



Real-time static Poisson's ratio prediction of vertical complex lithology from drilling parameters using artificial intelligence models

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Abstract

The experimental Poisson's ratio prediction is time-consuming and expensive and resulted in discontinuous profile. Besides, the limited applicability of the existing empirical correlations highlights the application of artificial intelligence with its booming utilization in petroleum industry. The purpose of this work is to develop several artificial intelligence models for predicting real-time static Poisson's ratio of complex lithology while drilling. The artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM) techniques were utilized using the drilling parameters as inputs. Data points (1775) from a vertical well, containing sand, shale, and carbonate lithologies, were used to develop the models. The models were validated using different dataset from another well. New empirical correlation was extracted based on the optimized ANN approach. The three developed models predicted the static Poisson's ratio at good matching accuracy. The correlation coefficient (R) and average absolute percentage error (AAPE) of the developed models range from 0.95 to 0.96 and 2.18 to 5.79% for training process, respectively, while in testing process, the R and AAPE values range from 0.92 to 0.93 and 5.81 to 6.74%. The validation process confirmed the reliability of the developed models with R values of 0.90, 0.91, and 0.90 and AAPE of 6.57, 7.25, and 8.12% for SVM, ANFIS, and ANN approaches, respectively. The developed ANN-based model was switched into a white box model with new empirical correlation, which is applicable with the extracted weights and biases. The constructed models can predict inexpensively the static Poisson's ratio for multiple lithologies in real-time at reasonable accuracy.

Keywords Poisson's ratio · Complex lithology · Artificial neural network · Adaptive neuro-fuzzy inference system · Support vector machine · Drilling parameters

Introduction

Poisson's ratio (ν) is a geomechanical feature defined as the ratio between lateral and longitudinal deformation. It is an elastic property that identifies the ability of the rock to recover from a deformation caused by external forces and define the relationship between these forces and the resulted deformation (Fjar et al. 2008). Poisson's ratio with the others rock elastic properties has an essential role in hydraulic fracturing design, in situ stresses estimation, drilling performance, and wellbore stability

(Kumar 1976; Labudovic 1984; Nes et al. 2005; Hammah et al. 2006). Hence, prediction of Poisson's ratio is highly important for developing well planning, drilling optimization, and completion and production strategies development.

Practically, Poisson's ratio is ranging from 0.0 to 0.5 and either determined from compressional tests on core plug samples which known as static Poisson's ratio (ν_{st}) or derived from shear and compressional wave velocities from well logs that resulted in dynamic Poisson's ratio (ν_{dyn}). For the static property, laboratory experiments on cores are expensive and cannot provide a continuous geomechanical profile; therefore, some empirical correlations were developed depending on the dynamic Poisson's ratio (ν_{dyn}) and compressional and/or shear-wave velocities (V_p , V_s).

Christaras et al. (1994) proposed a correlation (Eq. (1)) between static and dynamic Poisson's ratios (ν_{st} and ν_{dyn}) using 8 samples from different rock types (i.e., limestone, gypsum, basalts, granite, phonolite, and andesite). The

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correlation coefficient (R) of this model in the specified rock types is 0.737.

$$\nu_{st} = 0.71 \nu_{dyn} + 0.063, \quad (1)$$

Feng et al. (2019) followed the same approach and obtained a linear model (Eq. (2)) correlating the static and dynamic Poisson's ratios (ν_{st} and ν_{dyn}). Samples from sandstone and siltstone rocks (18 samples) were used with empirical parameters (a and b) change with the porosities. The coefficient of determination of this model is 0.92 and 0.7 for modeling and testing samples, respectively.

$$\nu_{st} = a \nu_{dyn} - b, \quad (2)$$

While Wang et al. (2009) used the compressional and shear-wave velocities (V_p and V_s) to develop two correlations for static Poisson's ratio (ν_{st}) prediction (Eqs. (3) and (4)) at several rock types. The used empirical coefficients (a, b, c, and d) vary with different rock types. The R values range from 0.467 to 0.834 and 0.668 to 0.914 for the two models, respectively.

$$\nu_{st} = a V_p + b, \quad (3)$$

$$\nu_{st} = c V_s + d, \quad (4)$$

The reliability and accuracy of these empirical correlations are limited with the few core samples from specific rock types and the availability of the compressional and shear-wave velocities. Moreover, the need for continuous prediction of Poisson's ratio and geomechanical profile using convenient method with high accuracy highlights the use of artificial intelligence (AI), since the AI techniques become hotspot and can be utilized to perform analysis of huge data and trends interpretation in least time and effort with less cost and errors (Agwu et al. 2018; Gomaa et al. 2020).

The applications of AI techniques in petroleum industry has been presented since early 1990s and used to predict several related parameters in different areas (Popa and Cassidy 2012; Bello et al. 2015). Many researchers used the AI in exploration for different prediction, such as feature recognition (Guo et al. 1992), travel time computation (Kononov et al. 2007; Elkatatny et al. 2016b, 2018c; Tariq et al. 2016; Gowida and Elkatatny 2020), and resolution and clarity of

Table 1 The developed AI models for static Poisson's ratio prediction

Author(s)	Inputs	AI techniques	No. of data points	Remarks
Abdulraheem et al. (2009)	Travel time and bulk density	ANN, FL, and FN	77	$R = 0.10 - 0.91$
Al-anazi et al. (2011)	Depth, porosity, overburden stresses, pore pressure, minimum horizontal stresses, bulk density, compressional and shear travel times	ACE	602	$R = 0.997$
Tariq et al. (2017)	Compressional and shear wave velocities	ANN	550	•Carbonate rocks • $R = 0.985$
Elkatatny et al. (2017a)	Bulk density, compressional and shear times	ANN	610	•Carbonate rocks • $R = 0.985$
Elkatatny et al. (2018a)	Sonic travel times and bulk density	ANN, ANFIS, and SVM	610	•Carbonate rocks • $R = 0.933 - 0.985$
Tariq et al. (2018)	Gamma ray, bulk density, porosity, compressional and shear wave velocities	FN	580	•Carbonate rocks • $R = 0.985$
Abdulraheem (2019)	Compressional and shear wave velocities	ANN and FL	75	•Carbonate rocks •AAPE* = 5.16 - 8.20%
Gowida et al. (2019a)	Bulk density and sonic log	ANN coupled with DE**	692	•Sandstone • $R = 0.964$

*AAPE average absolute percentage error

**DE differential evolution algorithm

Table 2 Statistical analysis for the collected dataset

Parameter	WOB (klb _m)	T (klb _f .ft)	SPP (psi)	RPM	ROP (ft/h)	Q (gal/min)	ν_{st}
Minimum	1.54	4.55	2140.20	77.94	27.41	697.31	0.17
Maximum	25.48	10.68	3075.56	162.49	119.57	854.01	0.43
Mean	15.41	7.83	2634.45	138.61	76.37	803.13	0.25
Mode	1.54	4.55	2140.20	77.94	27.41	697.31	0.17
Median	16.33	8.26	2685.07	139.16	79.90	809.79	0.20
Standard deviation	6.44	1.65	205.69	11.10	19.16	48.44	0.08
Skewness	-0.38	-0.37	-0.78	-1.98	-0.55	-1.20	0.51
Kurtosis	2.16	1.92	2.52	10.77	2.40	3.17	1.39

seismic data improvement (Ross 2017). For drilling aspects, many AI models were developed for prediction of drilling parameters and mud properties (Wang and Salehi 2015; Elkatatny et al. 2016a; Elkatatny 2016, 2018, 2019, 2020; Elkatatny and Mahmoud 2017; Elkatatny et al. 2017b; Abdelgawad et al. 2018; Al-Azani et al. 2018; Al-Abduljabbar et al. 2018; Elzenary et al. 2018; Abdelgawad et al. 2019; Ahmed et al. 2019; Gowida et al. 2019b, 2020a; Hassan et al. 2019a; Al-abduljabbar et al. 2020b; Gomaa et al. 2020). The AI was also applied in both reservoir and production engineering for several parameters estimation such as the prediction of reservoir properties, production rate, inflow performance, and many others (Ali et al. 2014; Ahmadi et al. 2015a, 2015b; Shokooh Saljooghi and Hezarkhani 2015; Alakbari et al. 2016; Oloso et al. 2017; Elkatatny and Mahmoud 2018a, 2018b; Elkatatny et al. 2018a, 2018b, 2018d; Mahdiani and Norouzi 2018; Moussa et al. 2018; Wood and Choubineh 2018; Hassan et al. 2019a, 2019b; Gowida et al. 2020b; Al-abduljabbar et al. 2020a; Khalifah et al. 2020; Wood 2020).

For application of AI in static Poisson’s ratio estimation, several models were developed using different AI techniques such as artificial neural network (ANN), fuzzy logic (FL), functional networks (FN), alternating conditional expectation

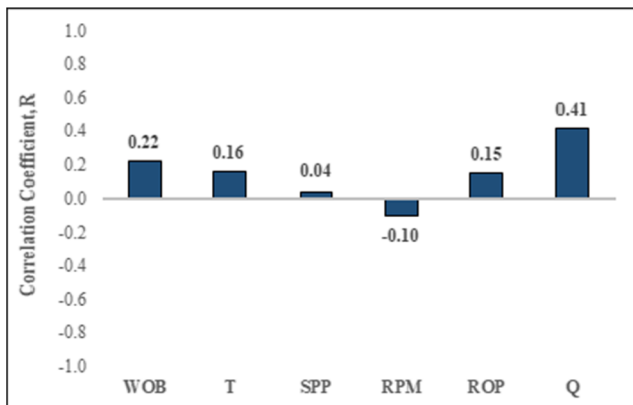


Fig. 1 Correlation coefficient between static Poisson’s ratio and drilling parameters

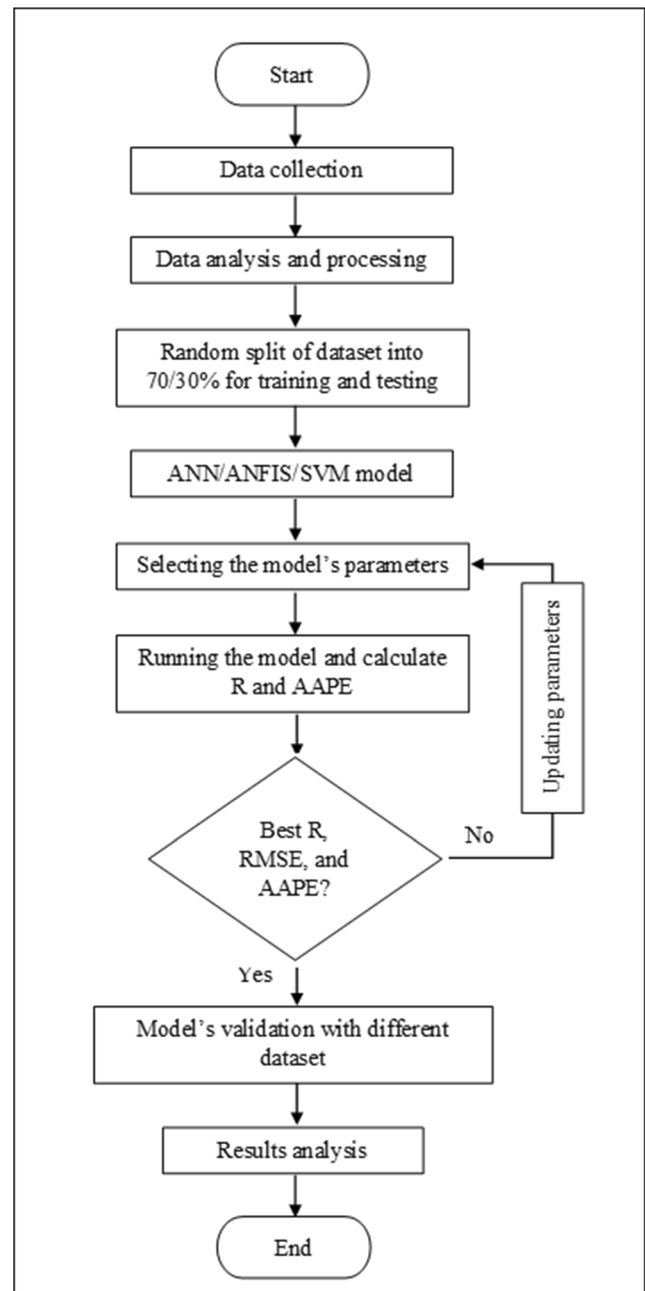


Fig. 2 Flowchart of developing the AI models

Table 3 Optimum set of parameters for the ANN model

Parameter	Value
Number of hidden layers	1
Number of neurons	35
Learning rate	0.12
Network function	Feed forward neural network (newff)
Training function	Bayesian regularization backpropagation (trainbr)
Transfer function	Hyperbolic tangent sigmoid (tansig)

(ACE), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM), as listed in Table 1.

From practical point of view, it is known that the drilling parameters, such as weight on bit (WOB), standpipe pressure (SPP), torque (T), rotation speed (RPM), rate of penetration (ROP), and pumping rate (Q), are related to the drilled formation characteristics (Bourgoyne et al. 1986; Mensa-Wilmot et al. 1999; González et al. 2018); therefore, the change in formation type can be accounted via the change in drilling parameters since they are linked to each formation signature. Accordingly, these parameters can be correlated to the geomechanical properties such as the static Poisson’s ratio as well and getting the beneficial for the availability of real-time measurements of these drilling parameters.

This work aims to develop several robust models for predicting real-time static Poisson’s ratio (ν_{st}) of vertical complex lithology while drilling. The ANN, ANFIS, and SVM techniques were utilized and the mechanical drilling parameters (i.e., WOB, T, SPP, RPM, ROP, and Q) were used as inputs. Also, a new empirical correlation was targeted by converting the optimized ANN model into a white box model. Developing a model that can be used in real-time regardless of the formation type and well logs data is advantageous, unlike

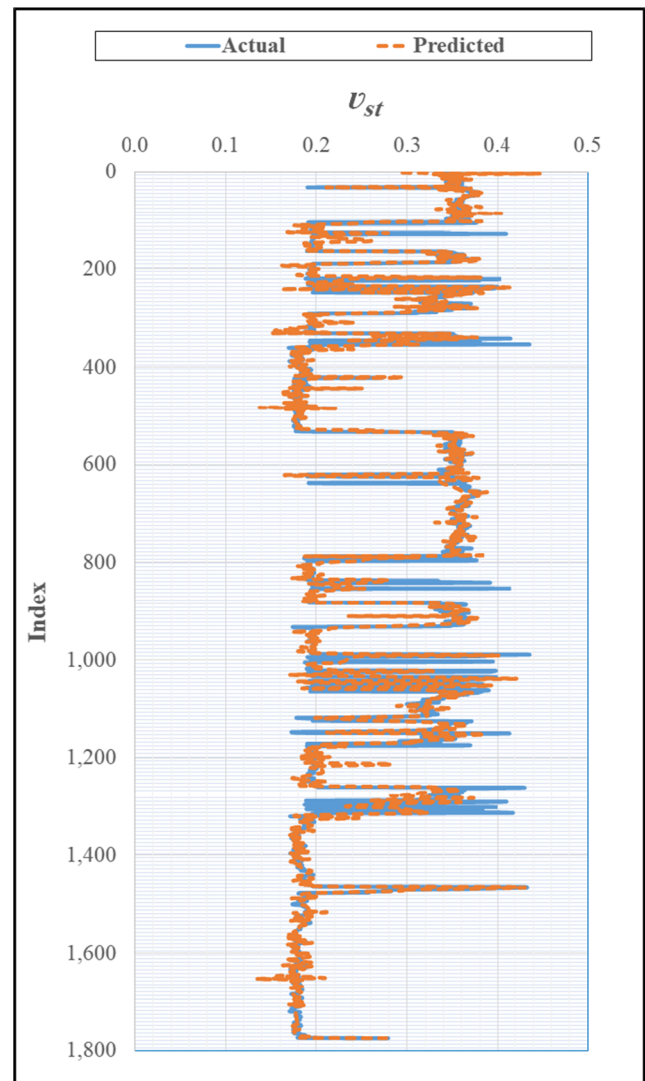


Fig. 4 Graphical presentations of actual and ANN-based predicted static Poisson’s ratio

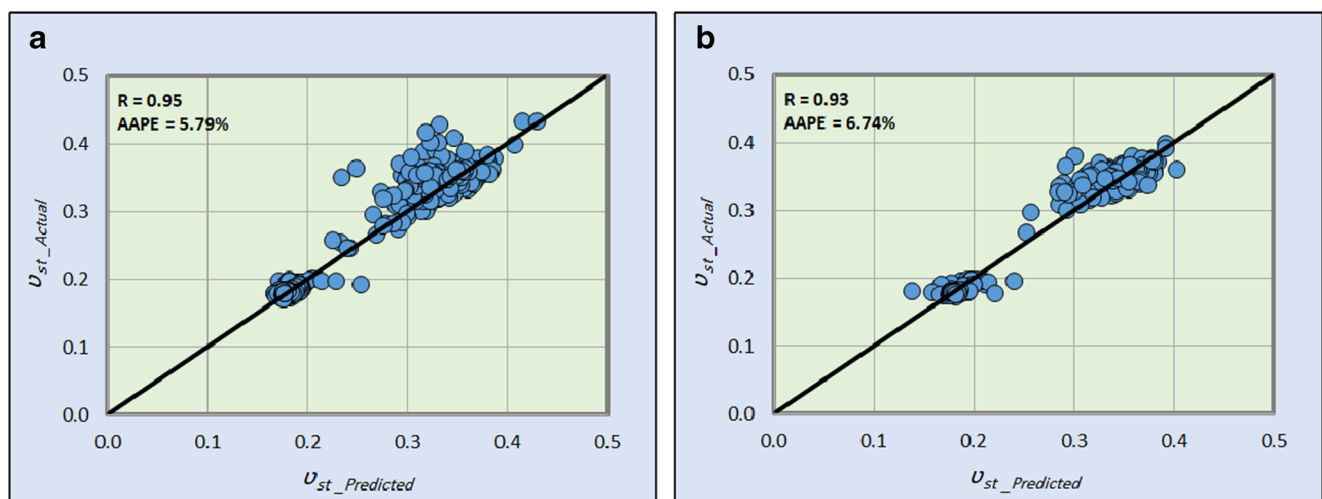


Fig. 3 Cross plots of actual and ANN-based predicted static Poisson’s ratio for (a) training and (b) testing

Table 4 Extracted weights and biases for the developed empirical correlation

i	$w_{1i, WOB}$	$w_{1i, T}$	$w_{1i, SPP}$	$w_{1i, RPM}$	$w_{1i, ROP}$	$w_{1i, Q}$	w_{2i}	b_i
1	-2.062	2.015	-5.926	2.329	1.069	2.853	3.89	-1.648
2	-1.856	0.521	1.415	-1.160	-3.966	1.501	3.475	-0.032
3	-2.064	0.908	0.433	-3.503	-5.191	2.730	-2.39	1.228
4	0.771	-1.496	3.357	-4.126	2.664	1.511	2.965	1.193
5	3.061	-2.875	5.329	1.011	-1.517	0.077	-3.16	-0.935
6	0.467	0.999	2.312	0.057	3.567	1.408	-2.84	-0.391
7	-2.532	4.010	-5.220	0.177	0.811	1.304	-5.44	-0.989
8	-2.146	4.805	-2.168	0.905	0.009	0.019	3.142	-1.068
9	1.368	2.495	1.791	-0.862	-2.804	-3.250	2.425	1.238
10	-0.100	0.417	-0.771	-0.896	2.403	0.824	-2.72	1.338
11	-0.250	-0.242	0.049	0.014	3.502	-0.116	3.532	0.303
12	0.492	-1.333	2.644	0.746	-0.416	-4.056	4.272	1.381
13	-1.433	2.905	0.878	-1.986	1.081	1.013	-2.99	-0.628
14	4.591	-1.253	-2.219	-0.611	-1.331	-0.384	-2.25	1.084
15	1.758	-0.492	1.330	3.819	0.184	0.027	2.579	-1.867
16	0.033	-1.047	-0.865	-0.337	1.733	-1.683	1.962	-0.639
17	3.941	-1.223	-2.851	-0.694	4.521	-1.451	-2.95	-1.419
18	1.359	3.570	-1.241	0.670	0.809	-0.993	3.777	2.555
19	-2.053	-3.476	-1.679	2.581	-0.025	3.580	-2.45	-1.028
20	3.971	1.996	-2.435	-0.913	3.102	0.098	1.99	-0.024
21	-1.151	-2.433	-0.751	3.145	-4.604	-0.722	-2.73	0.933
22	-1.032	1.854	-0.192	2.512	-1.100	1.496	-3.42	-0.187
23	-2.849	-1.940	1.760	0.463	-2.952	-0.364	-3.67	3.070
24	-5.087	-4.170	0.065	0.523	2.145	0.567	-2.16	-2.826
25	1.024	1.740	0.237	-3.536	5.217	-0.216	-2.89	-0.162
26	1.466	2.828	-3.879	-1.035	-2.687	2.143	-3.31	3.243
27	1.258	0.010	-0.968	0.979	0.883	-0.142	-1.59	0.262
28	-1.061	0.425	-3.149	-2.133	-2.658	0.841	5.007	1.574
29	1.398	-3.072	1.490	1.398	2.823	3.666	2.955	-3.644
30	-4.401	2.930	-1.133	0.176	0.116	-1.802	-2.83	2.179
31	0.976	-0.084	1.214	-0.503	0.223	3.811	3.619	0.479
32	-1.304	-0.600	1.736	4.048	0.704	-1.403	-2.61	-1.116
33	2.584	-1.074	0.189	2.499	0.099	-0.928	-2.45	-1.081
34	2.476	-0.506	-0.119	-1.682	-0.218	-0.043	-2.97	-1.183
35	-2.593	-3.158	0.212	1.656	3.367	0.840	2.12	-0.164

the existing models where each one requires logging measurements and is applicable for a particular formation. Moreover, the models will provide a continuous profile which solve the issue of missing data and reduce the experimental cost.

Methodology

Data description

A set of data containing more than 1775 data points was obtained from an intermediate section with 12.25"-hole diameter of a vertical well that has a complex lithology containing sand,

shale, and carbonate. This dataset included the real-time drilling mechanical parameters (i.e., WOB, T, SPP, RPM, ROP, and Q) which measured at the surface while drilling and the corresponding static Poisson's ratio from core experiments and conventional logs. The drilling parameters were used with their field units to feed the proposed models as inputs to predict the static Poisson's ratio as output.

Data analysis and processing

To check for data representation, reliability, and quality, the collected dataset was analyzed and processed before applying the AI techniques. The statistical analysis was performed by

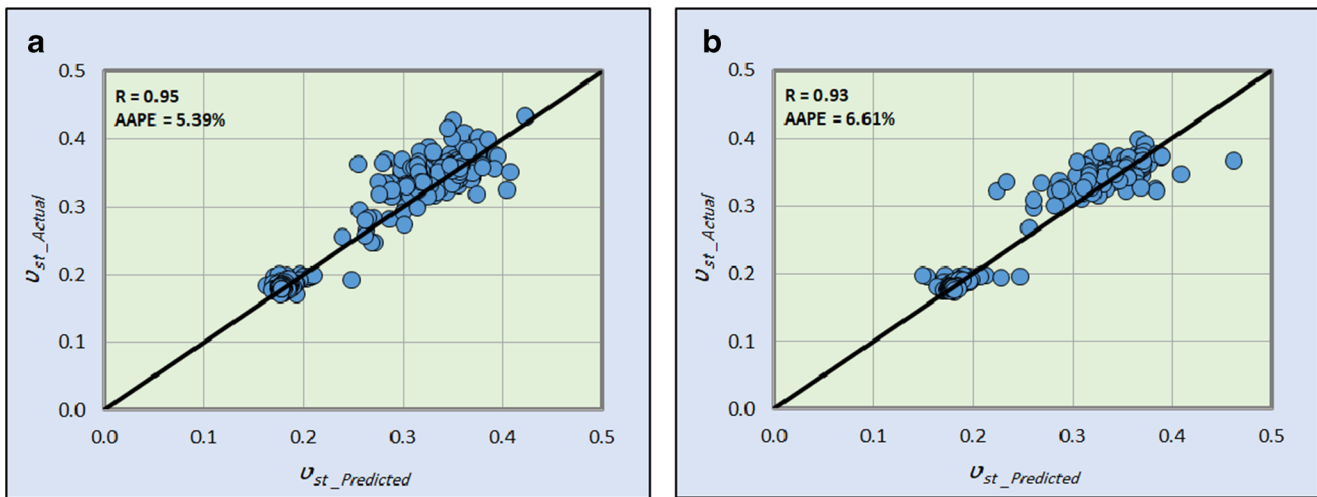


Fig. 5 Cross plots of actual and ANFIS-based predicted static Poisson's ratio for (a) training and (b) testing

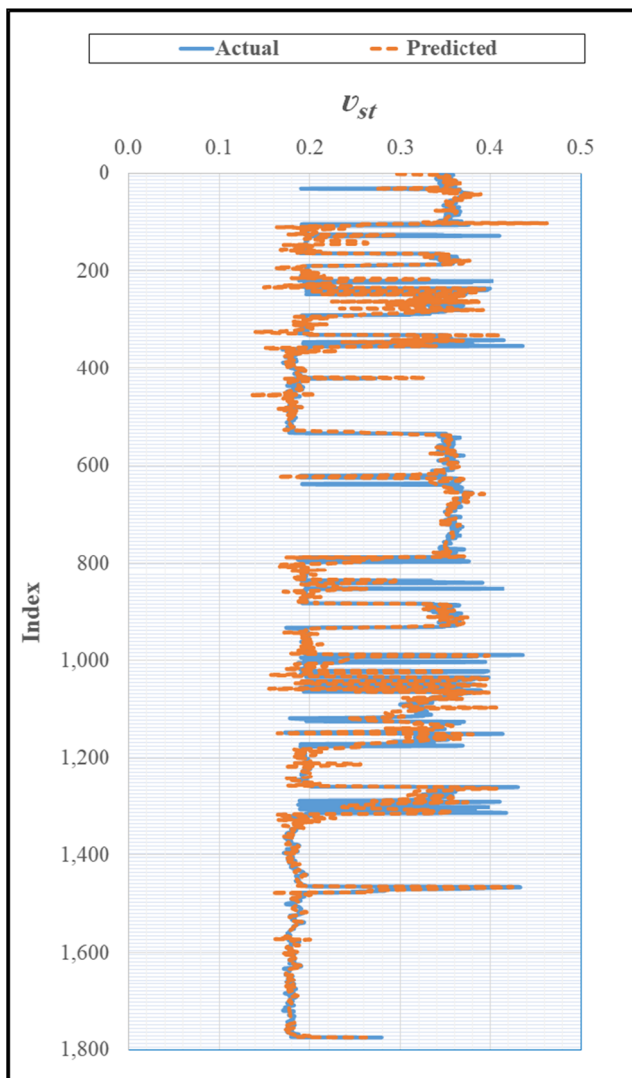


Fig. 6 Graphical presentations of actual and ANFIS-based predicted static Poisson's ratio

identifying the values of minimum, maximum, mean, mode, median, and dispersion parameters such as standard deviation, skewness, and kurtosis, as summarized in Table 2. The analysis showed that the dataset covered a wider range of mechanical drilling parameters and static Poisson's ratio and reflected good data representation and distribution.

Moreover, the strength of linear relationship between each drilling parameter and static Poisson's ratio was studied by calculating the correlation coefficient (R) to measure how each drilling parameter is relatively important for the static Poisson's ratio, as depicted in Fig. 1. The high R values of Q and WOB reflected their importance to v_{st} , whereas the T, RPM, and ROP showed lower R values. Although the correlation coefficient between the v_{st} and SPP is very small, the SPP behaves similarly to the other drilling parameters and varies significantly with changing in the static Poisson's ratio. As a result, all drilling parameters will be accounted as inputs.

To enhance the confidence and quality for the selected dataset, it was filtered and cleaned to eliminate noises, unrealistic values, and outliers. The dataset was processed using the practical ranges of drilling parameters, tools limitations, and statistical descriptions. The erroneous data such as negative and NaN values and missing data were eliminated. The outliers that show significant deviation from the other values of a variable were investigated to understand their underlying cause, and then the values beyond the three standard deviations away from the mean or outside the practical ranges were removed. The preprocessing approaches make the data ready for use in AI model development.

Models development

The filtered dataset was randomly split into 70% (1243 data points) to train the models and 30% (532 data points) for testing. Then, three supervised learning AI approaches (i.e., ANN, ANFIS, and SVM) were applied using MATLAB

Table 5 Optimum set of parameters for the SVM model

Parameter	Kernel-function	Kernel-option	Lambda	Epsilon	Regularization	Verbose
Value	Gaussian	10	1×10^{-5}	1×10^{-4}	100	1

software. The optimum parameters and functions in each model were selected by performing several tuning and sensitivity analyses. The developed models were then validated using different dataset.

The ANN, ANFIS, and SVM supervised learning techniques were selected to be applied as they were recently used in petroleum industry (Anifowose et al. 2015; Tariq et al. 2017; Gowida et al. 2019a, 2020b; Gowida and Elkhatny 2020) with promising outcomes.

The ANN is based on several neurons connected with proper weights and biases within a network to simulate the biological neural networks (Rao and Ramamurti 1993; Nakamoto 2017). This technique constitutes of three layers (i.e., input, hidden, and output layers) connected by using transfer functions and trained with different training functions (Lippmann 1987; Niculescu 2003). The back-propagation approach is used to identify the weights and biases in this system (Hinton et al. 2006; Yagiz et al. 2012). Different scenarios for number of neurons and function types of network, training, and transfer were examined to obtain the optimum parameters.

ANFIS technique processes data based on fuzzy inference approach (Jang 1993). It integrates the fuzzy logic concepts with neural networks system (Walia et al. 2015) and applies fuzzy “If-Then” rules to analyze the network. This tool defines the inputs and the targeted output and then assigns fuzzy rules to train and optimize the network (Tahmasebi and Hezarkhani 2012; Walia et al. 2015). Grid partitioning and subtractive clustering functions with various cluster radius sizes and several numbers of iterations were examined.

The SVM is applied generally for classification, regression, and complicated problems. It minimizes the generalization errors using a statistical learning algorithm and multidimensional hyperplane (Anifowose et al. 2015; Gowida et al. 2020b). The outcomes accuracy depends on the tuning process of its parameters. Several kernel functions were examined at different values of kerneloption, lambda, epsilon, regularization, and verbose parameters to develop the best model.

The optimality of each model was evaluated using the correlation coefficient (R) and average absolute percentage error (AAPE), where the highest R values and lowest AAPE are desired.

A simplified flowchart for the methodology of developing AI models is shown in Fig. 2.

Results and discussion

ANN model

The tuning process for the parameters showed that the best model is obtained with the optimized set of parameters listed in Table 3 with 35 neurons in one hidden layer.

The best obtained ANN-based model showed good fitting accuracy that indicated by R values of 0.95 and 0.93 and AAPE of 5.79 and 6.74% for training and testing, respectively. The good match was pointed by the cross plots and graphical presentations of actual and predicted static Poisson’s ratio, as shown in Fig. 3 and Fig. 4.

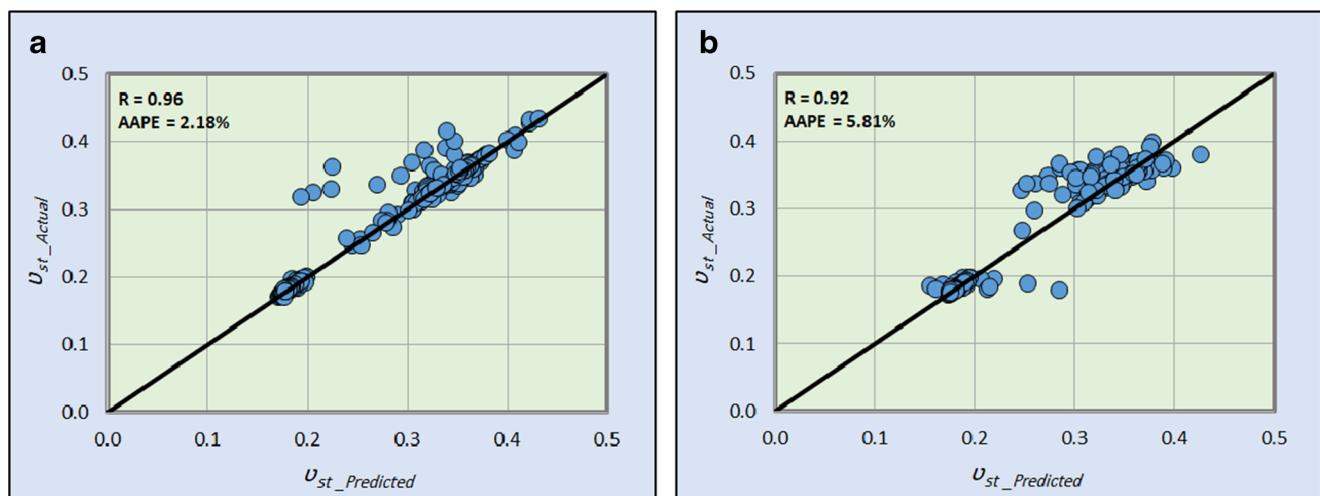


Fig. 7 Cross plots of actual and SVM-based predicted static Poisson’s ratio for (a) training and (b) testing

The constructed ANN-based model was transformed into white box model by deriving the optimized weights and biases, as presented in Table 4. These extracted weights and

biases were used to develop a new empirical correlation as derived herein Eq. (5).

$$v_{st} = \left[\frac{\sum_{i=1}^{NN} w_{2i} \left(\frac{2}{1 + \text{EXP}(-2(w_{1i,WOB} \times WOB + w_{1i,T} \times T + w_{1i,SPP} \times SPP + w_{1i,RPM} \times RPM + w_{1i,ROP} \times ROP + w_{1i,Q} \times Q + b_i))} - 1 \right) \right] + 0.679, \quad (5)$$

where i represents the neuron index, NN is the total neurons number in the hidden layer, w_1 and w_2 are the weights of the input and output layers, and b_i is the biases of the input layer. This new developed correlation can be applied directly using the extracted weights and biases without running the AI tool.

ANFIS model

The obtained results indicated that the subtractive clustering function with 0.2 cluster radius size and 150 iterations had the highest matching accuracy with R values of 0.95 and 0.93 and AAPE of 5.39 and 6.61% for training and testing, respectively. Figures 5 and 6 described the matching in the cross plots and graphical presentations of actual and predicted static Poisson's ratio, respectively.

SVM model

The sensitivity analysis for the tuning parameters resulted in the optimum SVM-based model with the set of tuned parameters listed in Table 5.

The obtained SVM-based model showed remarkable matching accuracy, as the R values are 0.96 and 0.92 and AAPE values are 2.18 and 5.81% for training and testing, respectively. This matching accuracy was highlighted by the cross plots and graphical presentations of actual and predicted static Poisson's ratio, as depicted in Fig. 7 and Fig. 8.

Models validation

The developed ANN-, ANFIS-, and SVM-based models were validated using new dataset from the same tested area. The set of validation contained 755 data points with drilling parameters and corresponding static Poisson's ratio.

The outputs indicated that applying the developed models for the validation dataset had reasonable accuracy with R values of 0.90, 0.91, and 0.90 and AAPE of 8.12, 7.25, and 6.57% for ANN-, ANFIS-, and SVM-based models, respectively. These

outcomes confirm the applicability and firmness of these models. The cross plots and graphical presentations of actual and predicted static Poisson's ratio are depicted in Fig. 9 and Fig. 10.

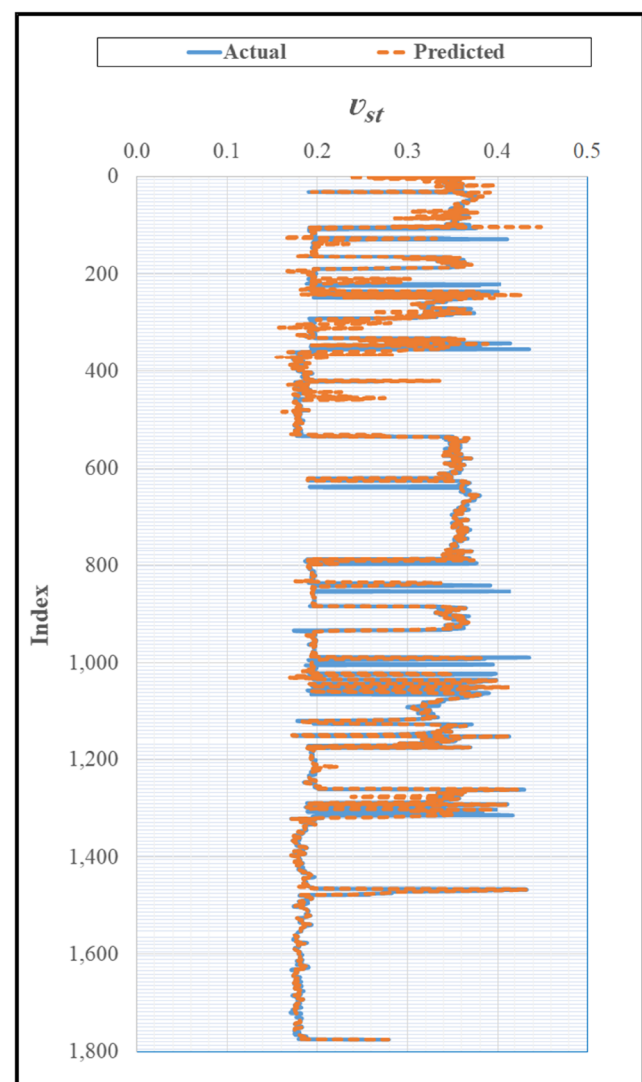


Fig. 8 Graphical presentations of actual and SVM-based predicted static Poisson's ratio

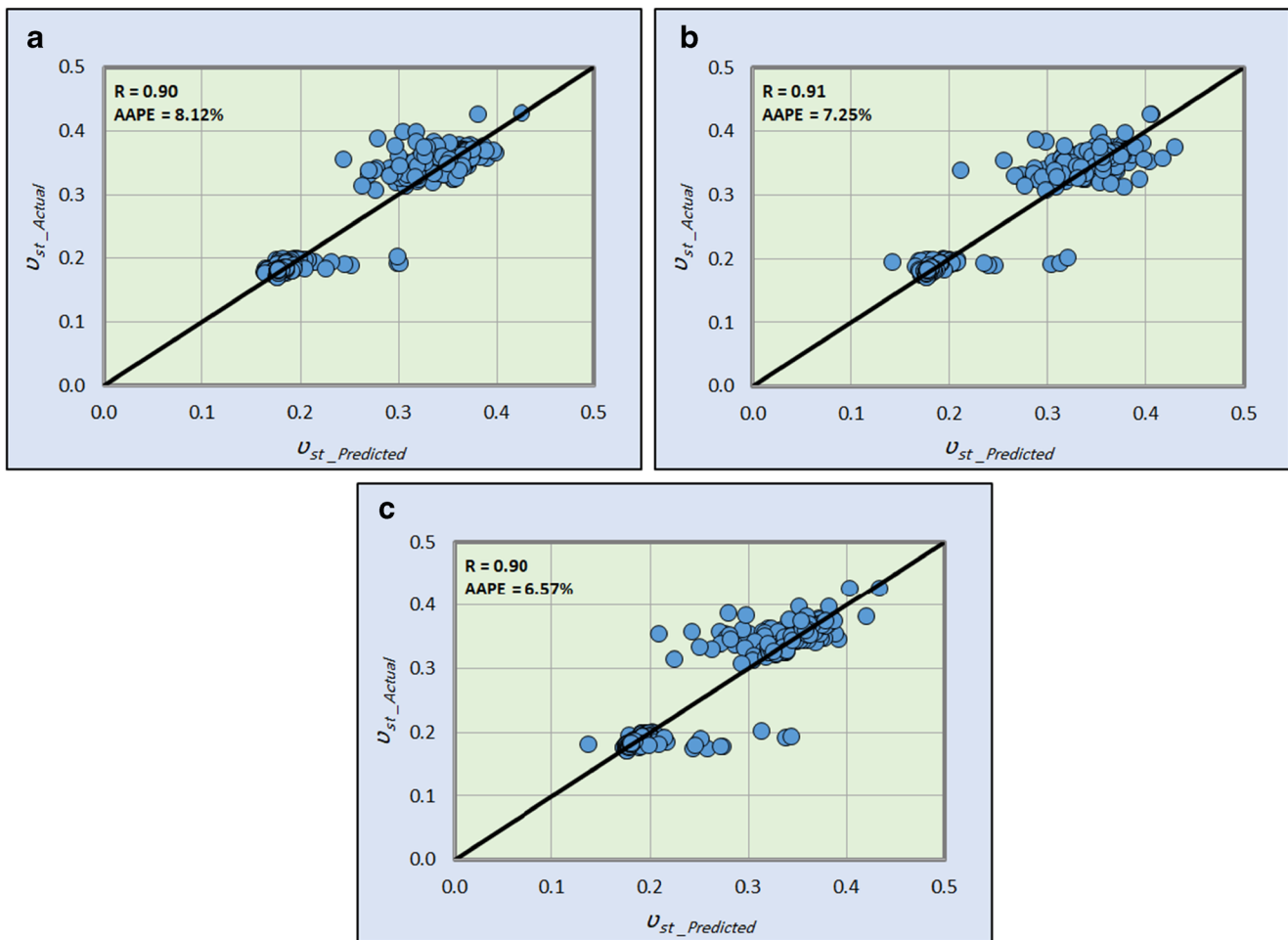


Fig. 9 Cross plots of actual and predicted static Poisson's ratio for validation using (a) ANN, (b) ANFIS, and (c) SVM

Discussion

This work addresses the benefits of predicting a geomechanical property (i.e., static Poisson's ratio) using the AI techniques, reducing the experimental cost and solving the issue of missing data to provide a continuous profile. It also presents an example of using real field data for scientific research and improvement in this scientific and professional field.

Tuning process using an iteration method was carried out to optimize the models' parameters. As a result, the best prediction in ANN technique was obtained with 35 neurons for one hidden layer and using newff, trainbr, and tansig as network, training, and transfer functions, respectively, with 0.12 learning rate, while the subtractive clustering function with 0.2 cluster radius size and 150 iterations was the optimum parameter for ANFIS approach. For the SVM, the optimum parameters were the Gaussian function, kernel option of 10, lambda of $1e-5$, epsilon of $1e-4$, regularization of 100, and verbose of 1.

The obtained results from the three models were evaluated based on the correlation coefficient, errors represented by the AAPE, and the plots and graphical representations. Accordingly, all the developed models can predict the real-time static Poisson's ratio with significant matching accuracy.

Since the prediction of continuous profile of static Poisson's ratio from experiment is highly expensive, the developed models can predict it in real-time and convenient method within the least time, effort, cost, and errors. Nevertheless, the limitations of this work were represented in the available data range for the variables, since these models were applied for the intermediate hole section and need to be investigated for the whole well sections with wider lithology types. Moreover, it is recommended to investigate the application of the other AI approaches in future work using a hybrid model instead of iteration methods for improving the models' parameters selection.

From comparison between the developed models, all of them can predict the real-time static Poisson's ratio with

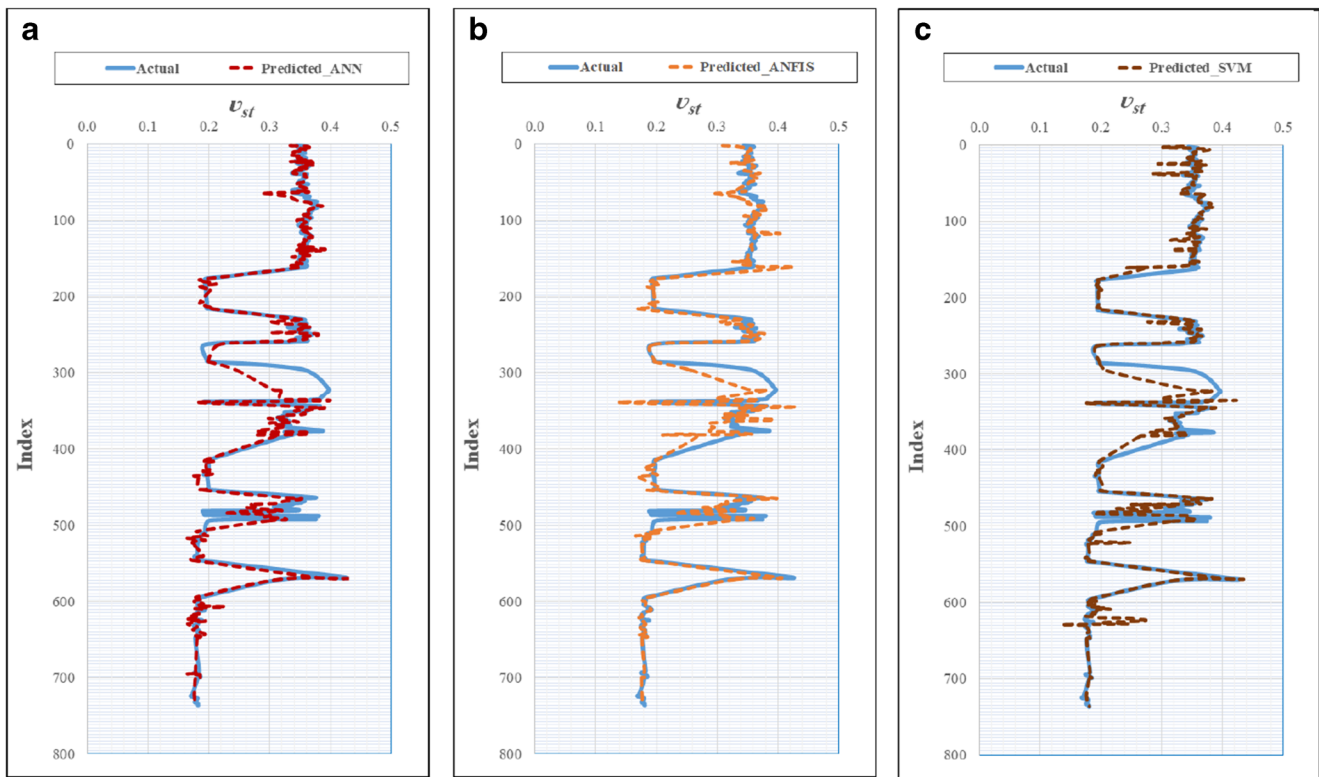


Fig. 10 Graphical presentations of actual and predicted static Poisson’s ratio for validation. **a** ANN **b** ANFIS **c** SVM

significant matching accuracy; however, the SVM technique gives better prediction with lower AAPE values, as indicated in Fig. 11. The matching accuracy indicators for the three models were summarized in Table 6.

Conclusions

In this work, different AI models were developed for real-time prediction of static Poisson’s ratio using mechanical drilling parameters (WOB, T, SPP, RPM, ROP, and Q). The ANN, ANFIS, and SVM techniques were applied in real field measurements from a vertical well with complex lithology containing sand, shale, and carbonate. The outcomes of this study are concluded as following:

- All models successfully predicted the static Poisson’s ratio with slightly outperformance in SVM technique comparing to the ANN and ANFIS approaches.
- The significant matching accuracy of the SVM-based model is indicated by the *R* values of 0.96 and 0.92 and AAPE of 2.18 and 5.81%, while the ANN and ANFIS techniques give *R* values of 0.95 and 0.93 and AAPE

- range of 5.39–5.79% and 6.61–6.74% in both training and testing processes, respectively.
- The reliability of the three models is evaluated using different dataset and resulted in remarkable accuracy with *R* values of 0.90, 0.91, 0.901, and 0.04 and AAPE of 8.12, 7.25, and 6.57% for ANN, ANFIS, and SVM techniques, respectively.
- A new empirical correlation for predicting the static Poisson’s ratio was extracted from the developed ANN white box model, and it can be used without the need for the ANN code.

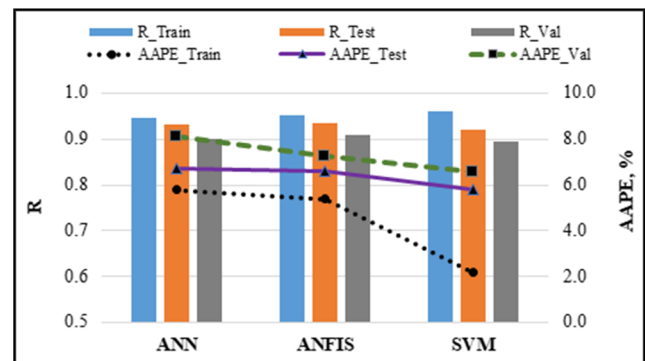


Fig. 11 Comparison between the developed models

Table 6 Summary of the matching accuracy for the developed models

AI approach	<i>R</i>			AAPE, %		
	Training	Testing	Validation	Training	Testing	Validation
ANN	0.95	0.93	0.90	5.79	6.74	8.12
ANFIS	0.95	0.93	0.91	5.39	6.61	7.25
SVM	0.96	0.92	0.90	2.18	5.81	6.57

Abbreviations AAPE, average absolute percentage error; ACE, alternating conditional expectation; AI, artificial intelligence; ANFIS, adaptive neuro-fuzzy inference system; ANN, artificial neural network; DE, differential evolution algorithm; FL, fuzzy logic; FN, functional networks; newff, feed forward neural network function; ROP, rate of penetration, ft/h; RPM, rotation speed, rotation per minute; SPP, standpipe pressure, psi; SVM, support vector machines; T, torque, klb_r.ft; tansig, hyperbolic tangent sigmoid transfer function; trainbr, Bayesian regularization backpropagation training function; WOB, weight on bit, klb_m

Symbols *a*, *b*, *c*, and *d*, different empirical constants; *b_i*, biases of input layer; *i*, neuron index; *NN*, number of neurons; *Q*, pumping rate, gal/minute; *R*, correlation coefficient; *V_p*, compressional-wave velocity, km/s; *V_s*, shear-wave velocity, km/s; *V_{sh}*, shale volume factor; *v_{dym}*, dynamic Poisson's ratio; *v_{st}*, static Poisson's ratio; *w₁*, weights between input and hidden layers; *w₂*, weights between hidden and output layers

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Declarations

Conflict of interest The authors declare no competing interests.

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