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Review

A Survey of Application of Mechanical Specific Energy in Petroleum and Space Drilling

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Abstract: The optimization of drilling operations is an ongoing necessity since the major proportion of the terrestrial hydrocarbon reservoirs has been exhausted. Furthermore, there is a growing tendency among the space exploration agencies to drill the subsurface formations of the remote planets, such as the Moon and Mars. To optimize the drilling efficiency in such complicated conditions, the mechanical specific energy (MSE) must be efficiently reduced. The available MSE models incorporate the different parameters related to the surface rig, drill bit, and the underlying rocks to estimate the MSE values. In this research, the current status of those MSE models is assessed, and their relevant assumptions, limitations, applications, and pros and cons are profoundly argued. From the current scrutiny, it was deduced that the available MSE models require more geomechanical parameters to be included in their formulations. Furthermore, the use of artificial intelligence (AI) techniques was identified as an effective solution to incorporate such geomechanical parameters in the MSE models. Moreover, the establishment of suitable MSE models for off-Earth drilling applications was also revealed to be very urgent and essential. The performed analyses together with the comparative assessments are contributing factors for the modification and establishment of future MSE models.

Keywords: drill bit; ROP; MSE; DSE; drilling optimization; space drilling; UCS; Moon; Mars; regolith

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1. Introduction

Drilling operation is considered an integral part of any Earth-related engineering project, i.e., in civil engineering, mining engineering, and petroleum engineering. It can be expressed that the depth of the drilling operations spans a few ten meters in the field of civil engineering, a few hundred meters in mining engineering, and a few thousand meters in petroleum engineering. The emergence of the hydraulic fracturing technique together with the extended reach drilling (ERD) technology have contributed to drilling operations in which the horizontal distance between the well-head and the target reservoir can be stretched unprecedentedly. The complexity of the drilling process chiefly stems from the uncertainties related to the subsurface formations, active tectonic regimes, pore pressure, rock fracture distribution, etc.

To minimize the cost and time related to the drilling operations, a number of different approaches have been proposed so far. Amongst them, the concepts of mechanical specific energy (MSE) and rate of penetration (ROP) have achieved rather significant popularity to enhance the whole efficiency of the drilling operations [1]. From the chronological standpoint, the concept of ROP was first suggested by Maurer in 1962 [2]. Then, it was followed by the proposition of the MSE concept by Teale in 1965 [3]. From that time onwards, several researchers have strived to improve those pioneering concepts through the incorporation of new parameters within the early models. Such improvements (models) of MSE and ROP are elaborated in the next sections of this research.

The preliminary utilization of the MSE concept was initially limited to the optimization of the drilling operations. Nevertheless, subsequent improvements extended the versatility of the MSE concept towards other conspicuous applications. Interestingly, in the last decade, such applications have been rather supported with state-of-the-art artificial intelligence (AI) approaches. Those approaches have contributed to processing the countless real-time drilling data in order to enhance drilling efficiency.

Traditional models of MSE have been developed using empirical studies on a limited degree of drilling raw data. In better words, every MSE model has been developed on the basis of drilling information related to one, or a few petroleum exploitation projects. The non-linear nature of the drilling raw data and their relevant uncertainties were neglected to some extent. This drawback could affect the predicted values of MSE and drilling efficiency. AI techniques have been adopted to import such large amounts of data generated during the real-time drilling operations [4]. AI techniques solve the MSE-related problems based on mankind's cognitive abilities. The most prevalent AI approaches have been the artificial neural network (ANN), generic algorithms, (GA), support vector machine (SVM), etc. [5,6] In the subsequent sections, the previous studies related to the application of AI approaches in the domain of MSE and ROP optimization have been elaborated.

Earth aside, the planetary bodies have undergone an unprecedented exploration executed by the national and private space agencies, such as NASA, the European Space Agency (ESA), SpaceX, Blue Origin, etc. [7]. Some of the future space programs, such as water extraction, mineral mining, and outpost construction, comprise drilling operations in their layouts. Thus, the off-Earth drilling technology may be presumed as the most practical application of geomechanics in future space missions. So far, several designs of lightweight and small-scale rigs have been proposed for drilling on the lunar and Martian surfaces [8,9]. To evaluate the drilling efficiency of such rigs, the concepts of ROP and MSE have been adopted by the researchers. Drilling in extraterrestrial environments encounters formidable issues, such as microgravity, cryogenic temperature, low atmospheric pressure, surface radiations, regolith abrasiveness, etc. [10]. The limitations pertinent to the applicability of the power hydraulic systems in vacuum conditions is another pressing problem [10].

Drilling operations in the extraterrestrial environments must be optimized in terms of the consumed specific energy of the drilling tools (robots). The reason for this is that on the remote planets, the essential power for the drilling operations is supplied from solar or nuclear resources since the common fossil fuels cannot be used in cryogenic temperature and vacuum conditions. Hence, during the drilling process, the consumed specific energy should be considered as a seminal output. On the Earth, generally, the specific energy of the drilling rigs is evaluated through the MSE concept. Therefore, similarly, the concept of MSE can be deployed in extraterrestrial drilling operations.

This research intends to integrate the previous and present applications of the MSE concept in terrestrial and extraterrestrial drilling projects. The structure of the article has been organized as follows. Firstly, the MSE models are presented in chronological order so that the relevant assumptions, parameters, and mathematical formulas for every model are elaborated. Secondly, the available models of ROP are also recounted since the parameter of ROP is a key variable within the MSE models. All the presented equations use API units. Afterward, the diverse applications of the MSE concept in the Earth-based drilling operations are discussed. Such applications encompass drilling optimization, completion optimization, estimation of the rock properties, determination of the location of energy lost in the drill string, design of bit and cutter, estimation of formation pore pressure, and control of salt creep. Finally, the last part of the paper concentrates on the most prospective applications of MSE models in space drilling. Such extraterrestrial applications encompass drilling optimization, bit and drill rig design, and the identification of ice content. We envisage that this survey can effectively contribute to the development of the mechanical specific energy concept in prospective terrestrial and extraterrestrial drilling applications.

2. Materials and Methods

To fulfill this research, at first, the available MSE models have been collated, analyzed, and integrated. Those models have been explained through two categories: empirical and data-driven models. Furthermore, a comparison has been conducted to weigh up the advantages and disadvantages of such models. Afterward, the focus is shifted to the existing models of ROP, which is the contributing factor in MSE calculation. Similar to the MSE models, the available ROP models have been presented in two groups, i.e., empirical and data-driven models. Then, the diverse applications of the MSE concept in on-earth petroleum engineering are elaborated. This section is then followed by concentrating on the current MSE applications in off-Earth drilling operations. In the next step, an inclusive assessment on the status of MSE models together with their pros and cons are discussed. Eventually, the paper terminates with a conclusion depicting the key findings, results, and propositions of the current research.

2.1. MSE Models

2.1.1. Available Empirical MSE Models

In petroleum engineering, to reduce the cost of drilling operations, it is very significant to maximize the drilling efficiency through the minimization of energy consumption. For this purpose, the models of mechanical specific energy (MSE) have been applied to a large extent [11]. The MSE concept refers to the amount of energy needed to drill a unit volume of the rock. This parameter is highly practicable to optimize the drilling process as it helps to figure out where drilling is efficient or not [12]. A simple definition of the *MSE* can be expressed as [13]

$$MSE = Input\ Energy/Volume\ of\ Rock\ Cut \quad (1)$$

Depending on the type of drilling, MSE models can be classified into three categories. The first category, which is the basic model of the MSE, is mainly practical for vertical drilling. The second one has been suggested for the horizontal and directional drilling, and lastly, the third one is appropriate for the rotating drilling in which positive displacement motors (PDMs) are applied. The first model of *MSE* was proposed by Teale in 1965, and is mathematically expressed through the following equation

$$MSE = \frac{WOB}{A_{bit}} + \frac{120 \times \pi \times N \times T}{A_{bit} \times ROP} \quad (2)$$

where WOB represents the weight on the bit, A_{bit} illustrates the bit surface area, N is the rotational speed of the bit, T demonstrates the measured torque, and ROP indicates the rate of penetration [7]. Rabia (1985) [14] introduced a simple model for bit selection based on the specific energy as [11]

$$E_S = \frac{20 \times WOB \times N}{d_{bit} \times ROP} \quad (3)$$

where E_S is the specific energy and d_{bit} is the bit diameter. Afterward, Pessier and Fear (1992) [15] optimized the previous model by proposing a method to calculate the torque at the bit when the reliable torque measurements are not available. Their model is expressed as the following equation [12]

$$MSE = WOB \times \left(\frac{1}{A_{bit}} + \frac{13.33 \times \mu_b \times N}{d_{bit} \times ROP} \right) \quad (4)$$

where μ_b is a dimensionless number indicating the bit-specific coefficient of sliding friction, and is defined as

$$\mu_b = 36 \frac{T}{d_{bit} \times WOB} \quad (5)$$

In this model, the parameters are easy to obtain on the ground. Commonly, the value of μ_b is presumed as 0.25 and 0.5 for tri-cone and PDC bits, respectively.

Many researchers have related the values of MSE to the confined compressive strength of rock (CCS) to evaluate the drilling efficiency. The empirical correlation between MSE and CCS of the rock can be stated as [16]

$$E_m = \frac{CCS}{MSE} \times 100 \tag{6}$$

where E_m is the mechanical efficiency of drilling. Dupriest et al. (2005) [17] included the parameter of E_m in their model for calculation of MSE. They used the new term of mechanical efficiency in Teale's model, and assumed that this parameter is always in the range of 30–40% [13]. Their model was as the following relationship

$$MSE = E_m \left(\frac{WOB}{A_{bit}} + \frac{120 \times \pi \times N \times T}{A_{bit} \times ROP} \right) \tag{7}$$

where, as mentioned, E_m is the mechanical efficiency of the drilling operation, and the rest of the parameters are the same as in Teale's model presented in Equation (2). Armenta (2008) [18] remarked that the usage of the unconfined compressive strength (UCS) of the rock is not an appropriate approach for the evaluation of the MSE or mechanical efficiency of the drilling operations. He mentioned two main disadvantages of using UCS as a comparative tool with MSE values for the prediction of drilling efficiency: Firstly, finding a correlation between MSE and UCS is a tough task because MSE is mainly much larger than UCS values. Secondly, based on the laboratory experiments, he added that the values of MSE are significantly much greater than the CCS in the bottom hole while the drilling operation was performed with high efficiency [11].

Hydraulic properties of the rocks play an integral part in their mechanical response to the drilling operations [19,20]. Similarly, the coupling between the hydraulic properties of the rocks and bit is of paramount importance in the magnitude of the mechanical specific energy. Armenta (2008) [18] remarked that the impact of the bit hydraulics must be considered for measuring the drilling specific energy (DSE). He stated that the field observations demonstrate that a proper design of the bit hydraulics can dramatically enhance the DSE. He defined the DSE as the necessary specific energy for fragmentation as well as the removal of a unit volume of the drilled rock. He developed his DSE on the basis of Teale's model by adding a term containing the bit hydraulics effect on the DSE:

$$DSE = \frac{WOB}{A_{bit}} + \frac{120 \times \pi \times N \times T}{A_{bit} \times ROP} - \left(\frac{1.98 \times 10^6 \times \lambda}{ROP} \times \frac{HP_b}{A_{bit}} \right) \tag{8}$$

where the third term includes the impact of the bit hydraulics on the DSE. Furthermore, the number of 1.98×10^6 indicates a convention factor, and λ is a dimensionless parameter called bit-hydraulics factor, which is related to the bit diameter. The ratio of $\frac{HP_b}{A_{bit}}$ shows the horsepower per square inch of the bit area (hp/in^2).

Mohan and Adil (2009) [21] included the bit hydraulics in the specific energy and introduced a new model on the basis of the Teale's model. Despite Armenta (2008) [18], they named the new model as hydro-mechanical specific energy ($HMSE$) rather than DSE. They defined the $HMSE$ as the hydraulic and mechanical specific energy for drilling and removing the rocks under the bit surface. They remarked that their $HMSE$ model includes the torsional, axial, and hydraulic energy while the single MSE does not consider those parameters. They introduced their new $HMSE$ model as

$$HMSE = \frac{W_A + W_B + W_C}{Volume\ of\ Rock\ Drilled} \tag{9}$$

where $HMSE$ demonstrates the hydro-mechanical specific energy, W_A represents the work carried out by the WOB on the rock, W_B represents the work carried out by the bit torsional movement on the rock, and W_C is the work carried out by the fluid force escaping the jet on the rock. The more expanded form of the Equation (9) is given as the following relationship

$$HMSE = \frac{WOB_e \times ROP + (120\pi \times N \times T) + \eta_1 \times \Delta P_b \times Q}{A_{bit} \times ROP} \tag{10}$$

where WOB_e is the effective WOB, N is the number of revolutions of the bit, η_1 represents the dummy factor for the reduction of energy, and ΔP_b is pressure drop on the bit. The parameter of WOB_e is calculated by the following equation

$$WOB_e = WOB - \eta_1 F_{jet} \tag{11}$$

where F_{jet} is the impact force.

Minghui et al. in [15] included the pulsed-jet drilling in the magnitude of the MSE, and developed the corresponding theories and applications. In their model, the hydraulic term of the pulsed jet was incorporated in the MSE model. That model was capable to estimate the MSE for jet-pulsed drilling, and more than this, could predict the abnormal conditions too. Their proposed model was defined as

$$MSE = \frac{WOB}{A_{bit}} + \frac{120\pi \times N \times c_1 \times WOB \times d_{bit}}{A_{bit}ROP} + \frac{120\pi \times c_2 \times WOB \times \sqrt{N \times d_{bit}}}{A_{bit}\sqrt{ROP}} + \frac{\beta HP_b}{A_{bit}ROP} \tag{12}$$

where c_1 and c_2 are coefficients which decrease with the reduction of the confining pressure according to the tests results of [22], and β is coefficient of hydraulic horsepower.

The direction of the drilling also has a great impact on the stresses acting on the bit penetrating into the ground [23]. Another *MSE* model was developed by Chen et al. (2018) for directional and horizontal drilling activities [11]. According to their model, two important factors should be considered for this model, including *WOB* and torque. They defined their *MSE* model as [1]

$$MSE = E_m \times WOB_b \left(\frac{1}{A_{bit}} + \frac{13.33 \times \mu_b \times N}{d_{bit} \times ROP} \right) \tag{13}$$

where

$$WOB_b = WOB \times e^{-\mu\gamma_b} \tag{14}$$

$$T_b = \frac{\mu_b \times WOB \times e^{-\mu\gamma_b} \times d_{bit}}{3} \tag{15}$$

where WOB_b is WOB at the bottom hole for the directional and horizontal drilling, μ is the viscosity of the mud, T_b is the bottom hole torque at the bit, and γ_b is the bottom hole inclination. Chen et al. (2018) [11] also offered a new model for *MSE* which is applicable for drilling with PDM by defining the mechanical work needed to break the rock, and to perform the total mechanical work as

$$MSE = E_m \times \left(WOB \times e^{-\mu_s\gamma_b} \frac{1}{A_{bit}} + \frac{1155.2 \times \eta \times \Delta P_m Q}{A_{bit} \times ROP} \right) \tag{16}$$

where

$$MSE = \frac{W_V}{V} \tag{17}$$

$$W_V = W_t \times E_m \tag{18}$$

$$W_t = WOB_b \times ROP + 60 \times 2\pi \times N_s \times T_s + 60 \times 2\pi \times N_m \times T_m \tag{19}$$

$$V = A_{bit} \times ROP \tag{20}$$

where ΔP_m represents the dropped pressure across the PDM, η illustrates the efficiency of PDM, Q is flow rate, μ_s is the coefficient of the friction of drill string, W_V is the mechanical work needed to break the rock per hour, V demonstrates the volume of the drilled rock per hour, W_t is the total mechanical work done by the bit during one hour, N_s represents the bit rotary speed, which is supplied via the surface rotation, T_s defines the provided torque by the surface rotation, N_m defines the rotary speed by the PDM output, and lastly, T_m is the torque provided via the PDM.

2.1.2. Comparative Evaluation between the Available Empirical MSE Models

The aforesaid empirical models encompass the most preferred techniques to evaluate the MSE values in the global petroleum exploitation industry. As it can be seen, those MSE models have been enhanced during the recent decades. However, there seems to be some gaps that have not been fulfilled yet. In this research, to detect those gaps, the available MSE models are evaluated in terms of the domain of their parameters. Generally, the parameters in the aforesaid MSE models are related to three sources: surface rig, the drill bit, and the underlying rocks. In better words, the available MSE models have incorporated different numbers of determining parameters related to each source. For instance, Teale's model and Rabia's model mainly incorporated the parameters related to the surface rig in their corresponding formulas. Furthermore, they only considered the effect of bit diameter on the MSE values, and the effect of bit hydraulics parameters, such as nozzle diameter, drilling fluid type, etc., were neglected. On a more negative note, both Teale's model and Rabia's model did not include the parameters related to the drilled formations, thereby leading to a considerable deficiency in their MSE calculation.

In the early 2000s, other researchers strived to further incorporate the effect of underlying formations on the MSE. An example was the MSE model proposed by Dupriest et al., which included the rock CCS in the concept of mechanical efficiency. Although this was a conspicuous advancement in the MSE models, it seems to be very inadequate since the CCS cannot perfectly represent the effect of rock on the MSE. In fact, rock drill-ability is dependent on many parameters, such as type (igneous, sedimentary, and metamorphic), hardness, abrasiveness, porosity, pore fluid type, pore fluid pressure, etc. The CCS is an indicator for the rock hardness, and hence, it cannot directly involve the effect of other influential characteristics on the MSE. The new MSE models also suffer from the adequate rock-related parameters in their formulations. Hence, an imperative necessity has been detected to consider more rock parameters in the future MSE models. Those parameters especially can be related to the abrasiveness of the rocks, shear strength, and hydraulic properties, such as porosity and permeability.

From the late 2000s towards now, researchers have focused on the incorporation of parameters pertinent to the bit hydraulics on the MSE models. Those examples are the models developed by Armenta in 2008 [18], Mohan and Adil in 2009 [21], and Minghui et al. in 2016 [16]. Although those models have taken into account the bit hydraulics parameter, the effect of rock parameters has not been included sufficiently. In fact, in all of them, only the CCS or UCS represent the hardness nature of the rock.

Our comparative assessment demonstrates that the MSE model developed by Chen et al. in 2018 had many advantages in comparison to the previous models. The first thing is that this model has incorporated sufficient parameters related to the surface rig and bit hydraulics. Furthermore, the effect of drilling direction, which even impacts the rock characteristics, has been incorporated in the MSE formulation. Furthermore, it can be applied for the PDMs, which represent an integral part of current petroleum exploitation in the world. However, this model can be improved by incorporating more rock-related parameters in its MSE formulation. A summary of the aforementioned models has been expressed in Table 1.

Table 1. Description of empirical MSE models.

Model Type	Refrence	Formation Effect	Hydraulic Impact	Type of Application	More Details
MSE model	Teale (1965)	No	No	Vertical well	The first empirical model for MSE.
Specific Energy model	Rabia (1985)	No	No	Vertical well	Introduced a model for the bit selection based on the specific energy.
MSE model	Pessier and Fear (1992)	No	No	Vertical well	This model introduced bit-specific coefficient of sliding friction that helped to calculate the torque at the bit.
MSE model	Dupriest et al. (2005)	Yes	No	Vertical well	This model included new term of mechanical efficiency on the Teale's model.
DSE model	Armenta (2008)	No	Yes	Vertical well	Included impact of the bit hydraulics and defined DSE (the necessary specific energy for fragmentation and the removal of a unit volume of the drilled rock) instead of MSE.
HMSE model	Mohan and Adil (2009)		Yes	Vertical well	HMSE or Hydro-Mechanical Specific Energy is defined as the hydraulic and mechanical specific energy for drilling and removing the rocks. This model included the torsional, axial, and hydraulic energy while the single MSE does not consider those parameters.
MSE model	Minghui et al. (2016)	No	Yes	Vertical well	The pulsed-jet drilling is included in the model.
MSE model	Chen et al. (2018)	Yes	Yes	Directional and HorizontalWell	They defined two new expressions for WOB and Torque at the bottom hole for the directional and horizontal drilling. They also considered bottom hole inclination as a new factor in their model.
MSE model	Chen et al. (2018)	Yes	Yse	PDM	Defined the mechanical work required to break the rock, and to perform the total mechanical work.

Apart from the parameters related to the three aforementioned sources, i.e., surface rig, the drill bit, and the underlying rocks, there seems to be other factors which can be included in the MSE formulations. As the depth of drilling operations increases as a result of exhaustion of the conventional oil and gas reservoirs, the need for the development of such sophisticated MSE models is heightened. In the deep formations, some external factors, such as temperature and in situ stress, state play more important roles than the near-surface formations. While the in-situ stress state can be indirectly defined in the rock properties, the effect of temperature must be taken into account independently. Furthermore, a proportion of the consumed MSE is related to the heat created at the interface of the bit and the hosting rocks. Hence, the heat transfer between the drilling tools and the rocks is dominated by the rock temperature and the characteristics of the bit and drilling fluid. Excessive heat due to the friction between the drill tools and the surrounding rocks can cause significant impacts on the predicted MSE, as it can have various effects on the variables included in MSE models. For instance, the geometry of tools [24], type of fluid [25], the capability of cooling of fluid [26], the quality of uniform distribution of heat on tools [27], and the influences of different physical parameters on the flow of fluid [28] must be considered to obtain more reliable, accurate MSE models.

2.1.3. Data-Driven MSE Models

During the drilling operations, a vast amount of data related to different sources, i.e., the surface rig, the bit, the drilling string, the surrounding rock, and the drilling mud, are recorded in real-time. The classic mathematical or empirical methods are not capable of discovering the concealed relations between such parameters. In this condition, a data-driven MSE model can be effectively utilized to recognize such hidden correlations between the different parameters. Nowadays, data-driven MSE models are increasingly adopted due to their capability of incorporation of the vast drilling parameters in a time efficient manner. In this section, some of the intriguing examples of data-driven models are presented.

In 2018, Anemangely et al. created a data-driven MSE model to predict the properties of underlying rocks in an oil field located in the south part of Iran [29]. Such rock properties included the Poisson ratio, internal friction angle, UCS, and CCS of the subsurface formation. For this purpose, they utilized MLP neural networks. Their findings confirmed the high capability of the applied AI methods in the accurate prediction of the rock properties. Furthermore, some other AI methods, such as MNLR methods, were deployed to weigh up the accuracy and reliability of those techniques in the estimation of the rock properties. They concluded that the nature of the type of input data can impact the results. In fact, they observed that using AI techniques delivers accurate results when the target is the prediction of the internal friction angle, UCS, and CCS. However, the prediction of Poisson ratio was not as successful as other parameters.

Hegde and Gray in 2018 developed an MSE model using the random forest algorithm [30]. They used the drilling real-time data, such as formation strain, WOB, mud flow rate, and rotary speed, to establish their data-driven MSE model. In this way, their model was capable of adjusting the optimal drilling parameters ahead of the drill bit. They reported that through the new MSE model, they could increase the ROP up to 20% and decrease the torque on the bit up to 7%. Therefore, they concluded that the data-driven MSE model contributed to a further lifetime of the bit as well as a less non-productive time. In a similar study, Ref. [31] used the MSE and torque to optimize the ROP. They adopted such a data-driven model to see the variations of the drilling efficiency with other drilling parameters.

In an innovative approach, Ref. [32] defined the term of ratio of the ROP to MSE for describing the drilling efficiency status. To do this, they created seven ROP models based on the ANN approach. The input data encompassed large field data obtained during the real time measurements of rotation speed, WOP, ROP, torque, and mud flow rate. The ROP models successfully anticipated the accurate values of ROP during the drilling operations. Then, they combined the results of the obtained values of ROP with the computed values of MSE to maximize the drilling efficiency. In this way, they defined the ROP/MSE ratio as an indicator of the drilling efficiency.

In another investigation, Ref. [33] developed a novel data-driven MSE model for forecasting the optimal values of rotary speed and WOB, so that a real-time optimization of drilling efficiency could be achieved. The MSE model functioned as an advisory tool to enhance the rate of penetration as well as the lifetime of the drilling equipment. Furthermore, it could predict the drilling dysfunctions and alert the drilling crew about the potential undesired events.

Liang et al. in 2022 utilized the supervised machine learning method of SVM approach to develop an MSE model for recognition of lithology ahead of the drilling bit [34]. They generated several SVM models based on the different raw data types. From the results, they deduced that the MSE concept can be effectively utilized for lithology recognition with an accuracy higher than 90%. The main advantage of the SVM approach was the capability of processing the enormous data with noises and outliers.

2.2. ROP Models

Apart from the mechanical specific energy, to reduce the cost of the wellbore drilling, the rate of penetration (ROP) must be optimized as much as possible. Several factors affect the ROP, including the formation type, formation abrasiveness, rock compressive strength, weight on the bit, rotatory speed, bit hydraulics, bit size, bit wear, jet nozzles, etc. There are several models to predict the ROP and to determine the effect of each parameter so that the ultimate ROP can be enhanced. The first category of models includes empirical models, and the second, data-driven ones.

The first category includes the empirical models based on the linear regression on the field drilling data. In fact, such models were created on the basis of the empirical correlations between the ROP and parameters affecting it. The second categories are new and use artificial intelligence (AI) methods to predict the ROP.

2.2.1. Empirical ROP Models

Empirical or linear regression-based models for the prediction of ROP are summarized as below:

The first empirical model for ROP prediction was developed by Maurer in [2]. Rock strength, *WOB*, *N*, and the size of the drill bit are the fundamental factors in this model. The relation of these parameters with *ROP* was stated in the following equation

$$ROP = \frac{K}{S^2}\left(\frac{WOB}{d_{bit}} - \frac{WOB_0}{d_{bit}}\right)^2 N \tag{21}$$

where K represents the constant of proportionality, S shows the rock compressive strength, and WOB_0 is the threshold WOB.

The second model was suggested by Galle and Woods in [35]. This model only included the worn-down height of the bit, and not bit body wear. The mathematical form was as

$$ROP \propto \left(\frac{1}{0.928125\,h^2 + 6h + 1}\right)^{b_7} \tag{22}$$

where h is fractional bit tooth dullness and b_7 is an exponent (suggested to choose as 0.5).

Another model to predict *ROP* was suggested by [36]. That model comprised the rock strength in the Maurer's model, [2], in the parameter K. The following relationship represents the basis of such a model

$$ROP = K\left(\frac{WOB}{d_{bit}}\right)^{b_5} N \tag{23}$$

where b_5 is the WOB exponent.

As a conspicuous proposition, Bourgoyne and Young in (1974) offered another model for ROP [37]. This model is considered as one of the most applicable empirical models to predict the *ROP* values. Equation (24) and the following functional relations define this model of *ROP*:

$$ROP = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \tag{24}$$

$$f_1 = exp^{2.303 \times a_1} \tag{25}$$

$$f_2 = exp^{2.303 \times a_2 \times (10000 - TVD)} \tag{26}$$

$$f_3 = exp^{2.303 \times a_3 \times TVD^{0.69} \times (g_p - 9.0)} \tag{27}$$

$$f_4 = exp^{2.303 \times a_4 \times TVD \times (g_p - ECD)} \tag{28}$$

$$f_5 = \left[\frac{\left(\frac{WOB}{d_{bit}}\right) - \left(\frac{WOB}{d_{bit}}\right)_t}{4 - \left(\frac{WOB}{d_{bit}}\right)_t}\right]^{a_5} \tag{29}$$

$$f_6 = \left(\frac{N}{60}\right)^{a_6} \tag{30}$$

$$f_7 = exp^{-a7 \times h} \tag{31}$$

$$f_8 = \left(\frac{F_{Jet}}{1000}\right)^{a_8} \tag{32}$$

In Equations (25)–(32), a_1 to a_8 manifest constants that are estimated from the real drilling data, TVD displays the true vertical depth, g_p represents the pore pressure gradient, ECD illustrates the equivalent circulating density, $(WOB/d_{bit})_t$ stands for the parameter of the threshold bit weight per inch of bit diameter when bit starts drilling (1000 lbf/in), (W/d_{bit}) represents the bit weight per inch of bit diameter, and F_{Jet} demonstrates the fluid motion force beneath the bit.

It is also worth mentioning that this model was improved by Oslougi in (2007) to include the hole cleaning for the directional and horizontal wellbores. This improved model is applicable for both roller cone bits and PDC bits [38].

The subsequent two models belong to Warren who introduced his first model [39]. Later, Warren declared a modification of the previous model in [40]. The first one, which is called the "Perfect-Cleaning Model", included parameters, such as bit rotary speed, rock strength, weight on the bit and bit diameter. Equation (33) describes this model:

$$ROP = 1/(\frac{aS^2 d_{bit}^3}{N^b WOB^2} + \frac{b}{Nd_{bit}}) \tag{33}$$

In this equation, a and b are constants which are dimensionless, and S demonstrates the rock strength. The applicability of this model appeared to be limited since it did not include the process of cuttings removal in ROP calculation.

The second model offered by Warren is called the "Imperfect-Cleaning Model" and is based on the previous model. However, this model includes the cuttings removal process, which is dependent on the properties of mud (density and viscosity), and the effect of jet impact force on ROP. This improvement rendered the new model superior to the former one. Equation (34) represents this model as

$$ROP = 1/(\frac{aS^2 d_{bit}^3}{N^b WOB^2} + \frac{b}{Nd_{bit}} + \frac{cd_{bit}\gamma_f \mu}{F_{jet}}) \tag{34}$$

where c is a dimensionless constant, γ_f stands for the fluid specific gravity, and μ indicates the viscosity of the drilling fluid.

The last well-known empirical model was suggested by Osgouei [38]. This model was established on the basis of the Bourgoyne and Young model. In his ROP model, Osgouei included the effect of the hole cleaning factor on the ROP values via adding three factors, f_9, f_{10}, and f_{11}, representing the hole cleaning term in the horizontal and directional wellbores as well as vertical wellbores for both roller cone and PDC bits. Osgouei's ROP model is stated as

$$ROP = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \times f_9 \times f_{10} \times f_{11} \tag{35}$$

$$f_1 = e^{a_1} \tag{36}$$

$$f_2 = e^{a_2 \times (8800 - TVD)} \tag{37}$$

$$f_3 = e^{a_3 \times TVD^{0.69} \times (g_p - 9)} \tag{38}$$

$$f_4 = e^{a_4 \times TVD \times (g_p - ECD)} \tag{39}$$

$$f_5 = \left[\frac{\frac{WOB}{d_{bit}}}{\left.\frac{WOB}{d_{bit}}\right|_t} \right]^{a_5} \tag{40}$$

$$f_6 = \left(\frac{N}{N_c} \right)^{a_6} \tag{41}$$

$$f_7 = e^{-a7\ h} \tag{42}$$

$$f_8 = \left(\frac{F_{Jet}}{F_{Jc}} \right)^{a_8} \tag{43}$$

$$f_9 = \left(\frac{A_{bed}/A_{well}}{0.2} \right)^{a_9} \tag{44}$$

$$f_{10} = \left(\frac{V_{Actual}}{V_{Critical}}\right)^{a_{10}} \tag{45}$$

$$f_{11} = \left(\frac{C_c}{100}\right)^{a_{11}} \tag{46}$$

In the mentioned equations, $a_1 - a_{11}$ represent constants that are estimated from the real drilling data, ECD is Equivalent circulating mud density at the hole bottom, N_c is the critical rotary speed that should be estimated by considering the properties of drilling string, bit type, and field data. Moreover, h shows the fractional tooth dullness, and the parameter of F_{Jc} depends on the bit type, drilling mud property, and pump pressure. The normalization value is assumed to be 1000 lb. The parameter of A_{bed} illustrates the area of the cuttings bed, A_{well} demonstrates the area of the wellbore, V_{Actual} is the volume of cuttings, $V_{critical}$ represents the critical volume of cuttings removal, and C_c is the concentration of cuttings constant.

To sum up, the empirical ROP models have undergone continuous modifications the same as the empirical MSE models. In this research, it was found that the reliability of the available ROP models can be judged through incorporation of five factors in their formulations. Those five factors include the bit wear, pore pressure, drilling fluid, applicability, and hole cleaning. Based on such factors, a comparison has been performed in Table 2. As can be seen, the model proposed by Osgouei satisfies all of five parameters. Hence, this model is an efficient tool which can be adopted together with the MSE models for enhancement of the drilling efficiency. It is noteworthy that the impact of external factors such as temperature can be included in all available ROP models.

Table 2. Description of Empirical ROP Models.

Refrence	Hole Cleaning	Bit Wear	Drilling Fluid	Pore Pressure	Applicatin
Maurer (1962)	No	No	No	No	Vertical well
Galle and Woods (1963)	No	Yes	No	No	Vertical well
Bingham (1965)	No	No	No	No	Vertical well
Bourgoyne and Young (1974)	No	Yes	Yes	Yes	Directional and horizontal well
Warren (Perfect–Cleaning Model) (1981)	No	No	No	No	Vertical well
Warren (Imperfect–Cleaning Model) (1984)	Yes	No	Yes	No	Vertical well
Osgouei (2007)	Yes	Yes	Yes	Yes	Directional and horizontal well

2.2.2. Data-Driven ROP Models

In recent decades, the conventional oil and gas reservoirs have been increasingly exhausted. Thus, the need for drilling operations in the lower depths and the application of more complicated methods, such as directional and horizontal drilling, call for more precise models to predict ROP [23,41]. This is why artificial intelligence approaches have been widely applied by a large number of petroleum engineers and researchers to predict the ROP. In fact, in the petroleum industry, a large amount of data is daily being recorded during the drilling operations. The best methods to analyse and find a mathematical pattern between the different drilling parameters are AI approaches. Those methods can solve diverse problems, which include a high complexity stemming from the numerous parameters influencing the drilling operations [42].

Hegde et al. [43] compared the results of the empirical models of ROP to obtained models by the data-driven methods. They concluded that the data-driven models provide a better prediction of ROP than the empirical counterparts. They stated that the main shortcomings of the empirical models include the usage of empirical coefficients (constants) and weak accuracy in predicted ROP values. Moreover, a number of empirical models do not consider the effects of bit hydraulics, bit properties, mud properties, etc. On the opposite side, they recounted two main advantages for data-driven models. Firstly, there is no need for empirical constants or bit properties, and secondly, the input data are real recorded information on the ground surface (from drill rig).

Arehart [44] used neural networks to determine the bit grade (state of the bit wear) while drilling. He predicted the bit grade by using drilling input parameters, such as ROP, hydraulic horsepower per square inch, WOB, rotary speed, and torque. He stated that the results of the bit grade predicted by the neural network were acceptably accurate. However, he pointed out that the input data were insufficient, and it was necessary to import more data to extract a better fitted trend between the variables and grade of the bit wear.

Furthermore, Bilgesu et al. in [45] introduced a novel method for predicting ROP by using the neural networks. They obtained 8000 measurements from a rig floor simulator. Those data included rotary speed, torque, WOB, formation drill-ability, the rate of mud pump circulating, bit type, bit tooth wear, bit bearing wear, and the rotation time of the bit. Those parameters were given to the neural network model to anticipate the values of ROP. Moreover, in his research, by using another data set, Bilgesu made a model to anticipate the ROP values without using the bit bearing wear and bit tooth wear parameters. This was because of the lack of underground data concerning the bits.

In addition, Amar and Ibrahim in 2012 used neural networks for predicting ROP by applying seven parameters, including ECD, WOB, rotary speed, depth, tooth wear, pore pressure gradient, and Reynolds number [46]. Similarly, Gidh et al. [47] applied neural networks to anticipate the bit wear. Then, they used their findings to improve the values of ROP.

Machine learning (ML) approaches have also been adopted in the modeling of ROP to enhance the drilling operation [48–50]. Dunlop et al. in 2011 used the WOB and rotary speed for the optimization of ROP during drilling activities. Furthermore, Ref. [51] developed a data-driven ROP model for anticipation of probable stuck pipe problems using ML techniques. Ref. [52] utilized the machine learning method to maximize the values of ROP using parameters, such as rotary speed, WOB, and mud flow rate.

2.3. Applications of MSE Models in Terrestrial Drilling

The quantification of MSE has been applied in several fields of drilling operations. The concept of MSE can be applied for planning and monitoring the whole drilling project as well as for analyzing, predicting, and evaluating the rate of penetration (ROP). Furthermore, other initiative applications, such as predicting pore pressure and rock characterization, are also feasible [53]. In the following section, the diverse applications of MSE concept in the drilling operations are elaborated:

2.3.1. Drilling Optimization

To enhance the specific energy consumed by the drilling rig, the concept of MSE has been frequently adopted so far [54–57]. As a new example, Hamlawi et al. in 2021, utilized a new MSE-based program for optimization of the drilling efficiency of a conventional drilling rig [58]. They developed a new MSE drilling advisory program based on the machine learning algorithms to determine the optimal values of the operational drilling parameters such as the WOB and rotary speed. They deduced that the new AI-based MSE program could remarkably decrease the tear and wear of the bits, fuel consumption, bit replacement, non-product time (NPT), and the total working days.

Analysis of the mechanism of the rock fragmentation is based on the comprehension of the relationship between the MSE and drilling parameters. Therefore, based on the MSE, a systematic approach for the management of the vibration risk was established. Fei et al. in 2017 used Teale's model to assign the bit torque for a special bit type to drill at a particular ROP in a specified rock type [59]. They applied the following equation for this work:

$$T = \left(\frac{CCS}{E_m} - \frac{4 \times WOB}{\pi \times d_{bit}^2} \right) \times \left(\frac{d_{bit}^2 \times ROP}{480 \times N} \right) \tag{47}$$

where CCS refers to the confined compressive strength of rock that is calculated for permeable rock to the bottom-hole condition as follows:

$$CCS = UCS + DP + 2DP \times \sin\varphi/(1 - \sin\varphi) \tag{48}$$

where UCS demonstrates the unconfined compressive strength of the rock, φ represents the rock friction internal angle, DP is equal to the ECD pressure minus the pore pressure. To calculate the pore pressure for a vertical well drilled in an impermeable rock, they used the Skempton pore pressure to calculate the compressive strength of the rock as

$$CCS_S = UCS + DP_S + 2DP_S \times \sin\varphi/(1 - \sin\varphi) \tag{49}$$

where CCS_S is the CCS for impermeable rock obtained using the Skempton pore pressure, and DP_S is defined as the differential pressure between the ECD pressure and Skempton pore pressure. Based on Equations (47)–(49), the modified MSE model was derived. This approach was associated with identifying the vibration issue based on the MSE and monitoring the environment of the down-hole in the real time to enable the drilling crew for an immediate reaction by adjusting and changing the drilling parameters. This was an effective approach to mitigate the effect of the stick-slip problems in drilling operations, and positively, it improved the ROP about 20% [59].

2.3.2. Estimation of the Rock Properties

Understanding of the rock properties, chiefly rock strength, contributes to the establishment of a more efficient plan of drilling operations. Trivedi et al. in 2020 introduced an updated MSE program to estimate the CCS of the subsurface formations [60]. Their MSE model included drill-string dysfunctions, such as vibration, mud motor dynamics, and frictional losses along the drill-strings. They found that a reliable correlation between the actual MSE and CCS is developable. In their model, two new parameters were introduced. The first parameter was the hydraulic specific energy (HSE) that estimates the function of the hydraulic impact force at the formation rather than the bit bottom. The second parameter was the vibration specific energy (VSE), which estimates the energy pertinent to the vibrations and its influence on the translational weight on the bit, and the rotational energy associated with the torque. The first parameter can be explained as follows

$$HSE = \sum_{N_i}\left(1 - A_v^{-0.122}\right) IF_{N_i}/A_{b,\ N_i} \tag{50}$$

where N_i is number of nozzles, A_v shows the ratio of jet fluid velocity for returning the fluid velocity, $A_{b,\ N_i}$ is the bit area per nozzle, and IF_{N_i} can be obtained as following relationship

$$IF_{N_i} = 0.01823 \times C_d \times (Q/N_i)\sqrt{MW \times \Delta p_b} \tag{51}$$

where C_d represents the fluid discharge coefficient, Q is flow rate of the mud, and MW demonstrates the mud weight.

The second introduced parameter can be explained as follows:

$$VSE = \sum f(KE,\ PE,\ DE)/Area_{bit} \tag{52}$$

where the term of $\sum(KE,\ PE,\ DE)$ describes the total kinetic, potential, and dissipation energies related to the vibration amplitude. Furthermore, the term of $f(KE,\ PE,\ DE)$ illustrates the force required for the total energy of the system, including mass matrix. The parameter of $Area_{bit}$ is the cross-sectional area of the bit.

Considering those two introduced parameters, their actual MSE model contributing towards the cutting process can be shown as follows:

$$MSE_{actual} = \left(\frac{WOB}{Aria_{bit}}\right)_{VSE} + \frac{120 \times \pi \times (N_{bit})_{mud-motor} \times T_{bit(mud-motor,\ friction,\ VSE)}}{Aria_{bit} \times ROP} + HSE \quad (53)$$

where $(N_{bit})_{mud-motor}$ and $T_{bit(mud-motor,\ friction,\ VSE)}$ can be calculated from the following equations:

$$T_{bit} = T_{bottom(VSE,\ friction)} + \left(\frac{Tmax_{mud-motor}}{DPmax_{mud-motor}}\right) \times DP_{mud-motor} \times \frac{Nmax_{mud-motor}}{N_{mud-motor}} \quad (54)$$

$$N_{bit} = N_{top-drive} + \left[Q \times (Rev_V)_{mud-motor}\right] \quad (55)$$

where T_{bottom} is the torque at the bottom of each drill-string element, $Tmax_{mud-motor}$ is the maximum torque rating of the mud-motor, $DPmax_{mud-motor}$ is the maximum differential pressure of the mud-motor, $DP_{mud-motor}$ indicates the actual differential pressure across the mud-motor, $Nmax_{mud-motor}$ is the maximum rotation per minutes (N) rating of the mud-motor, $N_{top-drive}$ is the rotation per minutes (N) at top-drive, and $(Rev_V)_{mud-motor}$ represents the revolutions per mud volume of the mud-motor.

Calculating the MSE baselines and averaging them can be utilized to check the values of the MSE in real-time. The obtained information of MSE baseline could also be adopted to manifest the UCS of the formations, and therefore, may be applied to formulate a trustworthy map of the hardness of the rock to improve the design of completion plan [61]. Gurtej et al. in [39] deployed the MSE baselines to create a multivariate physics-based decision tree approach for automatically classification and identification of the different dysfunction types. Some limitations in the technology, such as slow data rates, restricted the adoption of the MSE as an efficient approach for evaluation of the formation. However, this issue was solved by the modern coiled tubing drilling BHAs, which are designed for the underbalanced drilling operations. Utilizing this method offers the acquisition of information about the type of rock which is drilled in real time with an inch level resolution [62].

Arnø et al. in [63] successfully developed a new deep learning method by using the concept of MSE for real-time classification of the formation being drilled at the depth of bit penetration. After training and validation of the model, its accuracy in classifying a varying set of the different formations was examined. The tests were reported as very successful since the model could immediately report the type of layers at the different borders. This advantage can rapidly alert the operator about the class of the new formation which the drill bit commences to penetrate through.

2.3.3. Completion Optimization

As it was already mentioned, the *MSE* values could be applied to predict the *UCS* of the rock within each frac stage. This could be very beneficial to set the perforation clusters in the borehole sections with similar *UCS* values to reduce the negative influences of the rock heterogeneity [64,65]. The drilling experts can take advantage of the MSE by recognizing the close relationship between it and the unconfined compressive strength (*UCS*) for the completion operation. This close relation can be presented as follows:

$$MSE = UCS \times D_{eff} \quad (56)$$

where D_{eff} is the efficiency of transmitting the penetration power of the rig to the rock [66].

The corrected mechanical specific energy (CMSE) can be utilized where there is need to compute and account the friction losses in the wellbore and drill string in real time. The CMSE is applied for estimation of the geomechanical logs and creation of a live geomechanical model being applied to steer the bit through the fracable rocks.

When the drilling is fulfilled, according to the CMSE outputs (including pore pressure, stresses, and natural fracture index), the frac stage spacing and cluster density will be adjusted [67]. The technology of using CMSE for predicting geomechanical logs is a considerable step to optimize the completion process. Moreover, the most significant benefit of this technology is its versatility in any drilling operation without the need to use additional surface sensors, gauges, or down-hole measurement tools, thereby reducing the costs and risks related to the potential wellbore issues.

Furthermore, another significant benefit of this technology is that there will be no need for on-site personnel or authorizations since it uses the real-time drilling data to immediately steer in the rock. Furthermore, the instant design of the completion stage becomes feasible exactly at the end of the drilling operations. This technology is utilized to estimate the multiple factors that create the frictional losses in the real time. When these losses are perfectly assessed, they can be applied to MSE correction. In fact, CMSE is acquired from the surface drilling data that contain vital information which can be used for designing the optimal cluster placement [68].

2.3.4. Determination of Energy Flow, Lost and Location

Chen et al. in [69] pointed out that the term of MSE cannot directly provide information about the loss of energy in the components of the drilling system, such as drilling strings. In better words, during the drilling operations, a proportion of the provided energy may reside within the drill string in the forms of strain and kinetic energy. Furthermore, the root cause of the energy loss also remains undetected. They proposed an initiative approach for estimation of the drilling energy flow along the drilling string. In their method, the whole drilling string was modeled from the top to the bit using a number of 3D beam elements. The dynamic response history of the elements were solved by a numerical program of finite element method.

MSE is a function incorporating the drilling parameters to determine the overall drilling efficiency. However, it does not clearly distinguish the location of inefficiencies. This issue can be addressed by the concept of mechanical specific energy ratio (MSER). The location of the inefficiencies could be more easily identified by using the ratio of the MSE surface values to the MSE values of the down-hole. MSER can be defined as a correlation to optimize the drilling fulfillment in real time.

To find the ratio, firstly, it is necessary to calculate the MSE taken from the drillfloor values. The original MSE equation is changed by substituting the area of rock destroyed with the diameter (d) variable to account for only the volume of rock which is destroyed by the under-reamer. The following equations describe how the mechanical specific energy with drillfloor values and mechanical specific energy with MWD (Measuring while drilling) values are obtained.

$$MSE_{Drillfloor} = \frac{WOB_{DF}}{A_{rock\ destroyed}} + \frac{480 \times N_{DF} \times T_{DF}}{A_{rock\ destroyed} \times ROP} \tag{57}$$

$$A_{rock\ destroyed} = \left(\pi r^2_{under-reamer\ diameter}\right) - \left(\pi r^2_{bit\ diameter}\right) \tag{58}$$

$$MSE_{MWD} = \frac{4 \times WOB_{MWD}}{\pi \times d^2_{bit}} + \frac{480 \times N_{MWD} \times T_{MWD}}{d^2_{bit} \times ROP} \tag{59}$$

where $MSE_{Drillfloor}$ is mechanical specific energy from the drillfloor values, $A_{rock\ destroyed}$ is the area of rock which is destroyed, WOB_{DF} is WOB of drillfloor, N_{DF} is N of drillfloor, T_{DF} is drillfloor torque, MSE_{MWD} is mechanical specific energy from MWD tool, r is radius, and WOB_{MWD}, N_{MWD}, T_{MWD} are WOB, N, and T are obtained from the MWD tool respectively. The use of this ratio is applied in under-reaming process of the deep-water wells [70].

As a very useful application of MSE, it can be applied in the operation of reaming while drilling (RWD) that is limited to finer formations. A thermo-poroelastic model of MSE can be utilized in order to apply the RWD for a particular formation and a recommendation for reamer-pilot size ratio [71].

2.3.5. Bit and Cutter Design

Through the trial-and-error attempts together with the novel numerical modelling programs, the process of rock cutting and bit performance have been broadly investigated. In such investigations, the focus has been to design a well-functioning bit or cutter so that the minimum energy was required for the fragmentation of the rock. Those studies were conducted mostly for PDC drill bits, and can be categorized into two subgroups: PDC bit/rock interaction and PDC cutter/rock interaction [72]. One of the first pioneer PDC cutter/rock models was developed by Miedema [73], and it was used as a constitutive model for the subsequent investigations by the different researchers. The model was appropriate for evaluation of the PDC cutter/rock interaction in formations, such as clay, rock, and sand. The model could predict the cutting forces and the values of MSE on the basis of the force equilibrium equations.

A three-dimensional PDC cutter model developed by [72] to determine the forces at the cutter/rock interaction phase. The model used the poro-elasticity theory to compute the drilling-induced stress regime within the rock while the rock cutting cycle. After the calculation of stress state within the rock, the criterion of modified Lade was used to anticipate the rock failure. Their model was verified with the probe of the impact of the contributing factors on the process of rock cutting. Such factors included the depth of cut, hydrostatic pressure, back rake angle, side-rake angle, and worn depth.

Chen et al. in [74] investigated the effect of two simultaneous PDC cutters on the rock fragmentation. They witnessed that the rock is fragmented in front of and between the two cutters. In this case, the cutting volume was remarkable, thereby leading to lower magnitudes of MSE. They concluded that if double cutters are installed close to each other so that the depth of cut would be large, the value of the MSE decreases by 5–25% in contrast to a single cutter. They calculated the MSE for a single cutter (MSE_s) according to the following equation:

$$MSE_s = \frac{R_x}{A_c \cos \alpha} \tag{60}$$

where R_x is the cutting force, A_c is the contact area between the cutter and rock, and α represents the angle that depends on the tooth bit direction towards the rock surface. To calculate the MSE for the double cutters, they used another equation as follows:

$$MSE_d = \frac{R_x^I + R_x^{II}}{A_{cut}} \tag{61}$$

where MSE_d is the mechanical specific energy for double cutters, A_{cut} is the cutting area of two cutters, R_x^I and R_x^{II} are cutting forces by the two cutters. To facilitate the quantification of the integrated influence of double cutters, they proposed a parameter, integrated index ζ, being defined as follows:

$$\zeta = \frac{MSE_s}{MSE_d} \tag{62}$$

The MSE concept was applied to develop a methodology for optimization of the design of polycrystalline diamond compact (PDC) bit for the entire hole section according to the modelled MSE and UCS values [57].

2.3.6. Estimation of Formation Pore Pressure

The mechanical response of the natural porous rocks is a function of their minerals and pore fluid pressure [75,76]. Pore pressure affects the drilling process through the concept of effective stress law [77,78]. The more pore pressure, the less effective stress. In the drilling field, it has been long accepted that the energy required to drill the formation not only is dependent on the mud pressure but also on the formation pore pressure. Generally, it is accepted as common sense that the formation requires less energy to drill if the fluid pore pressure is higher. The cause is believed to be the weakening effect of the pore pressure. The effective principal stresses on the rock matrix decline due to the pore pressure, and this leads to an easier failure of the rock as a frictional-cohesive material. It is also widely observed that the extent of this effect can be significantly different from one rock type to another [79].

The first attempts to leverage the MSE in determining pore pressure from the drilling-mechanics data were not successful [80]. Akbari et al. [79] performed laboratory experiments to probe the impact of the pore pressure on the forces of a single PDC cutter by extracting the empirical correlations between the pore pressure and the MSE on a series of sandstone specimens. To perform the tests and extract the relevant correlations, they controlled the pore pressure and cell confining pressure, but the other conditions remained constant. The tests were conducted at two pore fluid pressure states; one state was atmospheric pore fluid pressure, and the second state pore fluid pressure was equalized to the confining pressure (zero differential pressure). They used the performed experimental data to produce well-fitting correlations between the MSE, the differential pressure, and the confining pressure that had a logarithmic nature. Their proposed correlation for estimating of the MSE based on the two parameters of pore pressure and confining pressure was defined as:

$$MSE\left(P_{confining}, P_{diff}\right) = UCS + \left(a' + b'^{\frac{P_{diff}}{P_{conf}}}\right) \ln\left(\frac{P_{conf}}{P_{atm}}\right) \tag{63}$$

where $P_{confining}$ is confining pressure, P_{atm} is the atmospheric pressure, P_{diff} is differential pressure, UCS is uniaxial compressive strength, and a' and b' are two constants that can be determined for a certain type of rock. The extracted correlation demonstrated that the impact of pore fluid on the MSE is similar to the impact of the confining pressure, but it was weakened via a coefficient.

Since, the required energy to remove a unite volume of the rock relies on the in-situ rock strength along with the differential pressure acting on the rock, Majidi et al. in [81] developed a method to estimate the the values of pore fluid pressure from the subsurface drilling mechanics parameters together with the in-situ rock data using terms of MSE and drilling efficiency (DE). The equation of DEMSE method or pore fluid pressure estimation method is defined as follows:

$$p = ECD - (DE_{trend} \times MSE - UCS) \times \left(\frac{1 - \sin\varphi}{1 + \sin\varphi}\right) \tag{64}$$

where p represents the pore pressure and DE_{trend} illustrates the normal drilling-efficiency trend line.

Through this approach, the concept of MSE for pore pressure estimation incorporated both WOB and torque to compute the energy needed to drill the rock. They showed that an MSE-based approach, as an independent source of information, can give results that are compatible favorably with the conventional petro-physical pore pressure estimation methods.

By performing a series of laboratory experiments, Curry et al. in [82] investigated the impact of borehole pressure on the ROP and MSE in salt formations. They concluded that the borehole pressure does not have noticeable effect on the ROP and MSE in salt formations. Consequently, in such formations, there would be a little penetration rate penalty if high borehole pressure is needed for the wellbore stabilization. However, increasing the mud weight causes considerable changes in the properties of the drilling fluid, except its density.

2.3.7. Control of Salt Creep

In the most oil/gas sites, salt formations function commonly as the low-permeability cap rocks to seal the oil and gas reservoirs. Hence, those geological structures are strong indicators of potential hydrocarbon reservoirs under them. However, salt rocks are considered as highly problematic formations in which the creep behavior can dramatically heighten the stresses around the wellbore. Prior to the drilling, the potentially available salt formations in the site must be precisely studied to investigate their creep behavior affecting the MSE and ROP during the drilling operations [83].

Recently, some researchers have concentrated on the studying of MSE while drilling in salt formations where the high MSE values have brought severe drilling problems, such as vibrations, stuck pipe, and torsional resonance [84,85]. Pinto et al. in [85] developed an initiative MSE-Index concept to control the salt creep and to increase the rate of drilling (penetration) in the Brazilian pre-salt formation.

For this purpose, they described the term of MSE_i as the maximum limit of energy in which the entire energy applied in the drilling system is used to cut the rock. MSE_i can be obtained through the following relationship:

$$MSE_i = UCS + m \times P_m \tag{65}$$

where m is a dimensionless parameter that depends on the drill bit design, and P_m shows the downhole pressure interpreted as the ECD. In fact, m is a coefficient that varies in the range of 3–20 for particular cutter structures [86].

The outstanding point of their work was the usage of the MSE concept for determination of the proper lower bound of the equivalent circulating density (ECD) while drilling [63]. For years, it has been generally accepted that the creep behavior relies remarkably on the upper and lower limits of the operational ECD. Therefore, choosing a proper mud weight is of paramount significance to prevent the wellbore from the potential closure (convergence). The upper bound of the ECD can be determined through the leak-off test (LOT), or alternatively, the formation integrity test (FIT). Hence, it is easy to estimate. During their studies on the Brazilian pre-salt formations, [85] observed that there is a strong relationship between the intensity of the creep behavior and MSE with depth. This relationship was more precisely studied so that they could develop an MSE index term as a function of drilling depth to predict the lower bound of the ECD [86]. This new concept resulted in a reduction of the needed energy together with the delayed times of drilling in the related projects.

2.4. Applications of MSE Models in Extraterrestrial Drilling

In recent decades, the idea of space colonization has received great attention from the side of both national and international space agencies. While before the 2000s, only the National Aeronautics and Space Administration (NASA) and Russian Federal Space Agency (currently as Roscosmos) were exploring the remote planets, in recent decades other space agencies from Europe, China, India, Japan, etc. have joined this discovery programs. As well as the potentially habitable planets, such as the Moon and Mars, the discoveries have also been stretched to comets and asteroids [87,88]. The exponential growth of the technology has led to many improvements in the manufacturing, transportation, landing, and long-duration stay of the multipurpose shuttles, landers, robots, and rovers in the planetary environments.

As the aforementioned agencies plan to execute diverse exploratory programs on the different spots of the solar system, a large proportion of them have focused on the habitable planets, such as the Moon and Mars [7]. Their objective is to study the inner lithosphere and outer atmosphere of such planets to colonize them as the second human civilization in the Milky Way galaxy. So far, dozens of the exploratory programs have provided a wealth of information about the surface characteristics of the Moon and Mars. However, the subsurface has remain markedly undiscovered. To reveal the nature of the subsurface, the drilling application on the planets is absolutely inevitable. Drilling applications on the Moon and Mars surfaces provide large information about the extinct and extant life on those planets, solar system evolution, feasibility of mining, water extraction, development of permanent outposts, etc.

To do this, drilling is a pre-requisite for a wide range of different applications, including the outpost construction, sample coring, space mining, anchoring and foundation, water extraction, and potential underground tunneling on the planetary surfaces. For this purpose, a large number of diverse drilling techniques and apparatuses have been designed and assembled [37–39].

2.4.1. Drilling Optimization

Nagaoka et al. in [89] introduced an extraterrestrial subsurface explorer being able to burrow itself to bury a scientific tool such as a seismometer. They explained that the span of traditional in situ measurements to lunar regolith is restricted as it cannot be extended more than the limited areas around the sampling location. However, they examined the efficiency of their suggested drill, and concluded that their method could address such problems. They also introduced indexes for their experimental analyses to check the drilling performance. In their study, the property of penetration in the chosen prototypes was estimated by applying specific energy as a principal index.

Joshi et al. in [90] found that if they analyze the trends of MSE, RPM, and the torque, they can detect different dysfunctions, such as inefficient cuttings transport, auger choking, and drilling vibrations, that can be then utilized in optimization of the drilling proficiency.

2.4.2. Bit and Drill Rig Design

Bit design is considerably important in the drilling efficiency not only on Earth, but also in space. In both Earth and space drilling, it is quite practical to compute the specific energy needed for a certain bit to drill a special type of rock [91]. Hence, there have been notable researches covering this subject to increase the efficiency of drilling performance, and consequently, to reduce the cost of those expensive projects. For this purpose, one of the significant parameters that can be considered to design the bit is MSE. To obtain this goal, Ref. [89] proposed two drills, including contra-rotor screw drill (CSD) and single screw drill (SSD). For comparison and evaluation of those drills, they used the concept of MSE as it demonstrates the efficiency of the drilling system. Eventually, according to their experimental analyses, based on specific energy (SE) and MSE, the proper driving situations of the CSD were evaluated.

2.4.3. Identification of the Ice Content

In the planetary space, water has applications ranging from drinking to propellant production. On the lunar poles, the presence of water–ice has been corroborated according to recent findings. The water available on the planetary bodies can considerably reduce the space exploration costs, and provides the invaluable hydrogen, oxygen, and propellant. Joshi et al. in [92] used MSE, ROP, torque, and WOB to estimate the UCS of the water-bearing specimens to establish a mathematical approach for pattern recognition. They calculated the water content of the samples by using the UCS, which was estimated through the pattern recognition algorithm. The results of their experiments illustrated that the values of UCS is higher when the quantity of ice content in the rock is higher. In other words, the specific energy increases significantly with ice content [90].

3. Results and Discussion

Drilling operations are commonly expensive, tough-to-do, and time-consuming. Furthermore, due to the exhaustion of conventional hydrocarbon reservoirs, the depth of drilling operations has increased dramatically in comparison to the past. In this situation, every drilling company seeks the optimization of drilling operations conducted in the field. To do this, MSE is considered as a prevalent concept to model, predict, and enhance the drilling efficiency.

In this research, a comprehensive assessment has been performed to integrate and evaluate the available MSE models together with their assumptions, limitations, applications, advantages, and disadvantages. Our close scrutiny has revealed that the empirical MSE models require further modifications, especially from the perspective of drilled rock properties. In reality, the amount of MSE consumed by drilling rig intensely relies on the drill-ability of the subsurface formations. The drill-ability of a rock is a function of the hardness (strength), abrasiveness, poro-elastic parameters, etc. It was concluded that the main shortcoming of the available, empirical MSE models is the insufficient incorporation of the rock geomechanical characteristics in their formulations. The majority of them have included only the CCS of the rock to involve the rock drill-ability effect on the MSE.

To incorporate the geomechanical properties of the rock in the empirical MSE models, one drastic solution is the utilization of AI techniques. Through using such techniques, a larger proportion of geo-mechanical parameters, recorded during the real-time drilling operations, can be incorporated in such MSE models. Consequently, those modified MSE models have more reliability than the traditional, empirical models, which are restricted because of the inadequate or local input data. Amongst the available AI techniques, machine learning approaches can be effectively adopted to train the data-driven MSE models, and to test them. Using such ML approaches strongly reduces the uncertainties related to the subsurface formations. In addition, the real time analyses of MSE values helps to curtail probable issues, such as stuck drilling pipe, bit balling, lost circulation, etc. Nevertheless, the different AI techniques may predict different values of MSE due to the difference in their approaches [93]. Since, during the drilling operation, the rock layers change, using a consistent AI technique for all rock strata may not be adequately efficient and reliable. Providing different AI approaches for different subsurface lithology is a sensible idea to tackle such issues. A good example of this application was provided by [94].

Furthermore, the effects of temperature and thermal properties of the surrounding rocks, bits, drill string, drilling fluid, and pore fluid are proposed to be included in the future empirical and data-driven MSE models. The reason for this is that the cooling performance of the drilling fluid [95,96], together with the geometry of the drilling tools [97,98], have a great impact on the friction generated on the rock/bit interface. Apparently, this phenomenon affects the MSE and ROP of the drilling operation.

Empirical ROP models also require for incorporation of further geomechanical data in their formulations. Such geomechanical parameters are rock shear strength, rock cuttings, pore pressure, and in situ stress regime (direction of the drilling). Moreover, a simultaneous combination of MSE and ROP models can strongly enhance the whole drilling efficiency. Such a combination has been recently conducted by [32] through depicting the ratio of ROP to MSE during the real time drilling operation.

On the Earth, some of the most practicable applications of MSE models include the drilling optimization, estimation of rock properties, completion optimization, determination of energy flow and loss location, bit and cutter design, estimation of the formation pore pressure, and control of the salt creep. On the planetary bodies, those applications encompassed the drilling optimization, bit and drill rig design, and identification of ice content in space. The applications of MSE models on the Earth are much broader than space. This can be justified due to the sporadic extraterrestrial drilling operations due mainly to the challenges on the planetary bodies. The effect of the different challenges and their relevant roles in affecting the values of MSE can be assessed through potent mathematical algorithms such as Monte Carlo simulation [99,100] as well as AI techniques.

While the current depth of the drilling operations conducted by the cutting-edge extraterrestrial robots have not exceeded 305 cm [101], the prospective space exploration programs tend to drill towards the much deeper formations. This objective necessitates robust drilling systems that are highly efficient in terms of the consumed MSE. So far, no specific MSE model has been developed for the remote habitable planets, such as the Moon and Mars. Therefore, the development of such models represent an urgent demand for the future space drilling programs. Obviously, since the challenges of energy supplement in space are considerably higher than on Earth, it is imperative to further work on MSE applications in space to reduce the unnecessary energy consumption and its loss during the drilling operation.

4. Conclusions

The empirical models of MSE and ROP require more parameters in their formulations to predict reliable, accurate values. Such parameters are mostly pertinent to the geomechanical properties of the subsurface rocks. Rock abrasiveness, porosity, and pore pressure are the main examples of such geomechanical characteristics. Furthermore, the effect of thermal features of the hosting rocks, drilling fluid, and drilling tools can be included to achieve more proper values of MSE.

The development of AI-based approaches and programs is also of significant importance for future MSE models. Through such data-driven models, more geomechanical parameters can be deployed to enhance the drilling efficiency by the prevention of predicted problems, reducing the non-productive time and cost. It should be noted that for different formations, the accuracy of a particular AI technique can be affected as a consequence of the nature of the input data. Therefore, it is a sensitive idea to predict the values of MSE via several AI techniques. Then, the obtained results from those different AI techniques can be compared with the real field data to select the most appropriate AI approach for the development of a reliable MSE model.

For extraterrestrial drilling, energy supply is very expensive, and problematic. Hence, further attempts must be made to develop some suitable MSE models for the design of energy-efficient drilling tools in off-Earth drilling applications. In addition, the main challenges, including the lack of atmospheric pressure, cryogenic temperature, nonuse of drilling fluids, and abrasiveness of the lunar and Martian regolith, intensify the MSE values in space drilling. Therefore, the future off-Earth MSE models must be established with the consideration of such prohibitive challenges. Another limitation related to the development of the off-Earth MSE models is that, due to the huge transportation cost from space to the Earth, the terrestrial simulants are used instead of the extraterrestrial regolith (or rocks) for the design of drilling tools. This leads to less accuracy of the predicted MSE values in the laboratory settings in comparison to the real conditions in the remote space.

So far, in space drilling, the amount of consumed energy has been used for estimation of the regolith's ice contact, design of drill bits, and optimization of the whole drilling efficiency. The concept of MSE can also be utilized to predict the undesirable dysfunctions during the real time off-Earth drilling operations. Such potential dysfunctions encompass the auger choking, inefficient cuttings transport, drilling vibrations, and stuck pipe issues. Through this application, the values of MSE can be combined with accessible AI techniques to prevent such operational problems.

To sum up, MSE models have provided an appreciable influence on the drilling operations up to now. With the ongoing need to deploy more sophisticated drilling tools in both on-Earth and off-Earth environments, the application of new methods to modify the classic models can support a accurate evaluation and optimization of the drilling operations. Such improvements will also extend the applications of MSE models for other possible purposes.

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