Engineering Research Journal
journal homepage: https://erj.journals.ekb.eg/

Creation and development of local geoid models using geometric methods for coastal areas in Egypt

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Abstract

Whereas engineering applications require orthometric heights of points, the Global Navigation Satellite System (GNSS) offers ellipsoidal heights. To determine the orthometric heights of points, levelling measurements must be made, which is a tedious and drawn-out procedure. In this study, an artificial neural network (ANN) was used to integrate the best global geoid model in this region with the original geoid model, resulting in a local geoid model with high accuracy. The accuracy of five global geoid models (GGMs) EGM2008, GECO, XGM2019e_2159, EIGEN-6C4, and SGG-UGM-1, were tested in this research. The geoid height accuracy in the study area, as determined by EGM2008, has an RMSE of around 0.20 m. While geoid height accuracy was calculated from EIGEN-6C4, GECO and SGG-UGM-1 has an RMSE of about 0.15m ,0.15m and 0.18m, respectively. The results showed that, XGM2019e_2159 is the most commonly used global model for geoid surface modelling in the Mediterranean Sea, with a standard deviation of 14 cm. It worth noted that, there has been a significant improvement in results with ANN created local geoid models. When creating the initial local geoid models in the study area, the ANN model accuracy ranged from 0.07 to 0.042 m. However, the local geoid model created by integration between the control points was done using ANN and the XGM2019e_2159 global model is about 60% more accurate than models created with the GNSS/leveling points only, and this becomes apparent as the distance between the control points increases.

Keywords: Global Navigation Satellite System; global geopotential models; local geoid model; GNSS-levelling; artificial neural networks

DOI: 10.21608/erj.2025.323451.1109~~https://doi.org/10.1016/j.ecmx.2022.100285~~
Received ~~xx~~ 29 ~~March~~ September ~~xxxx~~2024; Received in revised form ~~xx~~ 30 ~~July~~ January ~~xxxx~~2025; Accepted ~~xx~~ 13 ~~August~~ February ~~xxxx~~2025
Available online ~~xx~~ 01 ~~August~~ March ~~xxxx~~2025

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1. Introduction

The government has lately become more conscious of the need to invest in large, A number of new coastal cities, such as New Alamein and New Mansoura, are being built along these coasts. In recent times, The Egyptian government has focused on this area, finishing several important engineering projects.

GNSS has been widely applied for various engineering applications, e.g. surveying, geodesy, geophysics and navigation over the last few years. Point height determinations are one of the GNSS application areas. In GNSS technique, point positions can be defined as geodetic latitude, longitude, and ellipsoidal heights (Φ, λ, h) or as geocentric (X, Y, Z) based on the WGS84 ellipsoid. The user needs to change the ellipsoidal height to orthometric height in a number of GNSS applications. [1].
Height above the geoid, known as orthometric height, is used in engineering projects. To fully use GNSS's potential, geoid modeling must be used to create a relationship between geodetic and orthometric height. Equation 1 describes the relation between orthometric height (H), geoid height (N), and geodetic height (h).

$$N_{GNSS/level} \approx \text{H-h} \qquad (1)$$

As a result, using the GNSS positioning to determine the geoid heights through an accurate local geoid model or GGMs allows for the sufficient accuracy of orthometric heights to be obtained [2],[3] Using the GNSS, ellipsoidal heights were collected. the distance between the ellipsoid and geoid must be known for orthometric [4]). It is possible to forecast the geoid undulation using an ANN [5]).

The five GGMs were selected for this study based on a variety of factors, including the highest grade and order of each GGM, the range of data sources used in each GGM development, in recent years. EGM2008, GECO, XGM2019e_2159, EIGEN-6C4, and SGG-UGM-1 were selected based on these criteria. For example, in Egypt, there are many studies dedicated to the assessment of GGM. [6]. Many researches on the assessment of GGMs have lately been undertaken at the worldwide level [7],[8]).
There are several mathematical methods that connect the height of a geoid to its location in order to calculate the geoid's surface [9]. ANN are a method for interpolating geoid heights that was shown to be more dependable than other methods [10],[11]).

ANNs are made up of basic components that run concurrently. The biological nerve systems served as the model for these components. Similar to nature, the way a network functions are mostly determined by the connections among its members. By changing the values of the connections (weights) between elements in a neural network, you can train it to carry out a specific task.[12] Recently, the application of ANN has created a geoid surface. by interpolating between known geoid heights at precisely located and distributed control points on the ground. [13],[14].

Using five global geoid models EGM2008, GECO, XGM2019e_2159, EIGEN-6C4, and SGG-UGM-1, the study attempts to assess each model's accuracy, and then Developing a local geoid model for the Mediterranean coast using ANN. Finally, evaluating the integration between the created ANN model data with data from the best Global models in this area.

2. MATERIALS AND METHODS

2.1 Study Area and Measurement

The northern Egyptian research region is displayed in Fig. 1, which stretches from Sidi Barany to North Sinai along the Mediterranean coast. Extends from latitude 30° 49' 9.24" N to 31° 35'58.78" N, and

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from longitude 26° 36'18.81" E to 33° 0'21.82" E. The survey used a total of 99 GNSS/leveling data points. By attaching the leveling loops to the Egyptian national vertical coordinate system, precise leveling data was gathered with a Leica NA2 precision level.

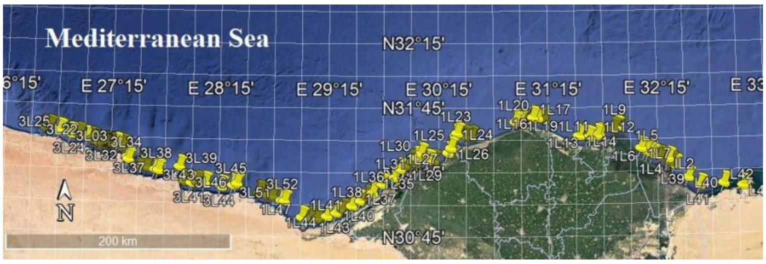

Fig. 1: Map of the study area

The orthometric heights' accuracy in relation to the nearest points of the State leveling network was less than a centimeter. They also took GNSS measurements for 99 benchmarks related to the Egyptian National Geodetic Coordinate System. To keep an eye on each rover, they used Trimble's 5700 dual frequency survey receivers at the base station for two hours in a static mode. They determined geodetic heights with an accuracy of up to 2.0 cm for each station during each session.

2.2 Research Methodology

The global geoid models are combined with GNSS / leveling points to create a geoid model of the Mediterranean coast. The purpose of this procedure is to apply global geoid models where GNSS/ leveling points are not available and to improve the accuracy of the model in the local area by reducing the long-wave errors of the geoids. This method is a cost-effective alternative to the costlier traditional leveling technique. In this study, the geoid surface is simulated using ANN. The approach for creating the geoid model of Egypt's Mediterranean coast includes the following steps:

- First, the geoid undulation ($N_{GNSS/level}$) of 99 reference points are calculated using Equation 1:

$$N_{GNSS/level} = H\text{-}h \qquad (1)$$

- Then, the ANN is used to interpolate these geoid heights for creating an initial geoid model. Based on this model, the geoid heights ($N_{GNSS/level\_ANN}$) of 99 control points are calculated.
- Afterwards, the latitude (φ) and longitude (λ) of the points in the five global models (N_{GGM}) to determine the geoid heights for 99 references points.txt format from the site of the International Centre for Global Earth Models (ICGEM), [15].

ICGEM belongs to a group of five services managed by the International Gravity Field Service (IGFS) of the International Association of Geodesy (IAG).

- Then, N_{GGM} from the different global models are assessed by comparing with $N_{GNSS/level}$ according to Equation 2:

$$\Delta N_{BGGM} = N_{GNSS/level} - N_{GGM} \qquad (2)$$

- From this evaluation, the best global model **(N_{BGGM})** on this territory is used in the next steps:

- The best global model inconsistencies are interpolated using the ANN. and the initial local geoid model to obtain (**ΔN_{ANN}**) as follows;

$$\Delta N_{ANN} = N_{GNSS/level\_ANN} - N_{BGGM} \qquad (3)$$

- Three different instances were created to investigate the impact of the distance between control points on the accuracy of the geoid model and the average distance between control points was roughly, 10, 15, and 25 kilometers, and three local models were generated.
- The final geoid height (N_F) at any point in this territory is calculated using Equation 4:

$$N_F = N_{BGGM} + \Delta N_{ANN} \qquad (4)$$

Fig. 2 shows a flow chart for creating a geoid model created by combining information from level points and GNSS /level points and data from the global geoid model.

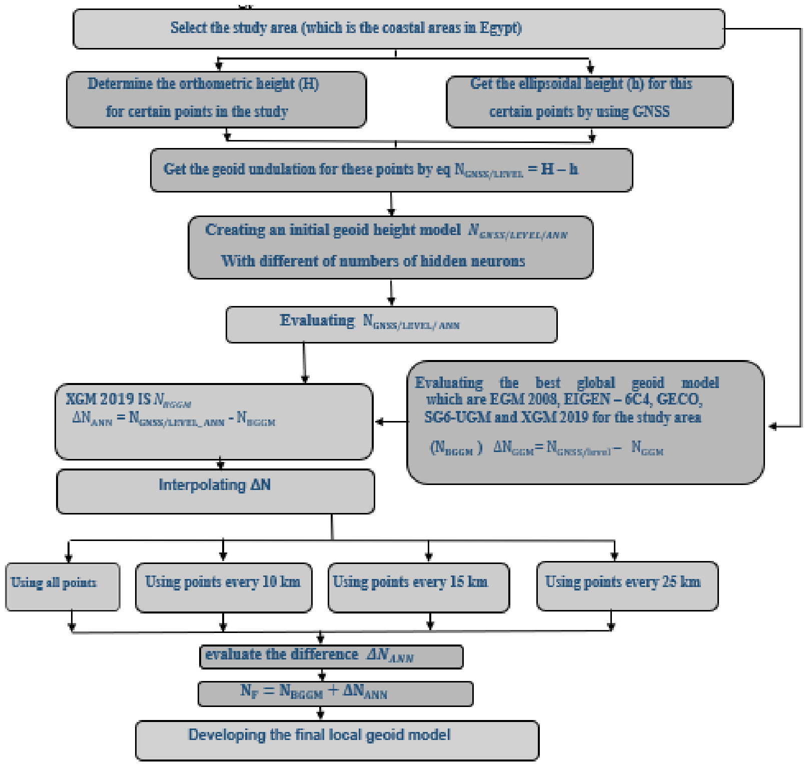

Fig. 2: Flow chart of the used methodology

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2.3 Creating an Initial Local Geoid Model

An artificial neural network (ANN) is a computer model that simulates the nervous system of humans. There are many different types and sizes of ANNs, but all of them compute their output using a set of parameters and mathematical operations. Using the Neural Network fitting app, you can select data, build and train a neural network, and test its performance using a set of mean square errors and regression analysis. A two-layer feed word neural network solves input-output fitting problems with a two-layer feedforward neural network. The network has two layers: a hidden layer with sigmoid neurons and a linear output layer with linear neurons. With consistent data and sufficient neurons in the hidden layer, the network is able to solve any multi-dimensional mapping problem. The network will be trained using Levenberg-McGrow backpropagation algorithms (trainlm) unless there is insufficient memory. In that case, scaled conjugate gradients backpropagation (trainscg) will be used. Data was randomly distributed into three percentages during the training, validation, and testing steps. As shown in fig. 3.

• In the training phase, 70% of the inputs were utilized; during training, they were shown to the network, and its error was used to make adjustments.

• The validation phase employed, 15% of the inputs; they were used to test network generalization and should generalization cease to improve, to stop training.

• In the testing procedure, 15% of the inputs were used; As a result, they offer an unbiased assessment of network performance both during and after training. They also have no bearing on training.

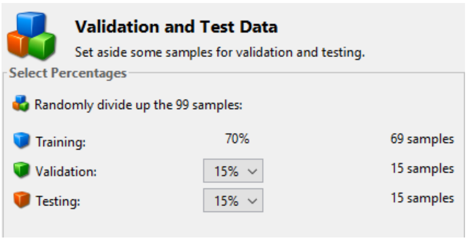

Fig. 3: The selected percentage of training, validation, and testing processes for 99 points

Neural network toolbox program contains several learning algorithms. Trainlm is usually the fastest training function. It is also the default training function of the direct distribution network. The quasi-Newtonian approach, Trainbfg, is also relatively fast. For large networks (thousands of weights), both strategies are often slower because they require more memory and compute time. In addition, trainlm performs better at finding functions (nonlinear regression) than it does at solving pattern recognition issues.

This strategy often requires more memory but less time. Once the improvement in generalization ceases, an increase in the verification samples' mean square error (MSE) indicates this, training is stopped immediately. Performance is measured using mean squared error (MSE) and regression (R). with smaller values indicating greater performance and zero indicating no mistake. The R-value measures the relationship between outputs and goals. In contrast to the random relationship indicated by an R-value of 0, a close link is indicated by an R-value of 1. Equations 5 and 6 include the equivalent mathematical representations:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \qquad (5)$$

$$R = \left(\frac{\frac{1}{n}\sum_{i=1}^{n}(t_i - \bar{a})(a_i - \bar{t})}{\sqrt{\sum_{i=1}^{n}(t_i - a_i)^2}\,\sqrt{\sum_{i=1}^{n}(a_i - \bar{t})^2}}\right) \qquad (6)$$

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Where the variable n denotes the number of points used in the processes, t_i and a_i are the network outputs and target outputs, $\overline{t}$ is the average of the network outputs, $\overline{a}$ is the average of the target outputs. respectively.

2.4 Evaluation of GGMs for the study area

To evaluate the accuracy of the global models EGM2008, GECO, XGM2019e_2159, EIGEN-6C4, and SGG-UGM-1, models, the following steps are performed:

- The $\mathbf{N_{GNSS/level}}$ of all reference points are calculated using Equation (1)
- The $\mathbf{N_{GGM}}$ of the same points are obtained.
- Finally, the results are compared to determine the GGMs' accuracy in the study region. using Equation (2) to compute the differences between $\mathbf{N_{GNSS/level}}$ and $\mathbf{N_{GGM}}$.

2.5 Influence of the Distance between Control Points on the Model's Accuracy

To evaluate how distance affects the accuracy of the geoid model, three instances were generated. The average distance from control point to control point was approximately, 10 km, 15 km, and 25 km. In each of these three instances, a Geoid model was generated using selected control points, and the remaining control points were used as checkpoint points. ANN was then used for the interpolation between the control points. The calculated $\mathbf{N_{ANN}}$ for the models was compared with the $\mathbf{N_{GNSS/level}}$ checkpoints. These models were generated first by using only the GNSS / leveling points, and then by combining between the GNSS/ leveling points and the global models to see how the inclusion of global models affected the accuracy of geoid model.

3. Results And Discussion

3.1 Creating an Initial Local Geoid Model on the Mediterranean Coast

ANN consists of numerous processing units known as neurons. The neurons are connected to each other through links called weights. The weights are initially assigned randomly during training. During the training phase, the predicted and actual values are compared to adjust the weights. The errors are then propagated through the network. The final weights are re-calculated to reduce the measured errors. An example of a three – layer ANN can be seen in Fig. 4. The structure of an ANN consists of K inputs, L neurons in the hidden layer, and M outputs. The ability of an ANN to predict multiple outputs at once, which emphasizes the strength of ANN [17].

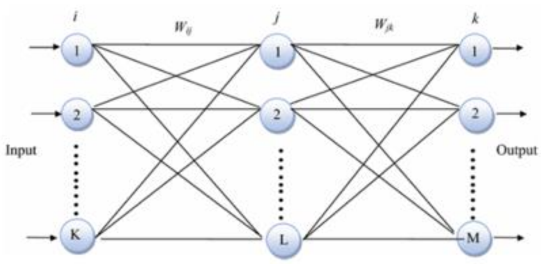

Fig. 4: Three-layer ANN structure [17]

The ANNs were created by MATLAB program with the help of the "nntool" toolbox. To assess the local geoid model's accuracy using the ANN method, the Levenberg and Marquardt approach was

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applied to adjust the known parameters (weight and bias) from gradient descent to Gaussian-newton updating to reduce the error. Fig. 5 shows the diagram of the architecture of ANN used. [18].

The interpolation operations for the latitude and longitude in seven examples, different number of hidden neurons from 8 to 12 and also 5 and 20 were used to test the accuracy of the ANN methodology in generating a geoid model. 69 points were utilized at random in the training phase (about 70% of the data), where as 30 points were used in both the validation and testing processes. In the seven procedures, the correlation function (R) between the target network and the output network, as well as the MSE evaluation of the ANN, are shown in Fig. 6. The training, validation, and testing techniques are all highly compatible with the MSE and *R* value, it can be noted that the training, validation and testing processes indicate the presence of a dependence when the value of R is closer to 1. These findings confirm the reliability of the ANN structure and its potential, which will be used to model new values. It's observed that the training, validation, and testing procedures suggest a reliance when the value of R is nearer to 1.

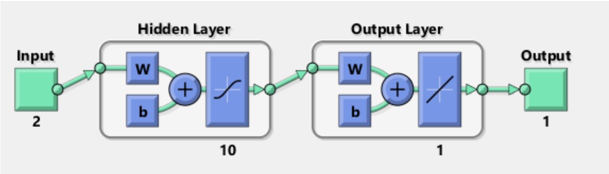

Fig. 5: The diagram of the architecture of ANN used

Results

	Samples	MSE	R
Training:	69	1.05517e-2	9.93497e-1
Validation:	15	1.17833e-2	9.91531e-1
Testing:	15	2.04249e-2	9.90781e-1

"5" hidden neurons

Results

	Samples	MSE	R
Training:	69	6.08354e-3	9.96389e-1
Validation:	15	5.56136e-3	9.96821e-1
Testing:	15	6.69713e-3	9.93977e-1

"8" hidden neurons

Results

	Samples	MSE	R
Training:	69	2.00807e-3	9.98754e-1
Validation:	15	1.20415e-3	9.99352e-1
Testing:	15	4.41181e-3	9.97066e-1

"9" hidden neurons

Results

	Samples	MSE	R
Training:	69	2.07356e-3	9.98446e-1
Validation:	15	2.77923e-3	9.98799e-1
Testing:	15	1.79838e-3	9.98796e-1

"10" hidden neurons

Results

	Samples	MSE	R
Training:	69	1.98702e-3	9.98816e-1
Validation:	15	4.28214e-3	9.96561e-1
Testing:	15	3.76098e-3	9.97138e-1

11" hidden neurons

Results

	Samples	MSE	R
Training:	69	5.32249e-3	9.96484e-1
Validation:	15	7.25957e-3	9.93461e-1
Testing:	15	1.03248e-2	9.96341e-1

"12" hidden neurons

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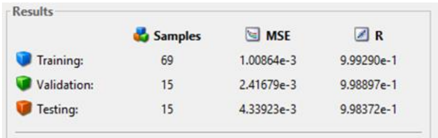

"20" hidden neurons

Fig. 6: The values of the MSE and R in the training, validation, and testing processes from the seven cases.

The trained neural network's error histogram for the seven examples during training, validation, and testing is also shown in Fig. 7. The distribution of the data fitting errors is around zero in terms of tolerance.as seen in this graph. The resilience and capacity to anticipate new values of the ANN structure are supported by these findings. The $\mathbf{N_{ANN}}$ values of geoid height from the eight scenarios were then compared to $\mathbf{N}_{\mathrm{GNSS/level}}$ for the same 99 reference points.

Table 1 demonstrates that the outcomes of the 9 and 10 models are nearly identical, with the 10 model somewhat better. The accuracy of the 8 and 12 models was the lowest. With a mean of -0.001 m and standard deviation of 0.032 m, the second model obtained a difference between -0.10 m and 0.08 m. The final geoid model was built using the geoid heights from this model ($\mathbf{N_{ANN-4th}}$) ,which with "10" hidden of neurons.

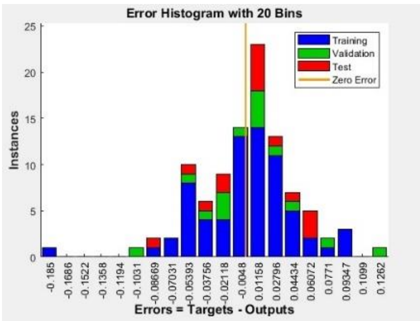

Fig. 7: The error histogram for the model ($N_{ANN-4\mathrm{th}}$)

Table 1: Descriptive statistics of discrepancies between N_{ANN} from ANN models and $N_{GNSS/level}$ for the reference points

	ANN models						
	No. Of hidden neurons 5	**No. Of hidden neurons 8**	**No. Of hidden neurons 9**	**No. Of hidden neurons 10**	**No. Of hidden neurons 11**	**No. Of hidden neurons 12**	**No. Of hidden neurons 20**
Mean (m)	0.009	0.006	0.002	0.002	0.003	0.006	0.002
Standard Deviation (m)	0.092	0.078	0.047	0.046	0.051	0.080	0.047
Range (m)	0.278	0.453	0.315	0.328	0.313	0.496	0.248

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Minimum (m)	-0.330	-0.236	-0.158	-0.134	-0.209	-0.250	-0.112
Maximum (m)	0.608	0.217	0.157	0.193	0.104	0.246	0.136

3.2 Evaluating the GGMs on the Mediterranean Sea Coast

The $N_{GNSS/level}$ and N_{GGM} of the 99 points were determined, calculated by ICGEM. To assess the accuracy of EGM2008, GECO, XGM2019e_2159, EIGEN-6C4, and SGG-UGM-1, the difference between $\mathbf{N}_{\mathrm{GNSS/level}}$ and $\mathbf{N}_{\mathrm{GGM}}$ was calculated using equation (2). Table 2 provides a comparison between $\mathbf{N}_{\mathrm{GNSS/level}}$ and $\mathbf{N}_{\mathrm{GGM}}$ at the 99 points. As Table 2 illustrates, that the XGM2019 model gives the smallest standard deviation for differences with a value of 0.15 m. While the GECO model takes second place in accuracy with a standard deviation of 0.16 m. The last place was taken by the EGM2008 model with a standard deviation of 0.20 m. For the study area, the EIGEN-6C4 and SGG-UGM-1 else give a noticeably better result than the EGM2008. The search for the best GGM for the whole territory of Egypt, according to Essam Al-Karargy and Gomaa Dawod, the best standard deviation of 0.13 m was found in XGM2019e_2159, while GECO had the lowest value of 0.16 m [6]. These findings are consistent with those of this research.

Table 2: Descriptive statistics of discrepancies between N_{GGM} and $N_{GNSS/level}$ on the Mediterranean Sea coast

deviation	EGM2008	GECO	XGM2019	EIGEN-6C4	SGG-UGM-1
mean (m)	-0.784	-0.808	-0.807	-0.804	0.839
standard deviation (m)	0.204	0.163	0.153	0.170	0.196
minimum (m)	-1.291	-1.299	-1.239	-1.296	-1.239
maximum (m)	-0.348	-0.427	-0.463	-0.415	-0.428
range (m)	0.943	0.871	0.776	0.880	0.811

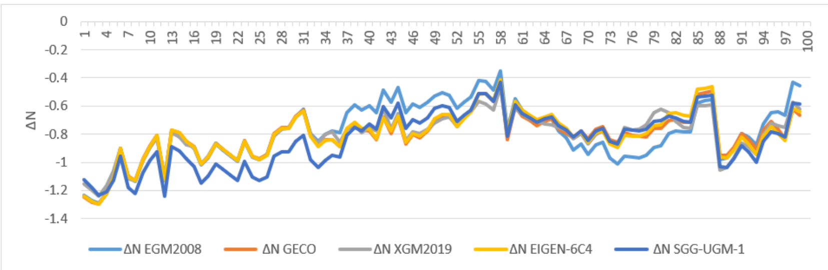

Fig. 8: Discrepancies between geoid heights from the GGMs and geoid heights of the GNSS/levelling points on the Mediterranean Sea coast

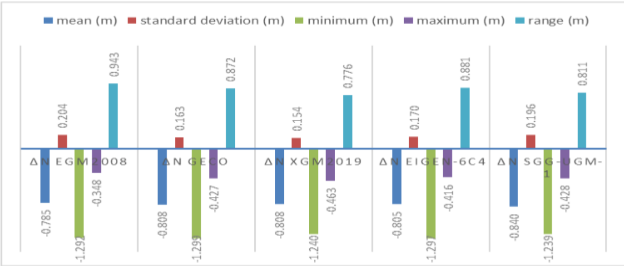

Fig. 9: Descriptive statistics of discrepancies between N_{GGM} and $N_{\text{GNSS/level}}$ for the 99 reference points

Considering these results, it can be concluded that the accuracy acquired using GGMs in the research area is insufficient for many engineering projects, necessitating the creation of a more accurate local geoid model.

3.3 Creating the Final Geoid Model on the Mediterranean Coast

In this phase, a combination of the best global model in this area, the XGM2019e_2159, and the created initial geoid model ($\mathbf{N}_{\mathbf{ANN-4th}}$) was built to create the final geoid model for the Mediterranean coast. To interpolate the differences between the two models, ANN was employed, resulting in a model that represented the differences.

The final geoid height at any position might then be calculated using the equation:

$$\mathbf{N_F} = \mathbf{N_{BGGM}} + \mathbf{\Delta N_{ANN}} \tag{4}$$

Where: $\mathbf{N}_{\text{BGGM}}$: the geoid height from the XGM2019e_2159 model at any points.

$\Delta\mathbf{N}_{\text{ANN}}$: the difference value at any points from the model of discrepancies that created by ANN.

For the 99 reference points ($\mathbf{N}_{\text{GNSS/level}}$), Table 3 shows the descriptive statistics of the discrepancies between the final model ($\mathbf{N}_{\text{F}}$) geoid heights and the observed geoid heights. The findings reveal that using ANN, a geoid model was built by combining GNSS/levelling data and the XGM2019e_2159 model with an accuracy of 6.3 cm, as shown in Table 3.

Table 3: Descriptive statistics of discrepancies between N_F and $N_{GNSS/level}$ for the 99 reference points

Mean (m)	0.004
Standard deviation (m)	0.063
Range (m)	0.362
Minimum (m)	-0.201
Maximum (m)	0.161

When using ANN to create the geoid model for the Mediterranean coast of Egypt, the accuracy was about 5.5 cm, according to [11]. Concerning the accuracy and difference between ANN and interpolated in geoid height prediction, these results are in line with the study's conclusions.

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3.4 The Effect of GNSS/leveling Point Distance on the Accuracy of the Geoid Model

The effect of leveling point and GNSS distance on the geoid model's accuracy, additionally, the effect of combining the global geoid models with the reference points on the geoid model's accuracy, were investigated in three cases: The average distances between GNSS/leveling points were 10 kilometers, 15 kilometers, and 25 kilometers.

A geoid model was built in each of the three situations GNSS/leveling points utilizing and the selected remaining GNSS/levelling points as checkpoints. The interpolation between the control points was done using ANN. The calculated $\mathbf{N_{ANN}}$ of the models was then compared with $N_{GNSS/level}$ at checkpoints. The standard deviation values from the three scenarios are shown in Fig. 10.

Fig. 10 shows that the accuracy of the geoid model created by the geometric technique increases with decreasing distance between the points used to generate the model.

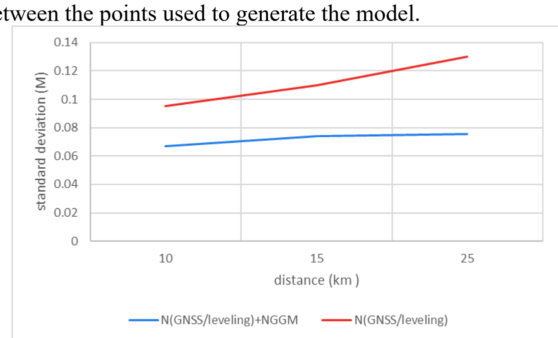

Fig. 10: Relation between standard deviation values and distance between GNSS/leveling points

4. CONCLUSION

The GNSS system is being used more and more in geodetic and engineering projects, so it's important to have a model that can convert the geodetic height into an orthometric height. This is especially important in coastal areas, since there's a lot of new cities and national projects are springing up. The challenge is to match and compare five of the most up-to-date global geoids, which are the EGM2008 model, the EIGEN-6C4 model, the GECO model, the XGM2019e_2159 model, and the SGG-UGM-1 model. Create a local geoid model for the Mediterranean coast that is accurate to the centimeter level. One of the most important geoid modeling approaches is the geometric approach. However, this approach is highly dependent on the methodology used to generate the geoid models. The method of creating the geoid model is based on the interpolation of the geoid heights known. For the local Mediterranean coast model, we integrated 99 GNSS / leveling points with the most suitable global model. The objective of this approach is not only to use global geoid models in locations with no GNSS / leveling observed points, but also to improve the model's accuracy in local areas by reducing long wave geoid errors. The results showed that the minimum standard deviation on the Mediterranean coast was ± 15 cm for the XGM2019 e_2159 model, and the maximum standard deviation was ± 20 cm for EGM2008.

The error was minimized using the Levenberg-Marquardt algorithm. With this approach, unknown parameters (weights and biases) are adaptively updated between the Gaussian-Newton update and gradient descent update. By Combining the model generated using ANN with the global model

XGM2019e_2159, the Mediterranean coast geoid model was developed. The main search results can be listed as follows:

1) On the Mediterranean coast, the minimum standard deviation value was ±15 cm with the XGM2019e_2159 model and the maximum standard deviation value was ±20 cm with the EGM2008 model.
2) ANN is an excellent alternative to standard prediction methods in surveying and engineering applications.
3) The results showed that in the coastal areas of the Mediterranean, using this model built by ANN, it is able to predict the height of the geoid with an error of about 4.6 cm.
4) The geoid model created by combining between the GNSS/leveling points and the XGM2019e_2159 global model is about 60% more accurate than models created with GNSS/leveling points only, and this becomes apparent as the distance between the control points increases, local geoid model with an error ranging from 0.0633 m to 0.0756 m in the study area when the distance between the control points is increased 10, 15 and 25 m.
5) The final model for the study regions was a digital geoid model with a (5` x 5`) point grid.

References

1. Hamdy, A. M., and B. A. Shaheen. "Global Geopotential Models Assessment Using Accurate DGPS/Precise Levelling Observations Along the Mediterranean Coastal Line, Egypt: Case Study." American Journal of Geographic Information System 9.1 (2020): 13-22.
2. Avsar, Nevin Betul, Senol Hakan Kutoglu, and Bihter Erol. "GNSS/Levelling data in assessing the fit of the recent Global Geoids in Turkey." International Symposium of Global Navigated System (ISGNSS) 2013 "Connecting Continents through GNSS where Europe and Asia meet" (Istanbul 2013). 2013.
3. Dawod, Gomaa M., and Tarek M. Abdel-Aziz. "Utilization of geographically weighted regression for geoid modelling in Egypt." Journal of Applied Geodesy 14.1 (2020): 1-12.
4. Mishra, Upendra Nath, and Jayanta Kumar Ghosh. "Development of a geoid model by geometric method." Journal of The Institution of Engineers (India): Series A 98 (2017): 437-442.
5. Elshewy, Mohamed A., Amr M. Elsheshtawy, and Ekaterina A. Chistiakova. "Developing a Local Geoid Model in Egypt using Artificial Neural Networks: A Case Study on the Red Sea coast."(2021).
6. Al-Karargy, Essam Mohamed, and Gomaa Mohamed Dawod. "Optimum combinations of GGM and GDEM models for precise national geoid modelling." Proceedings of Engineering and Technology Innovation 18 (2021): 15.
7. Kanushin, V. F., et al. "New global models of quasi-geoids: characteristic of accuracy and resolution." Vestnik of the Siberian State University of Geosystems and Technologies (SSUGT) 22.1 (2017): 30-49.
8. Mosquera, José Antonio Tarrío, et al. "Assessment of hybrid geoids in Chile and Spain, combining GG10M and GNSS/Leveling observations." Geodesy and geodynamics 12.2 (2021): 65-92.
9. Elshambaky, Hossam Talaat. "Application of neural network technique to determine a corrector surface for global geopotential model using GPS/levelling measurements in Egypt." Journal of applied geodesy 12.1 (2018): 29-43.
10. Kavzoglu, T., and M. H. Saka. "Modelling local GPS/levelling geoid undulations using artificial neural networks." Journal of geodesy 78 (2005): 520-527.
11. Ahmed, Hamdy M., Elshewy A. Mohamed, and Shaheen A. Bahaa. "Evaluating two numerical methods for developing a local geoid model and a local digital elevation model for the Red Sea Coast, Egypt." Journal of King Saud University-Engineering Sciences (2021).
12. Pikridas, Christos, et al. "Estimation and evaluation of GPS geoid heights using an artificial neural network model." Applied geomatics 3 (2011): 183-187.
13. Cakir, Leyla, and Nazan Yilmaz. "Polynomials, radial basis functions and multilayer perceptron neural network methods in local geoid determination with GPS/levelling." Measurement 57 (2014): 148-153. (2014).

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14. Erol, Serdar, and Bihter Erol. "A comparative assessment of different interpolation algorithms for prediction of GNSS/levelling geoid surface using scattered control data." Measurement 173 (2021).
15. ICGEM, 2020. International Centre for Global Earth Models (ICGEM)", Available from: < http://icgem.gfz-potsdam.de/calcpoints >, [Accessed: 05 June 2020]. [WWW Document].
16. Nilipovskiy, V. I., M. A. Elshewy, and A. M. Hamdy. "A Local Geoid for Egypt's Mediterranean Coast: A Model Based on Artificial Neural Networks." International Journal of Geoinformatics 18.3 (2022).
17. Badra, Niveen, et al. "Development of machine learning models for reliable prediction of the punching shear strength of FRP-reinforced concrete slabs without shear reinforcements." Measurement 201 (2022): 111723.
18. Beale, Mark Hudson, Martin T. Hagan, and Howard B. Demuth. "Neural network toolbox." User's Guide, MathWorks 2 (2010): 77-81.