Towards Improved Geodetic Modelling: Prediction of Gravity Values Using Artificial Neural Networks in Akure, Nigeria

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Abstract

The prediction of gravity values is a critical task in geophysics, with significant applications in geodesy, mineral exploration, and earthquake prediction. Traditional methods for gravity prediction, such as interpolation techniques, often struggle to capture the complex, nonlinear relationships present in gravity data, particularly in areas with sparse data coverage. This study explored a multi-layered artificial neural network for predicting gravity over the Akure. The geodetic positions (Latitude and Longitude) and Ellipsoidal Heights of 59 stations were observed using the South GNSS instrument on static mode at 1 hour per station for accurate measurements. A Lacoste and Romberg (G-512 series) gravimeter was used to measure the gravity values of all the fifty-nine (59) stations. The common corrections needed in a gravity survey, such as latitude, drift corrections, tide, free air, and Bouguer corrections were applied accordingly to a better result. The method uses a neural network model with 40 hidden layers to predict gravity values at different locations based on input data such as longitude, latitude, and ellipsoidal height. The neural network was trained using a large dataset of gravity measurements and corresponding geodetic data, and the performance was evaluated using RMSE, MAE, and R^2. The network predicted gravity values of the observed locations within the study area, with a Root Mean Square Error (RMSE) of 0.0286mGal, Mean Absolute Error (MAE) of 0.0220mGal and a coefficient of determination R^2 of

0.6268522276. While the model demonstrates the feasibility of ANN-based gravity prediction in Akure, the limited dataset constrains generalization. The findings are therefore region-specific and highlight the need for denser gravity observations to improve robustness and predictive reliability.

Keywords: Artificial Neural Networks; Gravity Prediction; Geodetic Modelling; GNSS Observation; Akure, Nigeria

1. Introduction

Gravity is the fundamental force that controls all the motion of objects in the universe, including the motion of planets, stars, and galaxies (Oja *et al.,* 2021). Gravity is one of the most critical phenomena in physics and geosciences source. Gravity observations play a fundamental role in geodesy and geophysics, supporting applications such as geoid determination, crustal studies, mineral exploration, and geodynamic investigations. Terrestrial gravity at a point can be measured either **absolutely**, using absolute gravimeters, or relatively, using relative gravimeters tied to reference stations such as the International Gravity Standardization Network of 1971 (IGSN71) (Morelli et al., 1974; Hackney, 2020). Relative gravity measurements require corrections for instrumental drift, Earth tides, latitude, elevation, and mass effects to ensure consistency and comparability.

Gravity prediction refers to the capacity to forecast how much gravitational force will be applied to an object at a specific location (Ando *et al.,* 2022; Zhu *et al.,* 2021). Predicting gravity values at unsampled locations is often required where dense measurements are unavailable. Traditional interpolation methods may be inadequate in capturing the nonlinear spatial behaviour of gravity, particularly in areas with complex geology. Consequently, machine-learning approaches, especially Artificial Neural Networks (ANNs), have gained attention due to their ability to model nonlinear relationships without explicit physical assumptions (Ahmed et al., 2019; Zhu et al., 2021; Heyuan *et al.,* 2022).

The artificial neural network (ANN) is an artificial intelligence method that draws inspiration from how the human brain functions (Ahmed, 2019). ANNs simulate both linear and nonlinear systems using learning and prediction methods that draw out intricate connections between the model's inputs and target(s). Benefits of ANN applications include, but are not limited to computational robustness; lack of need for prior knowledge of underlying physical phenomena; capacity to handle large and complex datasets; and capacity to derive complex and nonlinear relationships that could be used as forecasting tools (Konakoglu, & Akar, 2021).

It has been demonstrated that multi-layered neural networks handle complex relationships between input and output variables better than single-layer neural networks (Ahmadi *et al.,* 2016). The modelling of complex non-linear relationships between input and output variables is made possible by using multiple hidden layers in neural networks, leading to more accurate predictions.

Research studies on water resources management, streamflow forecasts, and climate projections have all made extensive use of ANNs. (Chang *et al.,* 2006; House-Peters and Chang, 2011; Maier, 2010; Moradkhani, 2014). In geodesy, ANN has been used by some researchers for geoid modelling (Akcin & Celik, 2013; Ahmadi *et al.,* 2016; Elshewy *et al.,* 2021; Kavzoglu & Saka, 2005), geodetic deformations (Miima, 2010; Luo *et al.,* 2020; Gu *et al.,* 2017), the prediction of the Earth orientation parameters (Konakoglu & Akar 2021; Krasilshchikov *et al.,* 2023; Zotov*et al.,* 2018) and prediction of gravity anomaly (Zhanakulova *et al.,* 2025). However, ANN based prediction of terrestrial gravity values using combined GNSS derived coordinates in Akure, Nigeria, remains limited in the literature.

In this study, a multi-layered artificial neural network for predicting gravity values for the Akure environment was adopted. The proposed model is designed to handle complex non-linear relationships between input data (Latitude, Longitude and Ellipsoidal) and gravity values and to provide accurate predictions at different locations within the study area.

1.1 Study Area

The study area is Akure metropolis, located in Ondo State, southwestern Nigeria (Figure 1). Akure was selected due to the availability of terrestrial gravity data, GNSS control points, and its location within the Precambrian Basement Complex terrain, which exhibits moderate elevation variability and structural heterogeneity. The area lies approximately between latitudes 7°15′N–7°30′N and longitudes 5°15′E–5°25′E, covering about 89 km².

The terrain is gently undulating to moderately rugged, characterized by hills and shallow valleys. Elevations range from approximately 330 m above mean sea level in the southwestern part of the city (near the Nigerian Army Barracks) to about 399 m in the northeastern area (Shagari Estate). Such topographic variation influences gravity measurements and provides a suitable test environment for evaluating ANN-based prediction.

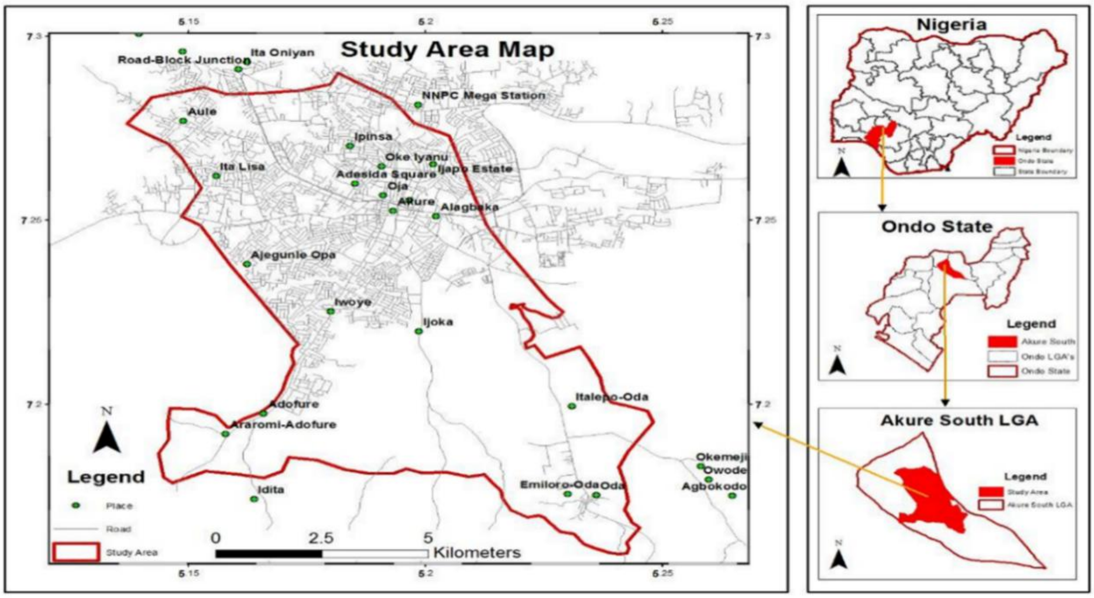

Figure 1: Distribution of Gravity/GPS point used for the study area

Source: (Tata and Ono, 2018)

2. Materials and Methods

2.1. Data Acquisition

Geodetic coordinates (latitude, longitude, and ellipsoidal height) were determined at 59 stations using South GNSS dual frequency receivers operating in static mode. Each station was observed for approximately one hour to achieve centimetre level positional accuracy. Data processing was carried out using proprietary South GNSS post processing software, with solutions referenced to a consistent geodetic datum.

Relative gravity observations were acquired at 59 stations using a LaCoste and Romberg (G 512 series) gravimeter. Measurements were referenced to established base stations within Akure. Standard gravity corrections such as latitude, drift, Earth tide, free air, and Bouguer corrections were applied following conventional gravimetric procedures. Only stations with collocated or nearby GNSS coordinates were used in ANN training and evaluation.

2.2 Data Processing

2.2.1 Training of Artificial Neural Network Model and Prediction of Gravity Values

Artificial neural network (ANN) aims to provide a model that can show the relationship between very complex input and output datasets by adjusting the weights and biases using a back-propagation algorithm. These datasets were randomly divided into three parts at a certain percentage. 70% of the datasets are used for Training, while 30% are used for validating and testing. During Training, the datasets are used to learn the ANN by adjusting the weights and biases used in the back-propagation algorithm based on the relationship between the input and output datasets. However, during the learning process, there is a possibility that the neural network over-fit the input and output datasets, which can cause a weak mapping between input and output datasets. In overcoming the problem of over-fitting, the datasets for validation are used through the learning process to guide and stop the training process once the validation error begins to rise. Once the training process was done, the testing dataset was used to predict the evaluation of the developed ANN model.

2.2.2 MATLAB Programming

A MATLAB program was written to predict the gravity values of the study area using the artificial neural network method. Then the predicted results obtained through ANN were compared with a terrestrial observation to know the accuracy of the prediction.

The data was firstly loaded from the working folder into the program environment using the **uigetfile** MATLAB inbuilt function. The data is an Excel file, so the **xlsread** function was used in reading the content of the Excel file. The file contains latitude, longitude, Ellipsoidal height, and gravity values for each of the 59 points. So according to the operations of ANN, there is a need to specify the input and target data for the training and testing dataset which is by default in a ratio of 70% and 30% respectively. Target is the parameter(s) we are keenly interested in, and input is the parameter(s) that contributes to getting the target. In the case of this research, one target is the **adjusted gravity,** while the input values are **latitude, longitude, and Ellipsoidal height.**

Table 1 presents the parameter settings for the ANN model. The artificial neural network was created using the **feedforwardnet** inbuilt function with a hidden layer size of 40, input and output layer of 3, and 1 respectively and with an iteration of 1000. The datasets were divided randomly into two categories in training the ANN model. 70% of the datasets were used for training the ANN model, and 30% were used for testing the ANN model. Also, the network uses the training algorithm called scaled conjugate gradient back-propagation (**trainscg**) for Training. After the training process, the testing dataset was used to predict the evaluation of the developed ANN model.

Table 1: Parameter Setting for ANN

Parameter	**Value**
Number of Neurons in the input layer	3
Number of Neurons in the hidden layer	40
Number of Neurons in the output layer	1
Number of Iteration	1000
Maximum validation failures	10
Minimum performance gradient	1e10

Figure 2 depict the structure of the ANN used for gravity prediction. The ANN is structure to have latitude, longitude and ellipsoidal height as the input layer, 40 hiddden neuron and predicted gravity value as the output layer

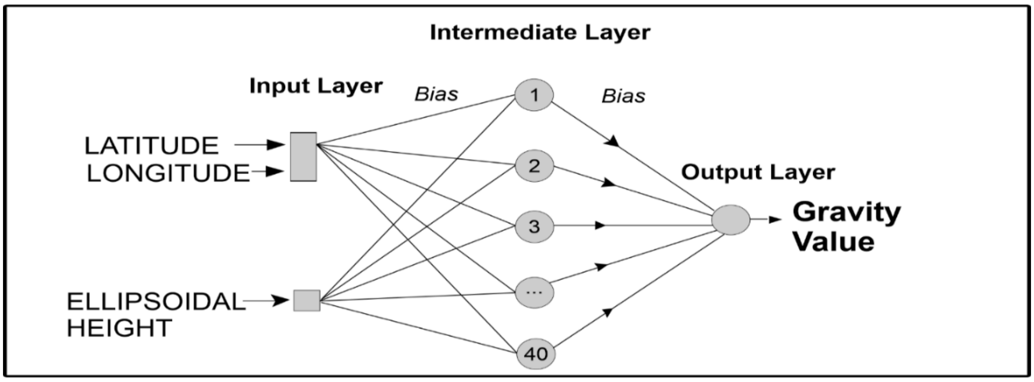

Figure 2: Structure of the Artificial Neural Network (ANN) used for Gravity value prediction.

Figure 3 presents the flowchart for the training of the ANN model and the prediction of gravity values.

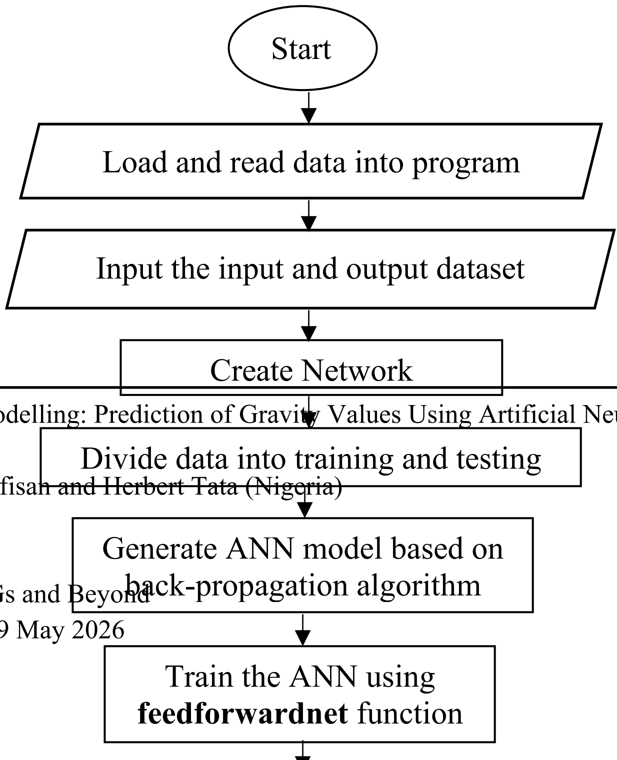

Figure 3: Flowchart of Artificial Neural Network

2.2.3 Performance Metrics for the ANN Model

The performances of the trained ANN model were evaluated using Mean Absolute Error (MAE), Root Means Squared Error (RMSE), and coefficient of determination (R-squared). The MAE, RMSE, and R^2 were computed using equation 1, 2 and 3 respectively. MAE helps to measure the average magnitude of errors in a set of predictions, without considering their direction. RMSE is a measure of the differences between predicted values and actual values. R^2 helps to assess the goodness of fit in regression models, indicating how well the model explains the variability of the data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(y_i - \bar{x})^2} \quad 3$$

y_i = Predicted gravity value of each station

x_i = Observed gravity value of each station

$\bar{x}$= Mean of Observed gravity value of each station

n = Observed gravity value of each station

3. Results and Discussion

3.1.1 Architecture of the ANN Model Network

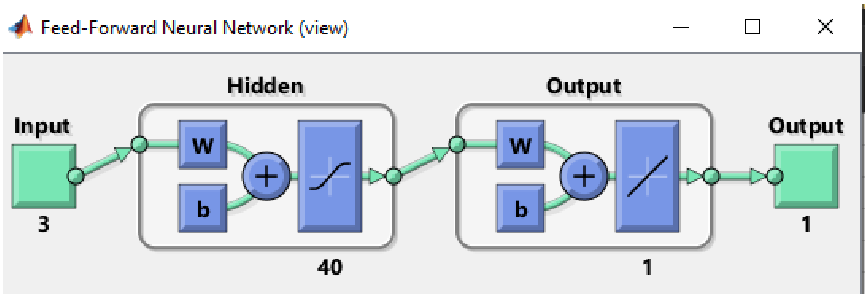

Figure 4: Architecture of the ANN model network.

Figure 4 depicts a feed-forward neural network with 3 input neurons, 40 hidden neurons, and a single output neuron. The network takes in 3 input features, processes them through the hidden layer, which consists of 40 neurons, and then produces a single output. The weights (W) and biases (b) associated with each neuron adjust during training to learn patterns in the data. Each neuron's output is passed through a nonlinear activation function, which helps the network capture complex relationships in the data. The output neuron provides the final result, which could be a continuous value for regression tasks or a class label for classification problems. This network is structured to make predictions or classifications based on the input data it processes.

3.1.2 Neural Network Training Progress

During the training process, the progress of the Neural Network Training is displayed as shown in Figure 5. A training algorithm called Scaled conjugate gradient back-propagation **(trainscg**) was automatically selected and used for training the network. **trainscg** is a network training function that updates weight and bias values according to the scaled conjugate gradient method. **trainscg** can train any network as long as its weight, net input, and transfer functions have derivative functions. Back-propagation is used to calculate derivatives of performance with respect to the weight and bias variables X. The Maximum iteration is 1000, but the training process stopped at the 275th iteration when the validation criteria were met. The Training was stopped when it was noticed that over-fitting would occur. The datasets for validation were used through the learning process to guide and control the training process once the validation error began to rise.

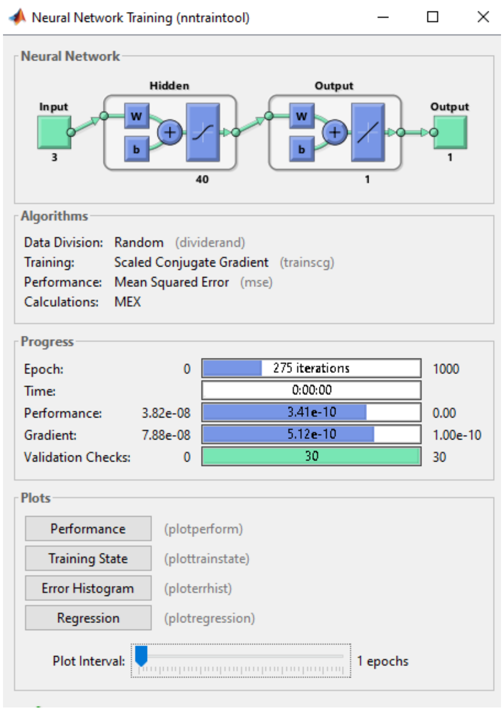

Figure 5: Neural Network Training Process

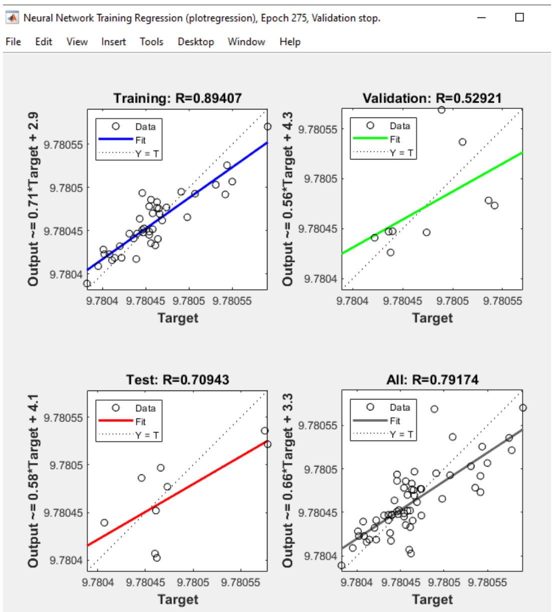

Figure 6: Regression plots of Training, Validation, and Testing of the ANN model

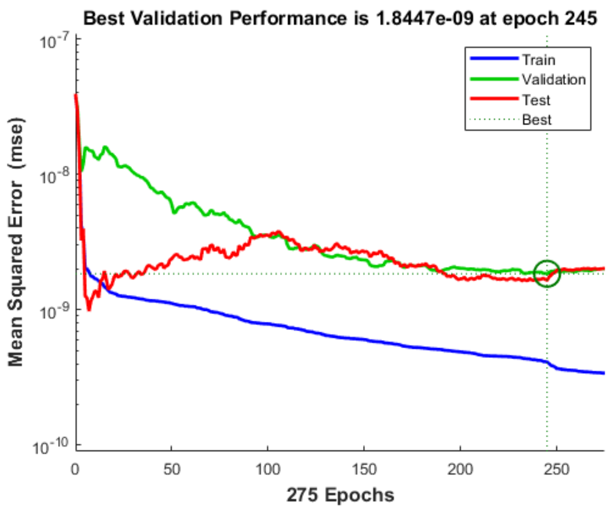

Figure 7: Training Performance of ANN model.

3.1.3 Training Performance

The performance of ANN was evaluated after the model was trained. It is shown in Figure 7 that the Training converged after approximately 245 epochs, where validation error reached a minimum. The difference between training ($R \approx 0.89$) and validation ($R \approx 0.53$) performance indicates a degree of overfitting, attributable primarily to the limited dataset size.

3.1.5 Gravity Prediction

The trained model predicted gravity values of points with known longitude, latitude, and ellipsoidal heights. For the test dataset, the ANN achieved an RMSE of approximately **0.03 mGal** and an MAE of **0.02 mGal**, with an overall R^2 of about **0.63**. These values reflect moderate predictive capability and fall within the expected precision range of relative gravimetric surveys. The ANN successfully reproduces the general spatial trend of observed gravity but shows localized discrepancies, particularly in areas with sparse training data.

The results should be interpreted as a proof-of-concept rather than a fully generalized gravity prediction model. The absence of an independent external dataset limits the assessment of true predictive performance.

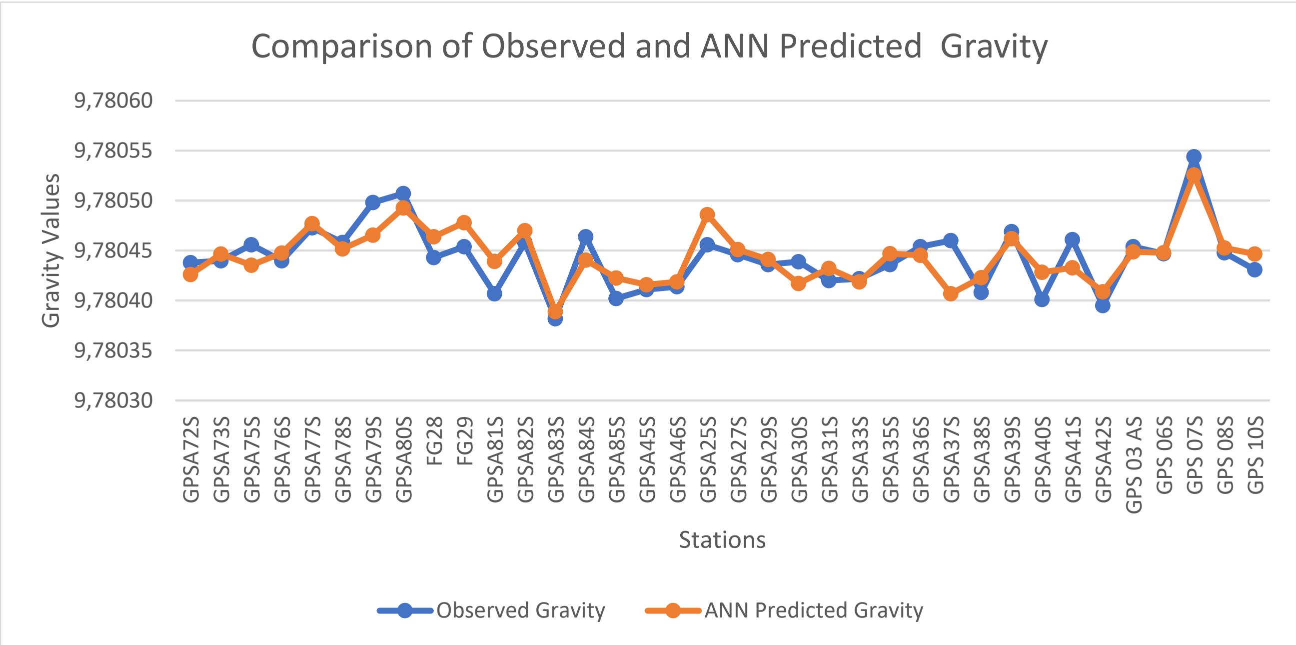

Figure 8: Graph showing the comparison between observed and predicted gravity

Figure 8 compares the observed gravity and the gravity values predicted by the ANN model. Observed gravity and ANN-predicted gravity values are represented in blue and orange lines respectively. It is observed that the predictions generally follow the trend of the observed gravity value which shows that the ANN model has done a fairly good job of capturing the patterns in the gravity values but there are noticeable differences at some stations can be improved by having more training data that are also consistent. The more training data, the more accurate the prediction can be.

4. Conclusion

This study demonstrates the feasibility of using Artificial Neural Networks to model and predict terrestrial gravity values in Akure, Nigeria, based on GNSS-derived coordinates. The ANN captured the nonlinear relationship between spatial position and gravity with moderate accuracy.

The neural network was trained using a large dataset of gravity measurements and corresponding geodetic data, and the model's performance is evaluated using RMSE, MAE, and R^2. The results of the prediction were compared with the classical observation, the root means square error (RMSE) and the Mean Absolute Error (MAE) of the prediction are 0.0286 and 0.0220, respectively. The value for the coefficient of determination R^2 as computed by MATLAB is 0.6268522276. The results demonstrate that the developed ANN model can provide accurate predictions of gravity values over the Akure environment using multiple input parameters. The proposed method can be used for various applications such as mineral exploration, geothermal energy exploration, and environmental studies.

However, the study is constrained by a relatively small number of gravity observations, which increases the risk of overfitting and limits generalization. The results are therefore region-specific and should not be extrapolated beyond the study area without caution. Future work should focus on expanding the gravity dataset, incorporating additional geophysical predictors, and testing alternative machine-learning models to improve robustness and predictive reliability.

Future research can explore using other machine learning algorithms and incorporating additional input parameters to improve the accuracy of gravity predictions further. Overall, the proposed method shows great potential in geophysics and can provide valuable information for various applications.

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