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Bayesian prediction of rotational torque to operate horizontal drilling

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Abstract

Horizontal directional drilling is usually used in drilling engineering. In a variety of conditions, it is necessary to predict the torque required for performing the drilling operation. Nevertheless, there is presently not a convenient method available to accomplish this task. In order to overcome this difficulty, the current work aims at predicting the required rotational torque (RT) to operate horizontal directional drilling on the 7 effective parameters including the length of drill string in the borehole (L), axial force on the cutter/bit (P), total angular change of the borehole (KL), radius for the i^{th} reaming operation (D_i), rotational speed (rotation per minute) of the bit (N), mud flow rate (W), and mud viscosity (V). In this paper, we propose an approach based on the model selection criteria such as various statistical performance indices mean squared error (MSE), variance account for (VAF), root mean squared error (RMSE), squared correlation coefficient (R^2), and mean absolute percentage error (MAPE) to select the most appropriate model among a set of 20 candidate ones to estimate RT, given a set of observed data. Once the most appropriate model is selected, a Bayesian framework is employed to develop the predictive distributions of RT, and to update them with new project-specific data that significantly reduce the associated predictive uncertainty. Overall, the results obtained indicate that the proposed RT model possesses a satisfactory predictive performance.

1. Introduction

The horizontal directional drilling has been used extensively throughout the world to construct underground pipeline systems [1-3]. Most pipelines including those employing horizontal directional drilling are installed in soil formations, for which engineers have accumulated a great amount of experience [4-8]. Reasonable mechanical models and corresponding equations have, therefore, been developed to calculate various construction-related parameters. However, there is a lack of such a methodology in more difficult situations. A major concern of many horizontal directional drilling projects is what amount of rotational torque (RT) should be used. However, relatively little quick research works have been done in this area. In this field, Lan et al. [4] have used the regression model for prediction of RT. Fattahi [9] has utilized rock engineering systems for estimation of the required RT to operate horizontal directional drilling. Akin and Karpuz [10] have utilized artificial neural networks for estimating the drilling parameters for diamond bit drilling operations. Adel and Zayed [11] have used the adaptive neuro-fuzzy inference system model to design the horizontal directional drilling productivity prediction model for underground pipe installations in clay soil. Feili Monfared et al. [12] have presented an adaptive neuro-fuzzy inference system model for an advanced prediction of bottom hole circulating pressure in under-balanced drilling operations.

In this paper, a new methodology based on the Bayesian model (using free software package WinBUGS [13-15]) is proposed aimed at identifying the most appropriate models to predict RT among several selected candidate models. The

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Bayesian inference is a method of statistical inference that uses the well-known Bayes' theorem to update the probability for a hypothesis as more information becomes available. This Bayesian updating is particularly important to predict the parameters of a model, and has been used for a wide variety of rock engineering projects [16-18]. In order to validate the performance of the proposed models, it is applied to field data given in the open source literatures.

2. Methodology

2.1. Bayesian statistics

Suppose that the observed data and unknown parameters are y and θ, respectively. The Bayesian approach to statistics is to treat all unknown quantities as random variables, and assign a *prior* probability distribution to each. By also specifying a joint probability distribution for the data, i.e. a likelihood, then obtain a full probability model for all the observable and unobservable quantities. In order to make inferences about θ used, the Bayes' theorem was used to construct the *posterior* distribution, i.e. the joint distribution of all the model parameters conditional on the observed data:

$$p(\theta|y) \propto p(y|\theta)p(\theta), \tag{1}$$

where throughout, $p(.|.)$ and $p(.)$ denote the conditional and marginal probability distributions, respectively. Thus the posterior is proportional to the likelihood $p(y|\theta)$ multiplied by the prior $p(\theta)$. An excellent introduction to the Bayesian data analysis has been given by Gelman et al. [19].

2.2. Markov chain Monte Carlo

In many realistic modeling situations, the joint posterior distribution $p(\theta|y)$ is high-dimensional, complex, and unavailable in a closed form. The Bayesian inference entails the evaluation of various summaries of the posterior. This requires integration, with respect to θ, of functions involving $p(\theta|y)$; it is these integrals that, until recently, have rendered the Bayesian analysis problematic. The Markov chain Monte Carlo (MCMC) methods alleviate these difficulties. Integrals are evaluated via Monte Carlo simulation from a Markov chain that is constructed so that its stationary distribution is the posterior [13]. Various algorithms exist for carrying out the required simulations including Gibbs sampling [13, 20, 21], which is particularly useful for exploiting conditional independence assumptions. The algorithm proceeds by iterative simulation from the full conditional distributions of each unknown stochastic quantity given the current values of all other terms (nodes) in the model. A detailed description of MCMC can be found in [22].

2.3. WinBUGS software

The BUGS (Bayesian inference using Gibbs sampling) language and program was developed by epidemiologists in Cambridge, UK, in the 1990s [23]. In the later years, a Windows version called WinBUGS was developed [24]. Despite imperfections, WinBUGS is a ground-breaking program; for the first time, it has made a really flexible and powerful Bayesian statistical modeling available to a large range of users, especially for users who lack the experience in statistics and computing to fit such fully custom models by maximizing their likelihood in a frequentist mode of inference. WinBUGS lets one specify almost arbitrarily complex statistical models using a fairly simple model definition language that describes the stochastic and deterministic "local" relationships among all the observable and unobservable quantities in a fully specified statistical model. These statistical models contain prior distributions for all top-level quantities, i.e. quantities that do not depend on other ones. From this, WinBUGS determines the so-called full conditional distributions and then constructs a Gibbs or other MCMC sampler and uses it to produce the desired number of random samples from the joint posterior distribution. A detailed description of WinBUGS can be found in [24, 25]. In this work, the WinBUGS software that uses the Bayesian analysis of complex statistical models and MCMC techniques was employed to compute the posterior predictive distributions. The mean values for the model parameters obtained via MCMC simulations are considered for the model prediction performance evaluation.

3. Database information

The required RT at the drill rig depends on various factors including geological conditions, drilling method, reamer cutter/bit size and type, rotary speed, axial force on bit, drilling mud properties, borehole diameter, length of drill string in the borehole, and borehole trajectory [4, 26, 27].

To establish the Bayesian method for prediction of RT to operate horizontal directional drilling, providing dataset that includes a wide geographic distribution is the most important requirement. To achieve this, the datasets given in a previous paper is borrowed [4]. The data (84 datasets) has been collected from nine projects using horizontal directional drilling for the China west–east natural gas transmission pipeline. Information regarding the mechanical parameters of rock strata (mainly sandstone, mudstone, gravels) has also been collected from these projects. However, due to different measurements made in each project, and practical difficulties in attempting to collect the wide range of information, some data is limited. A detailed description of the database can be found in Section 3.1 from [4]. Table 1 shows the statistical description of the datasets used in this work.

Table 1. Statistics description of input and output dataset.

Parameter	Symbol	Min	Max	Average	Std. Deviation
Axial force on the cutter/bit (KN×10)	P	2	30.50	13.84	5.71
Rotational speed of the bit (r/min)	N	15	50	31.58	12.38
Length of drill string in the borehole (m)	L	116.68	586.06	322.56	129.03
Total angular change of the borehole	KL	1.09	3.54	2.42	0.5366
Radius for the i^{th} reaming operation (mm)	Di	457.2	1117.6	760.79	185.33
Mud flow rate (L/min)	W	500	4000	2233.09	1033.04
Mud viscosity (s)	V	42	88	63.51	14.13
Rotational torque (KN.m)	RT	4	40	21.02	8.0132

4. Establishing Bayesian prediction of RT

4.1. Regression analysis and parameter selections

First of all, the correlation between the dependent variable (RT) and the independent ones was explored through a quick regression analysis. Overall, a weak linear correlation was found suggesting a non-linear relationship between the dependent variable (RT) and the independent variables. The results obtained are summarized in Table 2.

Table 2. Correlation between the model parameters (using the correlation coefficient).

	P (KN×10)	N (r/min)	L (m)	KL	Di (mm)	W (L/min)	V (s)	RT (KN.m)
P (KN×10)	1.00	0.64	0.58	0.58	-0.3	-0.49	-0.58	0.67
N (r/min)		1.00	0.63	0.57	0.32	-0.77	0.58	0.55
L (m)			1.00	0.77	0.57	0.22	0.58	0.82
KL				1.00	0.52	0.2	0.41	0.72
Di (mm)					1.00	-0.14	0.14	0.66
W (L/min)						1.00	0.39	0.44
V (s)							1.00	0.35
RT (KN.m)								1.00

Next, the database containing 84 datasets were divided into two. The first part representing 80% of the total datasets (i.e. containing 67 datasets) was used to establish the model, while the second part served for the model performance evaluation. Based on the training database, a Bayesian predictive model was proposed. Firstly, a preliminary correlation analysis was performed to investigate the possible type of relationships between RT (dependent) and each one of the independent variables (P, N, L, KL, Di, W, and V) in order to explore the potential candidate terms in developing the correlation for RT. The following candidates are used:

Model #1 $$RT = \frac{a_1.(P^{b_1}.N^{b_2}) + a_2.(L^{b_3}.KL^{b_4}) + c_1}{a_3.(Di^{b_5}V^{b_6}) + a_4W^{b_7} + c_2}$$

Model #2 $$RT = \frac{a_1P^{b_1} + a_2N^{b_2} + a_3KL^{b_3} + c_1}{a_4L^{b4} + a_5Di^{b_5} + a_6W^{b_6} + a_7V^{b_7} + c_2}$$

Model #3 $$RT = a_1(P^{b_1}.N^{b_2}) + a_2(L^{b_3}.KL^{b_4}) + a_3\frac{Di^{b_5}V^{b_6}}{W^{b_7}} + a_4$$

Model #4 $$RT = \left(\frac{V^a.N^b}{W^c}\right).\left((a+b).\exp(-(\frac{P^d.L^e.KL^f.Di^g}{c}))\right)$$

Model #5 $RT = \left(\dfrac{V^{a}}{W^{c}.N^{b}}\right).\left((a+b).\exp(-(\dfrac{P^{d}.L^{e}.KL^{f}.Di^{g}}{c}))\right)$

Model #6 $RT = a_1.P^{a_2}.N^{a_3}W^{a_4}V^{a_5}.\exp(L^{a_6}).Kl^{a_7}.Di^{a_8}$

Model #7 $RT = a_1.P^{a_2}.N^{a_3}.L^{a_4}.KL^{a_5}.Di^{a_6}W^{a_7}.\exp(V.a_8)$

Model #8 $RT = a_1.P^{a_2}.N^{a_3}.L^{a_4}.KL^{a_5}.Di^{a_6}W^{a_7}.\exp(V^{a_8})$

Model #9 $RT = a_1.P^{a_2}.N^{a_3}.L^{a_4}.KL^{a_5}V^{a_6}.\exp(Di^{a_7})W^{a_8}$

Model #10 $RT = a_1.P^{a_2}.KL^{a_3}V^{a_4}.Di^{a_5}W^{a_6}.\exp(N^{a_7}).L^{a_8}$

Model #11 $RT = a_1.P^{a_2}.N^{a_3}.L^{a_4}.\exp(KL.a_5).Di^{a_6}W^{a_7}V^{a_8}$

Model #12 $RT = a_1.P^{a_2}.N^{a_3}.Di^{a_4}W^{a_5}V^{a_6}.\exp(L^{a_7}).KL^{a_8}$

Model #13 $RT = a_1P + a_2N + a_3L + a_4KL + a_5Di + a_6W + a_7V + a_8$

Model #14 $RT = \dfrac{a_1.(P^{b_1}.N^{b_2}) + a_2.(L^{b_3}.KL^{b_4}) + c_1}{a_3.(Di^{b_5}V^{b_6}) + a_4\exp(W\,b_7) + c_2}$

Model #15 $RT = \dfrac{a_1P^{b_1} + a_2L^{b_2} + a_3Di^{b_3} + a_4V^{b4} + c_1}{a_5N^{b_5} + a_6KL^{b_6} + a_7W^{b_7} + c_2}$

Model #16 $RT = a_1.P^{a_2}.N^{a_3}.L^{a_4}.KL^{a_5}.Di^{a_6}.\exp(\dfrac{a_7}{W})V^{a_8}$

Model #17 $RT = \dfrac{a_1.(P^{b_1}.N^{b_2}) + a_2.(L^{b_3}.KL^{b_4}) + a_3.(Di^{b_5}V^{b_6}) + c_1}{a_4W^{b_7} + c_2}$

Model #18 $RT = a + b\ln(P) + c\ln(N) + d\ln(L) + e\ln(KL) + f\ln(Di)$

Model #19 $RT = a.P^{b}.N^{c}.L^{d}.KL^{e}.Di^{f}$

Model #20 $RT = \dfrac{a_1.(P^{b_1}.N^{b_2}) + a_2.(KL^{b_3}.Di^{b_4}) + a_3V^{b_5} + c_1}{a_4.(W^{b_6}.L^{b_7}) + c_2}$

In this work, the unknown parameters of the different candidate models are considered as random variables. The aim of this work, as stated earlier, is to identify objectively the most suitable models that fit best the RT datasets using a Bayesian framework, where the inference of model parameters is conducted in the WinBUGS software based on the MCMC methods. Therefore, one of the essential tasks in this work is to sample values of the unknown parameters from their conditional posterior distribution given the stochastic nodes that have been observed after having specified the model as a full joint distribution on all quantities for both parameters and observables.

4.2. Results

After specifying the models in the WinBUGS language at the logical nodes, normal (or lognormal or other distributions) was selected at the stochastic nodes for P, N, L, KL, Di, W, and V, respectively. Subsequently, the first group of the datasets was loaded and the models compiled and the MCMC sampler was applied to compute the model parameters. A trial-and-error approach was used to identify the optimal settings of the modeling. It can be seen that for model #2, the mean values of the unknown parameters $a_1, a_2, \ldots, a_7, b_1, b_2, \ldots, b_7$ and c_1, c_2 are -35.16, 7.298, -40.13, -0.1251, -0.1167, 47.44, -0.4808, -1.087, 0.3373, -20.7, -26.56, 0.3145, -0.6951, -25.39, -2.538 and 1.298, respectively. These values are the most probable that the model parameters would take for the predicted RT to have a maximum accuracy since those values correspond to the peak of the posterior distributions that are plotted in Figure 1. As seen in this figure, the posterior sampling distributions (or kernel density) of a_3, a_4, a_7 and c_1 are unimodal and are distributed normally. The unimodal distributions of a_3, a_4, a_7 and c_1 also indicate a good convergence of the model. The trace plots that examine sample values versus iteration provide a diagnostic of evidence of convergence. Also the summaries of Model #2 are provided in Table 3.

As the models contain a maximum number of 20, checking the convergence for every parameter could be afforded and were monitored. If the trace plots move around the mode of the distribution and do not show a trend in the sample space, then the model has converged as shown in Figure 2. As seen in this figure, an example of the dynamic traces of the model parameters corresponding to model #2 indicate convergence.

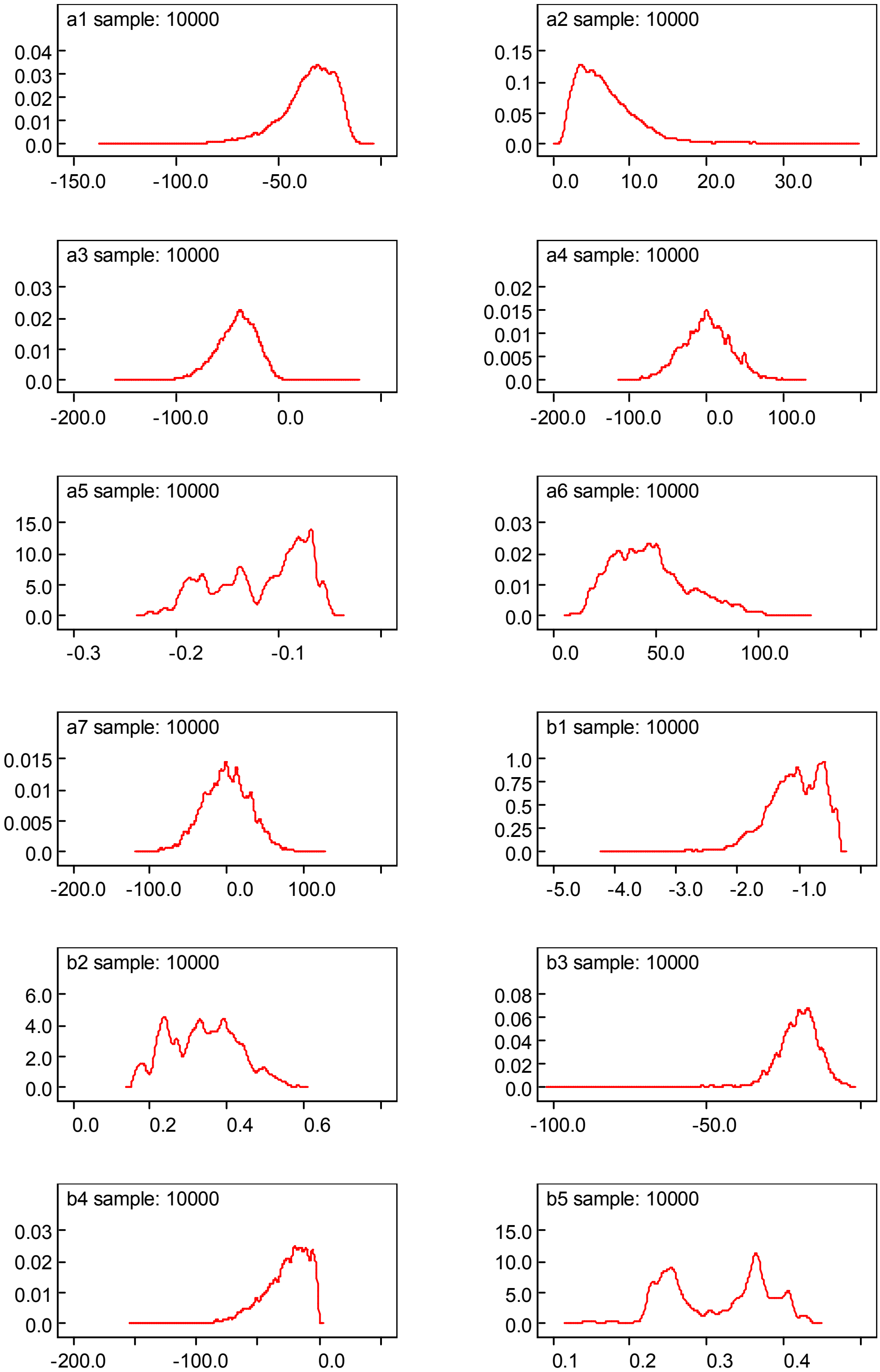

Figure 1. Posterior distributions of the model parameters ($a_1, a_2, \ldots, a_7, b_1, b_2, \ldots, b_7$ *and* c_1, c_2) corresponding to model #2.

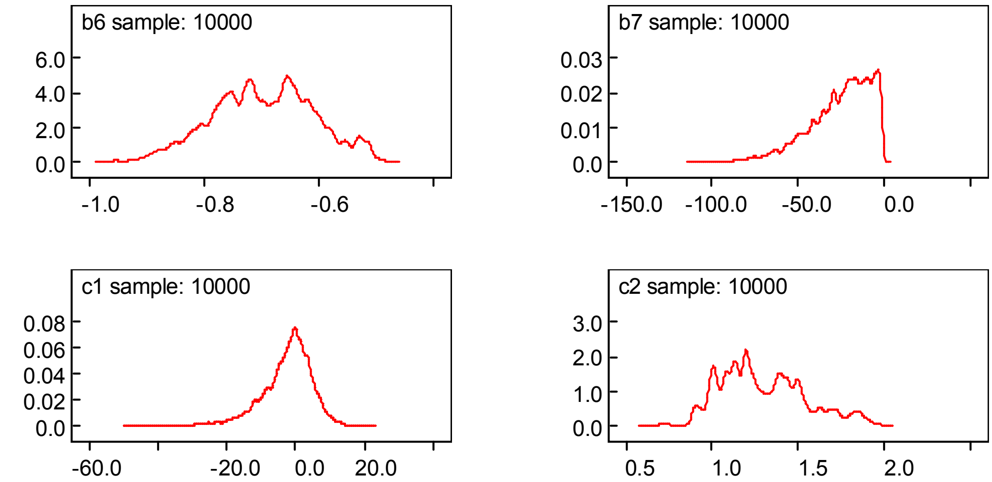

Figure 1. Continued.

Table 3. Summary statistics for the model #2 parameters computed with WinBUGS using MCMC.

Model Parameters	Mean	Std. Dev.	MC error	Percentiles (%) 2.50%	50%	97.50%	Start	Sample
a_1	-35.16	13.79	1.056	-69.93	-32.87	-16.29	4001	10000
a_2	7.298	4.775	0.4439	1.935	6.182	21.87	4001	10000
a_3	-40.13	20.15	0.5207	-83	-38.58	-5.965	4001	10000
a_4	-0.1251	31.67	0.7172	-62.01	-0.01581	61.94	4001	10000
a_5	-0.1167	0.04491	0.004463	-0.1991	-0.1044	-0.05498	4001	10000
a_6	47.44	18.93	1.673	18.47	45.26	90.79	4001	10000
a_7	-0.4808	30.54	0.6486	-59.05	-0.6268	57.91	4001	10000
b_1	-1.087	0.4978	0.04484	-2.183	-1.037	-0.3948	4001	10000
b_2	0.3373	0.09076	0.008908	0.1752	0.3376	0.5165	4001	10000
b_3	-20.7	8.376	0.3493	-40	-19.68	-8.749	4001	10000
b_4	-26.56	18.37	0.4852	-69.37	-22.95	-2.361	4001	10000
b_5	0.3145	0.06538	0.006512	0.2211	0.3308	0.413	4001	10000
b_6	-0.6951	0.08901	0.008387	-0.8717	-0.6954	-0.5227	4001	10000
b_7	-25.39	18.07	0.4169	-68.88	-21.73	-2.161	4001	10000
c_1	-2.538	7.531	0.6414	-21.1	-1.323	9.456	4001	10000
c_2	1.298	0.2503	0.02455	0.9057	1.249	1.852	4001	10000

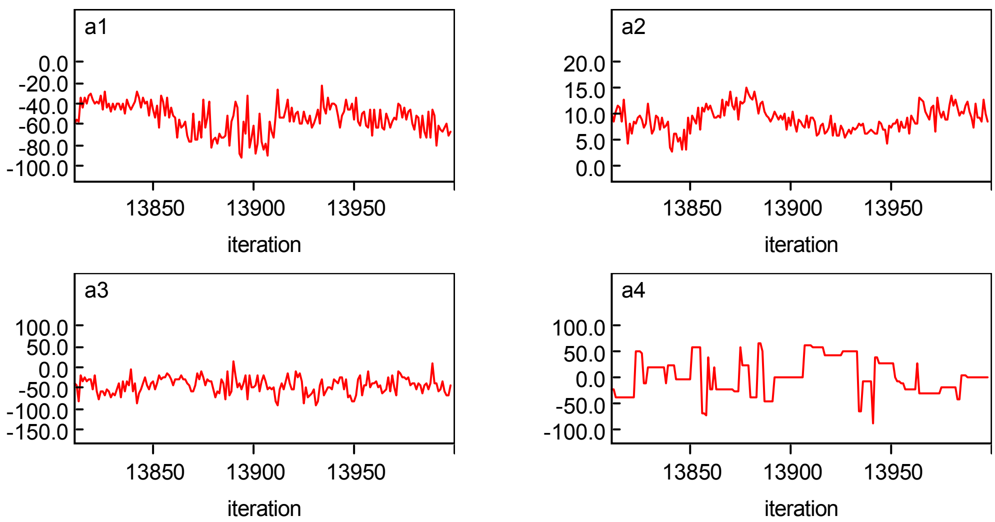

Figure 2. Dynamic trace of the model parameters ($a_1,a_2,\ldots, a_7,b_1, b_2, \ldots, b_7$ and c_1, c_2) corresponding to model #2. The dynamic trace plots of the sample values versus iteration suggested that the simulation appears to have stabilized.

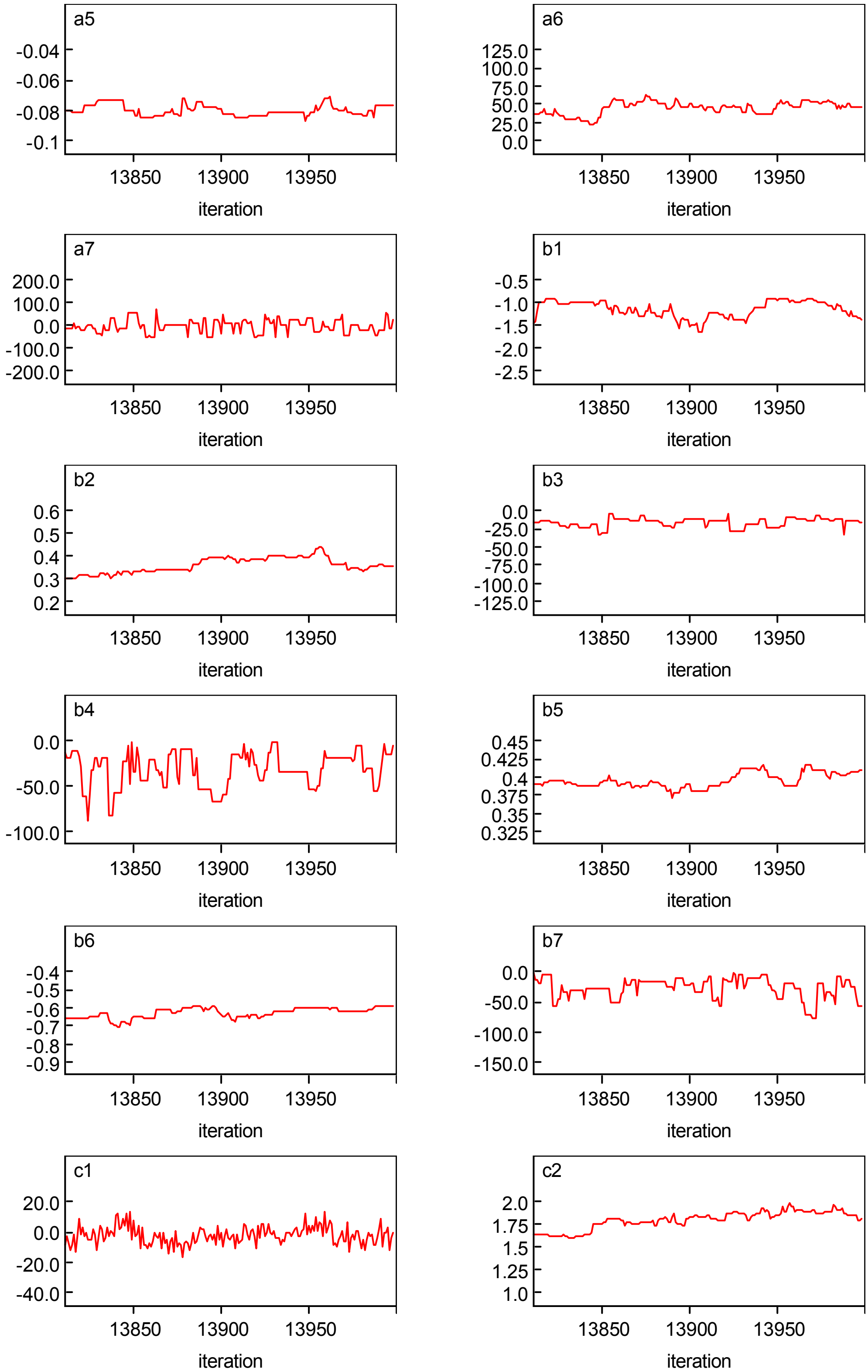

Figure 2. Continued.

4.3. Evaluation criteria

To verify the performance of the models, four statistical criteria viz. mean squared error (MSE), variance account for (VAF), root mean squared error (RMSE), squared correlation coefficient (R^2), and mean absolute percentage error (MAPE) were chosen to be the measure of accuracy. Let t_k be the actual value and $\hat{t}_k$ be the predicted value of the k^{th} observation and n be the number of observations; then RMSE, VAF, MSE, R^2, and MAPE could be defined, respectively, as follow:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(t_k - \hat{t}_k)^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n} \hat{t}_k^2}{n}} \quad (4)$$

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{t_k - \hat{t}_k}{t_k}\right| \times 100 \quad (5)$$

$$VAF = \left(1 - \frac{\mathrm{var}(t_k - \hat{t}_k)}{\mathrm{var}(t_k)}\right) \times 100 \quad (6)$$

With the purpose of evaluating the prediction performance of the model, the datasets (training and testing datasets) were used to assess the optimal model. The performance analysis of 20 models for training and testing datasets is shown in Table 4.

In general, the results obtained indicated that the proposed model (model #2) could be used to predict RT. Finally, model #2 is ranked the best candidate, while model #20 is the worst candidate for predicting RT using the training and testing datasets.

In addition, the results obtained were compared with the results obtained by Lan et al. [4]. This comparison is demonstrated in Table 5. As it can be seen, model #2 indicates better results relative to the previously published model.

Table 4. A comparison between the results of six models for training and testing datasets.

Model No.	Training datasets					Testing datasets				
	RMSE	MSE	MAPE	VAF	R^2	RMSE	MSE	MAPE	VAF	R^2
#1	0.1578	0.0249	64.4796	61.6523	0.6881	0.1474	0.0217	64.7961	67.5951	0.8760
#2	**0.1571**	**0.0247**	**26.7129**	**73.1925**	**0.7394**	**0.1249**	**0.0156**	**28.4332**	**86.2933**	**0.8632**
#3	0.2108	0.0444	80.5169	61.7842	0.6196	0.2145	0.0460	81.4396	82.0713	0.8419
#4	0.1717	0.0295	44.5368	69.9661	0.7116	0.1918	0.0368	46.4248	83.3083	0.8334
#5	0.1717	0.0295	44.5368	69.9661	0.7116	0.1918	0.0368	46.4248	83.3083	0.8334
#6	0.1267	0.0161	30.2042	68.4167	0.7036	0.1269	0.0161	31.5555	82.7554	0.8285
#7	0.1280	0.0164	49.6406	67.6059	0.7016	0.1307	0.0171	50.8921	73.7563	0.8240
#8	0.1279	0.0163	49.9066	67.7681	0.7018	0.1308	0.0171	51.1494	73.7501	0.8204
#9	0.1286	0.0165	30.4016	68.2533	0.6949	0.1311	0.0172	31.5286	80.5804	0.8086
#10	0.1274	0.0162	53.5853	65.9231	0.6990	0.1335	0.0178	54.4063	69.9905	0.8072
#11	0.1273	0.0162	51.0052	66.9145	0.7001	0.1295	0.0168	51.8745	71.1380	0.8055
#12	0.1413	0.0200	45.2216	67.9629	0.6815	0.1585	0.0251	46.2444	78.6955	0.8028
#13	0.1380	0.0191	18.4506	47.1539	0.6556	0.1512	0.0228	13.6838	72.9684	0.7821
#14	0.1711	0.0293	21.4498	62.4917	0.6889	0.1633	0.0267	19.0889	69.8855	0.7605
#15	0.2293	0.0526	35.5587	33.9040	0.6516	0.2176	0.0474	22.7701	34.0474	0.7595
#16	0.1397	0.0195	24.9485	68.1942	0.7033	0.1712	0.0293	26.6563	75.7761	0.7578
#17	0.1998	0.0399	28.7060	50.3312	0.6807	0.1995	0.0398	31.5621	58.2597	0.7471
#18	0.1651	0.0272	18.4760	23.3014	0.6412	0.1897	0.0360	16.5530	43.2724	0.7102
#19	0.1465	0.0215	29.0990	52.6001	0.6186	0.1461	0.0213	30.2096	67.4126	0.7071
#20	0.2346	0.0551	45.0154	38.1944	0.5546	0.2014	0.0406	46.6454	62.2617	0.7001

Table 5. Comparison of performance of model #2 and the previously presented model.

Description	R^2
Model #2 (Proposed in this work)	0.8632
Results obtained by Lan et al. [4]	0.8051

5. Conclusions

In this work, a new methodology based on the Bayesian inference was implemented to identify the most appropriate models for estimating RT among several candidate models that had been analyzed using the WinBUGS software. The input of the predictive model included the P, N, L, KL, Di, W, and V. Overall, the results obtained suggest that the proposed models RT possess a satisfactory predictive performance. Based on the R^2, VAF, MSE, MAPE, and RMSE, model #2 was the most adequate one (among those considered) that was in agreement with the performance indices. This work shows that MCMC can be applied as a powerful tool for modeling some problems involved in drilling engineering.

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آنالیز بیزی برای پیش‌بینی گشتاور چرخشی مورد نیاز عملیات حفاری انحرافی

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چکیده:

امروزه عملیات حفاری انحرافی به طور معمول در مهندسی حفاری استفاده می‌شود. در شرایط مختلف زمین‌شناسی پیش‌بینی گشتاور چرخشی مورد نیاز در عملکرد عملیات حفاری ضروری است. در حال حاضر روش مناسب برای انجام این کار در دسترس نیست. برای حل این مشکل در پژوهش حاضر برای ارائه راهکاری جدید برای پیش‌بینی گشتاور چرخشی مورد نیاز در حفاری انحرافی، تأثیر هفت پارامتر شامل نیروی محوری، سرعت چرخش مته، طول رشته حفاری، تغییر زاویه کلی گمانه، قطر i امین برقو، سرعت جریان گل و ویسکوزیته گل حفاری لحاظ شده است. در این پژوهش بر مبنای معیار انتخاب مدل، شاخص‌های آماری شامل میانگین خطای مربع، حساب واریانس برای، مجذور میانگین خطای مربع، ضریب همبستگی و میانگین خطای درصد مطلق برای انتخاب مناسب‌ترین مدل در میان مجموعه‌ای از ۲۰ مدل برای برآورد گشتاور چرخشی با توجه به مجموعه‌ای از داده‌های مشاهده شده به دست آمد. نتایج حاصل از این پژوهش بیانگر آن است که مدل پیشنهادی به کمک آنالیز بیزی می‌تواند نتایج رضایت‌بخشی را ارائه دهد.

کلمات کلیدی: گشتاور چرخشی، حفاری انحرافی، آنالیز بیزی، پیش‌بینی.