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Prediction of rock strength parameters for an Iranian oil field using neuro-fuzzy method

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Abstract
Uniaxial compressive strength (UCS) and internal friction coefficient (μ) are the most important rock strength parameters. They could be determined by either laboratory tests or empirical correlations. Sometimes, for many reasons, laboratory analysis is not possible. On the other hand, due to changes in the rock composition and properties, none of the correlations could be applied as an exact universal one. In such conditions, the proposed artificial intelligence method could be an appropriate candidate for estimation of the strength parameters. In this work, the adaptive neuro-fuzzy inference system (ANFIS), which is one of the artificial intelligence techniques, was used as a dominant tool to predict the strength parameters for one of the Iranian SW oil fields. A total of 655 datasets (including the depth, compressional wave velocity, and density data) were used. 436 and 219 datasets were randomly selected among the data for construction and verification of the proposed intelligent model, respectively.
To evaluate the performance of the model, the root mean square error (RMSE) and correlation coefficient (R^2) values between the reported values for the drilling site and the estimated ones were computed. A comparison between RMSE for the proposed model and that for the recent intelligence models shows that the proposed model is more accurate than the others. Acceptable accuracy and using conventional well-logging data are the highlight advantages of the proposed intelligence model.

Keywords: *Uniaxial Compressive Strength, Internal Friction Coefficient, Well-Logging, Adaptive Neuro-Fuzzy Inference System.*

1. Introduction

Uniaxial compressive strength (UCS) and internal friction coefficient (μ) are the most important rock strength parameters. These parameters have very high usage in the mechanical and geomechanical studies of rocks. Specially, in the stress-strain analysis problems such as wellbore stability, these parameters are essential. The values for UCS and μ are determined by either core analysis (laboratory method) or empirical correlations. Laboratory methods are very expensive and time-consuming. In addition, in practice, many geomechanical problems in reservoirs must be addressed when core samples are unavailable for laboratory testing. In fact, core samples of overburden formations, where many wellbore instability problems are encountered, are almost never available for testing [1]. To solve this problem, a number of empirical relations have been proposed that relate rock strength to the parameters measurable with geophysical well logs [1,2-8]. It should be noticed that each one of these correlations has been developed from the specific ranges of the well log data. Due to changes in the rock composition and properties, which result in changes in the data, none of the correlations could be applied as an exact universal one because the accuracy of no correlation is guaranteed for the data that is different from the one used for developing it. In such conditions, to overcome these problems, intelligence techniques could be very useful and helpful. In the recent years, there has been an increasing interest in developing intelligence models for prediction of the rock strength properties in the world. A review of the published-related studies is presented here.

Noorani and Kordani (2011) tried to estimate the uniaxial compressive strength of intact rocks using a neuro-fuzzy (NF) model and a multiple regression (MR) one. For this purpose, they used 15 laboratory datasets (including porosity, saturation, dry density, tensile strength, Schmidt Hammer number (SHN), sound velocity, point load index (PLI), and UCS). Among the data used, they used, respectively, 12 and 3 datasets as the training data and test data. To evaluate the performance of the models, the root mean square error (RMSE) index was calculated; it was 6.1 for the NF model and 13.63 for the MR one [9].

Amani and Moeini (2012) used the artificial neural network (ANN) and the adaptive neuro-fuzzy inference system (ANFIS) to predict the shear strength of the reinforced concrete (RC) beams. The ANN model, with multi-layer perceptron (MLP), using a back-propagation (BP) algorithm, was used to predict the shear strength of the RC beams. Six important parameters were selected as the input parameters including concrete compressive strength, longitudinal reinforcement volume, shear span-to-depth ratio, transverse reinforcement, effective depth of beam, and beam width. The ANFIS model was also applied to a database, and the results obtained were compared with the ANN model results and empirical codes. The first-order Sugeno fuzzy was used. Comparison between the models and the empirical formulas showed that the ANN model with the MLP/BP algorithm provided a better prediction for the shear strength [10].

Dadkhah and Esfahani (2013) applied two soft-computing approaches, neuro-fuzzy inference system (ANFIS) and genetic programming (GP), for the prediction of UCS. Block punch index (BPI), porosity, P-wave velocity, and density were used as the inputs for both methods, and were analyzed to obtain the training data and testing data. Of all the 130 datasets, the training and testing sets consisted of randomly-selected 110 and 20 sets, respectively. The results obtained showed that the ANFIS and GP models were capable of accurately predicting the uniaxial compressive strength (UCS) used in the training and testing phase of the study. The GP model results better predicted UCS compared to the ANFIS one [11].

Ceryan (2014) applied support vector machines (SVMs), relevance vector machines (RVMs), and ANN, which are intelligent technique-based, to predict UCS for the volcanic rocks in Turkey. In these models, the porosity and P-durability index representing microstructural variables were used as the input variables. Their results indicated that the SVM and RVM performances were better than the ANN model. Also the RVM run time was considerably faster, and it yielded the highest accuracy [12].

Mishra et al. (2015) applied some soft-computing techniques including ANN, FIS, and ANFIS to estimate UCS of intact rocks by the index tests. BPI, point load strength (PLS), SHN, and ultrasonic P-wave velocity (Vp) were used as the input data. Various statistical parameters (VAF, RMSE, and correlation coefficient) were determined to check the predictive performances of these models. On the basis of these statistical parameters, it can be said that all the three models are equally robust in estimating UCS from the corresponding index test results. However, the fuzzy inference system (Sugeno-type) emerges to be a more competent analysis technique than the other two models in this regard [13].

In this work, by using the adaptive neuro-fuzzy inference system (ANFIS), an intelligence model was proposed for the estimation of UCS and μ using the conventional well-logging data (including depth, compressional wave velocity, and density data) in one of the Iranian SW oil fields. Some advantages of this work are as follow:

- The estimation technique is relatively simple, cheap, and quick.
- The inputs (depth, compressional wave velocity, and density data) are available in most wells.
- Generally, well logs can provide a continuous record over the entire well, so the well-log data, as the input, can be estimated over the whole well.
- In the ranges of the data used, the proposed model is intelligent.

2. Materials and method

2.1. Methodology

Adaptive neuro-fuzzy inference system (ANFIS) was used as the dominant tool. It is a combination of fuzzy logic and ANN. For example, when the number of training pairs is small, the results obtained for the neural network system may be poor. In such conditions, if fuzzy systems are combined with a neural network system, the results can improve [14]. An ANFIS system, which was first introduced by Jang in 1993, constructs a FIS, whose membership function parameters are adjusted using a back-propagation algorithm either alone or in combination with a least-squares type of method [15]. This adjustment allows the fuzzy systems to learn from the data they are modeling [16]. ANFIS is capable of mapping the unseen inputs to their outputs by learning the rules from the previously-seen data [17]. An ANFIS system has five layers including an input layer, an input MF layer (for input fuzzification), a rule layer, an output MF layer (for defuzzification of outputs), and an output layer. Figure 1 shows the structure of an ANFIS system.

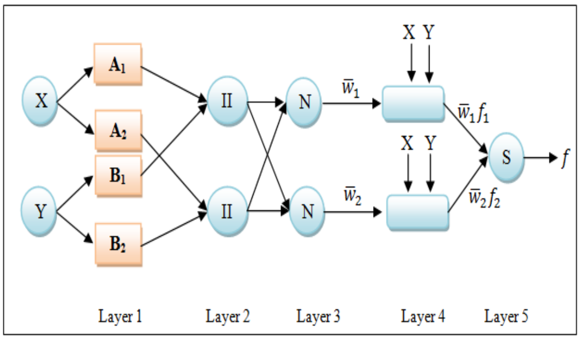


Figure 1. Structure of a simple ANFIS system.

2.2. Data analysis

This work was focused on one of the Iranian southwest oil fields. From the studied field, 655 wire-line log data was obtained and used to develop an intelligence model for prediction of either UCS or µ. The data consisted of the depth, compressional wave velocity (V_p), and density (RHOB log). Ranges of the data used are shown in table 1.

2.3. Constructing the model

Appropriate assignment of the inputs and outputs is the first step in any modeling process with intelligence systems. In this study, since the UCS and µ determinations were the objective, they were assigned as the output variables. The depth, compressional wave velocity (V_p), and density (RHOB log) were assigned as the input variables (Figure 2).

Table 1. Data ranges used.

PVT Property	Number of Points		Range		Mean	
	Training data	Test data	Training data	Test data	Training data	Test data
Depth (m)	436	219	3922-4916	3930-49150	4421	44419
Wave velocity (µs ft^{-1})	436	219	43.6-93.89	45.16-93.19	51.316	51.406
Density (g cm^{-3})	436	219	2.3-3.04	2.29-3.04	2.782	2.782
Uniaxial compressive strength (MPa)	436	219	1.9-100	2.01-89.91	64.93	64.87
Internal friction coefficient	436	219	0.2-0.72	0.2-0.71	0.6096	0.6128

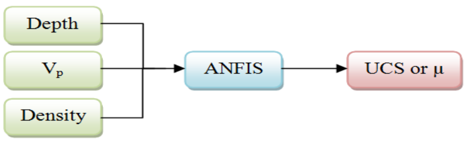


Figure 2. Schematic of output and input parameters of system (ANFIS).

A total of 655 input-output datasets, which were obtained using the wire-line logs in one of the SW Iranian oil fields were used. The data was divided into two groups. One group included 436 datasets, which were selected randomly and used for constructing the model, and the other one included 219 datasets that were used for validation of the model. There are three methods including Genfis1 and Genfis2, and Genfis3 to generate the fuzzy inference system (FIS) structure. They generate the fuzzy inference system structure from the data using the subtractive clustering and fuzzy c-means (FCM) clustering, respectively. After the accuracy tests, it was found that the Genfis2 result was better than Genfis1 and Genfis3 for either the UCS or the µ prediction. Therefore, to generate the FIS structure, Genfis2 was used. The properties of the constructed model are listed in table 2. Figure 3 shows the structure of the constructed model. After constructing the model, it was implemented twice. First, it was implemented to predict UCS, and, once again, it was implemented to predict µ. The results obtained for a comparison made between the values reported from the drilling site, which were obtained using the wire-line logs, and the values estimated from the test data using the intelligence model are shown in figures 4 and 5.

Table 2. Properties of constructed model (Genfis2).

Inference type	Method
AND	prod
OR	probor
Implication	Prod
Aggregation	max
Difuzzification	wtaver

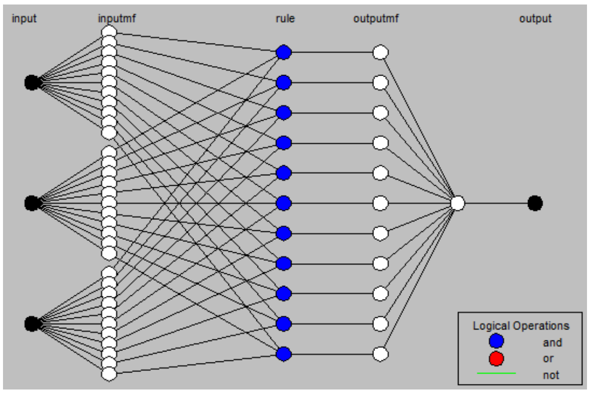


Figure 3. Constructed model to predict either uniaxial compressive strength or internal friction coefficient.

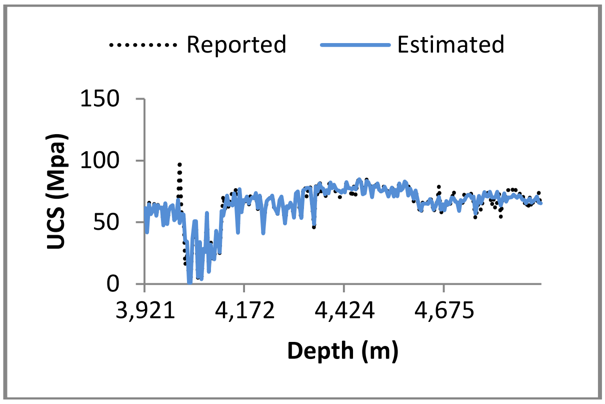
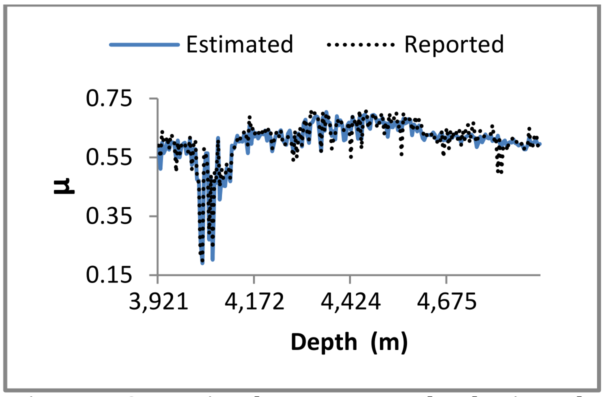


Figure 4. Comparison between reported and estimated values for the model in test data for uniaxial compressive strength (UCS).



Figurer 5. Comparison between reported and estimated values for the model in the test data for internal friction coefficient (μ).

3. Results and discussion

In this study, the adaptive neuro-fuzzy inference system (ANFIS) was applied for prediction of the uniaxial compressive strength (UCS) and internal friction coefficient (μ) in one of the Iranian southwest oil fields. ANFIS is one of the powerful artificial intelligence techniques that is a combination of the fuzzy logic and neural networks, and combines the advantages of both systems. After constructing and running the model, the correlation coefficient (R^2) between the reported values from the drilling site and the values estimated from the intelligence model was computed in the test data. They were 0.890 and 0.892 for μ and UCS, respectively (Figures 6 and 7). Also for a more accurate performance evaluation of the model, the root mean square error (RMSE) in the test data was computed using (1), which was compared with the accuracy of the recently-proposed intelligence and predictive models (Table 3).

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\left[(X)_{experimenal} - (X)_{predicted}\right]^2 / N} \qquad (1)$$

where, $X_{expimental}$ and $X_{predicted}$ are, respectively, the field reported and the model estimated values for either UCS or μ. N is the number of dataset used. According to table 3, the accuracy of the proposed model is more acceptable than that for the others. Moreover, in the previous models, most of the input data are obtained by laboratory tests, which are very time- and money-consuming. However, in the proposed model, the conventional wire-line logs, which are available in most wells, are applied as the input data.

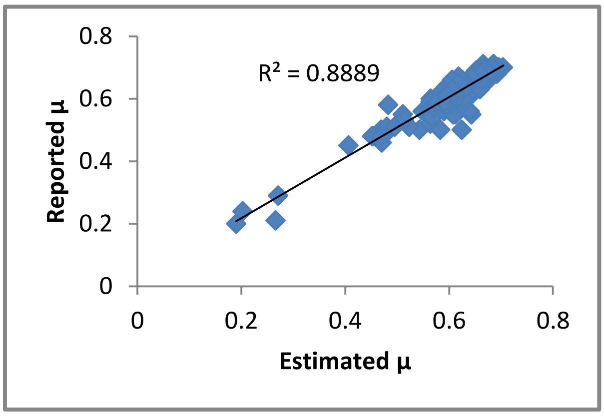


Figure 6. Correlation between experimental and predicted values from ANFIS in test data internal friction coefficient (μ).

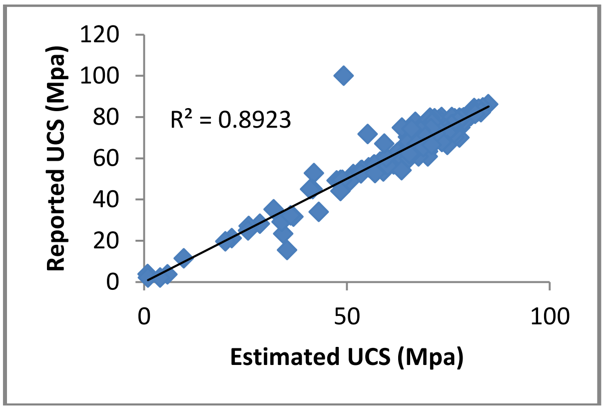


Figure 7. Correlation between experimental and predicted values from ANFIS in test data for uniaxial compressive strength (UCS).

4. Conclusion

For several reasons such as time and money limitations, laboratory determination of the rock strength properties (UCS and μ) is sometimes impossible. In such conditions, the experimental correlations are usually applied. Several correlations have been proposed. However, since the accuracy of no correlation is guaranteed for the data that is different from the one used for developing it, none of the correlations could be applied as a universal one. In this study, using the adaptive neuro-fuzzy inference system (ANFIS), an intelligence model was proposed to predict either UCS or μ for an Iranian SW oil field. For evaluation of the model accuracy, the correlation coefficient (R^2) between the values predicted from the model and the reported ones were calculated. They were 0.890 and 0.892 for μ and UCS, respectively. The results obtained for the proposed model could be acceptable, and this model could be applied as an appropriate one to predict UCS and μ when laboratory analysis is not possible. Acceptable accuracy and using conventional well-logging data are the highlight advantages of the proposed intelligence model.

Table 3. A comparison between proposed model and recent intelligence and predictive models.

Num.	Model	Year	Technique	Used variables		Number of data		RMSE	
				Input	Output	Training	Test	UCS	μ
1	Yurdakul et al. [18]	2011	ANN	SHN	UCS	25	6	7.92	-
2	Yurdakul et al.	2011	MR	SHN	UCS	25	6	46.51	-
3	Noorani & Kordani	2011	NF	φ, S, ρ, S_T, SHN, V_u, PLI	UCS	12	3	6.1	-
4	Noorani & Kordani	2011	MR	φ, S, ρ, S_T, SHN, V_u, PLI	UCS	12	3	13.63	-
5	Martins et al. [19]	2012	MR	φ, ρ, V_u, E_m	UCS	45	10	11.09	-
6	Martins et al.	2012	ANN	φ, ρ, V_u, E_m	UCS	45	10	11.49	-
7	Martins et al.	2012	SVM	φ, ρ, V_u, E_m	UCS	45	10	11.12	-
8	Mishra & Basu [20]	2013	FIS	φ, ρ, BPI, PLS, SHN, Vp	UCS	44	16	8.21	-
9	Mishra & Basu	2013	MR	φ, ρ, BPI, PLS, SHN, Vp	UCS	44	16	6.89	-
10	Ceryan	2104	SVM	φ, PDI	UCS	24	23	11.87	-
11	Ceryan	2104	RVM	φ, PDI	UCS	24	23	10.77	-
12	Ceryan	2104	ANN	φ, PDI	UCS	24	23	14.69	-
13	Mishra et al.	2015	ANN	BPI, PLS, SHN, Vp	UCS	44	15	16.9	-
14	Mishra et al.	2015	FIS	BPI, PLS, SHN, Vp	UCS	44	15	9.54	-
15	Mishra et al.	2015	ANFIS	BPI, PLS, SHN, Vp	UCS	44	15	13.72	-
16	This study	-	ANFIS	depth, Vp, ρ (RHOB log)	UCS, μ	436	219	5.24	0.025

where:

SHN: Schmidt Hammer number	BPI: Block punch index	PLI: point load index
PLS: point load strength	PDI: P-durability index	E_m : modulus of elasticity
S_T : tensile strength	V_u: ultrasonic velocity	Vp: P-wave velocity
φ: porosity	S: saturation	ρ: density

References

[1] Chang, Ch., Zoback. M. D. & Khaksar, A. (2006). Empirical relations between rock strength and physical properties in sedimentary rocks. Journal of Petroleum Science and Engineering, vol. 51, no. 3, pp. 223–237.

[2] Bradford, I. D. R., Fuller, J., Thompson, P. J. & Walsgrove, T. R. (1998). Benefits of assessing the solids production risk in a North Sea reservoir using elastoplastic modeling. SPE/ISRM Eurock, Trondheim, Norway, 1998.

[3] Fjaer, E., Holt, R. M., Horsrud, P., Raaen, A. M. & Risnes, R. (1992). Petroleum Related Rock Mechanics. Amsterdam: Elsevier.

[4] Freyburg, E. (1972). Der Untere und mittlere Buntsandstein SW_Thuringen in seinen gesteinstechnicschen Eigenschaften. Ber. Dtsch. Ges. Geol. Wiss., vol. 17, no. 6, pp. 911–919.

[5] Horsrud, P. (2001). Estimating mechanical properties of shale from empirical correlations. SPE Drilling & Completion, vol. 16, no. 2, pp. 68–73.

[6] McNally, G. H. (1987). Estimation of coal measures rock strength using sonic and neutron logs. Journal of Applied Geophysics, vol. 24, no. 4-5, pp. 381–395.

[7] Moos, D., Zoback, M. D. & Bailey, L. (1999). Feasibility study of the stability of openhole multilaterals, SPE Mid-Continent Operations Symposium, Oklahoma City, Oklahoma, 1999

[8] Vernik, L., Bruno, M. & Bovberg, C. (1993). Empirical relations between compressive strength and porosity of siliciclastic rocks. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, vol. 3, no. 7, pp. 677–680.

[9] Noorani, R. & kordi, H. (2011). A Robust Approach to Estimate the Uniaxial Compressive Strength of Intact Rocks. 6th National Congress on Civil Engineering, Semnan University, Semnan, Iran, 2011.

[10] Amani, J. & Moeini, R. (2012). Prediction of shear strength of reinforced concrete beams using adaptive neuro-fuzzy inference system and artificial neural network. Scientia Iranica, Transactions A: Civil Engineering, vol. 19, no. 2, p.p. 242-248.

[11] Dadkhah, R. & Esfahani, N. (2013). Application of genetic programming to modeling of uniaxial compressive strength. Middle-East Journal of Scientific Research, vol. 15, no. 6, pp. 840-845.

[12] Ceryan, N. (2014). Application of support vector machines and relevance vector machines in predicting uniaxial compressive strength of volcanic rocks. Journal of African Earth Sciences, vol. 100, pp. 634–644.

[13] Mishra, D. A., Srigyan, M., Basu, A. & Rokade, P. J. (2015). Soft computing methods for estimating the uniaxial compressive strength of intact rock from index tests. International Journal of Rock Mechanics & Mining Sciences, vol. 80, pp. 418–424.

[14] Jalalnezhad, M. J. (2012). Prediction of gas hydrates formation rate in gas production and transport operations, using fuzzy logic. Master science thesis, petroleum department, Shahid Bahonar university of Kerman, Kerman, Iran. 2012.

[15] Jang, J. S. R., (1993). ANFIS: adaptive-network-based fuzzy inference systems. IEEE Transactions on Systems, vol. 23, no. 3, pp. 585–665.

[16] MATLAB user's guide. (2007). Fuzzy logic Toolbox user's guide (MATLAB CD-ROM). Mathworks, Inc, Natick, MA, USA, pp. 299.

[17] Feili, M. A., Ranjbar, M., Nezamabadi –Poor, H., Schaffie, M. & Ashena. R . (2011). Development of Neural Fuzzy System for Advanced Prediction of Bottomhole Circulating Pressure in Underbalanced Drilling Operations. Journal of Petroleum Science and Technology, vol. 29, no. 21, pp. 2282–2292.

[18] Yurdakul, M., Ceylan, H. & Akdas. H. (2011). A predictive model for Uniaxial compressive strength of carbonate rocks from Schmidt hardness. The 45th US Rock Mechanics/Geomechanics Symposium. San Francisco, CA, June 26–29, 2011.

[19] Martins, F., Begonha, A. & Braga, M. (2012). Prediction of the mechanical behavior of the Oporto granite using Data Mining techniques. Expert Systems with Applications, vol. 39, pp. 8778–8783.

[20] Mishra, D. A. & Basu, A. (2013). Estimation of uniaxial compressive strength of rock materials by index tests using regression analysis and fuzzy inference system. Engineering Geology, vol. 160, pp. 54–68.

نشریه هوش مصنوعی و داده کاوی

پیش‌بینی پارامترهای مقاومتی سنگ در یکی از میادین نفت ایران با استفاده از روش فازی-عصبی

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چکیده:

مقاومت فشاری تک محوری و ضریب اصطکاک داخلی مهم‌ترین پارامترهای مقاومتی سنگ هستند. این پارامترها هم می‌توانند توسط روش‌های آزمایشگاهی و هم توسط روابط تجربی تعیین شوند. در اغلب موارد، به دلایل مختلف، انجام آنالیزهای آزمایشگاهی مقدور نیست. از طرف دیگر، بدلیل تغییر ترکیب و خواص سنگ، هیچ یک از معادلات تجربی نمی‌تواند به عنوان یک رابطه جامع دقیق مورد استفاده قرار گیرد. در چنین شرایطی، روش پیشنهادی هوش‌مصنوعی می‌تواند گزینه مناسبی برای تخمین پارامترهای مقاومتی باشد. در این کار، سیستم تطبیقی عصبی- فازی،که یکی از تکنیک-های هوش‌مصنوعی می‌باشد، به عنوان ابزار اصلی در پیش‌بینی خواص مقاومتی یکی از میادین نفتی جنوب غرب ایران مورد استفاده قرار گرفت. بطور کلی، تعداد ۶۵۵ دسته داده (شامل عمق، سرعت موج تراکمی و داده های دانسیته) مورد استفاده قرار گرفت. از این میان، تعداد۴۳۶ و ۲۱۹ دسته داده بطور تصادفی به ترتیب برای ایجاد و اعتبارسنجی مدل هوشمند پیشنهادی انتخاب شدند.

برای ارزیابی عملکرد مدل، ریشه میانگین مربعات خطا (RMSE) و ضریب وابستگی(R2) بین داده‌های گزارش شده از سایت حفاری و داده‌های تخمین زده شده توسط مدل، محاسبه شدند. مقایسه بین RMSE حاصل از مدل پیشنهادی و سایر مدل‌های هوشمند اخیر نشان می‌دهد مدل پیشنهادی بسیار دقیق‌تر از سایر مدل‌هاست. دقت قابل قبول و استفاده از داده‌های چاه نگاری مرسوم ویژگی‌های بارز مدل هوشمند پیشنهادی می‌باشند.

کلمات کلیدی: مقاومت فشاری تک محوره، ضریب اصطکاک داخلی، چاه پیمایی، سیستم تطبیقی عصبی- فازی.