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Utilizing Artificial Neural Networks for 2D Coordinate Transformation: A Case Study on the Reference System of Iraq

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Abstract

The study seeks to assess the efficacy of utilizing a Back Propagation Artificial Neural Network (BPANN) as an alternative to conventional methodologies for 2D coordinate transformation. Converting the previously used reference system in Iraq to the global system is one of the main requirements that play a main role in various applications requiring the standardization of geographic referencing for different data, including geospatial applications, remote sensing, image processing, and more. This necessitates researching and finding the most suitable methods to ensure high accuracy in the results. The Karbala 1979 (Clark 1880) of the Iraqi national geodetic network and the Iraqi Geospatial Reference System (IGRS) were currently used as geodetic reference frames in Iraq. In the context of transitioning between the local system (Karbala 1979) and the global system, specifically IGRS (ITRF2000 at epoch 1997.0), a crucial procedure involves the conversion of two-dimensional (2D) coordinate data. This conversion employed the BPANN method and conventional techniques such as affine and polynomial. The outcomes derived from the BPANN methodology are juxtaposed against those from the affine and polynomial methodologies. The findings reveal that the effective implementation of each approach within this study is contingent upon the spatial arrangement of the control points leveraged to develop the transformation model. Additionally, the root mean square error (RMSE) of BPANN ranging from 3 to 5 cm closely aligns with the outcomes achieved through affine and polynomial methods.

Keywords: BPANN; ITRF2000; IGRS, 2D; Affine; polynomial.

استخدام الشبكات العصبية الاصطناعية لتحويل الإحداثيات ثنائية الأبعاد: دراسة حالة عن نظام الإسناد في العراق

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الخلاصة

تسعى هذه الدراسة إلى تقييم فعالية استخدام الشبكة العصبية الاصطناعية للانتشار الخلفي (BPANN) كبديل للمنهجيات التقليدية لتحويل تنسيق ثنائي الأبعاد. يعد تحويل النظام المرجعي المستخدم سابقًا في العراق إلى النظام العالمي أحد المتطلبات الرئيسية التي تلعب دورًا رئيسيًا في التطبيقات المختلفة التي تتطلب توحيد

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المراجع الجغرافية للبيانات المختلفة ، بما في ذلك التطبيقات الجغرافية المكانية والاستشعار عن بعد ومعالجة الصور والمزيد. وهذا يتطلب البحث وإيجاد أنسب الطرق لضمان دقة عالية في النتائج. يتم استخدام نظام كربلاء 1979 (كلارك 1880) للشبكة الجيوديسية الوطنية العراقية ونظام المرجع الجغرافي المكاني العراقي (IGRS)حاليًا كأطر مرجعية جيوديسية في العراق. في سياق الانتقال بين النظام المحلي (كربلاء 1979) والنظام العالمي ، وتحديداً (ITRF2000) IGRS في عهد 1997). .حيث يستخدم هذا التحويل طريقة BPANNاضافة الى التقنيات التقليدية مثل الطرق الأفينية ومتعددة الحدود. تتم مقارنة النتائج المستمدة من منهجية BPANN مع تلك التي تنشأ من المنهجيات الأفينية ومتعددة الحدود. تكشف النتائج أن التنفيذ الفعال لكل نهج ضمن هذه الدراسة يعتمد على الترتيب المكاني لنقاط التحكم التي تم الاستفادة منها لتطوير نموذج التحول. بالإضافة إلى ذلك ، فإن الدقة التي تظهرها النتائج التي تم الحصول عليها من خلال نهج BPANN متقاربة مع الطرق البديلة وتتراوح من 3–5 سم اعتماد حساب الجذر التربيعي لمتوسط مربع الخطأ.

1. Introduction

Obtaining high accuracy in the process of 2D coordinate transformation between different systems plays a crucial role in various applications, including precise spatial applications, such as linking local systems to the global system and remote sensing applications that require accurately transforming the imaging system to the earth system, in turn, obtain high-resolution accurate information from the image. Therefore, numerous recent research efforts have addressed this topic with modern strategies to improve transformation quality and overcome some constraints, including differences in data quality between the systems necessary for transformation or the limited size of the available data. One of these modern strategies is machine learning, which was addressed in this research. On the other hand, it is known that the earth is defined as a complex dynamic system that is characterized by the parameters of velocity, displacement, and acceleration [1]. However, these parameters continuously change due to different geophysical phenomena constantly investigated while establishing coordinate reference systems (CRSs). Thus, local, regional, and global CRSs, attached to the rotation and orbiting earth with different origins, orientations, and scales, have continuously been established and updated based on the continuous changes in these parameters. The global CRS states the absolute and inertial frame of the reference coordinate system. It is characterized by three orthogonal axes that are conventionally fixed and strictly connected at the origin point of the system. The global system's origin point usually coincides with the earth's center of mass (CM); thus, the global CRS is a geocentric system. However, the geocentric coordinate systems vary due to the origin's position and their axes' orientation. The Conventional Terrestrial (CT) reference system is one of the geocentric Cartesian coordinate systems used in geodesy, mainly developed due to the remarkable advent of the global navigation satellite systems (GNSSs). The World Geodetic System 1984 (WGS84) is one of the most widely geocentric reference systems for geodesy and GPS [2-5]. Besides, the International Terrestrial Reference Frames (ITRFs), which are the realization of the ITRS and are updated continuously by international services of different space geodetic techniques, are extensively used by GNSS. However, to entirely utilize the WGS84 and ITRFs, datum transformation is required between different local data countries. Konakoglu et al. 2016 [7] stated that the applicable transformation approach selection depends entirely on the availability of the known standard stations, which have known positions in both coordinate systems, how much of the covered area, and the transformation's purpose. Ghilani. 2010 [8] employed the similarity, affine, and projective algorithms for 2D coordinate transformation. Over the last two decades, the geodetic science community has adopted Artificial Neural Networks (ANNs) to solve geodetic problems such as coordinate transformation, geodetic determination, and geodetic deformation modeling [4]. Various studies have assessed the efficacy of adopting ANNs for coordinate transformation [9-18]. The study aims to apply back propagation artificial neural network (BPANN), affine, and polynomial two-dimensional coordinate transformation approaches to explore the applicability and suitability for two-dimensional coordinates transformation between Karbala 1979 (Clark 1880) and ITRF2000 systems. To achieve the aim, a set of horizontal control stations distributed in the middle and the south of Iraq were used to run each transformation algorithm proposed. These control stations have known coordinates in Karbala 1979 (Clark 1880) and ITRF2000 systems. Additionally, the minimum number of stations that can be used to obtain a reliable solution for each proposed transformation algorithm was investigated. The coordinates yielded from 2D transformation for each approach were compared with corresponding known coordinates regarding the coordinate differences' root mean square error (RMSE).

2. Literature Review

Many academic studies have recently explored using neural networks for coordinate transformation, resulting in diverse recommendations and outcomes. A large part of these studies indicated that the effectiveness of the ANN is related to the size of the samples taken for training and validation. Accordingly, Lin and Wang [19] discussed the results of ANN for coordinate transformation from the datum of Taiwan 67 (TWD67) to the datum of Taiwan 97 (TWD97) based on three data sets with different sizes. Additionally, the results were compared with the affine transformation method. Thus, the ANN showed that it can be used effectively and produces better results than affine when an enormous quantity of data is used.
Moreover, the 2D coordinate transformation was examined by [20] based on the Radial Basis Function Neural Network (RBFNN) for Ghana's transformation datum from Accra to Leigon datum. The results from RBFNN were compared with classical transformation methods (six-parameter and four-parameter), and they presented more accurate and reliable results than those of classical transformation methods. In [21], the authors employed the Ann for the horizontal coordinate transformation according to the systems used in Turkey, which are European Datum 1950 (ED50) and International Terrestrial Reference Frame 1996 (ITRF96) coordinate systems. This study, depending on the procedure that divides available data into three data sets (35, 55, 74) as training data and 20 points in each set as validation data using three types of ANN models (Forward Back Propagation (FFBP), Radial Basis Function (RBFNN) and Cascade Forward Back Propagation (CFBP)). The findings showed that the variety of points in the three data sets did not appear to be a worthy change, while the selection of an optimum structure of ANN (the three types of ANN) shows that it has more effect on the obtained results. Hussein [22] employed the ANN for the georeferencing process that involved transforming the coordinates of the image to terrestrial coordinates (global coordinates system (WGS84)). The author used consecutive trial-and-error methods to reach the optimal structure of the ANN, including an optimum number of neurons in the ANN hidden layer.

The ANN results were compared using three numerical methods: Newton’s divided difference, affine, and polynomial transformation. Additionally, the author indicated that the inconsistency of the accuracy of the data gathered from the image with the data from the field survey had an impact on the results, which showed a clear difference in the superiority of ANN to the results of the numerical methods that were used in this study reached to about 50%. Abbas et al. [23] have drawn inspiration from the present study concerning its objective of transforming the 2D coordinate system from Karbala 1979 to IGRS (ITRF2000 at epoch 1997.0) in the same study area, and with the utilization of the same reference points employed in the training and validation process. Consequently, during the pre-print stage, Abbas et al. [23] cited this study as a reference for their research. It is worth mentioning that the main difference between the two studies is that Abbas et al. used the conformal equations to compare their results with the Neural approach and found that Neural outperforms conformal. On the other hand, this study relied on the affine equations and demonstrated that affine is superior. Accordingly, the difference between the results of the affine and conformal transformations can be attributed to several factors, including the mathematical properties of each transformation method and their suitability for the nature of the data used in the conversion, the quality of the input data, and other factors, where further studies are required to investigate this aspect. In general, this study stands out from previous research in that it aimed to investigate the impact of changes in data quantity and distribution within the study area on the performance of the Neural approach and other methods. Specifically, the study examined how such changes affect accuracy in three scenarios. The findings of this study provide insight into the effects of data variability on the accuracy of the three methods employed.

3. Iraq's Coordinate Reference Systems

In 2003, the Karbala 1979 (Clark 1880) coordinate system was used as the Iraqi national coordinate system (non-geocentric) for different geodetic and cadastral applications. Even though the Karbala 1979 (Clark 1880) was established as the CRS for Iraq, it has become inadequate for the implementation of most precise applications owing to the lack of the ability to use space geodetic techniques, such as GNSS. Furthermore, Karbala 1979 (Clark 1880) may not be considered appropriate for the long-term monitoring of huge structures, such as dams, due to crustal deformation and land movements. Consequently, the Iraqi Geospatial Reference System (IGRS) was established to replace the Karbala 1979 (Clark 1880) coordinate system [24]. Very little literature regarding establishing the Iraqi horizontal and vertical geodetic datum has been found. Coordinated reference systems (CRSs) in Iraq have evolved due to the significant developments of observation instruments, observation techniques, data processing approaches, and the advent of precise applications, which necessitate high accuracy and wider inclusiveness to deal extensively with the surrounding countries. [25] addressed the history of changes in the CRSs of Iraq from the Nahrwan 1934 to IGRS. Iraq's national geodetic control network was established initially by the Polish State Enterprise for Geodesy and Cartography GEOKART to support all the urban and infrastructure projects across the country. It was established late in 1974 and accomplished in the middle of 1979. The first-order horizontal national geodetic network, which consists of 2778 stations, was observed using trilateration methods and supported with some angle measurements. In addition to the horizontal network, a primary spirit-leveled vertical network was established and linked to the tide gauge in Basra in the South of Iraq. The coordinates of Iraq's first-order horizontal national geodetic network were assigned to Clark in 1880 using the Universal Transverse Mercator (UTM) projection to establish the Iraq National Grid covering most of all onshore Iraq. The fundamental point of the coordinates was selected in the southwest of Karbala, and consequently, the CRS of Iraq is known as Karbala 1979 [25]. The IGRS is a nationwide GPS/GNSS infrastructure geodetic system representing Iraq's new and modern geographic three-dimensional CRS. The IGRS was accomplished by the Ministry of Water Resources (MoWR) in Iraq in cooperation with the armies of the USA and Great Britain. [25] reported that several CPs of the Karbala 1979 network, which are still functional, were co-located using differential GPS technique based on six Continuously Operating Reference Stations (CORS) to establish IGRS. The IGRS geocentric datum was determined as an equivalent CRS to the International Terrestrial Reference System (ITRF2000) at epoch 1997.0 [24, 26]. The CORS network cooperates with Iraq's MoWR and the US National Geodetic Survey (NGS). For further details, the reader is referred to the National Geodetic Survey at (https://geodesy.noaa.gov/CORS/sort_sites.shtml). Along with the CORS network, the IGRS network also comprises 64 High Accuracy Reference Network (HARN) stations established in the South of Iraq based on the CORS network. The HARN stations are closely distributed to the vibrant areas, main roads and highways, and airports for different land survey works. The initial phase of HARN was to build up three-dimensional HARN stations [24]. As a result, the IGRS has become a national geodetic network of Iraq that combines the co-located CPs and HARN. The NGS Online Positioning User Service (OPUS) was employed to calculate the position for all HARN stations. The geodetic datum of IGRS is ITRF2000 at epoch 1997.0 where the geodetic datum of Karbala 1979 is Clarke 1880.

4. Study Area and Methodology

Eighty co-located reference control points (CPs) of the national geodetic network (Karbala 1979 network) were selected in the middle and the south of Iraq. Figure 1 illustrates the distribution of these CP. The term ‘training data’ was used in this paper to refer to the plane projected coordinates (E, N) in both Karbala 1979 and IGRS datum for 30 adopted CPs (Tr-CPs), which were used to construct the algorithm model for each coordinate transformation approaches. The term ‘testing data’ was used to refer to the plane projected coordinates of Karbala 1979 and IGRS for the rest of the 50 CPs (Ts-CPs), which were used for verification of the results of each solution. The IGRS datum coordinates (E_IGRS, N_IGRS) were used as the target data, whereas the Karbala 1979 datum coordinates (E_Clarke, N_Clarke) were considered input data in each coordinate transformation process.

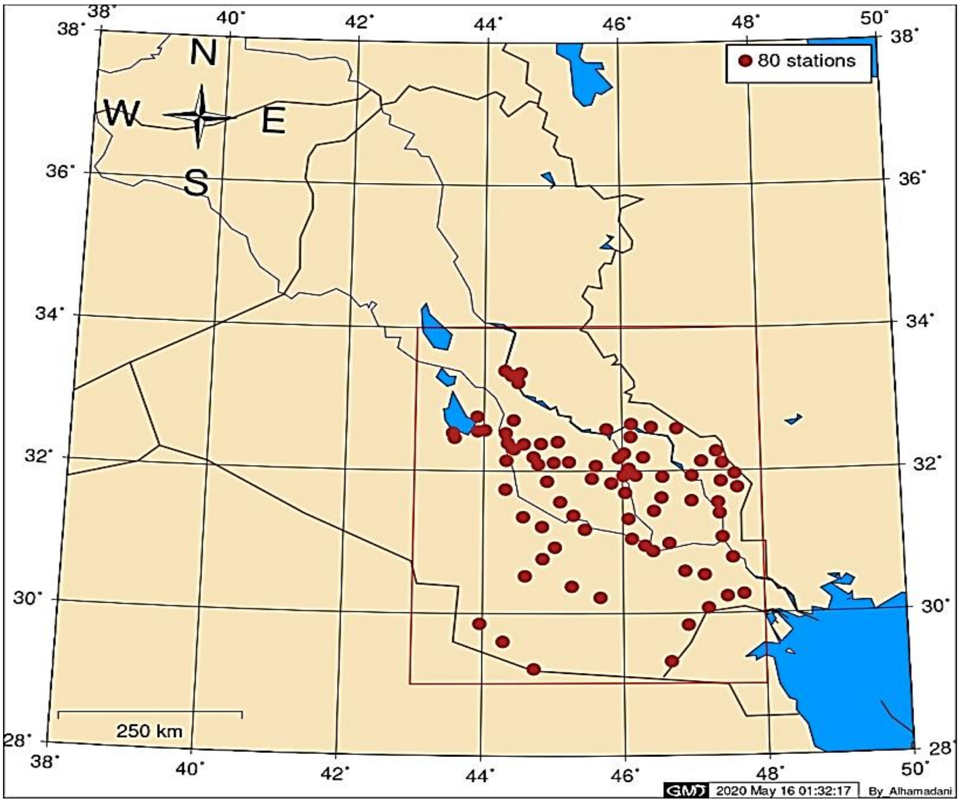


Figure 1: The Distribution of 50 Ts-CPs and 30 Tr-CPs**,** https://googlemapsgmd.com

Three strategies were considered when selecting the 30 Tr-CPs. In the first strategy (case 1), all the Tr-CPs were selected in a limited area. The economic factor and the time consumed to achieve the field survey suggest this strategy for distributing the Tr-CPs. In the second strategy (case 2), all 30 Tr-CPs were selected on the periphery of the study area. In the third strategy (case 3), the 30 Tr-CPs were selected in a regular distribution to cover all the study areas. Figure 2 shows the distribution of the 30 Tr-CPs in each case.

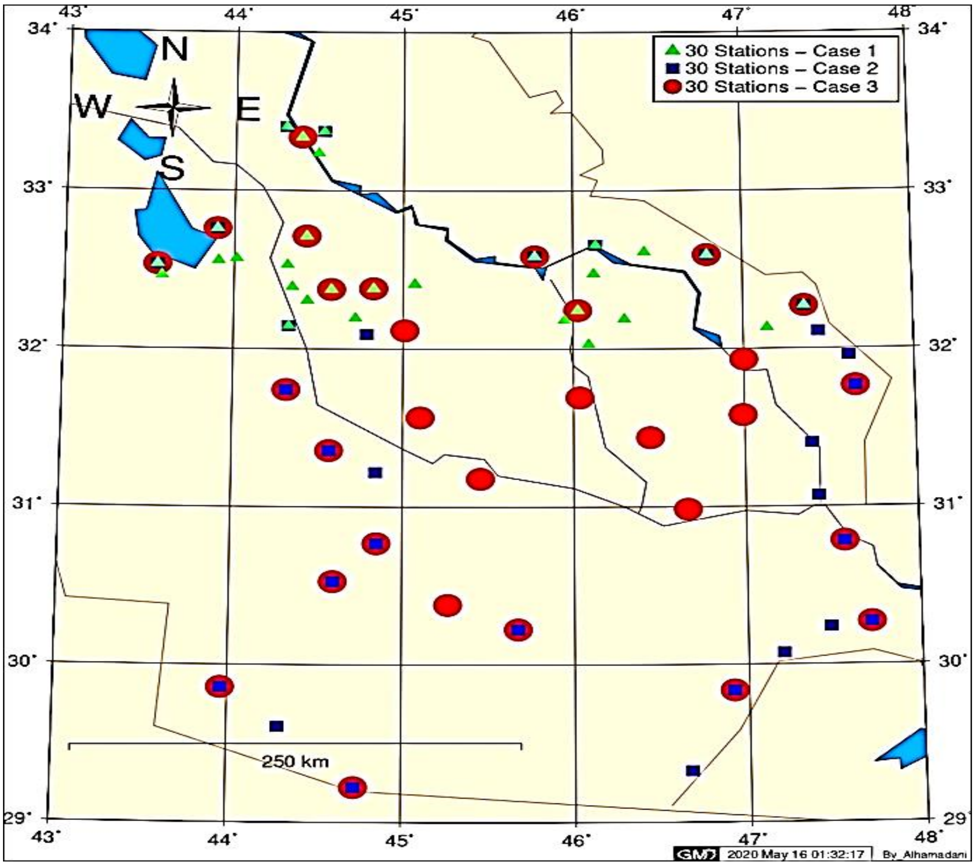


Figure 2: Three Strategies for the Distribution of 30 Tr-CPs, https://googlemapsgmd.com

Moreover, this study investigated the number of Tr-CPs used to obtain a reliable transformation solution for each CPs selection strategy in each transformation approach. Each Tr-CPs selection strategy in each coordinate transformation approach was run initially based on a minimum number of Tr-CPs. Thus, the backpropagation artificial neural network (BPANN) and the affine transformation algorithms were initiated based on 3 Tr-CPs, while the polynomial two-dimensional algorithm was initiated based on 6 Tr-CPs. To enhance the transformation results for each transformation approach in each selection strategy, three Tr-CPs were added gradually to explore the optimum solution in each case.

5. Artificial Neural Networks

Artificial neural networks (ANNs) have been introduced as effective computational models for dealing with different problems in geomatics, such as the determination of the velocity of land movement [27], determination of the geoid heights [28], heights transformation [29], and geospatial analysis [30]. ANNs are comprised of layers of artificial neurons that are interconnected by synaptic weights and transfer functions simultaneously in a similar manner to that of the nervous system of a human being. To clarify, neural networks were trained to accomplish a particular purpose by optimally selecting weight and bias scalar parameters that were adjusted based on a particular learning rule. The ANNs were trained to provide a solution for complex, noisy, and nonparametric data for different applications, such as identification, modeling, estimation, classification, prediction, control systems, and optimization. The geodetic data were somewhat controversial due to a multiplicity of sources, incorporating different types of data, and the necessity of continuously updating and linking them with the old data. However, ANNs have been successfully applied to deal with the complexity of the geodetic data [29]. ANNs apply linear or nonlinear transfer functions to yield output data that matches the target output data as closely as possible through a continuous comparison between the resultant output data and the target data. The output of a primary neuron of ANNs, which consists of a single-input neuron in one layer, is expressed according to [31] by:

$$a = f(wp + b) \quad (1)$$

Where b is a bias parameter (shifting the activation function), w is the scalar weight parameter, p is the scalar input, f is a transfer function, and a is the scalar neuron output. However, ANNs usually deal with multiple scalar inputs (r). These are weighted individually within one neuron in a single layer to contend with many specifications of the problem, as expressed in equation (2):

$$a = f\left(\sum_{i=1}^{r} w_{1,i} p_{i,1} + b\right) \quad (2)$$

Nevertheless, multiple inputs with one neuron may not be adequate to fulfill the objective function. Consequently, more than one neuron might be required to run in parallel in a single layer to obtain scalar neuron outputs close to the target outputs. The multiple inputs with multiple neurons (s), as all the inputs were linked to each neuron in a single layer, are expressed according to [31] by:

$$\begin{aligned} a_1 &= f\left(\sum_{i=1}^{r} w_{(1,i)} p_{(i)} + b_1\right) \\ a_2 &= f\left(\sum_{i=1}^{r} w_{(2,i)} p_{(i)} + b_2\right) \\ &\vdots \\ a_s &= f\left(\sum_{i=1}^{r} w_{(s,i)} p_{(i)} + b_s\right) \end{aligned} \quad (3)$$

To present the equations system (3) in matrices format, the weight matrix (W) has a size of(s x r), and both the bias vector (b) and output vector (a) have a size of(s), see equation (4)

$$W = \begin{bmatrix} w_{1,1} & \cdots & w_{1,r} \\ \vdots & \ddots & \vdots \\ w_{s,1} & \cdots & w_{s,r} \end{bmatrix}, p = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ \vdots \\ p_r \end{bmatrix}, a = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_s \end{bmatrix}, b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_s \end{bmatrix} \quad (4)$$

Besides, ANNs were constructed with multiple layers, and every layer consists of a particular transfer function, a weight matrix.$(\boldsymbol{W})$, a bias vector$(\boldsymbol{b})$, and an output vector$(\boldsymbol{a})$. The middle layers are the hidden, and the last layer is the output, which yields the final ANN outputs. The multi-layer ANN is more sophisticated than the single-layer ANN as the multi-layer ANN is trained to deal with more complicated data. Figure (3) shows the ANNs construction that consists of multiple inputs(r), multiple neurons(s) in each layer, and multiple layers(t). Additionally, equations (5) state that each layer has its number of neurons that differ from other layers. Therefore, the number of inputs for each layer equals the number of neurons in the previous layer. The number of neurons(s_t) of the output layer must be equal to the desired output network. Furthermore, choosing the output layer's transfer function depends on the output network's desired characteristics.

$$a_{s_t}^t = f^t\left(\sum_{i=1}^{s_t} w^t \cdots f^2\left(\sum_{i=1}^{s^2} w^2 f^1\left(\sum_{i=1}^{r} w^1 p_{(i)} + b_1^1\right) + b_1^2\right) \dots + b_{s_t}^t\right) \quad (5)$$

5.1 Back Propagation Artificial Neural Network (BPANN)

ANNs apply different learning paradigms to link between neurons for constructing various neural networks, e.g., back-propagation of error. Much literature has been published on using the backpropagation artificial neural network (BPANN) in Geodesy [11,15,22,23,24,32,33]. These studies stated the successful application of BPANN for transformation between different geodetic data due to its simple algorithm of BPANN and high learning capability. The construct of BPANN was primarily articulated by [34] and developed later by [35]. This study used Matlab language to configure the BPANN based on the sequential trial and error process to obtain a minimum number of hidden layers with an optimum number of neurons per hidden layer. The configuration of BPANN employed in this study was initially formed based on one hidden layer with two neurons for each layer. Based on trial and error learning, the number of hidden layers and neurons in each layer progressively increases to seek the minimum differences between the computed and target values.

Consequently, the optimal BPANN structure consists of only two hidden layers with a log-sigmoid transfer function and three neurons in each layer. Furthermore, the output layer was built based on a linear transfer function. Besides, an epoch value of 1000 was used to run the training algorithm over the whole training set. Moreover, a minimum batch size of only two was considered in processing the training dataset due to the limitation of the used GPU memory, Figure 3.

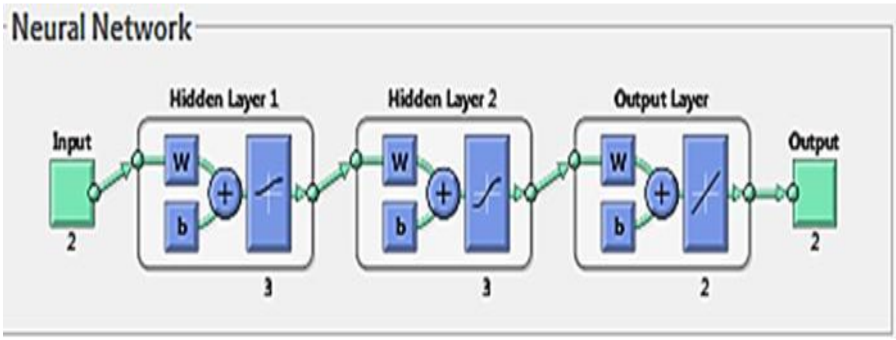


Figure 3: The Proposed ANN Construction, Matlab library functions.

6. Results

This study assessed the performance of BPANN, Affine, and Polynomial approaches for 2D coordinate transformation from Karbala 1979 (Clark 1880) datum to IGRS (ITRF2000) used in Iraq. Additionally, this study sought to apply three strategies for selecting a set of 30 CPs to perform each coordinate transformation approach individually, Figure 2. Moreover, the minimum number of CPs was investigated for each applied approach with each distribution strategy. The BPANN and Affine approaches yielded 10 solutions for each distribution strategy, while the polynomial approach yielded 9 solutions for each. The transformation model that formed in each solution was applied later to transform the coordinates for 50 Ts-CPs from Karbala 1979 (Clark 1880) datum to IGRS (ITRF2000) and compare the results with the corresponding IGRS-observed coordinates (observed IGRS-computed IGRS).

As previously mentioned, the Ts-CPs will be utilized to validate the accuracy of the three methods using the root mean square error (RMSE) calculation. The RMSE will be calculated for each method, considering variations in the number of points (Tr-CPs) ranging from 3 to

30. Three distinct point distribution strategies will be employed to test each method. In each strategy, the RMSE will be computed for different changes in the number of Tr-CPs.

In strategy 1, the training data will commence with 3 points (Tr-CPs) and progressively increase by 3 points until reaching 30, with all points confined to a specific area (Figure 2). As previously stated, the same progression applies to the second and third strategies, albeit with differences in the distribution patterns of points within the study area. The fluctuations in RMSE values for each strategy can be summarized in Figure 4

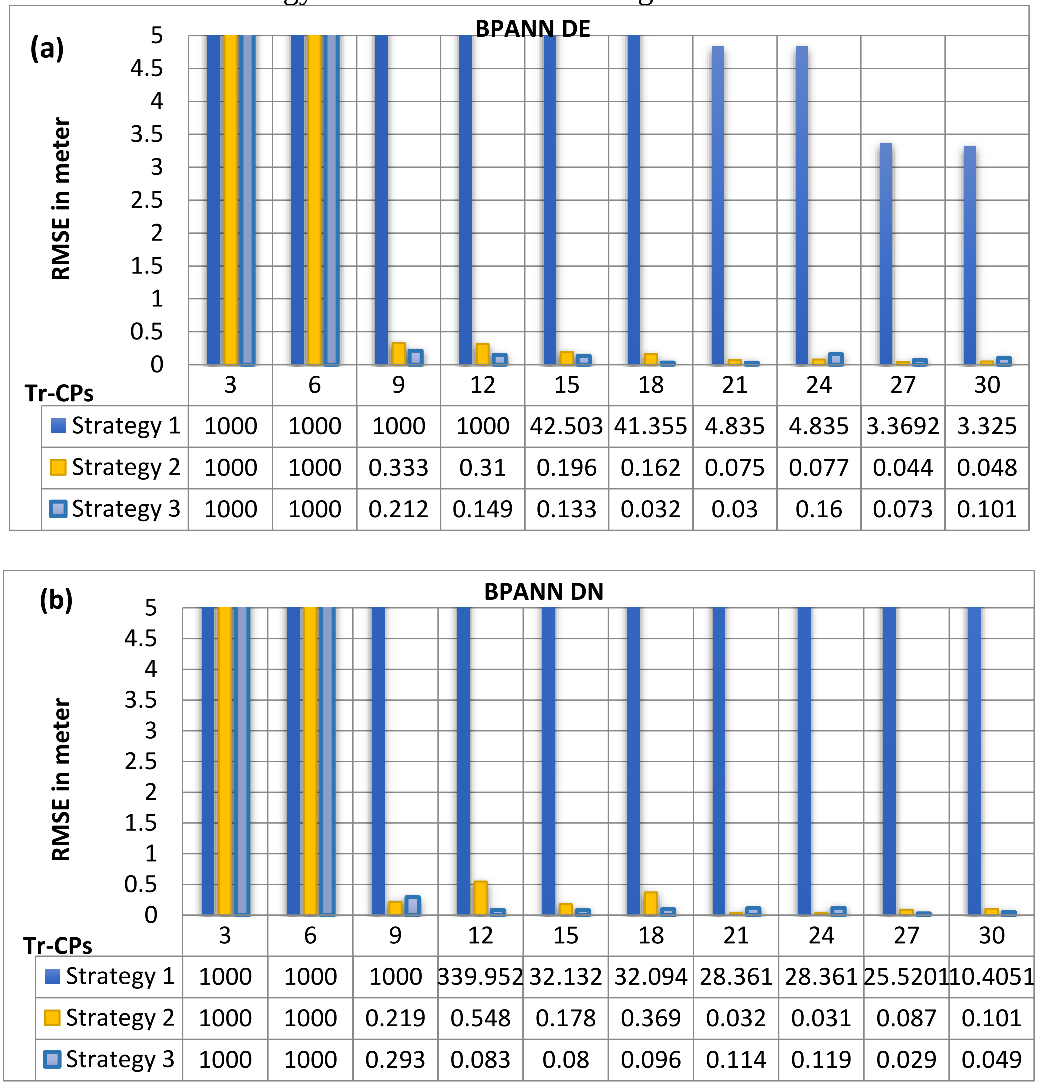
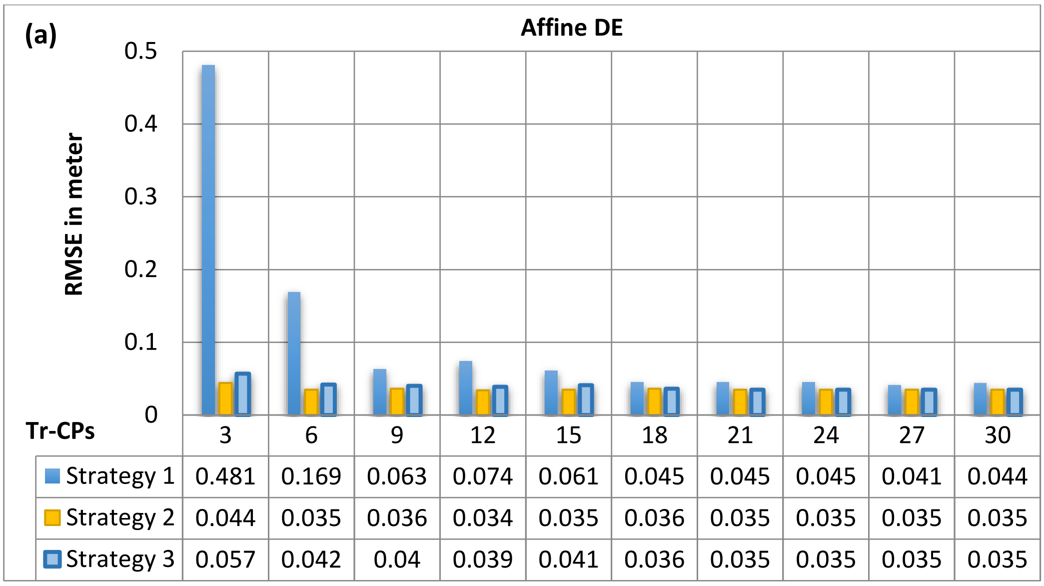
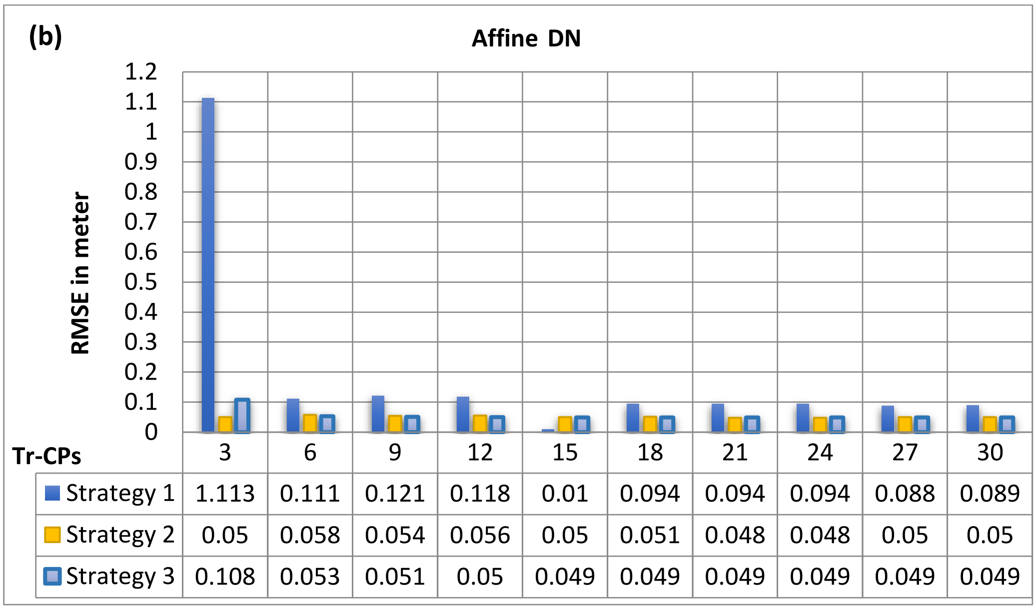


Figure 4: Easting (4. a) and Northing (4. b) Components Differences Based on BPANN method



Tr-CPs	3	6	9	12	15	18	21	24	27	30
Strategy 1	0.481	0.169	0.063	0.074	0.061	0.045	0.045	0.045	0.041	0.044
Strategy 2	0.044	0.035	0.036	0.034	0.035	0.036	0.035	0.035	0.035	0.035
Strategy 3	0.057	0.042	0.04	0.039	0.041	0.036	0.035	0.035	0.035	0.035



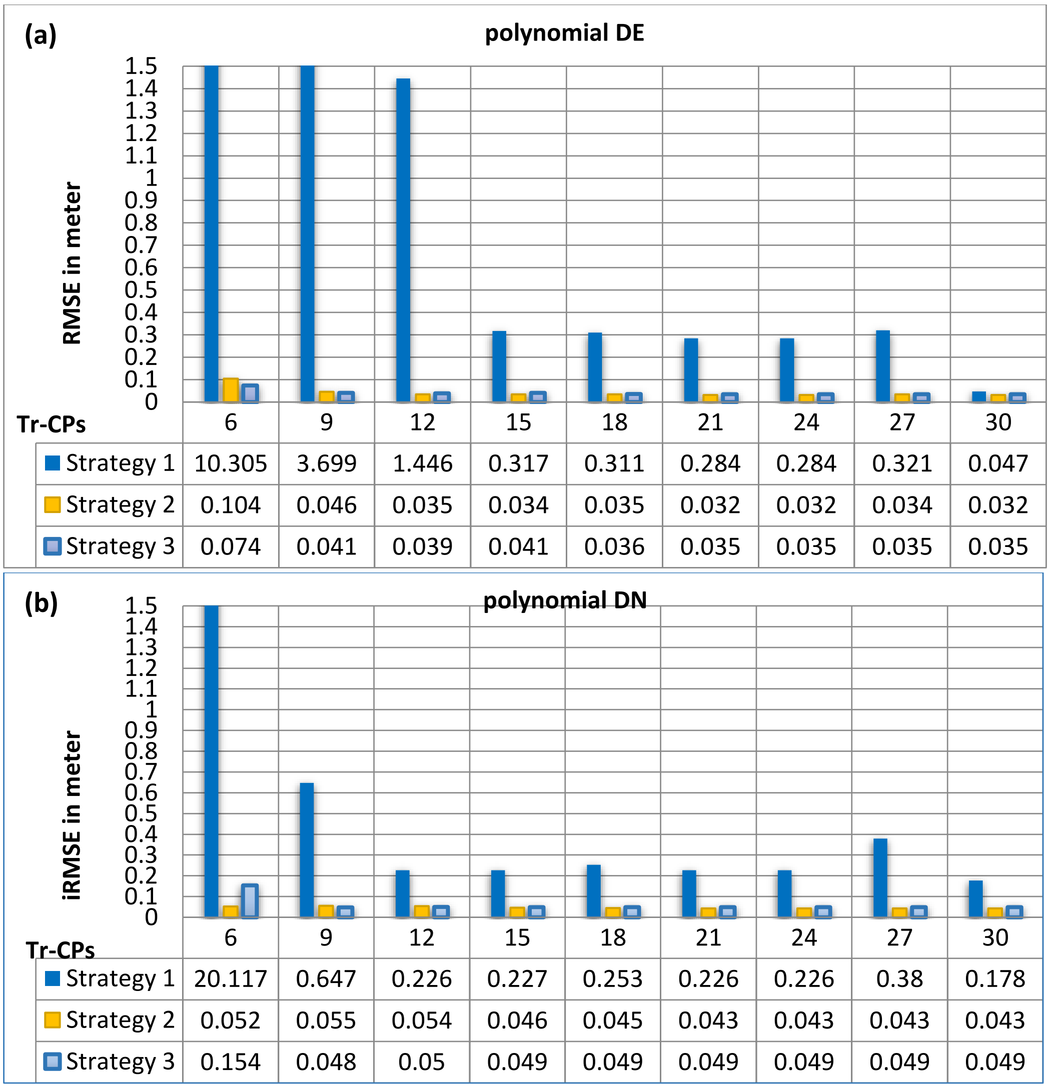
Tr-CPs	3	6	9	12	15	18	21	24	27	30
Strategy 1	1.113	0.111	0.121	0.118	0.01	0.094	0.094	0.094	0.088	0.089
Strategy 2	0.05	0.058	0.054	0.056	0.05	0.051	0.048	0.048	0.05	0.05
Strategy 3	0.108	0.053	0.051	0.05	0.049	0.049	0.049	0.049	0.049	0.049

Figure 5: Easting (5. a) and Northing (5. b) Components Differences Based on Affine method

Based on the observations depicted in Figure 4, it is evident that the BPANN method exhibits the poorest accuracy within Strategy 1, wherein point distribution was confined to a specific area within the study region. Conversely, ANN achieves better accuracy within Strategies 2 and 3. A substantial error exceeding one thousand meters was observed when employing Strategy 1 with a training dataset comprising 3 to 12 points. However, a significant enhancement in accuracy was observed when employing 15 or more points, resulting in an error of approximately four cm or less. Furthermore, within Strategies 2 and 3, point distribution spans the study area, either along the study area's borders or within the study area's interior. The ANN method demonstrates a notable improvement, achieving accuracy within the range of sub centimeters when utilizing 9 points or more. These findings underscore the profound influence of both the number and distribution of points on the performance of the ANN method.

In the context of the BPANN method, a notable discrepancy arises in the Affine method, particularly when employing strategy one. In this scenario, the largest observed error amounted to approximately half a meter in the east component and about one meter in the north component when employing three points for estimation. However, as the number of points increased to six, a significant reduction in error occurred, leading to an error value of less than twenty centimeters for both the east and north components. Subsequently, the error value reached a stable state with further increments in the number of points, measuring less than 5 cm for the east component and 9 cm for the north component. In contrast, the second strategy yielded more consistent results, with the error magnitude remaining relatively steady. The errors for both the east and north components ranged from 3 to 5 centimeters, and the discrepancy caused by variations in the number of points employed was minimal, not surpassing one centimeter over a range of 3 to 30 points.

Like the second strategy, the Affine method in the third strategy exhibited stable errors, not surpassing 5 cm for the north and east components. Based on the number of points used, the discrepancies between these components do not exceed 1 cm, except where only three points are utilized. This leads to an error value of approximately 10 cm for the north component. Consequently, the third strategy appears less stable than the second one, Figure 5.



Tr-CPs	6	9	12	15	18	21	24	27	30
Strategy 1	10.305	3.699	1.446	0.317	0.311	0.284	0.284	0.321	0.047
Strategy 2	0.104	0.046	0.035	0.034	0.035	0.032	0.032	0.034	0.032
Strategy 3	0.074	0.041	0.039	0.041	0.036	0.035	0.035	0.035	0.035

Tr-CPs	6	9	12	15	18	21	24	27	30
Strategy 1	20.117	0.647	0.226	0.227	0.253	0.226	0.226	0.38	0.178
Strategy 2	0.052	0.055	0.054	0.046	0.045	0.043	0.043	0.043	0.043
Strategy 3	0.154	0.048	0.05	0.049	0.049	0.049	0.049	0.049	0.049

Figure 6: Easting (6. a) and Northing (6. b) Components Differences Based on Polynomial method

Figure 6 demonstrates that the polynomial method's accuracy was influenced by the number of points and their distribution within strategy one. The observed error rates were approximately 10 m for the east component and 20 m for the north component. However, it is noteworthy that these errors decrease gradually as the number of points increases. Moreover, strategy one significantly impacts the accuracy consistency in the computed points through the polynomial method.

Strategies two and three also yield error rates comparable to those of the Affine method. The errors do not exceed 5 cm in the east and north components. Remarkably, these errors exhibit a high level of homogeneity, signifying that error values tend to converge when the number of points exceeds 9.

In a broader context, the variation in the number of points and their distribution significantly impacts the performance of the BPANN method compared to the Affine and Polynomial methods. Among the strategies analyzed, the one with the poorest distribution of points was observed when the points were confined within a specific area. Conversely, the second and third strategies, which involved spreading the points along the borders of the entire region or within it, yielded favorable and closely aligned results.

The findings underscore the importance of judiciously selecting and distributing points for optimal performance when using ANN, Affine, or Polynomial methods. Properly spread points across the region seem to contribute to enhanced accuracy and convergence of results, whereas confined distributions may lead to suboptimal outcomes. This observation emphasizes the significance of thoughtful point selection strategies in geospatial analysis to achieve accurate and reliable results when employing different interpolation techniques. Further research and consideration of point distribution strategies are recommended for refining the methodologies and advancing the efficacy of geospatial interpolation approaches.

Comparing the results of this study with a prior study that employed a similar methodology [23] revealed notable disparities between the outcomes achieved by Artificial Neural Networks (ANN) and affine transformations. These discrepancies likely stem from differences in data quality and accuracy across the two studies. In cases where data precision remains consistent across systems, as observed, affine transformations outperform ANN. However, ANN exhibits greater adaptability to fluctuations in data quality through increased iterations or larger datasets, ultimately achieving satisfactory accuracy. Therefore, further investigations with varying levels of data precision are recommended to validate the efficacy of both affine and ANN methodologies. This study distinguishes itself from previous research by specifically investigating the impact of variations in data quantity and distribution on the performance of the Neural approach and alternative methodologies. This investigation encompasses three distinct scenarios to elucidate how such variations affect resulting accuracy. Thus, the findings offer valuable insights into the influence of data variability on the accuracy of the methodologies under examination.

7. Conclusion

This study sheds light on the possibility of using BPANN as an alternative solution to traditional methods such as Affine and Polynomial. Furthermore, the study investigates the relationship between the number and distribution of points with the results of BPANN compared to the traditional methods.

This study has identified the high learning capability of BPANN for 2D coordinate transformation between Karbala 1979 (Clark 1880) and ITRF2000 in the middle and south of

Iraq. The findings of this study indicate that the discrepancy in the quantity and distribution of training points (Tr-CPs) significantly impacts the performance of the BPANN compared to alternative methods. Specifically, it was observed that strategy one, involving the distribution of points within a specific area, yielded the least favorable results, with substantial errors in the BPANN outcomes. Moreover, increasing the number of points did not lead to an acceptable level of accuracy for this strategy.
The Affine and Polynomial methods exhibited higher error rates than the other two strategies. However, their errors were considerably less pronounced than those observed in the BANN method. Notably, increasing the number of points for the Affine and Polynomial methods achieved satisfactory accuracy.
It is known that the BANN methodology necessitates a substantial corpus of data, and the scarcity thereof may impinge upon the accuracy of outcomes, as observed in the first strategy. However, this study mitigates such concerns by distributing data points across the entirety of the research domain, even in instances of limited data availability, as exemplified in the second and third strategies.
Given these insights, this research strongly recommends the thoughtful consideration of point distribution and quantity for the 2D coordinate transformation, particularly when employing the BPANN method. Such attention to these factors is crucial for enhancing accuracy and ensuring reliable outcomes. These findings will doubtless be scrutinized, but some immediately dependable conclusions exist for using BPANN for 2D coordinate transformation between local and global data. Moreover, it is recommended that further studies be conducted on this aspect, with further suggestions for the distribution of points and varying levels of data quality and accuracy between the two systems, to evaluate which of the methods above is more suitable for each case.

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9. Conflict of Interest Statement

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References

[1] A. A. Shabana, “Dynamics of Multibody Systems,” *Cambridge, UK: Cambridge University Press*, 2005. Available: https://www.sciencedirect.com/science/article/pii/009457658990057X

[2] C. Jekeli and O. Montenbruck, "Time and Reference Systems," *in Springer Handbook of Global Navigation Satellite Systems, P. J. G. Teunissen and O. Montenbruck, Eds. Cham, Switzerland: Springer International Publishing AG*, 2017.
Available: https://link.springer.com/chapter/10.1007/978-3-319-42928-1_2

[3] M.K.Mirdan, R. N. Hassan, and,B. Q. Al-Aboodi, "Performance Simulation for Adaptive Optics Technique Using OOMAO Toolbox," *Karbala International Journal of Modern Science*, vol. 8, no. 3, 2022.
Available: https://doi.org/10.33640/2405-609X.3233

[4] B. Q. Al-Aboodi, M.S. Mahdi, and Y.C. Bukheet, " Study of Land Cover Changes of Baghdad Using Multi-Temporal Landsat Satellite Images," *Iraqi Journal of Science*, vol. 57, no.3B, pp:2146-2160, 2016. Available:https://www.iasj.net/iasj/article/121018

[5] I.J. Muhsin, E.F. Khanjer, B.A. AL-Rizak, B. Sabah, and Rafah " 3D Building Reconstruction Using DEM and Mosaic Model," *Iraqi Journal of Science*, vol. 58, no.3A, pp: 1308-1316, 2017.

[6] B. Turgut, "A back-propagation artificial neural network approach for three-dimensional coordinate transformation," Scientific Research and Essays, vol. 5, no. 21, pp. 3330-3335, 2010.

[7] B. Konakoglu, L. Cakir, and E. Gokalp, "2D COORDINATE TRANSFORMATION USING ARTIFICIAL NEURAL NETWORKS," *in ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XLII-2/W1, pp. 183-186, 2016.

[8] C. D. Ghilani, "Adjustment Computations: Spatial Data Analysis. Hoboken," *NJ, USA: John Wiley & Sons, Inc*., 2010.
Available: https://scholar.google.com/scholar?q=Adjustment+Computations:+Spatial

[9] P. Zaletnyik, "Coordinate Transformation with Neural Networks and with Polynomials in Hungary," *in International Symposium on Modern Technologies, Education and Professional Practice in Geodesy and Related Fields, Sofia, Bulgaria*, 2004.
Available:https://docplayer.net/89929116-Coordinate-transformation-with-neural-networks-and-with-polynomials-in-hungary.html

[10] A. R. Tierra, R. Dalazoana, and S. D. Freitas, "Using an Artificial Neural Network to Improve the Transformation of Coordinates Between Classical Geodetic Reference Frames," *Computers & Geosciences*, vol. 34, pp. 726-734, 2008.

[11] M. Gullu, Y. Mustafa, I. Ibrahim, and T. Bayram, "Datum Transformation by Artificial Neural Networks for Geographic Information Systems Applications," *in International Symposium on Environmental Protection and Planning: Geographic Information Systems (GIS) and Remote Sensing (RS) Applications (ISEPP)*, Izmir, Turkey, 2011.
Available:https://www.researchgate.net/profile/Mustafa-Yilmaz-12/publication/268206049_

[12] M. Gullu, M. Yilmaz, I. Yilmaz, and B. Turgut, "Datum Transformation by Artificial Neural Networks for Geographic Information Systems Applications," *in International Symposium on Environmental Protection and Planning:Geographic Information Systems (GIS) andRemote Sensing (RS) Applications (ISEPP)*, Izmir, Turkey, 2012.

[13] M. R. Maria, "Coordinate Transformations for Integrating Map Information in the New Geocentric European System Using Artificial Neuronal Networks," *GeoCAD*, pp. 1-9, 2012.
Available: http://revcad.uab.ro/upload/21_68_Paper31_RevCAD12_2012.pdf

[14] A. Tierra and R. Romero, "Planes coordinates transformation between PSAD56 to SIRGAS using a Multilayer Artificial Neural Network," *GEODESY AND CARTOGRAPHY*, vol. 63, pp. 199-209, 2014.
Available: https://ui.adsabs.harvard.edu/abs/2014GeCar..63..199T/abstract

[15] Y. Y. Ziggah, H. Youjian, X. Yu, and L. P. Basommi, "Capability of Artificial Neural Network for Forward Conversion of Geodetic Coordinates (ϕ, λ, h) to Cartesian Coordinates (X, Y, Z)," *Mathematical Geosciences*, vol. 48, pp. 687-721, 2016.

[16] Y. Y. Ziggah, H. Youjian, P. B. Laari, and Z. Hui, "Novel approach to improve geocentric translation model performance using artificial neural network technology," *Boletim de Ciências Geodésicas*, vol. 23, pp. 213-233, 2017.
Available: https://www.scielo.br/j/bcg/a/HzqwCz7nwcDW3PDfdTN7FLp/?lang=en

[17] H. T. Elshambaky, M. R. Kaloop, and J. W. Hu, "A novel three-direction datum transformation of geodetic coordinates for Egypt using artificial neural network approach," *Arabian Journal of Geosciences*, vol. 11, no. 4, pp. 110, 2018.

[18] Y. Y. Ziggah, H. Youjian, A. R. Tierra, and P. B. Laari, "Coordinate transformation between global and local data based on artificial neural network with k-fold cross-validation in Ghana," *Earth* ***Sciences Research Journal*****, vol. 23, no. 1, pp. 67-77, 2019.**

[19] L.-S. Lin and Y.-J. Wang, "A study on cadastral coordinate transformation using artificial neural network," *in Proceedings of the 27th Asian Conference on Remote Sensing, Ulaanbaatar, Mongolia*, pp. 1-6, 2006.
Available: https://ah.nccu.edu.tw/bitstream/140.119/8217/1/H-2_H7.pdf

[20] B. Kumi-Boateng and Y.Y.J. Ziggah, "Horizontal Coordinate Transformation Using Artificial Neural Network Technology–A Case Study of Ghana Geodetic Reference Network," *Journal of Geomatics*, vol. 11, no. 1, pp. 1-11, 2017.

[21] B. Konakoglu, L. Cakır, and E. Gökalp, "2D coordinate transformation using artificial neural networks," *in Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci*., vol. XLII-2/W1, pp. 183-186, 2016, Available: https://doi.org/10.5194/isprs-archives-XLII-2-W1-183-2016.

[22] Z. E. . Hussein, "Image Georeferencing using Artificial Neural Network Compared with Classical Methods," *Iraqi Journal of Science*, vol. 62, no. 12, pp. 5024–5034, Dec. 2021. Available: https://ijs.uobaghdad.edu.iq/index.php/eijs/article/view/3690

[23] A.I. Abbas, O.Y.M. Alhamadani, and M.U. Mohammed, "The application of an artificial neural network for 2D coordinate transformation," *Journal of Intelligent Systems*, vol. 31, no. 1, pp. 739-752, 2022. Available: https:// doi.org/ 10.1515/jisys-2022-0033.

[24] M. W. Yenter, T. A. Wheeler, J. R. Mejia, M. Cline, and K. R. Joyce, "Development of the Iraqi Geospatial Reference System," *The American Surveyor Magazine*, 2005. Available:https://amerisurv.com/2005/10/31/development-of-the-iraqi-geospatial-reference-system/

[25] IOGP, "Guidance Note 22 Geodetic referencing in Iraq," *IOGP Guidance Note, International Association of Oil & Gas Producers, England and Wales*, 2015. Available: https://www.iogp.org/bookstore/product/guidance-note-22-geodetic-referencing-in-iraq/

[26] Z. Altamimi, P. Sillard, and C. Boucher, "ITRF2000: a new release of the International Terrestrial Reference Frame for earth science applications," *Journal of Geophysical Research: Solid Earth*, vol. 107, no. B10, pp. ETG 2-1-ETG 2-19, 2002.

[27] M. Güllü, İ. Yılmaz, M. Yılmaz, and B. Turgut, "An alternative method for estimating densification point velocity based on back propagation artificial neural networks," *Studia Geophysica et Geodaetica*, vol. 55, no. 1, pp. 73-86, 2011. Available: https://link.springer.com/article/10.1007/s11200-011-0005-6

[28] B. Stopar, T. Ambrožič, M. Kuhar, and G. Turk, "GPS-derived geoid using artificial neural network and least squares collocation," *Survey Review*, vol. 38, no. 299, pp. 513-524, 2006.

[29] M. Yılmaz, B. Turgut, M. Güllü, and İ. Yılmaz, "Application of artificial neural networks to height transformation," 2017. Available:https://www.researchgate.net/publication/320110892_Application_of_artificial_neural_networks_to_height_transformation

[30] S. Gopal, "Artificial neural networks in geospatial analysis," *International Encyclopedia of Geography, John Wiley & Sons, Ltd*, 2016. Available: https://onlinelibrary.wiley.com/doi/book/10.1002/9781118786352

[31] M.T. Hagan, H.B. Demuth, M.H. Beale, and O. De Jesús, "Neural Network Design," *2nd edn. Martin Hagan, Oklahoma*, 2014. Available: https://hagan.okstate.edu/NNDesign.pdf

[32] A. Tierra, R. Dalazoana, and S. De Freitas, "Using an artificial neural network to improve the transformation of coordinates between classical geodetic reference frames," *Computers & Geosciences*, vol. 34, no. 2, pp. 181-189, 2008

[33] B. Turgut, "Application of Back Propagation Artificial Neural Networks for Gravity Field Modelling," *Acta Montanistica Slovaca*, vol. 21, pp. 200-207, 2016. Available:https://www.researchgate.net/publication/311221951_Application_of_back_propagation_artificial_neural_networks_for_gravity_field_modelling

[34] P. J. Werbos, "Beyond regression: new tools for prediction and analysis in the behavioral sciences," *Ph.D. Dissertation, Harvard University, Cambridge, MA*, 1974. Available:https://www.researchgate.net/publication/35657389_Beyond_regression_new_tools_for_prediction_and_analysis_in_the_behavioral_sciences

[35] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," *Nature*, vol. 323, pp. 533-536, 1986. Available: https://www.nature.com/articles/323533a0