding suggests that poor road conditions contribute to higher fuel consumption and price volatility. Transport distances below 35 km have a minimal impact; however, load, speed, climate, and driving habits all contribute to variations. The results illustrate that the increase in distance influences higher price fluctuation for diesel than petrol. The study confirms that the application of ANN for predicting fuel price trends helps decision makers to make sustainable investments. The study recommends consolidation of transport and use of rail to reduce costs, although the limited rail network limits regional availability.

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INTRODUCTION

Energy has been a key factor driving global economies in the modern patterns of industrialization and economic advancement. In Tanzania, the primary energy sources utilized to sustain various sectors such as transportation, agriculture, manufacturing, health and education, as well as commercial and domestic applications are diesel and petrol. These types of fuel constitute 82% of Tanzania's overall energy consumption (EWURA, 2023). Price per litre of these fuels exhibits considerable disparities across different geographical locations. Further, it is worth noting that diesel and petrol markets show significant price volatility. The fluctuation in prices can be attributed to various causes, such as product pricing, import expenses, transportation and distribution costs, marketing expenditures, and government taxes and levies.

The volatility in monthly prices of diesel and petrol products in Tanzania has significant implications for economy and financial market, exerting a multiplier effect on both corporate and domestic spending. Due to their necessity, these types of fuels are essential commodities that have significant impacts on various sectors, including transportation systems, industrial production, food supply, and healthcare facilities. This study utilized artificial neural networks (ANNs) to forecast diesel and petrol prices in assessing the factors that influence the volatility of pricing of these commodities (Fauz *at al*., 2023). This initiative aims to facilitate the establishment of a mechanism that effectively mitigates the adverse effects of price variations in the diesel and petrol markets. By doing so, it will provide valuable support to various stakeholders, including petrol station investors, government entities, hedgers, and people, thus enabling them to make well-informed decisions in their dealings within these markets. Fuel transportation chain in Tanzania begins from the three Indian Ocean ports of Dar es Salaam, Tanga, and Mtwara. Due to the vast area of the country, the ports are located very far from upcountry regions, necessitating the use of road transportation spanning thousands of miles to connect with these sparsed areas. Vehicles powered by off-road diesel and petrol exhibit increased severity when encountering inclines with a gradient of up to 16% (Msabaha and Zhihong, 2020). The distinct circumstances surrounding the distribution of diesel and petrol lead to divergent pricing patterns. According to a report by the Citizen News (2023), there are significant variations in the costs of diesel and petrol throughout different zones in Tanzania, including the southern highlands, western, and lake zones. The prices in the eastern and southern regions, where ports are located, differ significantly from these variations. Hence, it is crucial to analyze the impact of input variables, such as the inflation rate, inventories of diesel and petrol, distance from the region's center to consumers, fuel transportation costs, and indigenous purchasing power, in order to forecast energy prices and mitigate the volatility of prices.

LITERATURE REVIEW

Numerous scholars have documented the utilization of ANNs in forecasting price fluctuations for industrial and agricultural products such as spare parts and timber (Ifraz *et al*., 2023; kozuch *et al*., 2023). For example, Zhu *et al*. (2023) applied ANNs to predict house prices in three cities and established average annual growth rate of between 2.49 to 3.57%. The study indicated that the deep learning strategy of ensemble ANNs exhibited superior performance compared to other approaches. In another study, Jammazi and Aloui (2012) employed various neural network designs, incorporating three distinct transfer functions to obtain the results which showed that ANNs yielded favorable outcomes in predicting crude oil prices. Similarly, Glorot and Bengio (2010) conducted a study whose findings showed that the utilization of the model resulted in a notable enhancement of 30% in the accuracy of volatility forecasting, as assessed using the heteroscedasticity adjusted mean square error model, in comparison to prior models. In a similar vein, Moner-girona *et al*. (2016) employed ANNs to reveal that the price of oil plays a significant effect in forecasting both the price of gold and the exchange rate of the Euro. Another study that had corroborative results was conducted by Wang *et al*. (2020) who employed the copula function and bivariate neural network to examine the dynamics of oil price changes. The findings indicated that the bivariate model exhibits exceptional predictive capabilities, while also highlighting the significant influence of oil price variations on the exchange rate.

The intelligence of ANNs is derived from the collective behavior of individual computational mechanisms located at distinct neurons (Ünal and Başçiftçi, 2023). Every individual neuron inside the neural network is subject to receiving many inputs, each of which is accompanied with a weight. These weights can be understood as approximate representation of the electrochemical impulses and synaptic connections that occur within the intricate network of the brain (Glorot and Bengio, 2010; Babu *et al*., 2023). The preceding discourse elucidated that the price of oil is subject to variability due to a multitude of causes. However, the majority of existing scholarly works have focused on analyzing oil prices within the countries of oil production. In contrast, the present study aims to forecast the prices of diesel and petrol that are imported and dispersed throughout different regions in Tanzania. Tanzania encompasses a total land area of 945,087 km^2, which is divided into 25 regions that are geographically dispersed. The distance among regions is a key factor accounting for oil price variations, as around 80% of regions are situated more than 200km apart. Hence, it is imperative to construct a set of shared parameters to determine pricing in various regions and to devise a predictive tool that aids decision-makers in establishing a foundational framework for oil price

MATERIALS AND METHODS

The study utilized monthly dataset of diesel and petrol prices from the Energy and Water Utilities Regulatory Authority (EWURA) over the span of ten years. A study was carried out in southern highlands regions of Tanzania, namely Ruvuma, Rukwa, Mbeya and Katavi. The inflation rate, monthly inventory levels, transportation costs, geographical distance involved in distribution of fuel, and purchasing power were variables considered in analysing the impact of price volatility. The distances of fuel distributions from main fuel deports in Dar es Salaam to the selected regions were obtained from the Tanzania Roads Authority (TANROADS). The average inflation rates of ten years from 2014 to 2023 were obtained from the National Bureau of Statistics (NBS). Questionnaires were used to collect the data for fuel inventory levels, transportation costs, and purchasing power from the owner of fuel stations and customers.

Simulation Setup

The experimental design encompassed the partitioning of data into three separate subsets, each serving specific purposes of training, testing, and model validation. ANNs utilize training data during the training phase to adjust the network's weights. The test subdivision was employed as a means of assessing the network's response to untrained data throughout the learning phase. The data utilized in the subset for analysis exhibited variations from the data employed for training purposes. Nonetheless, it is noteworthy that the ranges of the subset data fell within the restrictions of the training data. The computations were conducted using the MATLAB R2014a neural network toolbox. The validation subset was employed subsequent to the selection of the optimal network during the learning process in order to further assess the network's ability to generalize.

Dindarloo and Siami-Irdemoosa (2015) argue that there is a lack of established scientific recommendations pertaining to the optimal distribution of data percentages for training, testing, and validation purposes. Nevertheless, certain heuristics can be established, primarily derived from empirical knowledge and drawing a parallel between ensemble neural networks and statistical regression. On the other hand, Glorot and Bengio (2010) discussed on the ratio of sample to train the model that the smallest number of samples for training should be equivalent to the ratio of the total number of weight for the minimum goal error. Similarly, Kazemi *et al*. (2013)

recommended that sample-to-weight ratio for training the model should exceed four. However, Qiu and Ji (1999) suggested that 65% of the data should be allocated for training purposes, 25% for testing, and 10% for validation. According to Haykin (2009), it is recommended to allocate 20-30% of the total time for testing purposes; and Carney and Cunningham (2000) and Carney *et al*. (1999) proposed a 20% allocation for testing.

This study utilizes a dataset consisting of 120 months, wherein 78 months (65%) are allocated for training purposes, 30 months (25%) are utilized for model verification, and the remaining 12 months (10%) are used for validation purpose. The optimal topology for the ANNs was selected based on established two evaluating regression parameters, which are the coefficient of determination (R2) and the mean squared error (MSE). The most suitable model for predicting petrol and diesel prices is the one that exhibits the highest R2 value and the lowest MSE. The determination of R2 and MSE values are presented into equations (1) and (2).

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}\left(P_{ac} - P_{pred}\right)^2}{\sum_{i=1}^{n}\left(P_{pred}\right)^2}\right]^{\frac{1}{2}} \quad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(P_{ac} - P_{pred}\right)^2 \quad (2)$$

where P_{ac} is the actual petrol/diesel price, P_{pred} is the predicted petrol/diesel prices value and n is a number of datasets.

The study examined the impact of several input parameters on diesel and petrol prices in geographically sparsed regions in Tanzania. These parameters included the Tanzania currency inflation rate (TCIR), petrol fuel inventory (PFI), diesel fuel inventory (DFI), and fuel transportation cost (FTC) as indicated in Figure 1. Additionally, the pricing of diesel and petrol are influenced by factors such as indigenous purchasing power (IPP) and the distance between supply points at ports and regional headquarters, as well as the subsequent distribution to districts (DSDP). The determination of the number of hidden layers was conducted throughout the combination design stages as illustrated in the subsequent part on system verification.

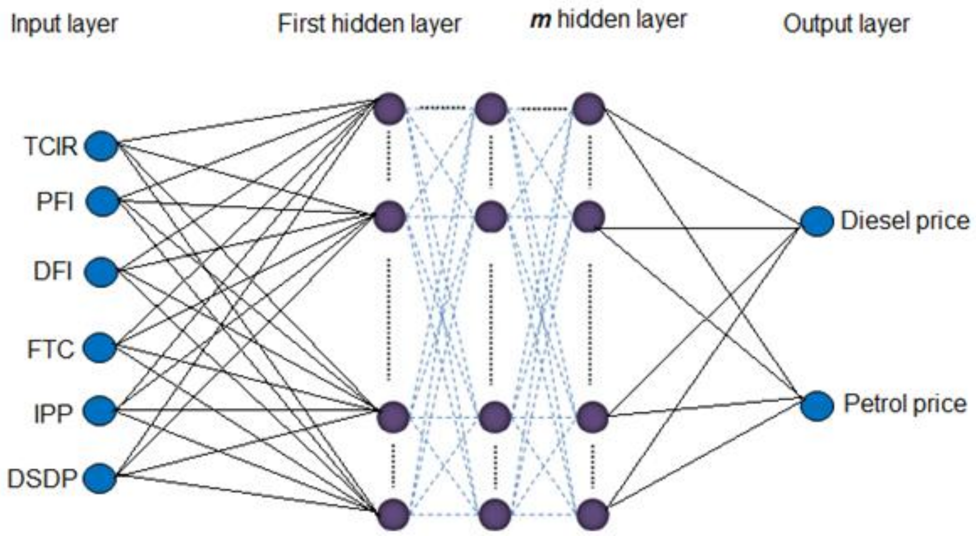

Figure 1. The main structure of the proposed ANN network.

Model Verification

The verification process encompassed the training of the ANN model using training and testing datasets. In order to determine the performance of the network, the MSE and R^2 were evaluated. The training of a back-propagation network (BPN) necessitated the identification of suitable values for network parameters and the determination of an adequate architecture for the specific application, which was achieved through the iterative process of trial-and-error. The training duration for various neural networks ranged from a few seconds to 15 minutes. The learning rate parameter and momentum terms were periodically modified in order to enhance the rate of convergence. In order to maintain the inherent simplicity of the modeling structure, the back-propagation network (BPN) multilayer perceptron network model was employed to 2 to 4 hidden layers each consisting of 3 to 25 nodes.

The aforementioned value was determined by the analysis of a set of neurons in the hidden layers, specifically 3, 6, 9, 12, and 25. The computational efficiency of the architecture featuring 4 and 6 neurons in the hidden layers was observed to be higher; however, it was noted that the rate of convergence was significantly slow. The convergence of the architecture consisting of 13 and 18 neurons in the hidden layer was found to be comparable to that of the architecture with 25 neurons. Hence, the neural networks with topologies of 6-10-10-2, 6-10-10-2, 6-10-9-2, and 6-10-10-2 were chosen for the headquarters of Rukwa, Katavi, Mbeya, and Ruvuma regions.

RESULTS PRESENTATION

The findings demonstrate the architectures of the created networks and their corresponding degrees of performance as presented in Tables 1 to 4. The coefficient of determination (R^2) values varied between 0.6598 for the 2-neuron two-hidden-layered network to 0.9998 for the 10-neuron network. The configuration of the highest performing network is depicted in Figures 2(a), 3(a), 4(a), and 5(a). The performance of the model for each region in terms of training, testing, and validation is presented in Tables 1 to 4. Mean squared error (MSE) for the training, testing, and validation of the model varies between 0.32% and 0.91%. The findings indicate the alteration of the neural network architecture by increasing the number of neurons in the hidden layers from 10 to 20, and concurrently decreasing the momentum coefficient (MC) value from 0.90 to 0.75, resulting in a drop in performance as measured by R^2 values. The results for the various models examined in the simulations are shown in Table 1. The chosen neural model's structure is enclosed by a rectangle-shaped line. Even though model network number 7 was determined to have the optimal structure for the testing data set as it revealed to have minimum error, validation data shows that model number 7 is outperformed by a model with 2 hidden layers and 10 hidden neurons in each layer. As a result, model network number 8 was chosen, which has a 6-10-10-2 architecture. Figure 2(a) depicts this network. Figures 2(b) and 2(c) depict the comparison between the projected and observed statistics for diesel and petrol cap prices on specific days. The ANN that has been developed replicates the patterns of price trends of diesel and petrol fuel**.**

Table 1: Structure of neural networks with variable numbers of hidden neuron for Rukwa Region headquarter

No.	Model	MSE Training	MSE Validation	MSE Testing	R^2 Training	R^2 Cross Validation	R^2 Testing
1	6-2-2-2	0.0032	0.0045	0.0062	0.7830	0.7460	0.6920
2	6-3-3-2	0.0015	0.0021	0.0029	0.8450	0.8051	0.7468
3	6-4-4-2	0.0046	0.0065	0.0089	0.9567	0.9115	0.8455
4	6-3-9-2	0.0014	0.0020	0.0027	0.9894	0.9426	0.8744

5	6-9-3-2	0.0034	0.0048	0.0066	0.9873	0.9406	0.8726
6	6-7-4-2	0.0019	0.0027	0.0037	0.9764	0.9303	0.8629
7	6-4-8-2	0.0013	0.0019	0.0026	0.9845	0.9380	0.8701
8	6-10-10-2	0.0017	0.0010	0.0028	0.9996	0.9985	0.9945
9	6-11-10-2	0.0027	0.0038	0.0052	0.9967	0.9496	0.8809
10	6-10-11-2	0.0039	0.0055	0.0076	0.9945	0.9475	0.8789
11	6-4-2	0.0048	0.0068	0.0093	0.9923	0.9454	0.8770
12	6-6-2	0.0059	0.0083	0.0114	0.9901	0.9433	0.8750
13	6-8-2	0.0070	0.0098	0.0135	0.9879	0.9412	0.8731
14	6-10-2	0.0080	0.0113	0.0155	0.9857	0.9391	0.8711
15	6-15-2	0.0091	0.0127	0.0175	0.9835	0.9370	0.8692

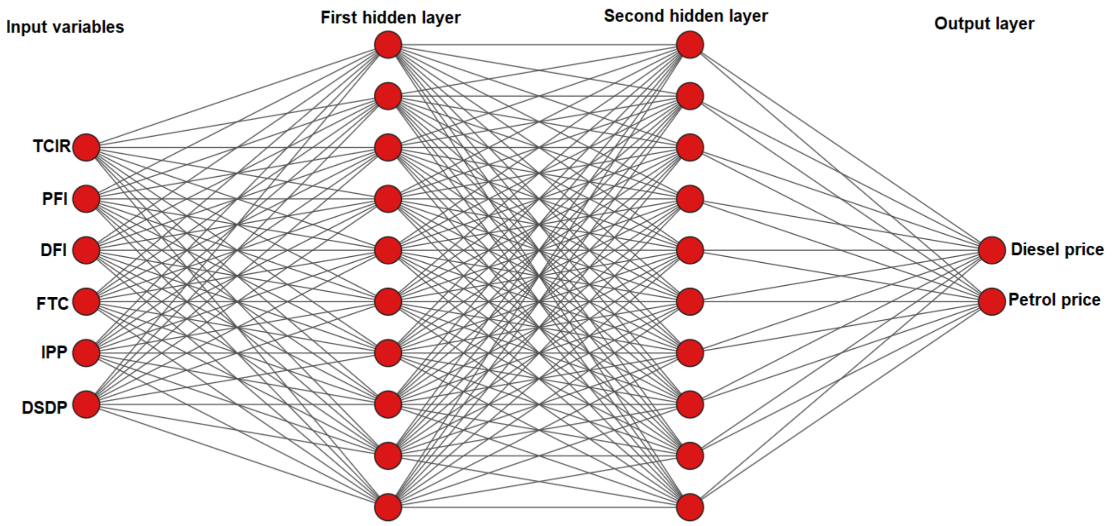

Figure 2(a): Proposed ANN model for prediction of diesel and petrol prices for Rukwa Region.

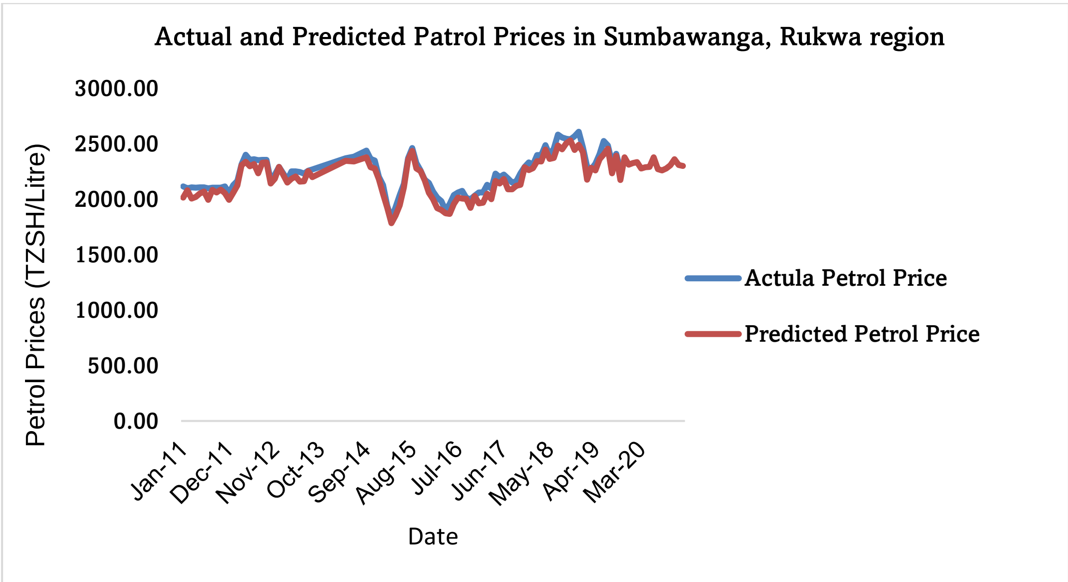

Figure 2(b): Actual against ANN predicted petrol prices in Sumbawanga, Rukwa Region.

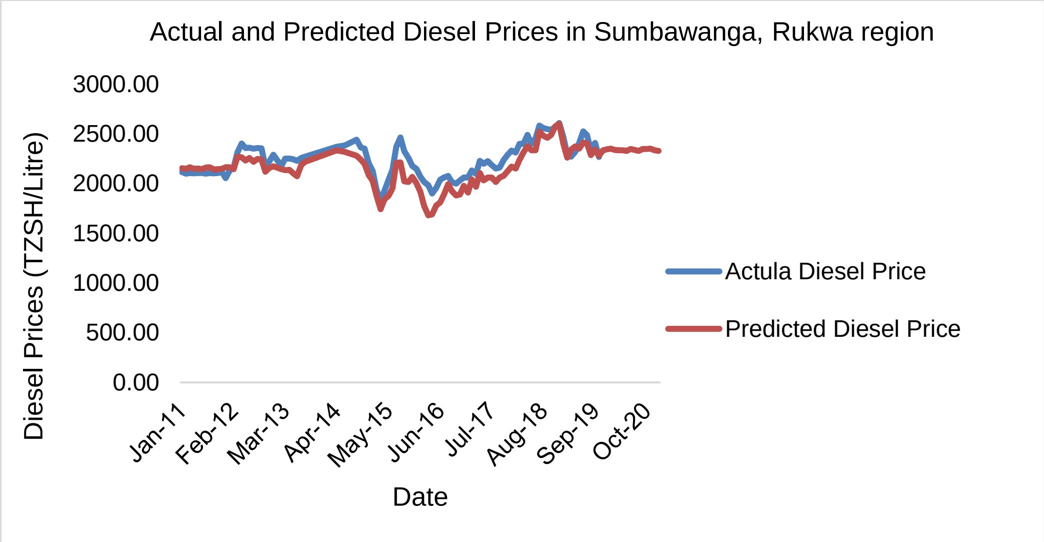

Figure 2(c): Actual against ANN predicted diesel prices in Sumbawanga, Rukwa Region.

Table 2 presents the quality of the results obtained for different models examined in the simulation stage at Mpanda, Katavi Region headquarters. A rectangle line encloses the structure of the selected neural model.

The findings show that model 5 exhibits the most optimal architecture, as evidenced by the outcomes obtained during the training and test phases. Nevertheless, the validation results indicate that a model comprising of two hidden layers, each consisting of 10 hidden neurons, exhibits superior performance compared to model number 6. Figure 3(a) shows the analysis model that was selected. The network architecture of this model, also known as model number eight, is 6-10-10-2. For this model, a learning rate of 0.6 and a momentum coefficient of 0.2 were used as hyperparameters. The comparison between the predicted and actual statistics for diesel and petrol fuel costs on a certain day is presented in Figures 3(b) and 3(c). The patterns seen in the time series data of diesel and petrol prices can be replicated by the ANNs that have been built.

Table 2: Structure of different neural networks with the variable number of hidden neurons for Mpanda, Katavi Regional headquarters

No.	Model	MSE Training	MSE Validation	MSE Testing	R^2 Training	R^2 Cross Validation	R^2 Testing
1	6-2-2-2	0.0025	0.0035	0.0046	0.8956	0.8945	0.8845
2	6-3-3-2	0.0035	0.0049	0.0064	0.8450	0.8440	0.8345
3	6-4-4-2	0.0046	0.0064	0.0085	0.9567	0.9555	0.9448
4	6-3-9-2	0.0018	0.0025	0.0033	0.9894	0.9882	0.9771
5	6-9-3-2	0.0024	0.0034	0.0019	0.9873	0.9861	0.9751
6	6-10-10-2	0.0047	0.0024	0.0031	0.9996	0.9982	0.9943
7	6-10-9-2	0.0023	0.0033	0.0043	0.9986	0.9974	0.9862
8	6-9-10-2	0.0030	0.0042	0.0055	0.9964	0.9952	0.9841
9	6-8-10-2	0.0036	0.0051	0.0066	0.9942	0.9930	0.9819
10	6-10-8-2	0.0043	0.0060	0.0078	0.9920	0.9908	0.9797
11	6-5-2	0.0049	0.0069	0.0090	0.9898	0.9886	0.9775
12	6-9-2	0.0055	0.0077	0.0102	0.9876	0.9864	0.9754

13	6-13-2	0.0062	0.0086	0.0114	0.9854	0.9842	0.9732
14	6-16-2	0.0068	0.0095	0.0125	0.9832	0.9820	0.9710
15	6-20-2	0.0075	0.0104	0.0137	0.9810	0.9798	0.9688

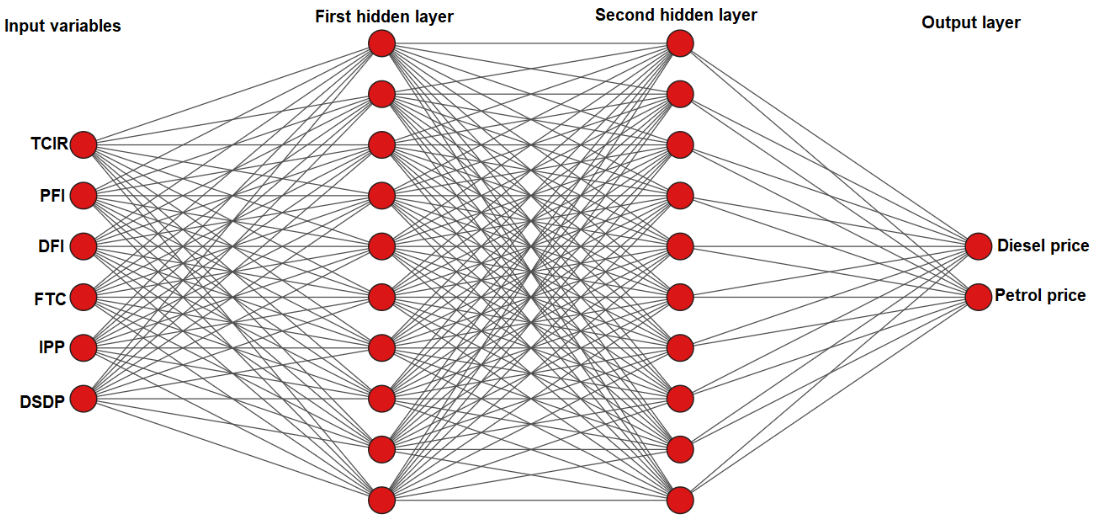

Figure 3(a): Proposed ANN model for prediction of diesel and petrol prices in Mpanda, Katavi Region headquarters.

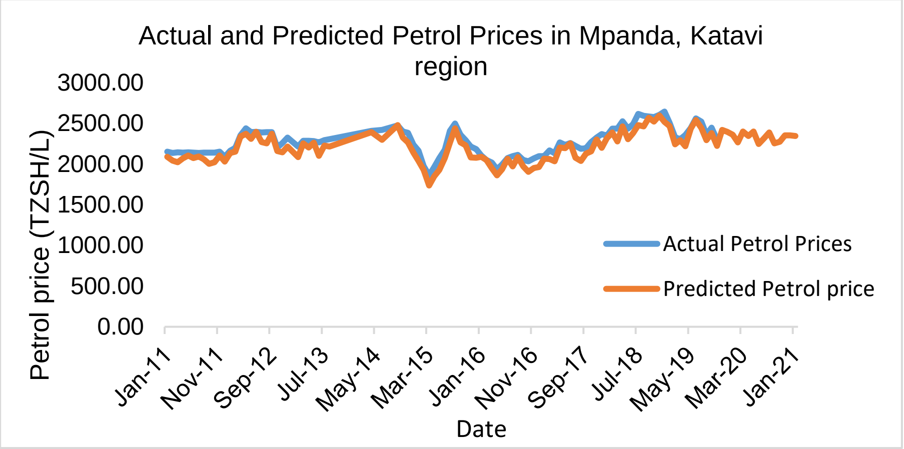

Figure 3(b): Actual against ANN predicted petrol prices in Mpanda, Katavi Region.

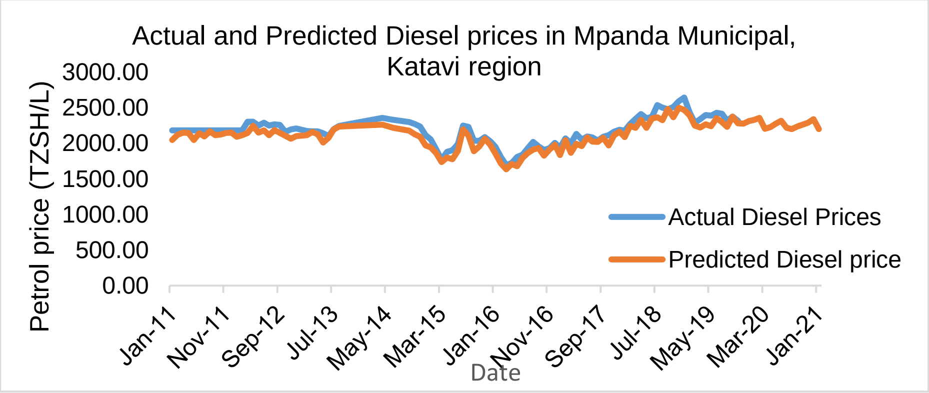

Figure 3(c): Actual against ANN predicted diesel prices in Mpanda, Katavi Region.

Table 3: Structure of different neural networks with a variable number of hidden neurons for Mbeya, Mbeya Region headquarters

No.	Model	MSE Training	MSE Validation	MSE Testing	R^2 Training	R^2 Cross Validation	R^2 Testing
1	6-3-2-2	0.0035	0.0029	0.0039	0.8745	0.8923	0.8721
2	6-2-3-2	0.0058	0.0048	0.0065	0.8960	0.8781	0.8985
3	6-4-3-2	0.0049	0.0041	0.0055	0.9685	0.9492	0.9712
4	6-3-4-2	0.0028	0.0023	0.0031	0.9794	0.9599	0.9821
5	6-9-4-2	0.0019	0.0016	0.0021	0.9372	0.9185	0.9398
6	6-9-9-2	0.0021	0.0018	0.0019	0.9895	0.9698	0.9922
7	6-10-9-2	0.0013	0.0012	0.0014	0.9986	0.9897	0.9995
8	6-9-10-2	0.0038	0.0032	0.0043	0.9964	0.9765	0.9991
9	6-8-10-2	0.0045	0.0038	0.0051	0.9942	0.9744	0.9969
10	6-10-8-2	0.0052	0.0043	0.0058	0.9128	0.8946	0.9153
11	6-5-2	0.0059	0.0049	0.0066	0.9098	0.8917	0.9123
12	6-9-2	0.0066	0.0055	0.0074	0.9776	0.9581	0.9803
13	6-13-2	0.0073	0.0061	0.0082	0.9765	0.9570	0.9792
14	6-16-2	0.0080	0.0067	0.0090	0.8792	0.8617	0.8816
15	6-20-2	0.0087	0.0072	0.0097	0.9345	0.9159	0.9371

The quality of the outcomes for the various models investigated during the simulation phase for the Mbeya Region headquarters is shown in Table 3. The chosen neural model's structure is enclosed by a rectangle line. As a result, the model with network architecture of 6-10-9-2, learning rate of 0.4, and momentum coefficient (MC) of 0.2 was chosen, as shown in Figure 4(a). Figures 4(b) and 4(c) compare the predicted diesel and gasoline cape prices to the actual recorded data for a specific date. The created ANNs mimic the time series trend of the diesel and petrol fuel prices.

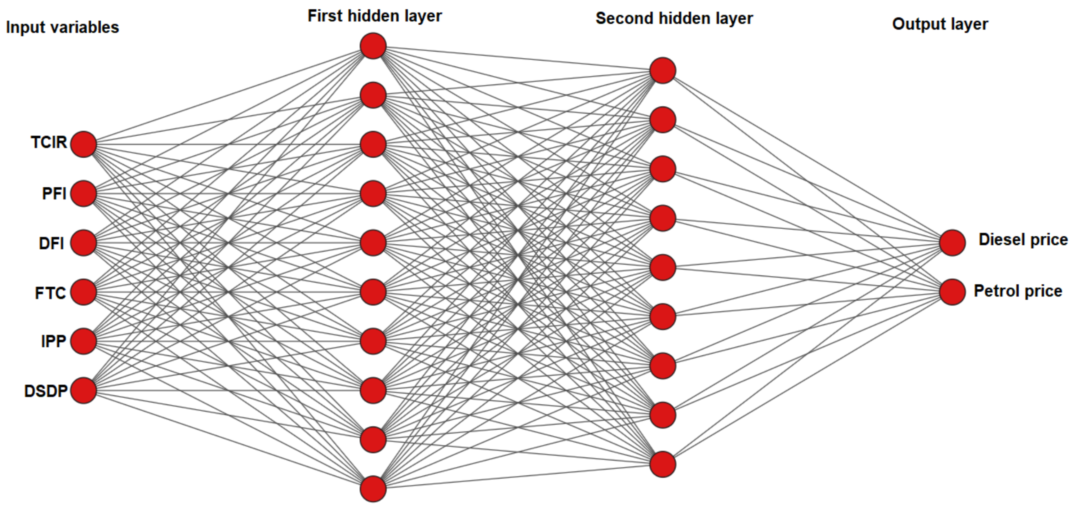

Figure 4(a): Proposed ANN model for prediction of diesel and petrol prices in Mbeya Region headquarters.

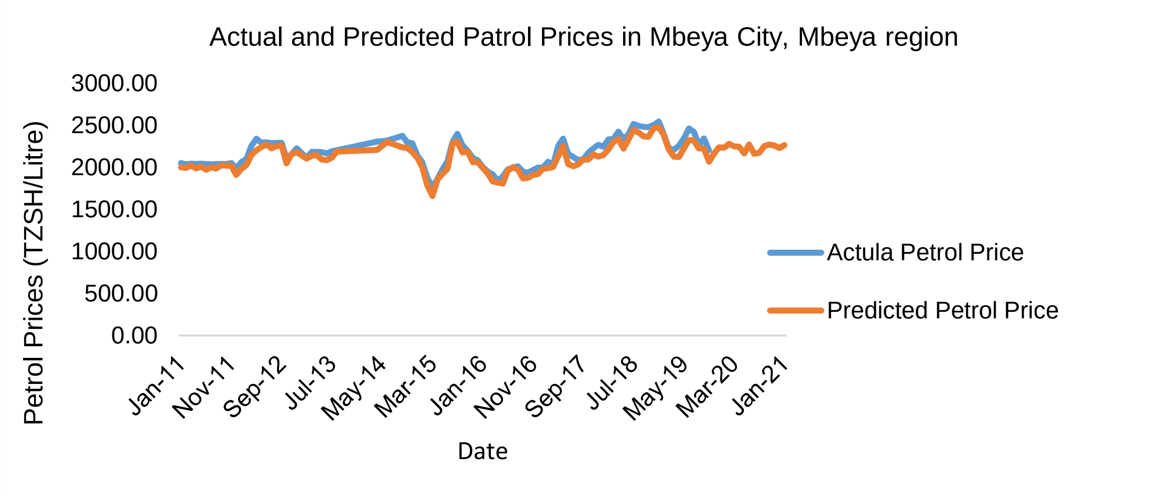

Figure 4(b): Actual against ANN predicted petrol prices in Mbeya Region headquarters.

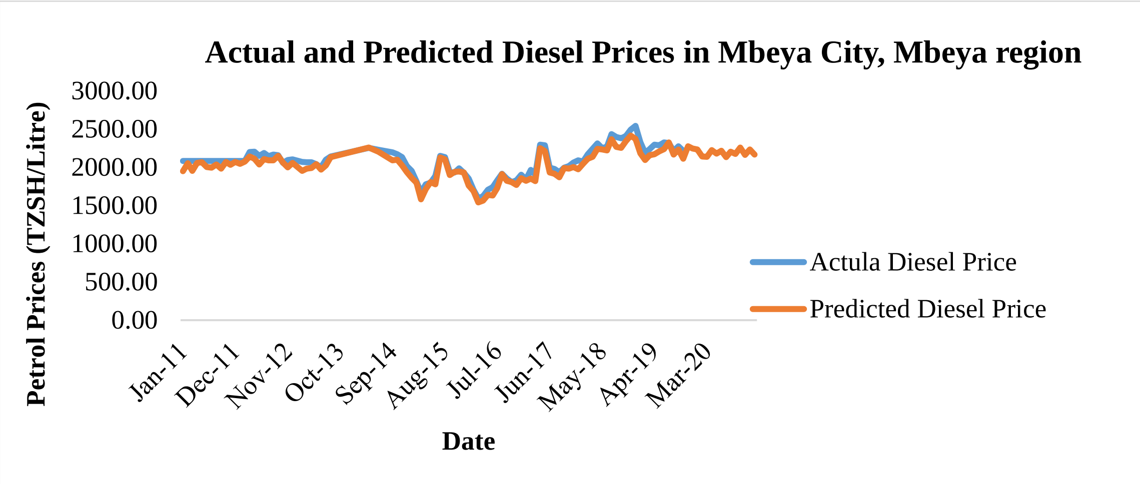

Figure 4(c): Actual against ANN predicted diesel prices in Mbeya Region headquarters.

Table 4: Structure of different neural networks with a variable number of hidden neurons in Songea, Ruvuma Region headquarters.

No.	Model	MSE Training	MSE Validation	MSE Testing	R^2 Training	R^2 Cross Validation	R^2 Testing
1	6-3-3-2	0.0053	0.0068	0.0076	0.8664	0.8563	0.8456
2	6-4-3-2	0.0038	0.0048	0.0054	0.8758	0.8539	0.8435
3	6-3-4-2	0.0036	0.0046	0.0051	0.8864	0.8642	0.8537
4	6-4-4-2	0.0031	0.0040	0.0044	0.8878	0.8656	0.8550
5	6-6-4-2	0.0028	0.0036	0.0040	0.9921	0.9673	0.9555
6	6-4-6-2	0.0023	0.0029	0.0033	0.9895	0.9648	0.9530
7	6-6-6-2	0.0018	0.0023	0.0026	0.9986	0.9736	0.9617
8	6-10-10-2	0.0019	0.0014	0.0032	0.9972	0.9723	0.9604
9	6-11-10-2	0.0012	0.0037	0.0025	0.9842	0.9596	0.9479
10	6-10-11-2	0.0037	0.0047	0.0053	0.9698	0.9456	0.9340
11	6-12-10-2	0.0053	0.0067	0.0075	0.9865	0.9618	0.9501

12	6-15-2	0.0067	0.0085	0.0095	0.9905	0.9657	0.9539
13	6-18-2	0.0081	0.0103	0.0115	0.9864	0.9617	0.9500
14	6-20-2	0.0095	0.0121	0.0135	0.8792	0.8572	0.8467
15	6-25-2	0.0109	0.0139	0.0155	0.9276	0.9044	0.8934

While model number 9 was identified as the optimal configuration throughout the training and testing stages, the validation outcomes indicate that a model featuring two hidden layers and ten hidden neurons in each layer surpasses the performance of model number 9. Therefore, the model designated as number eight, seen in Figure 5(a) and characterized by a network architecture of 6-10-10-2, a learning rate of 0.5, and a momentum coefficient (MC) of 0.3, was chosen. Figures 5(b) and 5(c) depict the comparison between projected diesel and petrol fuel prices and the actual recorded data on specific days. The ANNs that have been developed exhibit the ability to accurately replicate the patterns observed in the time series data of diesel and petrol fuel.

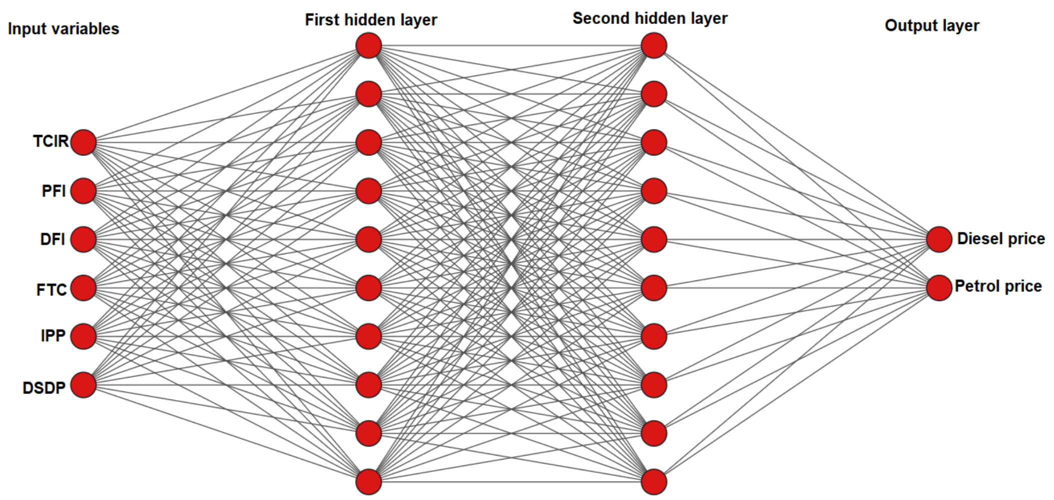

Figure 5(a): Proposed ANN model for prediction of diesel and petrol prices in Songea, Ruvuma Region headquarters.

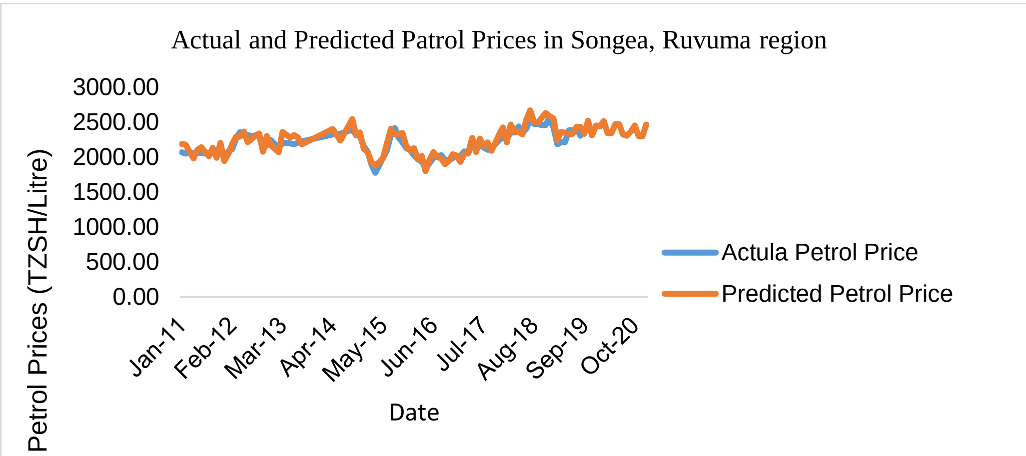

Figure 5(b): Actual against ANN predicted petrol prices in Songea, Ruvuma Region headquarters.

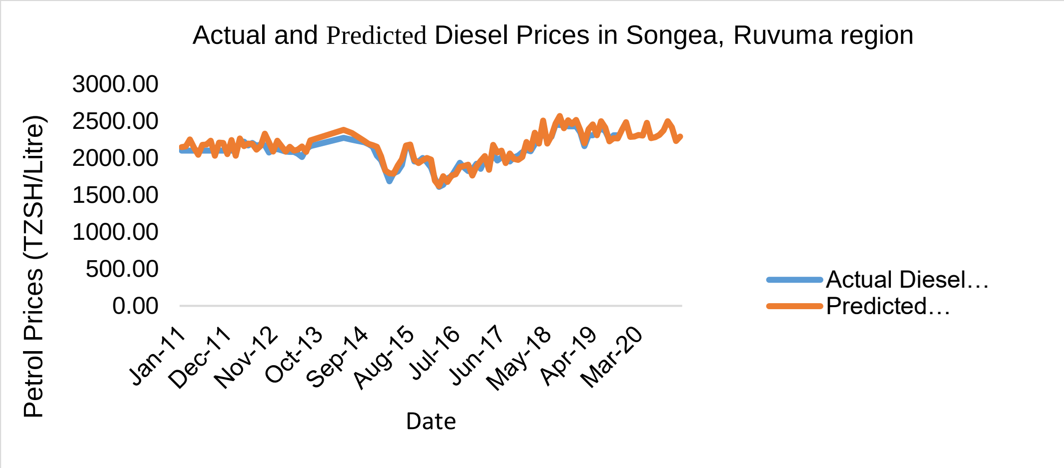

Figure 5(c): Actual against ANN predicted diesel prices in Songea, Ruvuma Region headquarters.

DISCUSSION

The study results demonstrated a correlation between the prevailing inflation rate and the fluctuations in diesel and petrol prices. This finding is supported by previous research that has consistently shown that fuel prices are highly sensitive to macroeconomic indicators such as inflation, as fuel is a critical input in many sectors (Hasan *et al*., 2019). Other factors that were found to influence price volatility include transport costs and the distance of fuel supply, which aligns with previous studies that emphasize the significant impact of logistics and geographical distance on fuel pricing in remote regions (Al-Dmour and Hasan, 2018; Asif and Bashir, 2018).

The rise in service costs across sectors such as transportation, health, and industry can be attributed to fluctuating diesel and petrol prices, which are influenced by variables such as transportation cost index rates, fuel tax credits, and domestic supply and demand patterns (Koutroumanidis *et. al*., 2017). There exists a direct cause-and-effect relationship between the prices of diesel and petrol and the inflation rate, whereby a rise or drop in inflation leads to a proportional increase or fall in prices, respectively (Jahangir *et al*., 2022). This phenomenon occurs because diesel and petrol play significant roles as essential inputs in key economic sectors, including transportation, healthcare, and food processing. Consequently, when input costs rise due to increasing fuel prices, there is a corresponding impact on the pricing of products and services, as these are contingent upon fuel price fluctuations (Chang and Lin, 2021; Wang *et al*., 2019). This dynamic is particularly pronounced in geographically sparse regions where the cost of transporting fuel is higher, further exacerbating the impact of fuel price volatility on the broader economy (Adebiyi *et al*., 2017**)**. Additionally, the prices of diesel and petrol are intricately linked to the geographical distance of fuel supply, exerting a significant impact on the volatility of transportation expenses. These findings align with the work of Asif and Bashir (2018), who highlight the strong correlation between distance and fuel transportation costs in remote regions. The study revealed that as the distance of fuel supply increases, there is a corresponding rise in transportation expenses, including bus fares and cargo transportation rates, confirming previous research that emphasized transportation as a key determinant in fuel pricing (Al-Dmour and Hasan, 2018).

Empirical findings from the study indicate that increasing the distance between locations from 200 km to 400 km results in fuel price variations ranging from 0.1199 to 0.1349 Tanzanian shillings per litre of petrol, respectively. Similarly, extending the distance for fuel supply from 200 km to

400 km led to fluctuations in diesel prices, which rose from 0.1203 to 0.1502 Tanzanian shillings per litre. This observation is consistent with the conclusions of Koutroumanidis *et al*. (2017), who noted that long-distance fuel transport significantly contributes to fuel price volatility.

The ANN model used in this study further demonstrated that variations in distance below 35 km have a minimal impact on the costs of petrol and diesel, as also suggested by Hasan *et al*. (2019), where short-distance transportation showed less price sensitivity. This finding highlights the critical threshold beyond which geographical distance begins to substantially influence fuel prices.

The reduction of fuel transportation costs and supply distances can be achieved by implementing strategies aimed at minimizing transportation and logistics expenses. Key strategies include consolidating shipments and utilizing trains as a more efficient mode of transportation, as opposed to relying solely on road-based truck transportation. Research by Jahangir *et al*. (2022) supports the notion that optimizing logistics, particularly through bulk transportation, can significantly reduce operational costs associated with fuel distribution.

An illustration of potential cost savings with the implementation of a railway transportation system can be observed in the reduction of transportation expenses over longer distances. The advantages of rail transportation are well-documented, including its capacity to transport larger quantities of fuel at a reduced cost, making it particularly effective for covering geographically sparse regions (Chang & Lin, 2021). Moreover, rail transport enhances delivery speed, improves security, and reduces the susceptibility to weather-related disruptions, which are often a challenge for road transport during Tanzania's rainy seasons (Wang *et al*., 2019). However, it is essential to acknowledge the current limitations of Tanzania's railway network, which is restricted to a few regions, thereby limiting the full potential of this cost-saving measure in remote areas. Expanding and modernizing the railway infrastructure could further optimize the fuel supply chain, particularly in rural regions (Adebiyi *et al*., 2017). Further, additional variables were added to examine their impact on the variation in diesel and petrol prices, such as road features specifically, paved versus dusty roads. The findings revealed that gravel roads had a significant impact on fuel consumption and price, with an average effect of 0.9685 km/l, compared to 0.1325 km/l for paved roads. These results are consistent with prior research highlighting the influence of road conditions on fuel efficiency, where rough and unpaved roads contribute to higher fuel consumption (Koutroumanidis *et al*., 2017; Jahangir et al., 2022). Variables such as truck road lengths, top permitted speeds, climatic conditions, and road conditions played a pivotal role in this variation, with each factor contributing to increased wear and tear on vehicles and, consequently, higher fuel usage (Hasan *et al*., 2019).

In addition to technical factors, the abilities and driving habits of truck drivers were found to directly influence fuel consumption, leading to increased costs for transporting diesel and petrol. This observation aligns with findings from Al-Dmour and Hasan (2018), who noted that driving behaviors, such as excessive acceleration or poor route planning, contribute significantly to transportation inefficiencies. Despite these findings, the study concluded that these variables did not improve as quickly as Tanzania's currency inflation rate, fuel transportation costs, and diesel and petrol supply distances. To address these challenges, the use of forecasting tools, such as Artificial Neural Networks (ANNs), can provide regulators and decision-makers with valuable insights into future trends in diesel and petrol prices. By accurately projecting future price trends, decision-makers can better control these factors and ensure fuel affordability for end-consumers (Chang and Lin, 2021; Wang *et al*., 2019).

CONCLUSIONS

The study examined six input parameters as significant determinants of the volatility in diesel and petrol prices in Tanzania. The chosen artificial neural network (ANN) model for price prediction indicated that the inflation rate (IR) was the primary variable of significance in forecasting variations in diesel and petrol prices. It was also established that the indigenous purchasing power (IPP) had minimal importance in the model. As result, this study warns that utilizing indigenous purchasing power as a measure for diesel and petrol price volatility is not a suitable approach, as it is subject to several factors such as family size, age distribution within the family, geographic region, shopping patterns, and lifestyle preferences.
The implementation of preventive measures, such as cost reduction strategies in supply chain transportation logistics, including shipment consolidation and the utilization of railways instead of trucks, has the potential to decrease the expenses associated with the fuel and petrol transportation. Consequently, this reduction in costs may contribute to a decrease in the volatility of the diesel and petrol prices. This might facilitate the accessibility of cost-effective and dependable social services, including transportation, healthcare, food, and processed goods. Additional research is necessary to expand the scope of investigation and incorporate additional variables, such as product quality, household size, and household income, in order to obtain a more comprehensive understanding of the subject and its empirical results.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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