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Engineering with Computers

Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques --Manuscript Draft--

Manuscript Number:	EWCO-D-18-00737R1
Full Title:	Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques
Article Type:	Original Article
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Corresponding Author's Institution:	Chongqing University
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First Author:	Xiufeng Liao
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Order of Authors:	Xiufeng Liao Manoj Khandelwal Haiqing Yang, PhD Mohammadreza Koopialipoor Bhatawdekar Ramesh Murlidhar
Order of Authors Secondary Information:	
Funding Information:	
Abstract:	<p>One of the important factors during drilling times is the rate of penetration (ROP), which is controlled based on different variables. Factors affecting different drillings are of paramount importance. In the current research an attempt were made to better recognize drilling parameters and optimize them based on an optimization algorithm. To this purpose, 618 data, including RPM, flushing media, and compressive strength parameters, were measured and collected. After initial investigation, the compressive strength feature of samples, which is an important parameter from the rocks, was used as a proper criterion for classification. Then using intelligent systems, three different levels of the rock strength and all data were modeled. The results showed that systems which were classified based on compressive strength showed a better performance for ROP assessment due to the proximity of features. Therefore, these three levels were used for classification. A new artificial bee colony algorithm was used to solve this problem. Optimizations were applied to the selected models under different optimization conditions, and optimal states were determined. As determining drilling machine parameters is important, these parameters were determined based on optimal conditions. The obtained results showed that this intelligent system can well improve drilling conditions and increase the ROP value for 3 strength levels of the rocks. This modeling system can be used in different drilling operations.</p>
Response to Reviewers:	Response Letter Ref.: EWCO-D-18-00737 Title: Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques To: Engineering with Computers

Dear Editor,

I would like to thank you for giving us the opportunity to evaluate our paper with your expert and knowledgeable reviewers. The revised format of our paper is now ready based on the comments and advises of reviewers. In the revised manuscript, the changes are shown using red color. In addition, certificate of English proofreading service is attached as a figure. Our responses to the comments of reviewers can be seen in the following lines.

- Response to Reviewer #1
- Response to Reviewer #2

Thank you for your time and kind consideration.
Best regards,
Haiqing Yang
Corresponding author

Response to the reviewer #1:

Dear Prof. / Dr.

I would like to appreciate your precise comments. Please consider our explanations and clarifications.

The literature study is quite nice as well as the quality of the research presented from the authors. Some more clarity is required though, in order to properly outline the decisions behind the implementation of the proposed modeling approach and to further illuminate its aspects. Some more issues for the authors to consider are:

Reply: Thank you very much for your time to review our paper and also for your positive feedback.

1. In section 3 the data is divided in two subsets (80-20). How was this made?

Reply: Thank you for mentioning this point. We divided all data into two sections of training and testing (80% and 20%, respectively) according to literature. Many researches mentioned that the best combination of train and test is 80-20. Some researchers have suggested these percentages.

In the present study, 618 drilling data were measured at different thrust, RPM and flushing media on 6 different types of rock. Among them, 495 data sets (80% of all) were used for the training and testing of the ANN network, whereas 123 data sets (20% of all) were chosen for validation of the network.

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2. In section 3 it is concluded that the optimum architecture of the ANN model is 4x8x1, using one hidden layer with 8 neurons. As this is of crucial importance to the network's ability to generalize the details behind this selection should be included in the manuscript.

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4. Please refer to the software package or code that is used for the ANN and the ANN-ABC models. Also please indicate how the data are passing from the ANN response to the ABC for further processing.

Reply: Many thanks for these comments. We constructed this new network in the MATLAB environment. The training section was introduced as a function for the ABC algorithm. This algorithm obtains the least errors for this function, and then the performance of the model improves.

5. Is the optimum number of fireflies relevant to the ANN structure? Please explain.

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Cover Letter

Date: 16 January, 2019

Subject: Submission of a revised manuscript for evaluation and publication

Dear Editor,

I am enclosing herewith a **revised** manuscript entitled “*Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques*” for possible evaluation and publication in “*Engineering with Computers*”. The helpful and constructive comments by the reviewer are greatly appreciated. The revised format of our paper is now ready based on the comments and advises of reviewer. As seen in the enclosed documents, the content of the manuscript has been rewritten entirely with better understanding and clearer concept.

Sincerely Yours,

Haiqing Yang, PhD
Associate Professor
School of Civil Engineering, Chongqing University, China
Email: yanghaiqing06@163.com,
Tel:+86 13594082723, Fax:+86 23 65123511,

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10 Xiufeng Liao¹, Manoj Khandelwal², Haiqing Yang^{*3}, Mohammadreza Koopialipoor⁴,
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12 Bhatavdekar Ramesh Murlidhar⁵
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4 **Abstract**
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7 One of the important factors during drilling times is the rate of penetration (ROP), which is
8 controlled based on different variables. Factors affecting different drillings are of paramount
9 importance. In the current research an attempt were made to better recognize drilling parameters
10 and optimize them based on an optimization algorithm. To this purpose, 618 data, including RPM,
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12 investigation, the compressive strength feature of samples, which is an important parameter from
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16 assessment due to the proximity of features. Therefore, these three levels were used for
17 classification. A new artificial bee colony algorithm was used to solve this problem. Optimizations
18 were applied to the selected models under different optimization conditions, and optimal states
19 were determined. As determining drilling machine parameters is important, these parameters were
20 determined based on optimal conditions. The obtained results showed that this intelligent system
21 can well improve drilling conditions and increase the ROP value for 3 strength levels of the rocks.
22 This modeling system can be used in different drilling operations.
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46 **Keywords:** Compressive strength feature; ROP; Optimization; ABC.
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7 **1- Introduction**
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10 Drilling is one of the most crucial processes in excavation industry, starting from exploration stage
11 and continuing at every phase of production, till completion of mining activity [1]. Drilling has
12 important role in mining as well as petroleum industry to reduce excessive costs and subsequently
13 to enhance effectiveness of project [2]. Of the various purposes for which the rock is drilled,
14 drilling takes a unique place due to its wider applications in civil purpose, e.g. transport, hydro,
15 power, etc. Rotary drilling is a three dimensional cutting operation involve a combination of one
16 or several cutting processes commonly known as indentation [3–5], cutting and crushing [6],
17 ploughing, grinding and shearing [7]. However, the rock fragmentation at the bit rock interface is
18 a combined action of thrust force as well as torque compound.
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32 Drilling penetration rate is influenced by machine design related parameters, geological conditions
33 and geotechnical properties of rocks [8]. Drilling machine parameters can be controlled, but the
34 geological conditions and geotechnical properties of rocks cannot be altered. Rate of penetration
35 (ROP) is influenced by many variables that comprise controllable as well as uncontrollable
36 parameters. The bit diameter and type, the rotational speed, the blow frequency, the thrust, and
37 flushing rate are the controllable parameters, whereas the rock properties and geological conditions
38 are uncontrollable parameters. These typical factors affect ROP in diverse means [9]. Penetration
39 rate (PR) or Rate of penetration (ROP) is expressed in m/h and refers to the linear meter excavation
40 per unit time [10]. Having some prior knowledge of the TBM penetration rate in rock excavation
41 projects is very helpful to plan construction time and to control cost. Penetration rate prediction is
42 considered as a complex and difficult work because of the interaction between rock mass and drill
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4 machine, but a meaningful task because it is significant for time planning, cost control and
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6 choosing the excavation method [11].
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9 The performance improvement in penetration rate of drill can improve the overall economics of
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11 the project. This includes improvement in penetration rate and life of bit or decrease in bit wear
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13 rate. In order to reduce the drilling cost, investigations in the past have been carried out to reach at
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15 suitable working level of machine parameters for particular rock type. The detailed study for the
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17 relationship between the rate of penetration and various rock as well as machine parameters are
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19 carried out by numerous researchers [3, 4, 12, 13]. However, the work in this regard has not
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21 considered all machine parameters and has been confined to laboratory tests only.
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25 To study the influence of various parameters on the performance of drilling, various researchers
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27 work have been reviewed [5, 12, 14–17] and found that the rate of penetration increases linearly
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29 with the increase of thrust on bit for each rotational speed. However, for each rpm there exists an
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31 optimum thrust on bit and beyond which there is no appreciable increase in rate of penetration.
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33 The magnitude of torque developed at the bit rock interface increases linearly with the increase of
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35 the thrust on bit at each rotational speed.
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39 Since, most of the investigations are empirical in nature and therefore, their application has not
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41 made universal. In order to know a greater applicability of these characteristics in the drilling, a
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43 lot of work has been carried out to find and suggest a definite model, which can be rock friendly.
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45 On the basis of detailed investigation, a viable approach for the prediction is necessary, and an
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47 Artificial Intelligence (AI) comes in handy to fulfill this approach.
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51 Methodology of artificial intelligence (AI) for application for civil and mining engineering projects
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53 have been represented with examples [18, 19, 28–35, 20–27]. When type of inputs and outputs are
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55 not known including their nature for resolving a problem, the same can be solved quickly through
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4 artificial neural network (ANN) which is section of AI [36, 37]. Inputs and output(s) in a given
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6 problem is connected through non-linear function which is designed through ANN. Relations are
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8 produced between inputs and outputs based on sample data by ANN connected with non-linear
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10 function. With the support of activation function and weights between different sample data set,
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12 the established relations are utilized for subsequent sample data set [38]. Any eminent algorithm
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14 is not available for connecting between inputs and outputs with dynamic conditions. While above
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16 mentioned networks have played important role in uncertain conditions.
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22 An algorithm which is optimized based on simulation of raw behavior of bee is either on their
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24 foraging behavior or breeding process. The problems requiring combinatorial optimization are
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26 solved using algorithms on the basis of process connected with mating for life reproduction. On
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28 the other hand, many problems requiring optimized solution are obtained through algorithms based
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30 on simulation of honeybees' nature of foraging behavior. The Bee Colony Optimization [39, 40],
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32 Virtual Bee [40], Bee [41] and Artificial Bee Colony [42, 43] are various algorithms developed on
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34 the basis of behavior of honeybee swarms which is foraging in nature. Even though complete set
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36 of bee algorithms have standard characteristics, every algorithm differs in certain features. The
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38 problem of travelling salesman was solved by developed algorithm of Bee Colony Optimization
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40 (BCO) by Teodorovic and co-workers [39, 40]. Various numerical examples were also solved by
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42 BCO. Additionally, some more potential problem areas of traffic engineering and transportation
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44 were identified for solving using BCO algorithm. Intelligent principles used by Swarm for
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46 developing the BCO algorithm was useful to solve problems in engineering which are complex in
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48 nature as reported by Teodorovic [39]. Yang [44] suggested the Virtual Bee Algorithm (VBA) and
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50 established methodology to solve numerical problems which are two dimensional in characteristics
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52 using VBA. Yang [44], on the basis of his judgment, he concluded that VBA was as productive as
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4 genetic algorithms. He further stated that VBA was efficient as compared to a conventional
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6 algorithm for optimization by virtue of multiple agents working in parallel. Pham et al. [41]
7
8 recommended the Bee Algorithm (BA) initially. BA is utilized for resolving optimization problems
9
10 in unconstrained function. BA is also useful in training perceptron networks which are multi-
11
12 layered to identify various patterns in control charts. They further asserted that BA usually
13
14 provides more excellent results as compared to the GA and ant colony algorithm which is due to
15
16 higher speed to optimize and correctness in outcome. One of disadvantage of BA algorithm is that
17
18 many parameters are to be initiated before BA algorithm is executed. The Artificial Bee Colony
19
20 (ABC) algorithm was suggested by Karaboga and Basturk [45]. The problems of constrained and
21
22 unconstrained function were optimized using ABC algorithm. The results achieved using ABC
23
24 algorithm were evaluated by Karaboga and Basturk. They announced that ABC produced better
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26 results as compared to particle swarm optimization and an evolutionary algorithm or differential
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28 evaluation. For solving engineering problems, an evolutionary algorithm produced better results
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30 and can be deployed efficiently. In recent times, Singh [46] for solving leaf- constrained discrete
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32 problems which are optimized consisting of least possible spanning tree utilized the ABC
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34 algorithm. Optimization of ant colony algorithm, genetic algorithm and tabu search algorithm were
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36 compared with the ABC algorithm. Singh recommended that ABC algorithm which is newly
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38 developed performed the best results as compared to various ways and provided solutions in
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40 shorter time with a quality. In this research, an essential feature of the data was extracted. Then,
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42 various parameters were used to define a meaningful relationship. Finally, optimization models
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44 for ROP were obtained.
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2. Data collection

In the present study, 618 drilling data were measured at different thrust, RPM and flushing media on 6 different types of rock. Among them, 495 data sets (80% of all) were used for the training and testing of the ANN network, whereas 123 data sets (20% of all) were chosen for validation of the network. The thrust was kept at seven different levels, viz. 325, 410, 490, 560, 641, 728 and 820 N, whereas RPM was kept constant at four different levels 285, 471.1, 687.1 and 1122.2 for each rock type. Plain tap water with poly-ethylene-oxide (PEO) mixed with different ppm was used for the measurement of ROP. PEO mixed with water was kept at four different levels, viz. 0, 10, 15, 20 and 30 ppm. In this, plain tap water is considered as a zero ppm. Flushing rate of 285 l/min was kept constant for the whole study.

Six different rock types were used for this analysis, namely, sandstone, limestone, rock phosphate, dolomite, marble and quartz-chloride-schist. In this study, 120 drilling data sets were measured on sandstone, 124 on limestone, 128 on rock phosphate, 139 on dolomite, 56 on marble and 51 on quartz-chloride-schist. The statistical data for the whole of the data is presented in Table 1.

Table 1 A view of All Data

Parameter	Unite	Max	Min	Average
Thrust	N	820	325	547.95
RPM	Rad/min	1122	285	632.74
flushing media	l/min	30	0	13.58
compressive strength	MPa	77.8	24.5	45.36

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7 **3. Methods**
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10 **3.1 Artificial Neural Network (ANN)**
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13 With an objective of data transmission to solve science and engineering problems, ANNs are
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15 treated as approximate resemblance mechanism which are motivated by human brain. It is
16
17 commonly accepted conditions that whenever there is complicated and not linear correlation
18
19 between input sample data and output of model, most suitable applications depend upon ANNs
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21 [47–49]. Several categories of ANNs have been suggested and multilayer feed-forward (FF) ANNs
22
23 are very common which are connected with different weights having multiple layers linked to
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25 many hidden nodes (neurons) [50, 51]. Learning algorithms is must for ANNs for training purpose
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27 in order to find approximate solution. In order to train ANNs, the most commonly adapted
28
29 algorithm is the back-propagation (BP) [34, 52–54]. For minimizing model error between goal
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31 standards (acquired by the system) and output, BP algorithm is most suitable. **Whenever the error
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33 of model is greater than predefined error for example root mean square error (RMSE), the network
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35 weights are adjusted by the system through back propagation.** Figure 1 shows outlook of structure
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42 of BP-ANN model.
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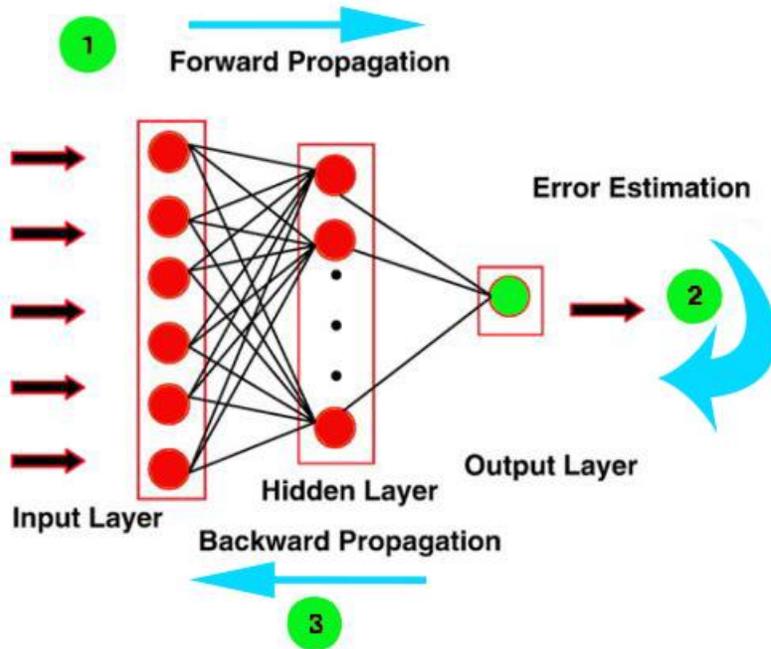


Figure 1 Outlook of structure of BP-ANN model [55]

3.2 Artificial Bee Colony

Motivated on the basis of life of bees Karaboga [56] created the ABC algorithm which was optimized where every bee is elementary constituent. If these elementary constituents make arrangements for a colony of bees binding together, even though their behavior will be complicated but still understandable to produce integrated system and bunch of flowers containing sweet honey drink can be exploited. Every colony of bees having three groups of bees and each group has to perform different duty. Scout bees are the first group whose task is to discover new sources. The scout bees concentrate on core honey bearing environment and may not explore external environment. Information on food is collected and stored in memory of scout bees. When every scout bee returns to hive, information on food source is shared through a waggle dance. The employed bees are second group whose responsibility consists of exploiting the food source based

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4 information shared during waggle dance based on memory of scout bees. Onlooker bees are the
5
6 third group in hive. They wait for second group of bees to return to hive and during waggle dance
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8 they gather information on suitability and fitness of food source and concentrate to exploit one
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10 resource at a time. Several mathematical problems, industrial and engineering issues are solved
11
12 using this algorithm [18, 57].
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17 The major four steps of the ABC algorithm are stated below [43]:
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20 Step 1:
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23 On the first occasion, in the ABC algorithm, 50% of the bees' community are employed bees and
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25 the balance 50% are non-employed bees. For each supply point of honey, the employed bees
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27 consist of one batch only. Alternatively, the total employed bees are equivalent to total supply
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29 point of honey surrounding the hive. Thus, an employed bee is assigned to each supply point of
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31 honey, which implies that total supply point of honey produces basic solution which is within
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33 range of possible solutions. Once basic solution is produced, problem linkage must be utilized to
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35 find out the amount for every solution.
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41 Step 2:
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44 In the present portion of the program, for every problem solution, a fresh answer is produced
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46 utilizing the linkage:
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$$48 \quad v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}) \quad (1)$$

$$49 \quad i \in \{1, 2, \dots, BN\}$$

$$50 \quad j \in \{1, 2, \dots, D\}$$

$$51 \quad k \in \{1, 2, \dots, BN\} \ \& \ k \neq i$$

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4 $\varphi \in [-1.1]$
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10 where $x_{i,j}$ is derived from the answer i using the dimension j ,

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12 $v_{i,j}$ is dimension j in the fresh answer, i is the number one answer among various answers to the
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15 problems,

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17 φ is a random number in the negative interval of one to one,

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20 k is a random number produced among various answers to the problem,

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22 BN is the number of introductory answers for the problem, and

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25 D is the number of dimensions to be optimized.

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27 After producing a fresh answer, if the amount of this answer is more than the amount of the former
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29 answer, it will be restored, alternatively the present answer will be abandoned.

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33 Step 3: During this phase, the probability of gathering bees from every site is computed by the
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35 equation given below:

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$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (2)$$

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45 where the fitness of source i is fit_i and the onlooker bees selecting source i depends upon the
46
47 probability p_i . On the basis of fitness of every item, allocation of total bees is decided. During this
48
49 phase, on the basis of fitness all the bees may be allocated to honey source. A fresh answer is
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51 created among various picked up answers by utilizing equation (1) by computing the value of every
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53 honey source. If fresh answer gets better value than prior answer, fresh answer will succeed the
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55 prior answer or alternatively fresh answer will be improvised. The objective of improvising answer
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4 is for making a tally for the number of failures to enhance the response, and if answer is not
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6 upgraded, one entity will be added to it.
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10 Step 4: During this phase, if the tally count of non-improvising answer turns up to pre-specified
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12 limitation (Cmax), fresh answer will be succeeded by a random answer. During this phase,
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14 surrounding circumstances of end of repetitions are also scrutinized. Repetitions will finish if
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16 circumstances of end conditions are found as per the algorithm, alternatively it will restore to step
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18 two. Various researchers have elaborated on ABC structure including working of the same [42,
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20 43, 56]. Outlook of ABC algorithm is given in Figure 2.
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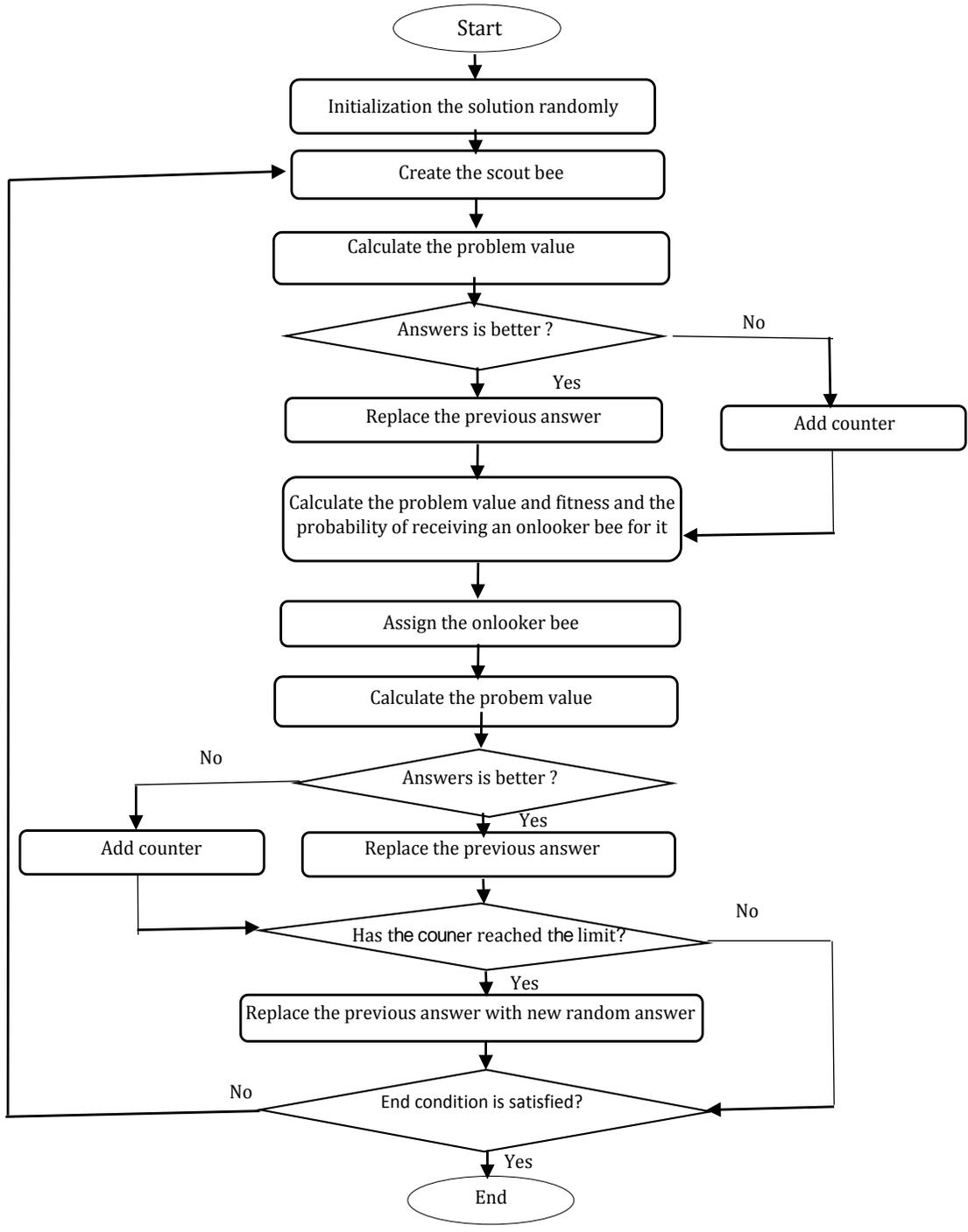


Figure 2 Outlook of ABC algorithm to optimize the ROP [57]

4. Result and Discussion

4.1 Initial Classification

In the current research 618 data from different samples were collected and measured. The precise investigation of parameters affecting ROP can provide a useful aid for drilling in different types of rocks. As shown in **Table 1**, 4 parameters including compressive strength, thrust, RPM, and flushing media, were assessed for all samples. As each parameter affects ROP, the correct choice of these parameters can produce more precise results in calculations and modeling. Three parameters: thrust, RPM, and flushing media are related to the characteristics of drilling machine and the compressive strength parameter was used from different investigated and measured rocks. As aforementioned, compressive strength parameter is among the main characteristics of rocks, which has the main effect on drilling and ROP. For this reason, in this research, at first, all parameters were divided into some groups based on their strength level. **Figure 3** displays different values of compressive strength for all samples.

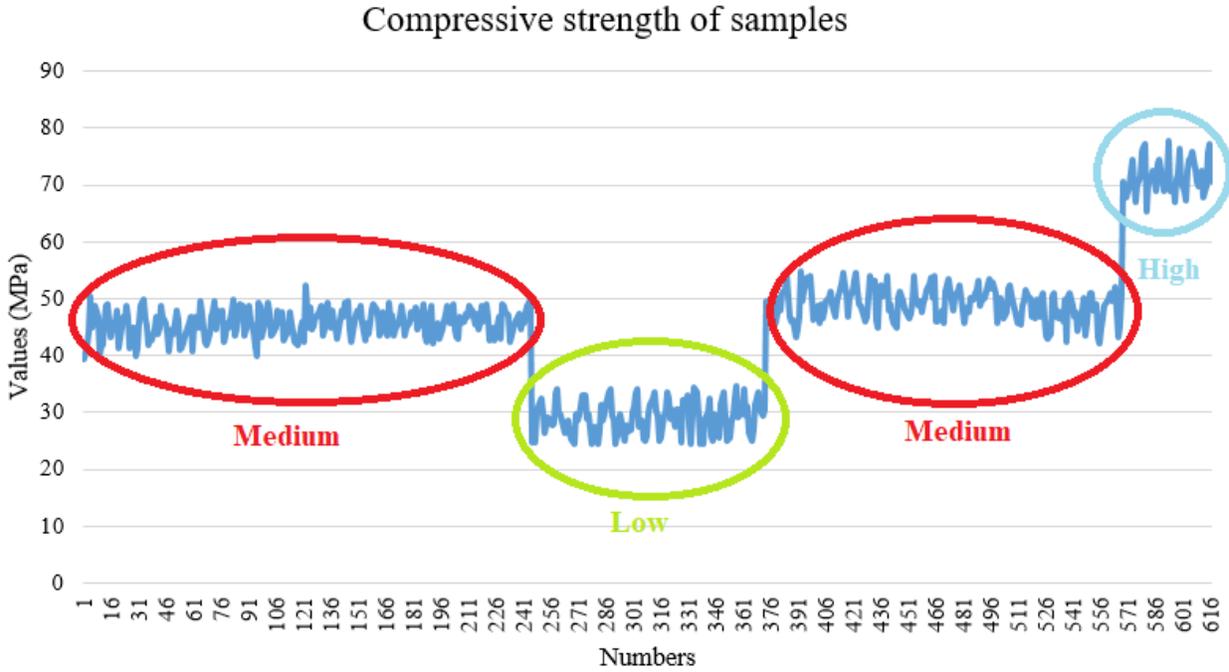


Figure 3. Compressive strength of all types of used rocks

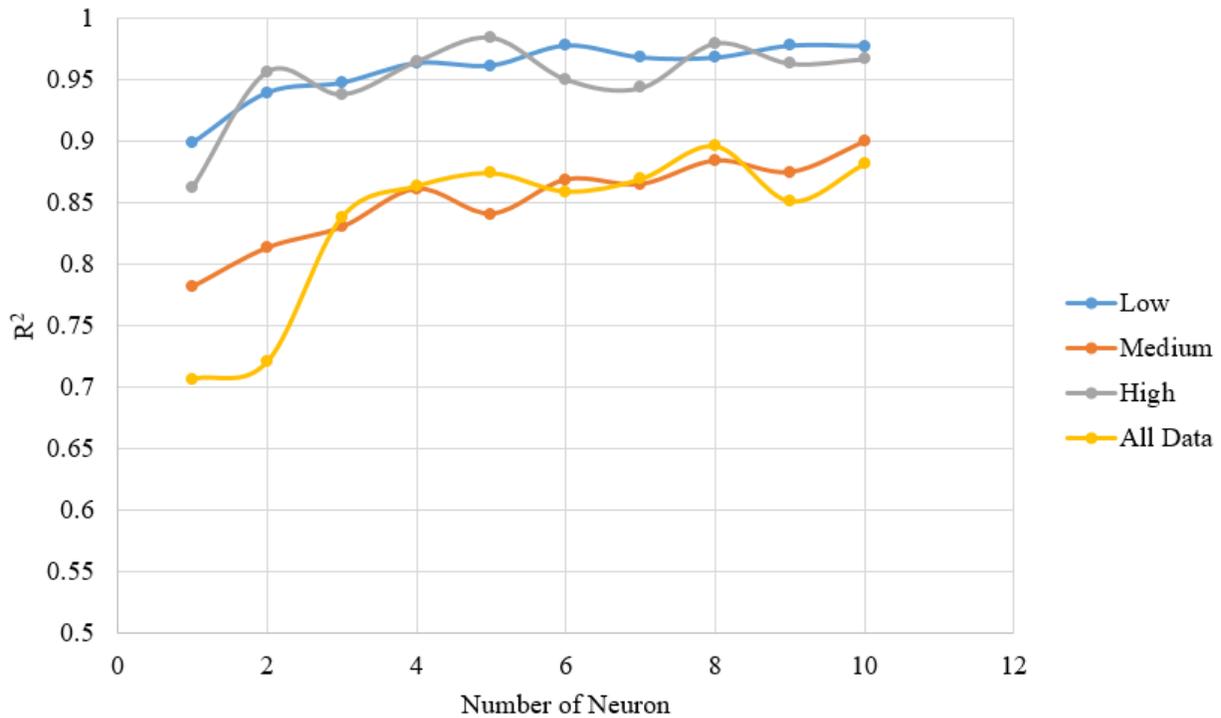
As seen, the compressive strength range is divided into three groups of low (128 samples), medium (439 samples), and high (49 samples). This classification was done so that we can present the appropriate models of ROP for different strength levels. Given the conducted studies, in the following, different models for ROP assessment are presented and discussed for all data as well as three levels of data which were classified based on their strength.

4.2 Modeling of Predictive systems

In the present study, problem was solved using Perceptron ANNs due the complexity of the problem. Learning of the ANN was done based on the learning function of the Markvart-Levenberg. On the established methodology of many researchers, selection of the number of layers in neural network model was carried out [31, 36, 58]. These layers consist of input, output and

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4 hidden layers. Input layer in this study is considered as 4 nodes, while output layer is set as one
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6 output. According to [59, 60], any non-linear function can be solved by a hidden layer. Various
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8 research works have been done for selecting suitable number of neurons in hidden layers. Trial
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10 and error methodology needs to be adopted for fitting correct number of hidden neurons.
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15 The number of iterations and neurons are considered as two important parameters in neural
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17 network designing. Therefore, the effect of these parameters was investigated on all data and three
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19 levels. The values proposed by previous researchers were investigated for the number of neurons
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21 between 1 and 10 and the number of iterations between 20 and 100. Using this method, one can
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23 obtain a more precise estimation of conditions as well as the models results. The results from
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25 prediction models based on R^2 and RMSE are presented in Figures 4-7.
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56 **Figure 4** The results of prediction models based on the number of neurons in terms of R^2
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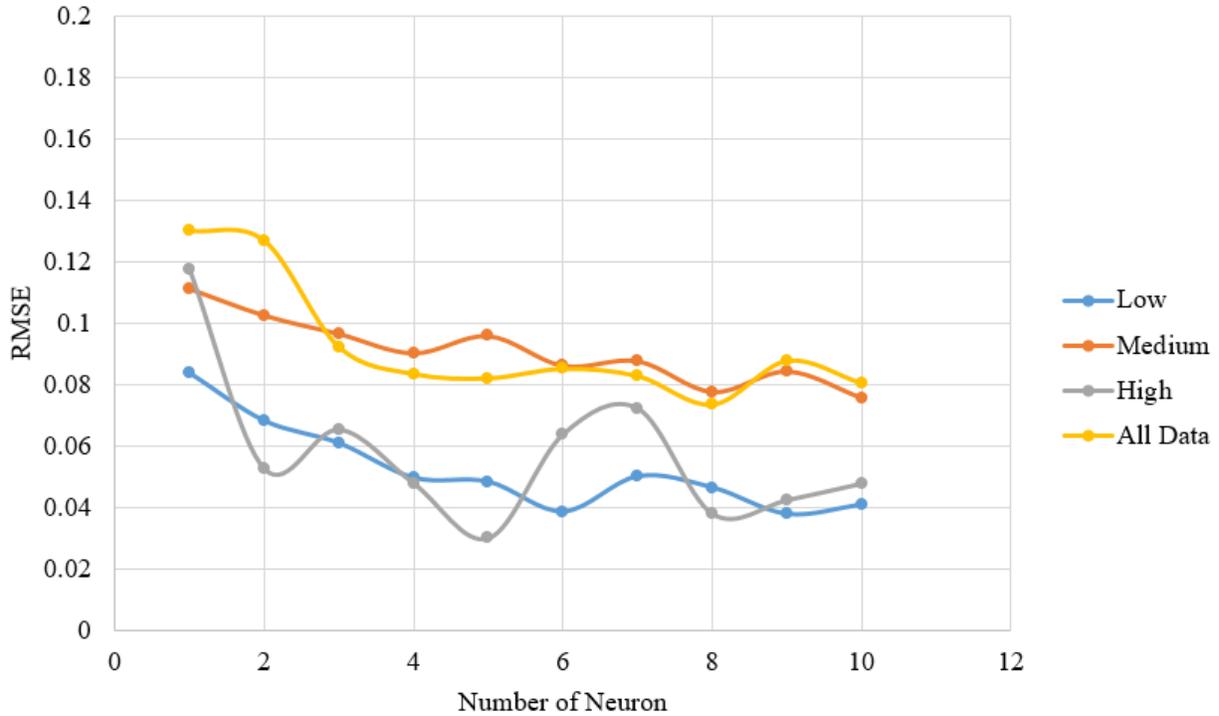


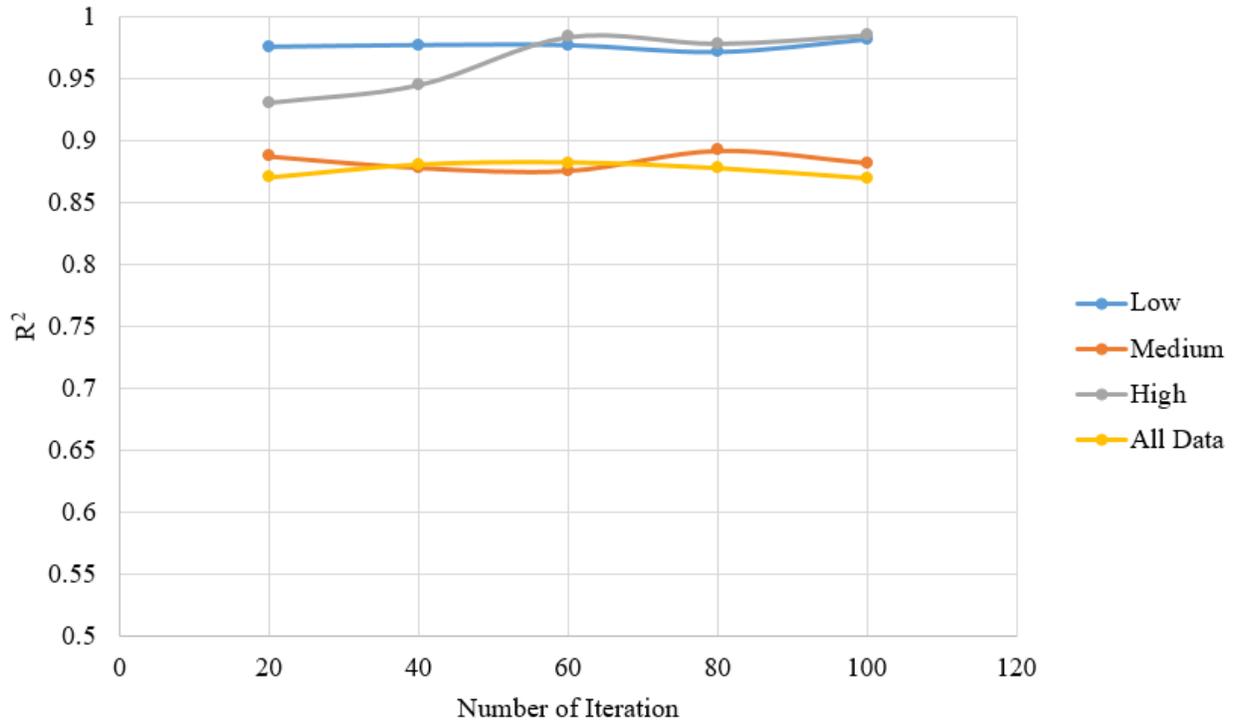
Figure 5 The results of prediction models based on the number of neurons in terms of RMSE

As shown in Figure 4, the number of neurons has significantly increased R^2 values. As the number of neurons increases, an increasing trend can be seen in R^2 values. Choosing the state presenting the most optimal result of prediction can take priority. Additionally, Figure 5 shows the decreasing trend in system errors. Overall, increasing the number of neurons leads to obtaining better models with higher performance prediction. In these conditions, a number of 8 neurons for the whole data is the best and the most optimal state of prediction. In order to select 3 strength levels, the values 5, 10, and 6 were selected for the high, medium, and low levels.

Another comparison that can be made using Figures 4 and 5 is to investigate the results of these 4 groups of modeling. Considering that all data were investigated besides 3 groups, which have been divided based on strength, one can better recognize the results of analysis. As seen, dividing data

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4 based on strength, which is directly dependent on the rock conditions, presents generally a better
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6 criterion. In these conditions, the use of models capable of presenting predictions simply and for
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8 different conditions can provide better conditions during drilling and a proper rate of ROP.
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10 However, this process is suggested so that better conditions can be provided for optimization
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12 through its precise investigation.
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17 Figure 6 and 7 display the results for the investigation of the number of repetitions for R^2 and
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19 RMSE. Considering the points mentioned in the previous section, their optimal selection can affect
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21 the program's run time.
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51 **Figure 6** Results of prediction models based on the number of repetitions in terms of R^2
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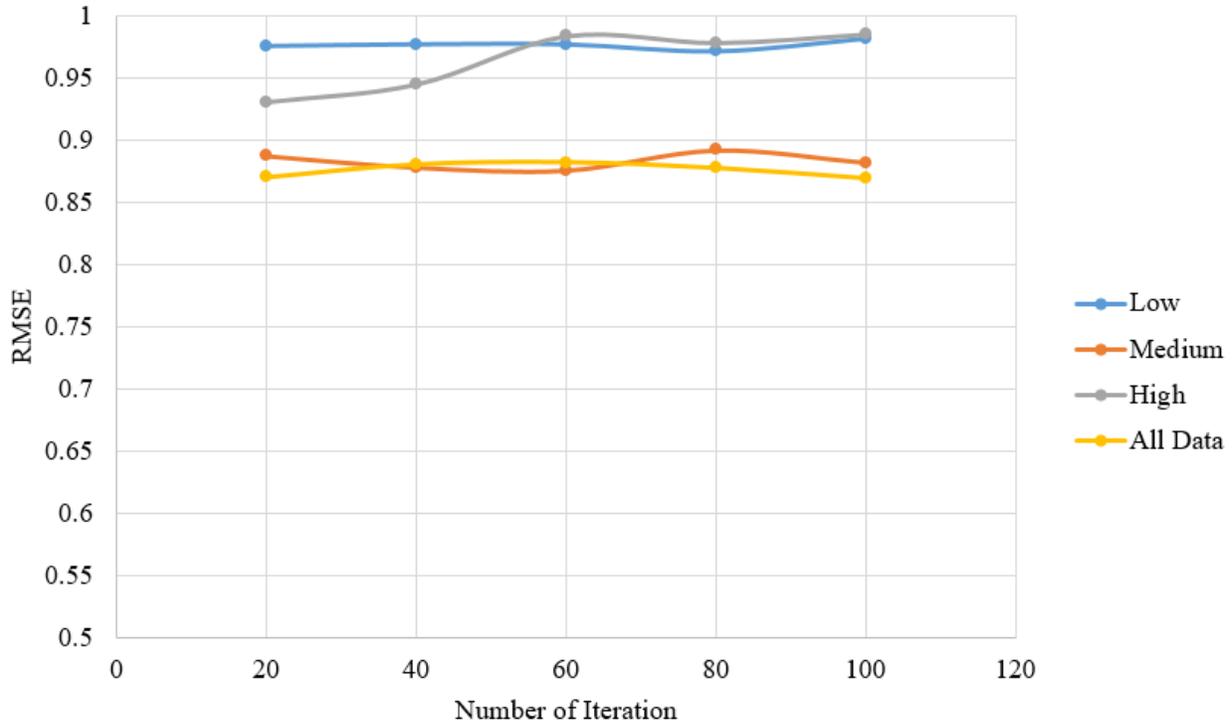


Figure 7 Results of prediction models based on the number of repetitions in terms of RMSE

A general investigation of the results of Figures 6 and 7 shows that like the number of neurons, the number of iteration improves accuracy and decreases the error. Figure 6 shows that for all models, R^2 has an upward trend as the number of iteration increases. This is while the error has a decreasing trend in results, indicating the reduction of error. The optimal selection is also applied to these models. For a model designed based on all data, the number of 60 iterations were obtained for optimal state, and for models divided in 3 groups of high, medium, and low based on the rock strength, 60, 80, and 60 were obtained, respectively.

As it was observed in the previous section, leveling provides a better performance in the model constructed based on all data. This shows the division done based on the important characteristic

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4 in data can significantly help with better recognition of models. Finally, the results of top models
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6 are provided in Table 2.

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10 **Table 2** Models proposed for 4 types of prediction models

11 Best Model	12 R²	13 RMSE
14 Low model	15 0.96	16 0.373
17 Medium Model	18 0.91	19 0.714
20 High Model	21 0.97	22 0.313
23 All data Model	24 0.89	25 0.727

26 Considering models selection based on the rocks strength criterion, these 3 models are assessed
27 and optimized in the next section.

28 29 30 31 32 33 34 **4.3 Optimization of ROP**

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37 In the present study, the performance of ANN model was improved using ABC algorithm.
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39 Generally, for training ANN, the BP algorithm is utilized. The performance of ANN is reduced
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41 due to certain defects. One of the greatest critical problems is catching of the least possible local
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43 in the entire search space. Whenever the least possible local is achieved, BP algorithm declares to
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45 the systems that these coefficients are the most efficient and hence this is known as a bug in BP
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47 algorithm. Under such circumstances, global minimum is best achieved through optimization
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49 algorithm. In the present research study, an ABC algorithm is utilized for optimization of network
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51 coefficients and reduction of RMSE errors.
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57 In this algorithm, a set of fresh coefficients are generated for every solution after creating basic
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59 coefficients by solving Eq. (1). After computation of values for prediction and error for each
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4 problem, if there is improvement, the fresh coefficients will take the place of prior coefficients.
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6 Alternatively, the coefficients will be improvised and the fresh coefficients will be omitted. The
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8 probability is calculated for selecting coefficients and fresh items were generated around the
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10 coefficients with better benefit and excellence. The reason behind fine tuning coefficients is that
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12 later hardly any queries search at the space and time is not wasted. Through this process, search
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14 speed is enhanced and optimization of internal system of ABC algorithm takes place. In the last
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16 phase of the algorithm, if the penalty value of every coefficients approaches a target determined
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18 value, then, fresh coefficients will be created randomly.
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24 Considering the results of the previous section in which the models were designed for 3 strength
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26 levels, 3 types of optimization were considered for these models. For optimization, it needs to
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28 obtain the parameters affecting ABC algorithm. As aforementioned, the number of bees and the
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30 number of iteration parameters affect this algorithm performance. Its other parameters are
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32 introduced as coefficients which are less effective. For this reason, the best conditions for selecting
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34 factors affecting ABC algorithm are introduced in Table 3. These parameters are applied to
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36 optimization of models.
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42 **Table 3** Proper parameters for designing ABC algorithm
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Parameters	Value
Number of bees	200
Number of iteration	400
Acceleration Coefficient	1

4.4 Optimizing Design

In this section, the optimal models are presented for 3 levels of the rocks strength. Considering the problem conditions, the optimization algorithm can search for the effective parameters, and optimize. The problem defined by this research is the use of 4 parameters to determine ROP parameter. As the compressive strength of rock was selected as a determinant feature, this feature created 3 different strength levels in data. Therefore, data affecting ROP are determined supposing 3 strength levels based on drilling machines characteristics. These parameters, which are shown in Table 1, including RPM, flushing media, and thrust. For this reason, in the intelligent modeling section, some models were designed and developed. To the extent one can improve the accuracy of these models, the accuracy in selecting the optimization models and determining the best conditions increase. Here, the best models of these 3 levels were selected from the previous stage and the optimal parameters of ABC algorithm which shown in Table 3 were determined. **Figure 8 displays the best optimization conditions for these 3 levels.**

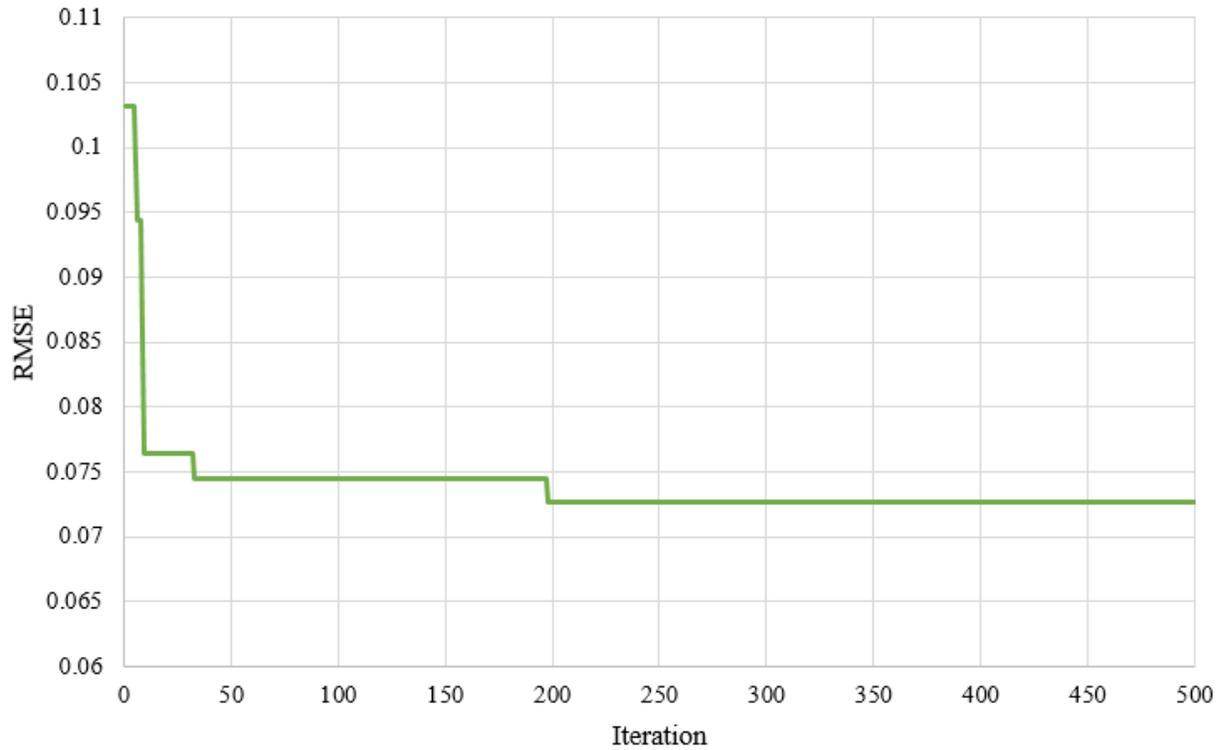


Figure 8 Three models optimization to determine the optimal conditions of drilling machine

The search continues until the system error decreases, that is, ROP can be increased. Considering the prediction model conditions as well as the number of parameters, all 3 models present results. The results show a proper improvement over their initial state. Identifying parameters which are able to determine these conditions for drilling machine is among the important parts of this optimization. Therefore, the effective machine parameters are shown in Table 4. As table displays, the optimal state is shown besides its initial state. The results show that having effective parameters at any moment and drilling based on these parameters can be effective in future drillings.

Table 4 Comparison of initial state and optimal conditions

Model	Thrust			RPM			flushing media			compressive strength		ROP		
	Mi	Ma	O	Mi	Ma	O	Mi	Ma	O	Mi	Ma	Mi	Ma	O
Low	325	820	743	285	1122	985	0	30	19	24.5	34.5	0.568	14.285	17.4
Medium	325	820	762	285	1122	1054	0	30	25	39.5	54.8	0.490	18.111	19.7
High	325	820	790	285	1122	1080	0	30	26	65.4	77.8	0.244	6.250	12.3

O=Optimal, Mi= Minimum, Ma= Maximum

As different measurements have been recorded at each drilling stage, a comparison between optimal conditions and the best and the worst drilling conditions can better shows the importance of this optimization. **Figure 9** displays the results of this comparison for 3 models which have been classified based on the compressive strength of the rock. The improvement of optimal systems performance indicates that the intelligent and optimization models outperform the traditional and empirical methods. **It should be noted that all ANN and ABC models were coded and designed using MatLab environment.**

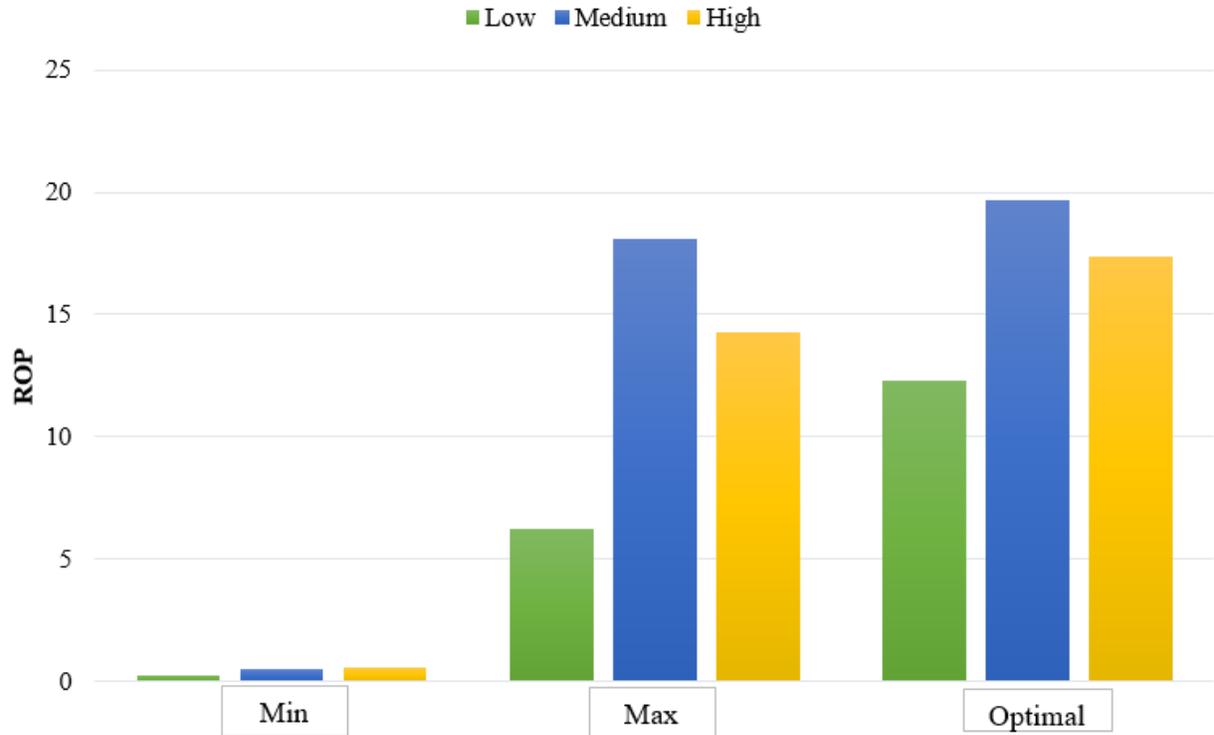


Figure 9 Final results of optimization

5. Conclusions

As drilling is always investigated under a variety of conditions, studying its different aspects using new methods can offer a proper perspective in this regard. ROP in drilling systems is a key feature which is capable of determining the performance of drilling. Therefore, in the current research, 618 measurements were done on different samples using different values of the drilling machine. These parameters included Thrust, RPM, flushing media, and compressive strength. Since the compressive strength of rocks was divided into 3 parts, 3 levels of high, medium, and low were introduced for ROP analysis. As this feature was only dependent on the sample, it was selected as

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4 a criterion for classification. The intelligent models were designed and developed based on these
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6 3 levels as well as all models, and different models were designed to determine the optimal model
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8 for each system. Finally, it was found that, selecting simpler models in which samples are closer
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10 to each other in terms of strength, can present better models. Therefore, 3 optimal models designed
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12 based on compressive strength of the rocks were selected. **The ABC optimization algorithm was**
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14 **used to design the problem of ROP.** These problem's parameters were determined at the first stage.
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16 Then considering the performance of created models based on intelligent systems, drilling
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18 optimization was performed to increase the performance of ROP and determine the optimal
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20 parameters for 3 levels. Generally, the results showed that under conditions appropriate to each
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22 level, effective parameters can be improved based on drilling machine. This research presents the
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24 trend appropriate to the measured data. Further studies can be done to expand it.
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