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(Research Article)

A New Approach for Electromagnetic Log Prediction Using Electrical Logs, South California

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Abstract

Well logging data shows the change of physical properties of rocks and fluids in lithology units with depth. Well logging is one of the main parts of natural resources exploration. But in some cases, due to the lack of geophysical equipment or due to high exploration costs, it is not possible to record some geophysical logs. In this paper, electromagnetic log predicted using electrical logs for the first time. In such cases, estimating the desired log using other geophysical logs is a suitable solution. For the estimation of geophysical logs, machine learning algorithms are used in most cases. In this research, a new strategy developed for processing and preparation of geophysical logs. This strategy consists of three parts: data smoothing, correlation intensifier, and MLR (Multiple Linear Regression) or ANN (Artificial Neural Network). The purpose of the data smoothing and correlation intensifier section is to remove outliers and identify the pattern of main changes in the log data, and as a result, the accuracy in estimating the target log increases. In this article, the determination of the electromagnetic log has been done using electric logs. The well logging data have been recorded in Southern California and the Central Valley. A total of six wells have been selected, four wells for MLR and ANN training and two wells for testing. By applying data smoothing and correlation intensifier to these data, the correlation between electrical and electromagnetic data increased significantly and caused the estimation accuracy of electromagnetic log to be above 95%. The use of this strategy is not limited to the estimation of electromagnetic log and can be used in all well logging data.

Keywords: Electromagnetic Log, Groundwater, Well Logging, Data Smoothing, South California.

1. Introduction

Groundwater is an essential water resource for humanity. 50% of the world's population's drinking water and 43% of irrigation water are entirely or in part supplied by groundwater (Köhn et al., 2002). Well logging is the essential and routine part of groundwater (Köhn et al., 2002; Folch et al., 2020; Mosaad & Basheer, 2020; Aftab et al., 2023a), oil (Qin et al., 2020; Aftab et al., 2023b; Leisi & Saberi, 2022), gas (Senosy et al., 2020; Prasad, 2018), geothermal (Fiordelisi et al., 2020), and ore deposits explorations (Tixier & Alger, 1970; Pant & Gupta, 1998), which our new society seriously needs water and hydrocarbon sources. The main application of well logging is to measure the petrophysical parameters in the subsurface earth formations through a drilled borehole to characterize the subsurface physical properties of fluids and rocks (Hsieh et al., 2005). Usually, our studied geological area for detection of the aquifer, hydrocarbon specifically minerals complex fractured media in which the fluid is able to flow through the porous media (Revil et al., 2015). Undoubtedly, for creating a subsurface model, the geological environment needs to be investigated in detail and properly quantified (Rasouli & Masoudi, 2020). Well logging measurement techniques include resistivity, acoustic, nuclear, fluid sampling, magnetic resonance, and coring (Donaldson, 1989; Liu, 2017; Asfahani, 2005).

EM well logging tool is one of the well logging classes used for applications in groundwater explorations. EM logs have been designed to maximize vertical resolution and depth of geophysical investigation and to minimize the effect of the borehole fluids. The EM logs record the electrical resistivity (conductivity, vice versa) of the rocks and fluids surrounding the borehole. Electrical resistivity and

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conductivity are affected by clay content, porosity, and permeability of the rocks and by the dissolved-solids concentration of the water within the rocks. The EM logging data depend on structure resistivity and geometrical parameters such as invasion zones and the geological layer boundaries (Kaufman & Itskovich, 2017; Zhang et al., 2000).

Geophysical techniques have been used extensively for groundwater exploration, but EM methods present a real opportunity for advanced perception of hydrogeological conditions. Ground Penetrating Radar (GPR) method was applied successfully for field applications. However, the GPR method has limitations for clay minerals, conductive structures, and soil. EM is the non-invasive geophysical method that measures the bulk electrical conductivity of the geological structure and soils. Bulk electrical conductivity is affected by clay minerals, salinity, and temperature of the area (Robinson et al., 2012). Thus, the EM logs are sensitive to mentioned parameters, which help for accurate interpretation of the subsurface. Due to the correlation between water salinity and electrical conductivity, electrical methods such as the EM method and Electrical Resistivity Tomography (ERT) are suitable tools to measure water salinity. Also, EM logs are used to monitor changing chloride concentration of groundwater in the San Joaquin sedimentary basin (Folch et al., 2020; Metzger & Izbicki, 2013).

EM investigations are more sensitive when aquifer conductivity is high and low sensitive when aquifer conductivity is low; therefore, EM is the best tool to distinguish the saline and freshwater, in which a big conductivity contrast exists. One of the first field applications of EM logging in the upper Florida aquifer was by Stewart and Hermeston in 1990, who showed that EM could be used to pore fluid conductivity estimation and determine seawater penetration into Karstic aquifers. Most of the published scientific papers about EM logging involve monitoring the changes in groundwater quality resulting from the seawater intrusion into freshwater aquifers (Metzger & Izbicki, 2013).

Each of the electromagnetic and conductivity (resistivity vice versa) logs have unique characteristics that make each of these logs useful in a special situation. Electromagnetic logs are sensitive to conductivity, which perform accurately in formations with low to medium electrical resistance. Conductivity logs are sensitive to non-conductive materials and perform better in formations with medium to high electrical resistance. Electromagnetic logs detect more conductive zones, while conductivity logs are mostly sensitive to resistive zones. Therefore, when resistivity of the invaded zone is greater than resistivity of the uninvaded formation, electromagnetic log data preferred for determination of uninvaded zone resistivity because conductivity logs dominantly affected by invaded formation. In the case, the resistivity of the invaded zone is less than resistivity of uninvaded zone, the conductivity logs preferred for determination of uninvaded zone resistivity. The electromagnetic logs recommended for wells drilled with moderately conductive or non-conductive mud and for air-drilled or empty wells. However, conductivity logs suitable for wells drilled with highly conductive mud (Novo et al., 2008; Xing et al., 2008).

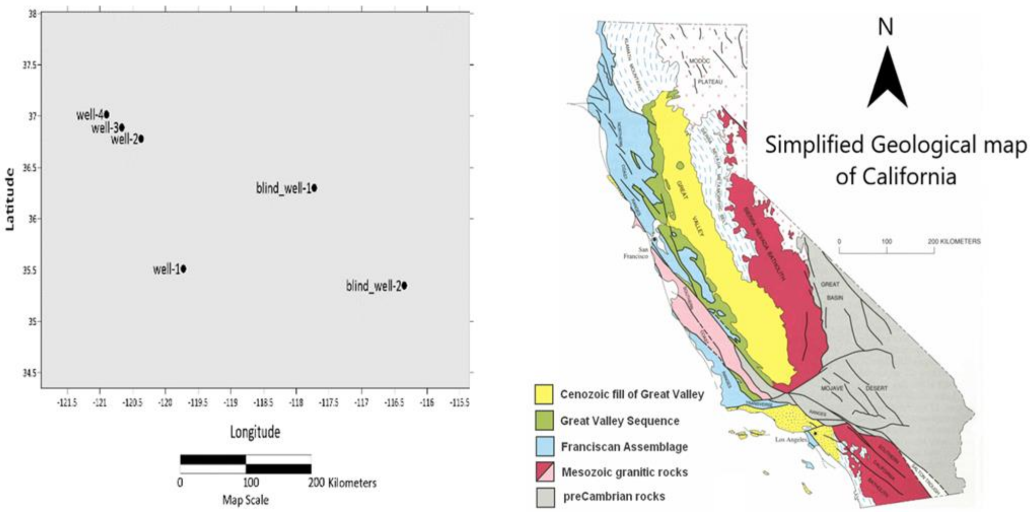
The innovation of this research has two aspects. The first innovation is the estimation of the electromagnetic log using electric logs, which is the first time to propose the estimation of the electromagnetic log. And the second innovation is processing and preparation of well logging to increase the target log estimation accuracy. This approach consists of three parts. The first part consists of RLOESS (Robust Locally Estimating Scatterplot Smoothing), which is intended to remove outliers and smooth the data. The second part of this system consists of CI (Correlation Intensifier), in this step, it is tried to increase input logs correlation with the target by combining the input logs. The third part of this strategy consists of an MLR (Multiple Linear Regression) or an ANN (Artificial Neural Network). Consecutive use of these three parts causes accurate estimation of geophysical logs, which will be given in the results of this article.

2. Site geology

Of all the fifty states of the United States, California's geology and history are the most amazing and interesting parts. The rocks of California date back 1.8 billion years and erupted volcanoes just a century ago. The geology of California is highly complicated, with numerous expansive mountains, active tectonic and significant faults, rich mineral deposits and hydrocarbon resources, and a history of both ancient and comparatively recent intense geological activity. One of California's distinct geological features is its Central Valley, a long flat trough-shaped depression between the sierras and the Coast Ranges. However, the term Central Valley is usually used to the topographic feature but the term Great Valley is used to describe the geological basin (including the surface and bedrock) that lines beneath the Central Valley. The average rainfall (snow and rain) for California is quite low, only 58 cm falling per year. Northern parts of California are typically watered (more than 240 cm) and mountains, particularly the Sierras get significant snowfall and rainfall. In contrast, the south part of California is semi-desert or full desert, which is not enough water to support its people and agriculture. Therefore, groundwater exploration in California is an essential issue (Prothero, 2017). The location of the used wells and the geology map of California state illustrated in Figure 1.

The Great Valley of California consists of heterogeneous materials, which are filled deposits. Gravel and sand are constructing the Great Valley aquifer systems. Page (1983) studied the texture and grain size of the Great Valley sedimentary deposits using 685 geophysical logs.

Great Valley is one of the prominent geological units and sedimentary basins in the United States and the world. The Great Valley, is usually divided into two significant sections: the first section known as Sacramento Valley (northern part) and the second section known as San Joaquin Valley (southern part). Hundreds of scientific studies have been performed about the geology, geochemistry and hydrology of the Great Valley. Mendenhall et al. (1916) and Bryan (1940) have reported valuable information about the Great Valley geology and hydrology. Clay minerals of the San Joaquin basin studied in detail by Davis et al. (1959). Another comprehensive study has been reported by Olmsted and Davis (1961) concerning the Sacramento basin geology, hydrology and geological history. Also, many other reports have been written with the aim of Great Valley detail recognition. Great Valley is a sedimentary basin that is filled by sediments between the Sierra Nevada Mountains and Coast Ranges. These sediments include marine deposits, deltaic, and continental origin (Prothero, 2017). The thickness of the Great Valley sediments varying from 0 in Sierra Nevada to 16 km in middle and western edge of the basin (Wentworth et al., 1995). The average thickness of the continental sediments is 730 m, but the thickness of these sediments in the south part of the Great Valley is 2750 m (Planert & Williams, 1995). Note that, the continental sediments are gravel and sand which are blended and interbedded with silt and clay minerals. Fine-grained sediments are mostly slit and clays that consisting 50% of valley sediments (Planert & Williams, 1995).



(a) (b)

Figure 1. (a) Location map of the wells. Blind well-1 and blind well-2 are test wells. (b) The simplified geological map of California state (Prothero, 2017).

3. Methodology

3-1. Motivation

Electric and electromagnetic systems are different in the way they generate and transmit signals. Electric systems primarily use electric currents and fields to transmit signals, while electromagnetic systems use both electric and magnetic fields to transmit signals. While electric and electromagnetic systems have differences in the way they generate and transmit signals, they also share similarities. Both systems involve the movement of electrons or ions within fluid (water), and both can be used to power devices and transmit information. Understanding both electric and electromagnetic measurements can help in optimizing the aquifer detection process. Because electric and electromagnetic methods measure the conductivity or resistance of subsurface formations, for this reason, the estimation of electromagnetic logs using electric logs is possible and can even be considered the best option. Estimating the electromagnetic log can be a fundamental step to reduce groundwater exploration costs and expand the study of groundwater in sedimentary basins.

3-2. RLOESS

RLOESS is a robust well logging data smoothing algorithm which was presented recently by Aftab and Hamidzadeh Moghadam (2022). This algorithm is used to remove outliers and to weight the well logging data. RLOESS is powerful non-parametric regression model that combine multiple regression patterns in a KNN (K Nearest Neighbor). The behavior of this algorithm is such that it gives more weight to the data that is close to the mean of the data in each section, and the weight of the data changes as it moves away from the average. In addition, this algorithm considers zero weight to data that are outside six standard deviations. The use of this algorithm causes the removal of outlier data, and as a result, the correlation between the input data and the target increases, which will be presented in the results section of this article (Figure 2). For more information about this algorithm, refer to Aftab and Hamidzadeh Moghadam (2022).

3-3. CI

CI is the second stage of the well logging data preparation. In this step, an input log that has the highest correlation with the target log should be selected and added to all the input logs to create combined logs (new inputs for MLR or ANN). This will increase the correlation of the input logs with the target log significantly. The main aim of this step is combining logs to increase correlation of new inputs with target log (Figure 2).

3-4. Linear Regression

In machine learning and statistics, linear regression is a linear method for modeling the relationship between the response and one or more variables (Leisi et al., 2022; Kheirollahi et al., 2023). The case of one variable is known as simple linear regression, and the case of two or more variables is called multiple linear regressions. Regression is the central part of the statistical modeling and machine learning. From a machine learning point of view, we are not concerned about the model fitting performance, but rather care about how well it predicts new observations. For minimizing fitting error, OLS (Ordinary Least Square) method has been used (Johansson, 2018). Out of six well logging data, four wells are considered for training the model (70% for train, 15% for validation, and 15% test) and two wells for predicting (blind wells) EM log. Note that the performance of a machine learning algorithm depends on data. Data conditioning before feeding to the algorithm is a significant issue, in which the accuracy of the results is highly affected by data. Outliers are observations that are significantly different from other data points. Even the best machine learning algorithms will underperform if outliers are not handled in data. Outliers can adversely affect the training process of a machine learning algorithm, resulting in a loss of accuracy (Figure 2).

3-5. Artificial Neural Network (ANN)

Used ANN in this research involves an input layer, one middle layer (hidden layer), and an output layer, that middle layer connects the input layer to the output layer. Hidden layer includes 10 neurons and sign function used as activation function. Levenberg–Marquardt algorithm is used to train ANN system. The number of hidden layers depends on the problem's complexity and nature. Like linear regression, four wells were considered for training the ANN (70% train, 15% validation, 15% test), and two wells as blind wells. Data conditioning is performed before feeding data to ANN (Figure 2).

4. Results and Discussion

As mentioned, the well logging data was selected from California, United States. Out of six existing wells, we have only shown well-1(Figure 3). The well-1 data is Kern County data in the south part of California. The county's economy highly depends on the agriculture and the petroleum industry. One of California's most significant geological features is its Central Valley, a long flat trough-shaped depression between the sierras and the Coast Ranges. The Conductivity 16N, conductivity 64N, and lateral conductivity logs are information, and the EM log is the unknown geophysical log.

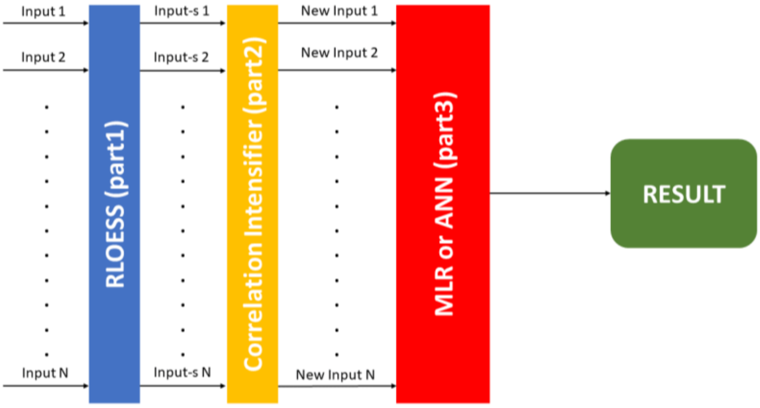


Figure 2. A brief infographic of strategy used in this paper consists of RLOESS, CI, and MLR or ANN. The inputs are geophysical logs.

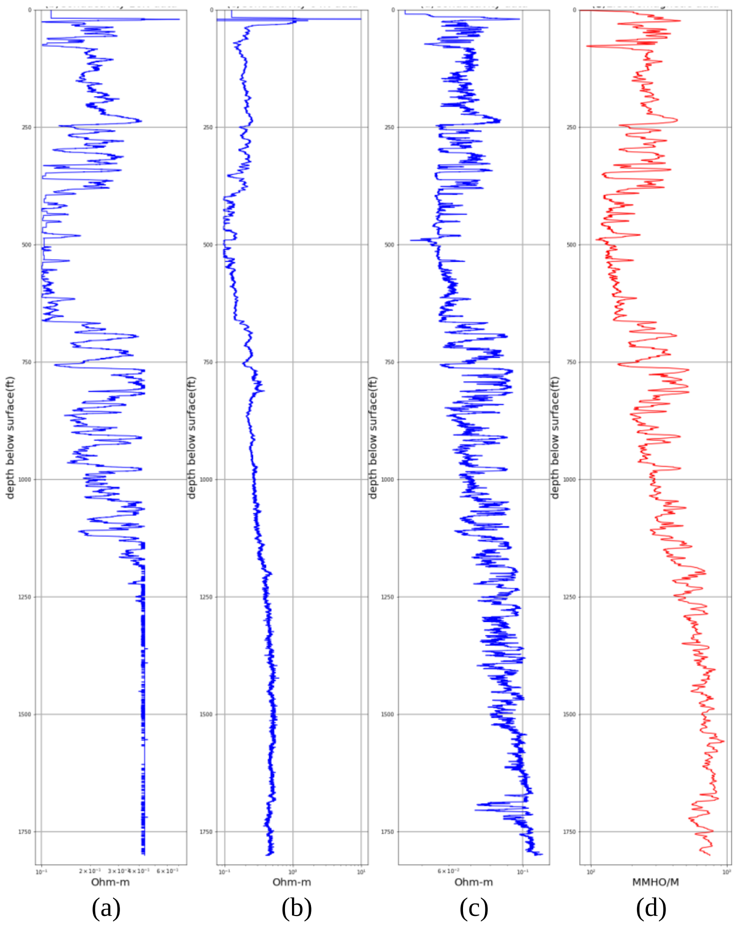


Figure 3. The well-1 (a) conductivity 16N, (b) conductivity 64N, (c) conductivity, (d) EM (Target log).

The correlation between the input logs and the target log is given in Table 1. In this table, the correlation between the raw data, the correlation after RLOESS, and the correlation after CI are given. From the results of Table 1, it is clear that RLOESS and CI have a significant effect on the correlation between the input logs and the target log, and will increase the accuracy of the estimation using MLR and ANN. For this reason, in Table 1, the correlation between the conductivity logs and the electromagnetic log is given. Note, due to the type of lateral conductivity data recording, RLOESS and CI does not have much effect on this data.

The training results of the MLR and ANN after RLOESS and CI procedures for train wells are illustrated in Figure 4. The training results of the MLR and ANN show that the ANN has better performance in comparison with MLR. However, the performance of the MLR is acceptable. It seems that, there is a reliable relationship between combined electrical logs with electromagnetic logs, the training results of which are satisfactory. The test results of the MLR and ANN for blind well 1 and 2 is illustrated in Figures 5 and 6, respectively. The results show that the ANN performance is better than MLR in predicting test wells. Figure 7 shows the comparison of the MLR and ANN predicted electromagnetic log with actual electromagnetic logs in blind well 1 and 2.

The performance of this approach in estimating the electromagnetic log is acceptable. Preparation and processing of the well logging data before feeding to MLR and ANN is the main reason of high accuracy estimation. In the blind well 1, the geology of the area is not so complex, but in the blind well 2, the geology of the area is complex. Note that, the distance of the wells used in this research is far enough from each other. Using MLR, the RMSE (Root Mean Square Error) in estimating the electromagnetic log in blind well-1 and blind well-2 is 0.33 and 2.68, respectively. In the case of the ANN, the estimating error for blind well-1 and 2 is 0.17 and 1.76, respectively. However, the relationship established in MLR and ANN has worked acceptable in blind wells that are geologically different from each other. The MLR relationship for estimating electromagnetic log using electrical logs is as follows:

$$\mathrm{EM} = -0.0134 + 0.2295(\mathrm{C1} + \mathrm{C3}) + 0.1012(\mathrm{C2} + \mathrm{C3}) + 0.1623(\mathrm{C3}) \qquad (1)$$

where $\mathrm{C1}$ is conductivity16N, $\mathrm{C2}$ is conductivity 64N, and $\mathrm{C3}$ is lateral conductivity.

The estimation results of MLR and ANN for raw data and for smoothed data (input logs just smoothed with RLOESS) are given in Table 2. Comparison of Table 2 results with Figure 7 results shows that the significant effect of data processing on estimation results.

Table 1. Comparing the correlation of raw data with processed data after RLOESS and CI.

Raw data correlation			
	Conductivity16N	Conductivity64N	Conductivity (Lateral)
EM	0.8601	0.6728	0.9310
Correlation of data after RLOESS			
	Conductivity16N	Conductivity64N	Conductivity (Lateral)
EM	0.8904	0.7869	0.9348
Correlation of data after RLOESS and CI			
	Conductivity16N+Conductivity (Lateral)	Conductivity64N+Conductivity (Lateral)	Conductivity (Lateral)
EM	0.9428	0.9229	0.9348

Table 2. The correlation between actual and estimated electromagnetic log for raw and smoothed data. The RMSE for each case is given in the table.

MLR (for raw data)			MLR (after RLOESS)	
	Blind well-1	Blind well-2	Blind well-1	Blind well-2
Correlation	0.8924	0.8712	0.9532	0.9261
RMSE	10.3%	12.15%	4.7%	7.4%
ANN (for raw data)			ANN (after RLOESS)	
	Blind well-1	Blind well-2	Blind well-1	Blind well-2
Correlation	0.8911	0.8865	0.9592	0.9374
RMSE	10.1%	11.45%	4.1%	6.3%

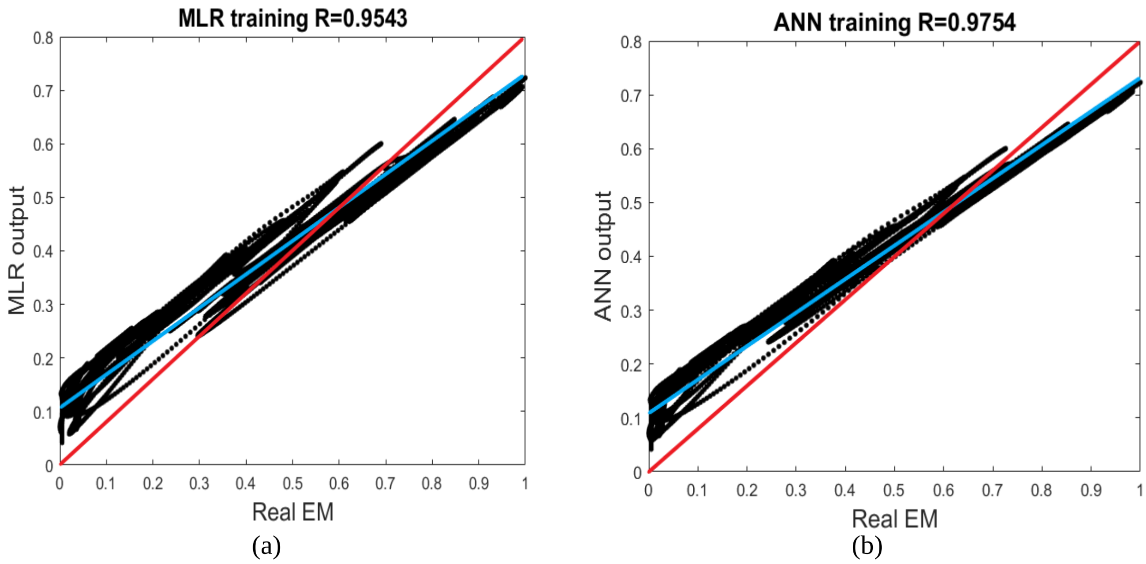


Figure 4. (a) Training result for MLR after RLOESS and CI processes in test wells, (b) Training results for ANN after RLOESS and CI processes in test wells.

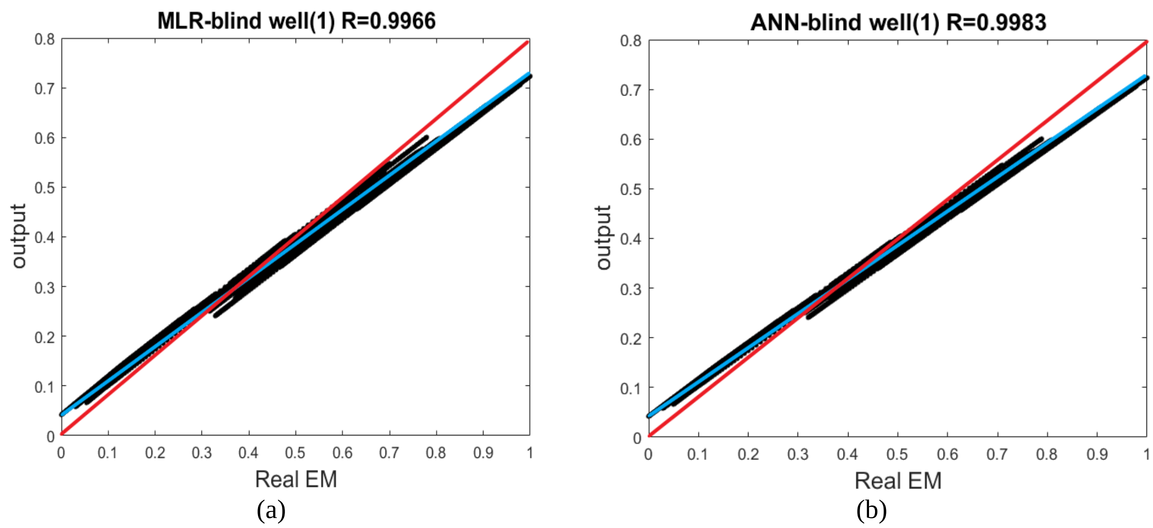


Figure 5. (a) The MLR performance in predicting electromagnetic log in blind well 1, (b) The ANN performance in predicting electromagnetic log in blind well 1.

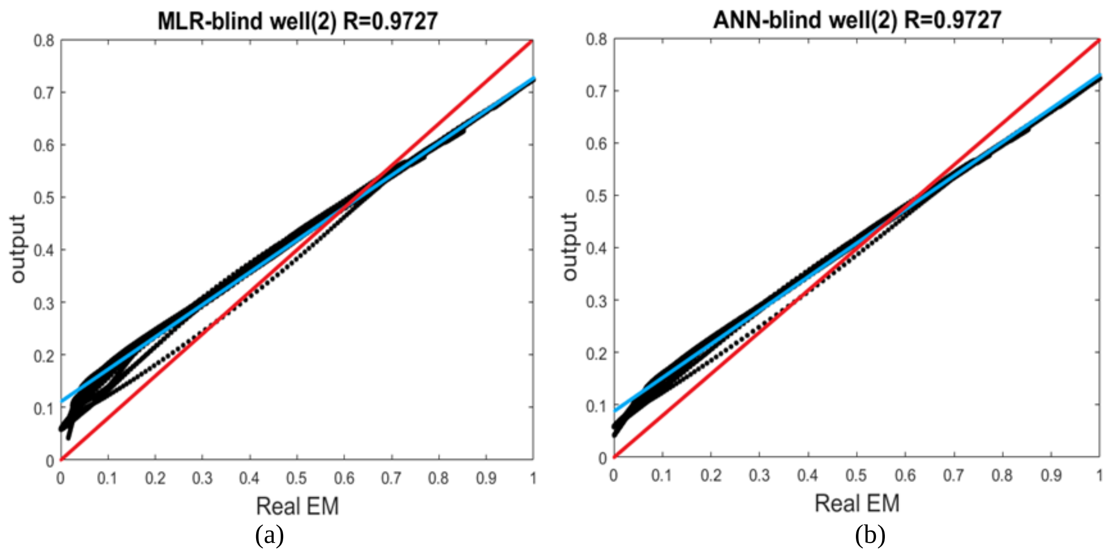


Figure 6. (a) The MLR performance in predicting electromagnetic log in blind well 2, (b) The ANN performance in predicting electromagnetic log in blind well 2.

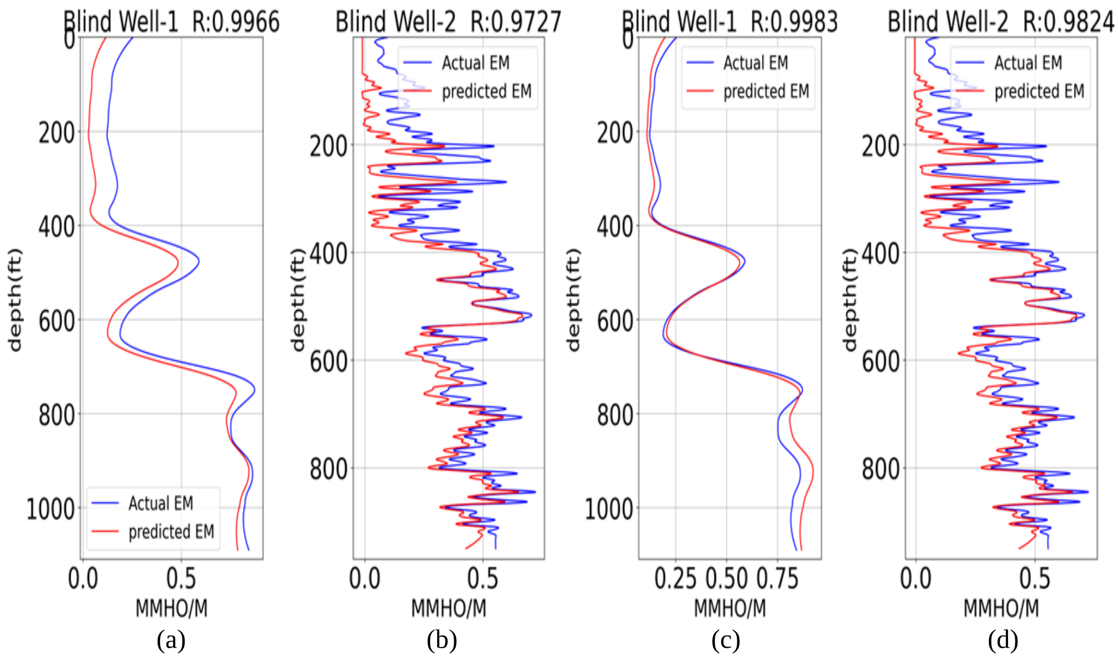


Figure 7. (a) and (b) the MLR results for blind well 1 and 2. (c) and (d) ANN results for blind well 1 and 2.

Regarding the errors and accuracy of the estimates obtained in this research, it should be noted that the quality of the estimated EM log depends on the quality of the electrical logs. If the electrical logs are measured with good quality and accuracy, the accuracy of the estimated log will also be good. Geological and lithological conditions also affect the accuracy of the results. For example, the presence of clay minerals in aquifers reduces porosity and permeability, which causes electrical conductivity to decrease. On the other hand, the presence of clay minerals increases electrical conductivity due to their mineralogical nature. Therefore, in some unexpected conditions, very high accuracy of electromagnetic log by-estimation may not be achieved.

For realization of geophysical logs connection with geological parameters, the significant reports about Great Valley have been studied below and then the relationship of geophysical logs with geological aspects introduced.

Texture change of sediments affect the different geophysical logs. The electrical logs changing can reflect the changing from finegrain to coarse grain zone or transition from glacial to interglacial condition. Studies showed that the various factors affect the electrical measurements of sedimentary layers, including grain size of sediments, the percentage of ions in the pore fluids, sediments' distance from source rocks, and the sediments' density. Recognition of these relationships in geophysical logs can spread up to sedimentary basin. Studying these connections in different zones of Great Valley, will lead to better identification of sedimentary basins and decrease the geophysical surveys and operating costs. Note that, recording three types of the conductivity measurements for electromagnetic log prediction and invasion parameters is essential.

5. Conclusion

In this article, a fast, robust and accurate technique for estimating electromagnetic log is presented. The main finding of this research is that the preparation and processing of input logs have a significant effect on the estimation results. Considering the well logging data that was used in this research, the corrections made on the data led to the correlation between the input logs and the target log to increase significantly. Doing these corrections made the estimation of electromagnetic log to be done with high accuracy. The data used in this article is for southern California. This area is facing a water shortage crisis due to low rainfall. Estimating the electromagnetic log can be effective in reducing the costs of groundwater exploration and expand the process of investigating groundwater in this area. In this research, by applying data smoothing and correlation intensifier to input (electrical data) and output (electromagnetic data) data, the correlation between electrical and electromagnetic data was increased significantly and caused the estimation accuracy of electromagnetic log to be above 95%. The use of this strategy is not limited to the estimation of electromagnetic log and can be used in all well logging data.

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