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Can Artificial Intelligence and Machine Learning Predict the Performance of Nano-based Drilling Fluids? A Review

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Abstract

Drilling fluids play a crucial role in the control and functionality of oil and gas well operations. Continuous monitoring, enhancement, and optimization of their properties are essential for successful drilling processes. Recently, a variety of additives, including nanoparticles (NPs) and novel polymers, have been introduced to modify and improve the performance of drilling fluids, addressing the emerging challenges in the field. The behavior of these fluids can change over time or under extreme drilling conditions, necessitating the use of predictive models to optimize their properties, particularly their rheological characteristics. In the past decade, there has been a growing trend of developing new models and correlations through artificial neural networks (ANN) and machine learning (ML) techniques within the petroleum industry. These methods enable the development of mathematical formulas that can predict the behavior of specific parameters based on known variables. Compared to traditional models, ANN and ML offer enhanced reliability and accuracy in predicting drilling fluid properties. This review aims to provide a comprehensive overview of the latest applications and mechanisms of various additives, with a particular focus on NPs, in drilling fluids. Additionally, it highlights the valuable insights and advancements in using ANN and ML techniques to predict and optimize the behavior of drilling fluids, which could pave the way for innovative applications and more efficient utilization of these technologies.

Keywords: Drilling fluids, Nanoparticles, Novel additives, Artificial intelligence, Machine learning

Nomenclature

AAPE	=	Average absolute percentage error
AARE	=	Average absolute relative error
AI	=	Artificial intelligence
AdaBoost	=	Adaptive gradient boosting
ANN	=	Artificial neural networks
ARE	=	Average relative error
AV	=	Apparent viscosity
COA	=	Cuckoo optimization algorithm
DT	=	Decision tress
ECD	=	Equivalent circulation density
FCNN	=	Fully connected neural networks
HTHP	=	High pressure high temperature
GB	=	Gradient boosting

GS	=	Gel strength
gel-10 s	=	Initial gel strength at 10 s
gel-10 min	=	Final gel strength at 10 min
k	=	Consistency index
KNN	=	K-nearest neighbors regressor
LTLP	=	Low temperature low pressure
MAE	=	Mean absolute error
MAPE	=	Mean absolute percentage error
MELM	=	Multilayer extreme learning machine
MSE	=	Mean square error
ML	=	Machine learning
n	=	Flow behavior index
NPs	=	Nanoparticles
OBM	=	Oil-based mud
PAR	=	Passive aggressive regressor
PE	=	Processing element
PSO	=	Particle swarm optimization
PV	=	Plastic viscosity
R	=	Coefficient of correlation
RD	=	Relative deviation
RF	=	Random forest
RMSE	=	Root mean square error
RSS	=	Residual sum of squares
SBM	=	Synthetic-based mud
SD		Standard deviation
SVM	=	Support vector machines
WBM	=	Water-based mud
XRF	=	X-ray fluorescence
XGB	=	Extreme gradient boosting
YP	=	Yield point

Introduction

Drilling fluids, also known as drilling muds, are essential in oil and gas drilling operations. They perform several critical functions, including cooling and lubricating the drill bit, carrying drill cuttings to the surface, maintaining pressure control, and stabilizing the wellbore [1,2]. Drilling fluids can be divided into 2 main categories [1]; the liquid-based fluids which are the most common and the gas-based fluids which are rarely used. There are 3 main different types of the commonly used liquid-based drilling fluids; water-based mud (WBM), oil-based mud (OBM), and synthetic-based mud (SBM). The selection of suitable drilling fluid depends mainly on the performance, the cost, and the environmental impact. WBMs are well known for their lower cost than the OBMs and SBMs, their better impact on the environment, and better chemical solubility [3,4]. However, some of their disadvantages are that they might cause problems with the wellbore stability, hydrate the clay formations, and less lubricity than the OBMs. The properties of these fluids - such as rheology, viscosity, filtration, thermal stability, and density - must be continuously monitored and optimized to ensure the efficiency and safety of drilling operations[5-7]. As industry advances, the increasing complexity of reservoirs and drilling environments presents new challenges that require more sophisticated solutions for fluid performance.

In response to these challenges, a variety of additives have been introduced to enhance the properties of drilling fluids. Among the most promising are nanoparticles (NPs) and novel polymers, which offer the potential to improve the rheological, mechanical, and thermal characteristics of drilling fluids. These advanced additives allow for better fluid control under harsh drilling conditions, such as extreme temperatures, pressures, and aggressive chemical environments.

However, the behavior of drilling fluids can change over time due to the dynamics of the reservoir or variations in operational parameters. Therefore, effective monitoring and optimization strategies are required to predict and manage these changes.

Several mathematical models are used in describing the non-Newtonian rheological behavior of drilling fluids. Rheological models, such as Power Law, Hershel-Buckley, Casson, and Bingham Plastic models [6,8-10]. A proper model must be selected accurately to illustrate the shear stress/shear rate relationship of the drilling fluids. Over the past decade, there has been a noticeable trend in utilizing artificial intelligence (AI) techniques, such as artificial neural networks (ANN) and machine learning (ML), in the petroleum industry to predict and optimize the behavior of drilling fluids field [11,12]. These data-driven approaches are increasingly replacing traditional models by offering more reliable and accurate predictions of fluid properties based on known parameters [13,14]. By developing mathematical formulas through ANN and ML, it is possible to predict the behavior of drilling fluids under various conditions, which can greatly enhance operational efficiency and decision-making.

This paper aims to present a comprehensive review of the latest advancements in drilling fluid additives, particularly focusing on NPs, and the role of advanced computational techniques in optimizing fluid behavior. Furthermore, the review explores the growing importance of ANN and ML in predicting the performance of drilling fluids and discusses their potential for future applications. Ultimately, this paper seeks to highlight the synergistic effects of innovative additives and predictive modeling techniques, which can pave the way for more efficient, cost-effective, and sustainable drilling operations.

Nanoparticle applications as drilling fluid additives

The drilling fluids are non-Newtonian fluids which means that their viscosities are directly impacted by shear rate. In other words, shear dominates most of the viscosity related functions of drilling fluids. Hence, the sheer viscosity of drilling fluids is the property that is most tracked and optimized. Four viscosity-related parameters are usually measured and optimized for drilling fluid which are plastic viscosity (PV), apparent viscosity (AV), yield point (YP), and gel strength (GS).

According to the standard protocol (*API RP 13B-1*, 2003), AV is one-half of the dial reading at 600 rpm (1,022 s^{-1} shear rate) using a direct-indicating, rotational viscometer [5,6]. PV contingent on the solid content size, shape, and distribution and the friction between the inert solids. Minimum PV is always required to save the energy used by the mud pumps to circulate the drilling fluid, reduce losses that occurs due to excrescent equivalent circulation density (ECD) that may fracture the formation, and increase the rate of penetration required [7].

YP is an indication of the ability of the drilling fluids to lift the cutting to the surface. However, high YP can cause high frictional losses which will lead to high ECD. In large diameter wells high YP is regularly used for efficient hole cleaning. In addition, low YP may cause drilled cuttings and barite sag.

GS shows the capability of drilling fluids to suspend the solids and the cuttings cutting in times of no circulation. In other words, GS is the shear stress at very low shear rate after the drilling fluids were allowed to rest for a period. There are 2 types of GS, which are the initial GS or (gel-10 s) and the final GS or (gel-10 min). Both initial and final GS are measured based on the abovementioned protocols by stirring the fluid at high speed then allowing it to rest for 10 s and 10 min, respectively. The maximum value the knob reached at low speed (usually 3 rpm) after the resting time is observed and recorded as initial and final GS.

Recently, the oil industry is giving nanotechnology growing interest and expectations. NPs opened the door to the development of nano-fluids that can be used for drilling [15,16], production, and well stimulation applications. The optimistic performance of NPs can be attributed to their tiny sizes and their extraordinarily massive surface area to volume ratio. Nanotechnology might play an important role in all the aspects of the petroleum industry. NPs are key factors in the coming developments as they are friendly to the environment, more efficient and used in small quantities so they are less expensive materials. Many applications of NPs are still in the laboratory and research phases; however, their significant impact might fast their field applications. Different types of NPs have been investigated as rheological property controllers, fluid loss reducers, and shale stabilizers in many drilling fluid applications [17-19] brief discussion about the most valuable findings in the field of using them as drilling fluid property modifiers will be summarized herein.

In 2011, Amanullah *et al.* [20] formulated and investigated 3 nano-based drilling fluids. It was noticed that without using chemical additives it was difficult to stabilize the NPs in the drilling fluid. To reach a stabilize and homogeneous nanofluid, highly effective surfactants or polymers with high neutralizing capabilities were used. Further, Jung *et al.* [21] examined the rheological behavior of 5 wt. % bentonite drilling fluids containing ferric oxide NPs of 3 and 30 nm at different temperatures (20 - 200 °C) and pressures (1 - 100 atm). The results revealed an increase in the yield stress and viscosity by increasing the concentration of NPs. Later, Abdo and Haneef [22] produced and tested a new type of clay NPs that is mainly composed of montmorillonite. The drilling fluid formulated using this clay NPs with bentonite was found to have low viscosity and high GS at high pressure/high temperature conditions.

Ferric oxide NPs can maintain optimal rheological properties, reducing the filtration, and forming thin/low-permeable filter cake when used at small concentrations. Further, a custom-made magnetic iron oxide and iron oxide clay hybrid NPs were found to be able to improve the properties of bentonite-based and low solid content bentonite based drilling fluids under downhole conditions [23-28]. Moreover, a combination of Multi-Walled Carbon Nanotube (MWCNT) and nano silica, which showed improvements in PV, YP and GS of the drilling fluid as well as a fluid loss reduction lubricity and shale inhibition at temperatures up to 250 °F and pressures up to 500 Psi [29,30]. The fluids having NPs showed no phase-separation unlike the base-fluid that suffered from sagging effect and had 2 visible separate layers of fluids **Figure 1** [31,32].

According to Aftab *et al.* [33], Zinc oxide NPs-acrylamide composite enhanced the lubricity of the WBM by 25 % as well as slightly increased the rheological properties (AV, YP, GS) of the treated fluids. Nizamani *et al.* [34] investigated a drilling fluid having titania-bentonite based nanocomposite as an additive at low (80 °F) and high (150 °F) temperatures. The base mud met the required operating values at 80 °F but it failed to meet them at 150 °F. Addition of titania-bentonite nanocomposite showed an improvement in the rheological properties as the AV, YP, GS increased by 19, 64 and 40 %, respectively. The addition of 1 g of titania nanocomposite at 150 °F helped in maintaining the rheological properties of the fluid at the correct operating values.

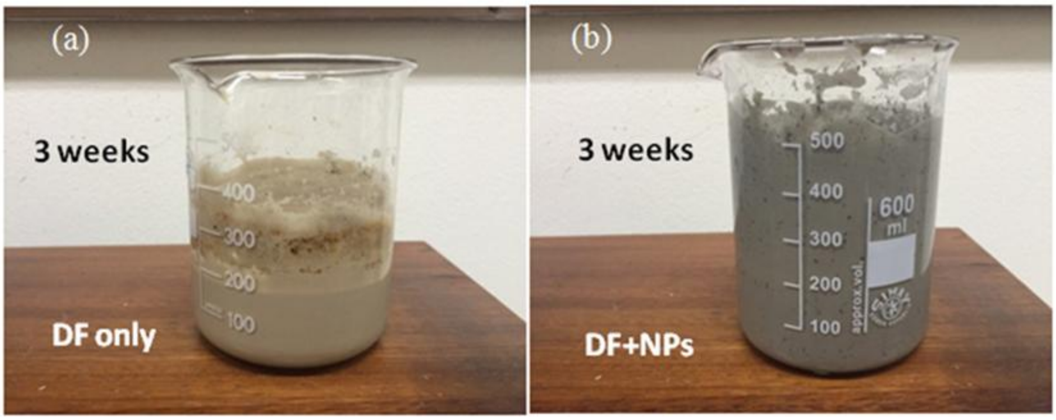

Figure 1 Sagging effect of the prepared drilling fluid after 3 weeks (a) without any additives and (b) with NPs [31].

Adding Fe_2O_3 NPs at small concentration yielded better rheological and filter cake characteristics of bentonite-based drilling fluids. However, the addition of silica NPs decreased the YP but showed better rheological stability [35-38]. Also, adding 0.05 vol % silica dioxide NPs can reduce the power consumption by up to 27 % [39]. It was also reported that the surface charge of NPs and their stability in suspension played a key role in NPs' dynamics with the other drilling fluid additives as revealed from zeta potential measurements. Moreover, the effect of using different types of NPs (Fe_2O_3, Fe_3O_4, ZnO and SiO_2) with a bentonite-based drilling fluid was evaluated [40]. A thorough discussion about the interaction of NPs with bentonite was presented in this study. **Figure 2** shows the embedding of iron oxide NPs in the randomly formed pore structure on the surface of bentonite particles and the weak edge-to-edge platelet structure in the case of using SiO_2 NPs at elevated temperatures

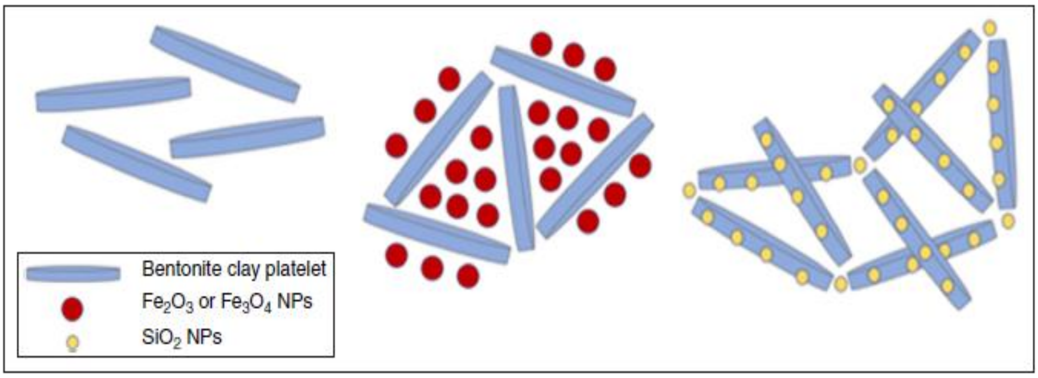

Figure 2 Schematic illustration shows the embedding of iron oxide NPs (Fe_2O_3 or Fe_3O_4) in the randomly formed pore structure on the surface of bentonite particles and the weak edge-to-edge platelet structure in the case of using SiO_2 NPs at the elevated temperatures [35].

Al_2O_3, CuO, SiO_2 and MgO NPs were examined at different concentrations and conditions with WBM [41-43]. The addition of NPs increased the GS with the best performance when adding higher concentration of CuO. However, increasing the concentration of Al_2O_3 and MgO decreased the gelation. Adding NPs were also reported to improve YP and PV at the studied conditions [41]. In 2018 a new type of NPs (Yttrium oxide, Y_2O_3) was introduced to be used as a drilling fluid additive at low and high pressure/temperature conditions [44]. It was found that the PV, YP, and GS increased with the increase in the concentrations of NPs at ambient temperature and pressure. It was also noticed that they decreased with the increase in temperature but with different reduction percentages. Further, WBM that doesn’t contain any NPs produced a very high shear thinning behavior and lost its viscosity and the ability to suspend cuttings. However, the mud treated with NPs was found to be more stable under high pressure and temperature with neither high thinning shear behavior nor high thickening shear behavior. Optimum concentration of Yttrium oxide NPs was reported to be 2.5 g [44].

It was found that with the increase in the concentration of the ZnO nanowires the reduction rate of density with the increase in the temperature becomes smaller. Using the same concept, the rate of reduction in the fluid viscosity with the increase in temperature was found to be decreasing with the increase of the ZnO nanowires concentration [45]. Later, Aramendiz *et al.* [46] checked both SiO_2 and Graphene-NPs (GNPs). A significant improvement in the filtration properties were observed when using a mixture of 0.5 wt. % of SiO_2 and 0.25 wt. % of GNPs with a neglect effect on the spurt loss, PV, and YP. However, the GNPs samples yielded higher gel strength compared to the fluids containing SiO_2 NPs. adding graphene oxide NPs enhanced the stability of both fresh water and saline water in the saline environment [47]. In addition, nano graphene the thermal stability and the shale swelling properties of the salt polymer WBM at High Temperature High Pressure (HTHP) conditions [48].

Later, NPs-based KCL-Polymer drilling fluid was formulated and examined based on the rheological and filtration characteristics. The impact of 4 different types of NPs with one of them having 2 particle sizes had been tested at 5 different concentrations. Based on the rheological properties of the tested nano-based fluids, higher NPs-concentrations (greater than 0.5 wt. %) were found to negatively affect the properties of KCL-Polymer mud because of the agglomeration of the excessive NPs. Adding 0.3 wt. % of nanotitanium, nanoaluminium-15 nm, and copper oxide NPs were found to cause a reduction in the PV of drilling fluid by 72, 10, and 10 %, respectively. On the other hand, using both nanosilica and nanoaluminium-40 nm increased the PV. Nanotitanium at 0.3 wt. % showed an increase of 30 % in the YP compared to the base-fluid, which implies less solids sagging and higher drilled cuttings carrying capacity. An increase in the GS was observed when using any concentration of nanosilica with the highest at NPs’ concentration of 0.7 wt. %, which caused an increase in gel-10 s and gel-10 min by 26 and 38 %, respectively. However, all the other NPs at the same concentration were found to have minimal or no effect on gel strength. **Figure 3** shows the effect of NPs on the PV and YP of the KCl-Polymer mud [19]. Moreover, silicon oxide can improve the rheological properties, lubricity and colloidal stability of the OBM [49].

The impact of different NPs (Al_2O_3, TiO_2 and CuO) on the rheological and filtration properties of WBM was investigated [50-52]. Cellulose nanofibers cellulose nanocrystals and different factors like flow rate, rheological properties, and hole size were studied in parametric research to explain their effect on the efficiency of cutting transport and hole cleaning [53-55]. Moreover, the influence of dual-functionalized cellulose nanocrystals on the toxicity, thermal tolerance, rheological and filtration properties of bentonite based drilling fluids have been investigated under variant temperatures [56]. The results revealed that NPs can be used as a promising additive to improve rheological behavior. In addition, using NPs has improved hole cleaning efficiency. The abovementioned study showed both the size of the cuttings, and the rheological properties have the largest effect on the hole cleaning efficiency. On the other hand, when the rheological properties were elevated the effect of the flow rate was minimal. Furthermore, especially in holes with big diameters, the addition of NPs enhanced the cleaning of the wellbore significantly regardless of the cutting sizes. Recently, Aftab *et al.* [57] showed that WBM treated with titania-bentonite nanocomposite has improved lubricity at different temperatures.

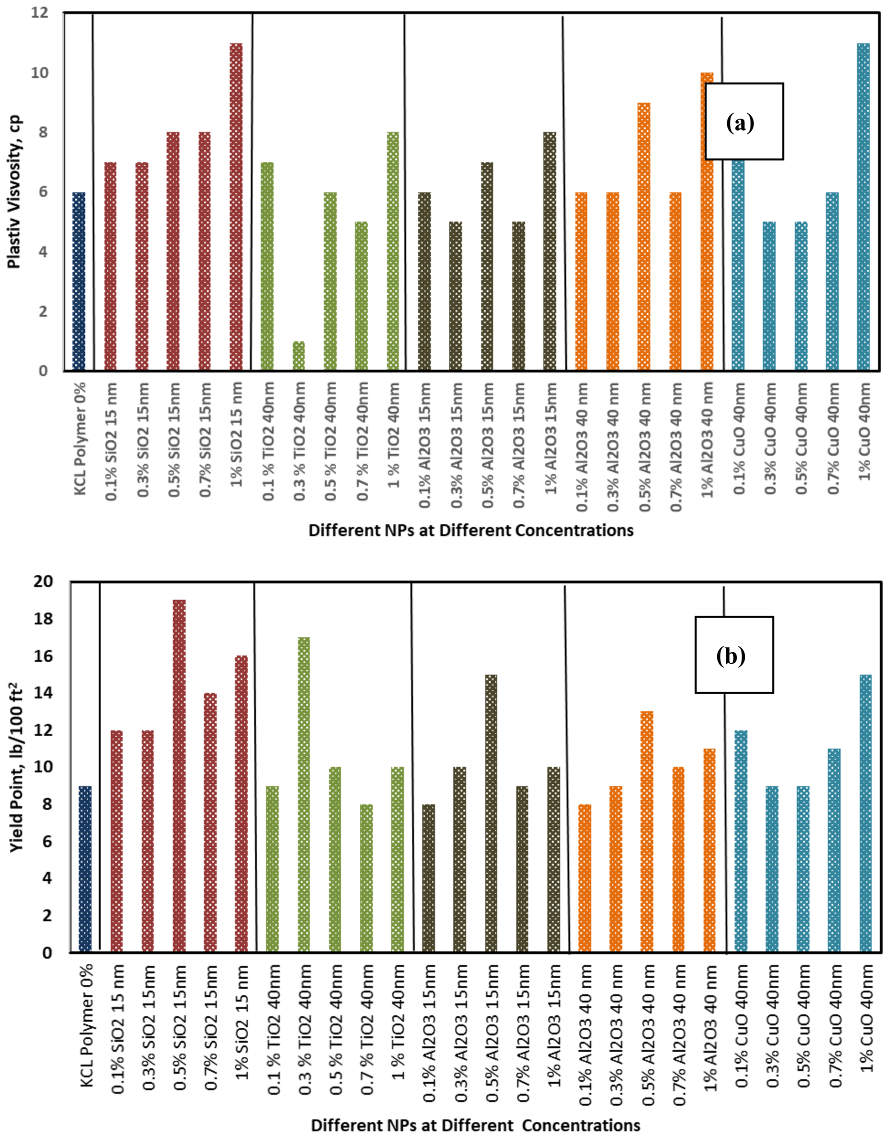

Figure 3 Impact of NPs on the (a) PV and (b) YP of the KCl-Polymer mud [19].

In 2021 the addition of synthetic zinc oxide NPs to WBM was investigated at 25 [58], 40, and 80 °C [59]. At 40 °C and 0.1 wt % concentration the YP and gel-10 s have increased by 61.54 and 125 %, respectively. While, at elevated temperatures the lower NPs concentrations show better enhancements for the rheological properties. Also, 0.05 wt. % concentration of ZnO NPs showed an increase of 60 and 50 % for YP and gel-10 s. The addition of ZnO and associative polymer with ratio of 0.1 to 1, respectively showed the highest impact on rheology, filtration and shale inhibition [58]. The effect of aluminum oxide and copper oxide on KCl-Polymer WBM was investigated. The addition of both NPs within the range of 0.3 - 0.5 wt. % improved the rheological parameters. While the filtration characterization was improved on the addition of 0.5 and 1 wt. % of aluminum oxide and copper oxide, respectively. Also, SEM and EDX have shown that the addition of NPs smoothens the surface and made it less pours compared to the base fluid [60].

Later in 2021, Mirzaasadi *et al.* [61] have extracted silica oxide from agriculture wastes (rice husks) and then silica NPs were produced using 2 different approaches; one without any chemical addition and the other with chemically treating. The purity of the chemically treated and untreated NPs was 97.4 and 94.5 %, respectively, determined by x-ray fluorescence method (XRF). The effect of both NPs on WBM rheology and thermal stability were studied at 121.11 and 148.88 °C, which simulates the downhole conditions. The study showed that both NPs improved the rheological properties but increased the filtration loss. The chemically treated NPs prevented thermal degradation and improved rheological properties more than the untreated NPs. Among the tested the concentrations 3 % of chemically treated NPs showed better effect in enhancing the properties of the drilling fluids [61].

A comparison between the effect of silica oxide and copper oxide NPs on the polyamine based non-damaging drilling fluids and bentonite-based drilling fluids. Silica oxide NPs acted as a mud thicker in non-damaging drilling fluids while having the opposite effect on the bentonite-based drilling fluid. The addition of copper oxide NPs worked as mud thinner in both drilling fluids [62]. Furthermore, copper oxide and zinc oxide were used to enhance the thermal, electrical, and filtration properties of Polyethylene glycol-based and polyvinylpyrrolidone-based drilling fluids. It was observed that the addition of NPs to the drilling fluids enhanced all the above mentioned properties at room temperature [63]. Moreover, aluminum oxide nanorods were used to develop a thermally stable ethyl octanoate ester-based drilling fluid. The rheological properties for both the base and the nanomodified drilling fluid samples were measured at low (2.6 °C), room (26.8 °C) and elevated (70 °C) temperatures. While the filtrate loss was measured at the room temperature and 690 KPa. The addition of aluminum oxide nanorods enhanced the thermal stability of the drilling fluids over the wide range of the investigated temperatures [64].

In 2023, a systematic study of the influence of nano-additives of various concentrations, average sizes, and composition on the temperature dependence of the viscosity and rheological behavior of WBM was conducted [50]. Typical compositions of drilling fluids, such as water suspensions of various clay solutions and gammaxan-based polymer solutions, were considered. Hydrophilic silicon and aluminum oxides NPs were used as nano-additives at concentrations ranging from 0.25 to 3 wt. %. The average NPs size varied from 10 to 151 nm. The temperature of drilling fluids varied from 25 to 80 °C. It was found that the addition of NPs leads to a significant change in the rheological properties of WBM depending on the temperature. With increasing temperature, the yield stress and consistency index of drilling fluids with NPs increase, while the behavior index, on the contrary, decreases. This behavior depends on the size of the NPs. As the particle size increases, their influence on the temperature dependence of the drilling fluids' viscosity increases. In general, it was shown that the addition of NPs makes the viscosity of drilling fluid more stable with regard to the temperature, which is an essential fact for practical application [50].

A modified polystyrene micro-nano spheres (MPS) was synthesized, then characterized, and tested to achieve wellbore stability by changing the hydrophobicity of the shale surface and plugging the micro-nano pores [65]. The inhibition and plugging performance of MPS were evaluated through linear expansion, shale recovery, and plugging of polytetrafluoroethylene (PTFE) microporous membrane. Contact angle, pore size distribution, and SEM analysis were performed to study the inhibition and plugging mechanisms of MPS. The results showed that MPS was spherical with a particle size distribution of 91 - 712 nm and had good thermal stability. The MPS had excellent compatibility with drilling fluids and better inhibition than KCl, polyamines, and SiO_2. When using PTFE microporous filter membrane as a filtration medium, the API filtration loss volume of 3 wt. % MPS aqueous solution was only 42 mL, while that of the solution without MPS was 260 mL. The pore size of the PTFE microporous membrane decreased after plugging. The MPS adsorbed on the shale surface to form a hydrophobic layer, which could weaken the hydrophilicity of shale. The contact angle of shale slices treated with 2 wt. % MPS was 108.2 °. Furthermore, SEM observations indicated that MPS can improve the quality of mud cakes and plug the small pores [65].

Nano-WBM was prepared using nano-copper oxide and multiwalled carbon nanotubes (MWCNTs) as modification materials [66]. The effects of the temperature and concentration of the NPs on the rheological properties were studied using a rotational rheometer and viscometer. Also, the influence of 2 NPs on the filtration properties was studied using LTLP filtration apparatus, as well as a scanning electron microscope (SEM). It is found that MWCNTs with a concentration of 0.05 w/v % have the most obvious influence on the NWBDFs, which improves the stability of the gel structure against temperature and decreases the filtration rate. Also, a theoretical model predicating the YP and the PV as a function of the temperature considering the influence of the NPs was developed based on DLVO theory [66]. Tahr *et al.* [67] inspected the investigations' results and any gains made by utilizing a new material in drilling fluids. As biodegradable materials, the filtration and rheological capabilities were indicated to be significantly improved by the powders of rice husk and pomegranate peel. Titanium oxide NPs and nano-clay also significantly altered the drilling fluid's characteristics. Therefore, these qualities may be enhanced, and the wellbore stability may be provided by combining these 2 unique materials - titanium and pomegranate peel.

Ultrafine barite was utilized to obtain good suspension stability. Also, the method of modifying zwitterionic polymers on the surface of nano-silica was used to develop a temperature-resistant and salt-resistant fluid loss reducer FATG with a core-shell structure, and it was applied to ultra-fine clay-free WBM [68]. The results showed that the filtration loss of clay-free drilling fluid containing FATG can be reduced to 8.2 mL, and AV can be reduced to 22 mPa·s. The clay-free drilling fluid system obtained by further adding sepiolite reduced the filtration loss to 3.8 mL. After aging at 220 °C for 15 d, it had significant salt tolerance, the filtration loss was only 9 mL, the viscosity did not change much, a thinner and denser mud cake was formed, and the viscosity coefficient of the mud cake was smaller. The linear expansion test and permeability recovery evaluation were carried out. The hydration expansion inhibition rate of bentonite reached 72.5 %, and the permeability recovery rate reached 77.9 %, which can meet the long-term drilling fluid circulation work in the actual drilling process [68].

An industrially prepared silica NPs coated with AEAPTS ([3-(2-Aminoethylamino) propyl] trimethoxy silane) was used as an additive to enhance the rheology and control filtration of WBM [69]. Silica NPs were coated separately in a 2-step process, which involved the addition of a hydroxyl group first and then coating with AEAPTS. Different rheological and filtration tests were done with varying NPs concentrations of 0.2, 0.3, and 0.4 w/v %. The rheological values of the mud samples were recorded both before and after the thermal aging of mud in the roller oven at 105 °C for 16 h. The filtration test was carried out according to API standards with 100 psi differential pressure for 30 min. Both PV and AV of the drilling fluid were found to be increasing with silane-coated silica NPs when tested at 30 and 60 °C. The degradation in the rheology of the base mud without NPs after thermal aging was found to be around 60 % which was reduced to around 20 % with the addition of the coated silica NPs. Also, a remarkable reduction in the filtrate volume, when compared with base mud, was achieved with the addition of the silane coated NPs [69].

Martin *et al.* [70] aimed to establish the optimum concentration of a cationic surfactant that would successfully modify the surface of silica NPs and thereafter, evaluate the performance of modified nano silica as a rheological and filtration property enhancer in WBM. The surface of silica NPs was successfully modified by adding Hexadecyltrimethylammonium bromide (CTAB) to silica solution. Different mud formulations containing modified nano silica with varying zeta potential values, SNP3 -S2, SNP3 -S4, SNP3 -S5, SNP3 -S6, and SNP3 -S7 with −17.7, 20, 28.2, 35.4, and 37.1 mV, respectively, were investigated. Results showed that modified nano silica with the highest absolute value of zeta potential enhanced drilling mud rheology as temperature increased from 149 to 232 °C. The optimal amount of CTAB was found to be between 1.0 and 2.0 wt. %. Filtration loss was reduced by 11.4, 17.6, and 29.5 % on average for mud samples SNP3-S5, SNP3-S6, and SNP3-S7, respectively, at all temperatures. Mud cake thickness was reduced by 19.9, 11.6, and 28.7 % on average by mud samples SNP3-S5, SNP3-S6, and

SNP3-S7, respectively, at all temperatures [70]. **Figure 4** shows the interaction between unmodified silica NPs and bentonite as well as the interaction between modified silica NPs and bentonite.

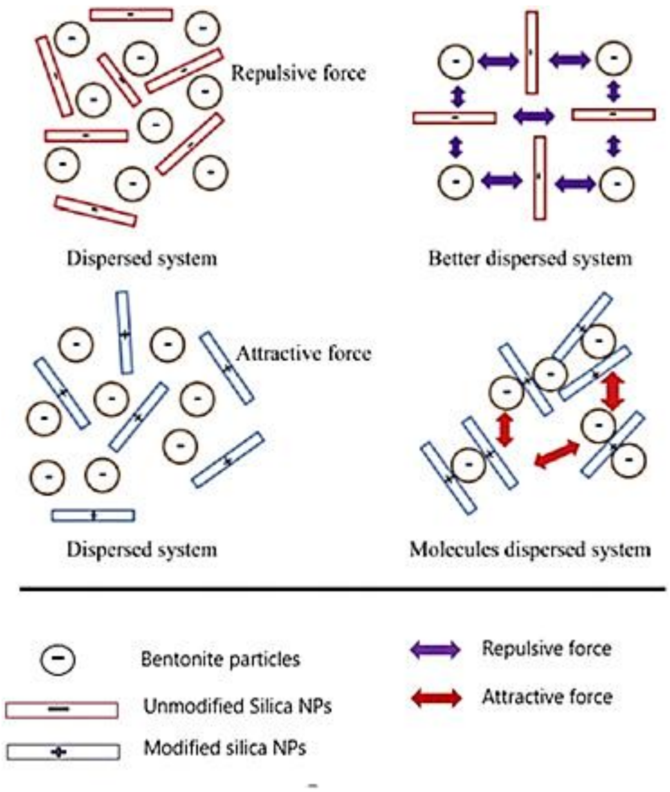

Figure 4 Interaction between unmodified silica NPs and bentonite (top) and Interaction between modified silica NPs and bentonite (bottom) [70].

In 2024, CuO NPs were synthesized using a natural extract from *Colocasia esculenta* leaves and the potential of the biogenic CuO NPs to enhance the lubricity in mud had been explored [71]. The ability to form a continuous and thin lubricating film at the mud-drill string interface was expected to reduce the frictional resistance between them significantly. Besides this, the filtration and rheological performance of the developed mud had been investigated. The formulation exhibited significant enhancements in lubricity, with a 27 % increase, and filtering performance, with a 48 % increase. The rheological profile, which exhibited shear-thinning behavior, demonstrated strong agreement with the Herschel-Bulkley model. Furthermore, the NPs showed the capability of reducing the negative effects of heat-induced deterioration on the characteristics of mud [71]. This highlights their potential as advantageous substances for drilling operations conducted at high temperatures. The results emphasize the advancement of drilling fluid technologies that are both environmentally benign and economically feasible.

Ahmed *et al.* [72] synthesized SiO_2/g-C_3N_4 NPs hybrid and investigated its addition in different concentrations to WBM and studied the impact on the rheological and fluid loss properties of the fluids. The studies were carried out at various SiO_2/g-C_3N_4 NPs concentrations under before hot rolling (BHR) and after hot rolling (AHR) conditions. The outcomes demonstrated that the rheological and fluid loss properties were enhanced by the addition of SiO_2/g-C_3N_4 NPs, as it worked in synergy with other additives. Additionally, it was discovered that the NPs improved the drilling fluid thermal stability. The experimental findings indicate a significant influence of SiO_2/g-C_3N_4 NPs on base fluid properties including rheology and fluid loss as the most remarkable, especially at higher temperatures. The significant improvements in YP and gel-10 s were 55 and 42.8 % under BHR and 216 and 140 % under AHR conditions, respectively. Permeability plugging test fluid loss was reduced by 69.6 and 87.2 % under BHR and AHR conditions, respectively, when 0.5 lb/bbl NPs were used in formulations [72].

Abdullah *et al.* [73] conducted a comparative analysis between hydrophobic nanosilica (HNS) and potassium chloride (KCl), a widely used shale inhibitor but has negative impact on the environment and subsurface activities, to better understand how HNS can effectively manage water and shale interactions by restricting mud filtration into the formation. In this work, shale samples were collected from the Kolosh Formation in the Kurdistan Region of Iraq, known for being one of the most challenging formations to drill. Investigations into the properties of drilling fluid were conducted using LTLP and HTHP filter press, alongside analyzing rheological properties at 3 different temperatures (25, 50 and 75 °C). In addition, the impact of the HNS on clay swelling was examined using the liner swelling meter test, shale dispersion test and capillary suction time test. The obtaining results revealed that the shale hydration in the drilling fluids was reduced 24.36 - 15.53 % and the shale recovery at high temperatures was improved from 80.2 to 94 % by adding 0.4 wt. % HNS[73]. Furthermore, HNS demonstrated improved clay suspension in the capillary suction time test wherein the suspension time reduced from 303 to 80 s at the same HNS concentration. Utilizing HNS effectively reduced clay swelling in all experiments and enhanced the rheological properties of the mud, showcasing stability across a range of temperatures and significantly reducing the formation of filter cake and fluid loss. **Figure 5** illustrates the results of shale dispersion test for the base mud and drilling fluids with KCl and HNS with 4 different concentrations of 0.05, 0.1, 0.2 and 0.4 wt. %.

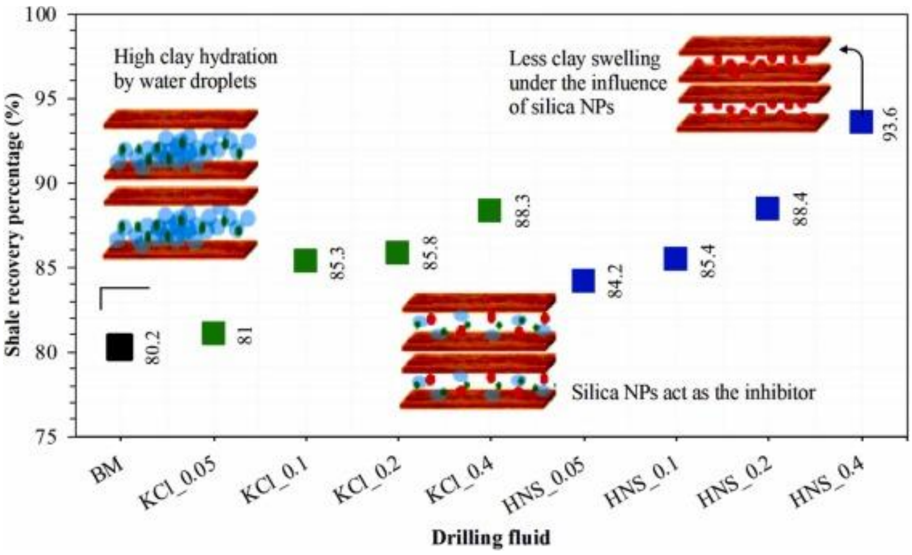

Figure 5 The result of shale dispersion test for the base mud and drilling fluids with KCl and HNS with 4 different concentrations of 0.05, 0.1, 0.2 and 0.4 wt. % [73].

Bardhan *et al.* [74] introduced Mesoporous Nano-Silica (MNS) to enhance WBM's inhibitive, rheological, and fluid loss characteristics. MNS was synthesized with a particle size of 134.47 nm and zeta potential of −32.2 meV. MNS was added to the fixed base formulation at varied concentrations (0.05, 0.1, 0.2, 0.5 and 1 wt. %) and were subjected to hot rolling at 180 °C temperatures at 100 psi pressure for 16 h to evaluate the influence of thermal aging on the properties of the drilling fluid. The rheological investigation was performed at 25 and 70 °C while the inhibitive properties were checked via shale recovery test and capillary suction timer. The filtration properties were examined at 100 psi and 500 psi pressure at 150 °C. The results revealed that MNS can substantially improve the thermal properties of WBM, maintaining rheological characteristics and drastically reducing fluid loss while imparting some shale inhibitive properties, which may be attributed to either the size effect or the synergistic influence of materials. After hot rolling PV of MNS-infused mud was 77 % better than that of the base mud [74]. **Figure 6** presents the PV at 25 and 70 °C variations with increasing concentrations of MNS in the drilling fluids before and after hot rolling.

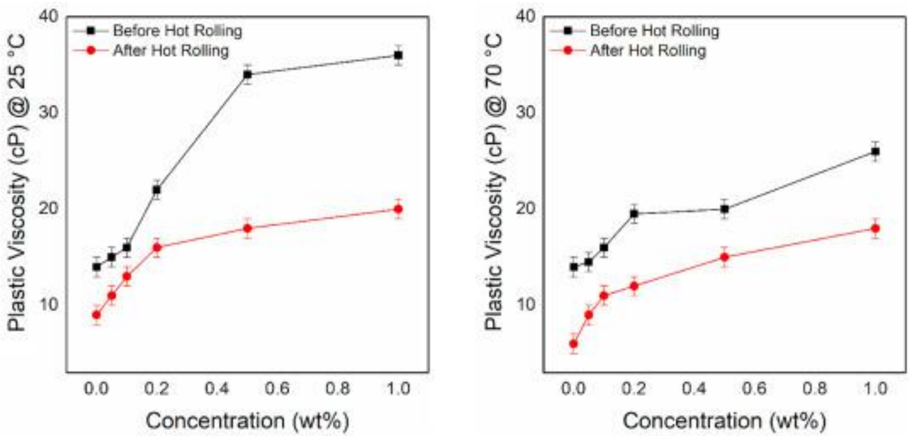

Figure 6 PV at 25 and 70 °C variations with increasing concentrations of MNS in the drilling fluids before and after hot rolling [74].

Promising drilling fluid additives

Different rheological models as well as new additives have been introduced in the literature. Some of them showed optimistic performance. A pioneer trial had been presented by Vipulanandan and Mohammed [75] by introducing the hyperbolic model to predict the rheological behavior of bentonite WBM. In this study, acrylamide polymer was added to bentonite-based drilling mud at different concentrations. The results showed that the addition of bentonite increased the yield stress, while the addition of acrylamide polymer decreased the yield stress depending on the bentonite content. Also, the addition of bentonite increased the maximum shear stress. while the addition of 0.24 wt. % acrylamide polymer reduced the maximum shear stress as well as decreased the AV. The authors compared between the rheological parameters predicted using their hyperbolic model and that of Herschel-Bulkley [9]; Casson [10] models. The hyperbolic model was found to be more effective in predicting the shear stress, strain rates, and thinning behavior than the other models. Moreover, the model was the only one that can predict the maximum shear stress while the other 2 models can only predict the finite shear stresses [75].

In 2015, ball-milled functionalized -COOH carbon NPs with average size of 10 nm was dispersed in the drilling fluid sample with different concentrations ranging from 0 to 1 wt. %. The addition of NPs enhanced the thermal conductivity by 6 % and increased the viscosity of the nano-modified drilling fluid compared to the base fluid [76]. Green synthesized α-MnO_2 NPs can help improve the thermal degradation of the polymer WBM under harsh conditions. Adding a small concentration of 0.01 w/v % of α-MnO_2 NPs can improve the rheological properties and they keep increasing with the increase of concentration. Both HTHP and Low Temperature Low Pressure (LTLP) filtrate loss are reduced compared to the base fluid and the electrical conductivity increased on the addition of NPs [77].

Later, in 2018 the shear stress-shear strain rate was predicted for bentonite WBM treated with bentonite-based nano clay using the hyperbolic model [78]. The study aimed to reduce the fluid loss of the drilling fluids, alter the rheological properties, and improve the electrical resistivity using the nano clay particles. For all the drilling fluids studied in this work and compared to the other rheological models, Vipulanandan rheological model predicted shear stress-shear strain rate relationships better. Furthermore, the addition of 1 wt. % of nano clay particles yielded more than double the maximum shear stress tolerances and yield stresses for all cases except the one containing 8 wt. % bentonite at 25 °C.

In 2017, Afolabi *et al.* [79] investigated the mutation in rheological properties of bentonite mud on the addition of silica NPs using an optimization-based statistical approach. A feasible area was constructed for multiple parameters using an overlaid contour plot. The concentrations of 6.3 wt. % bentonite and 0.94 wt. % silica NPs were selected to be the optimal factors for minimum rheological properties using the steepest method. The rheological properties of the formulated mud were evaluated using the hyperbolic model [40] and compared with other rheological models. The shear stress limit and the rheological properties of the nano modified drilling fluids were precisely predicted using response surface design and the hyperbolic model [75], respectively. **Figure 7** shows the overlaid contour plots of PV, YP, AV, and shear stress limit [79,80].

In 2016, a local bentonite clay had been collected from South Hamam, Egypt and investigated versus a commercial one in formulating drilling fluids [81]. The mineralogical and elemental analysis of the local bentonite had shown that it is composed mainly of Na-montmorillonite with the elemental composition shown in **Tabel 1**. The local bentonite had been activated using a constant ratio of polyvinylalchol, chitosan which was mixed with various ratios of N-vinyl-2-pyrolidene with and without diethyleglycal dimethylacrylate. The new prepared composition polymers were evaluated as filter loss additives and viscosifier. The results showed that the increase in the 3 mixtures concentrations increased the rheological properties of the fluids such as the PV, AV, YP and gel-10 s and gel-10 min. However, the efficiency of the formulated drilling fluids increased with the increase in the cross links in the polymer mixture and the decrease in the amount of N-vinyl-2-pyrrolidone [81]. Later, the effect of different types of clays like Organophilic clay with associative polymer, clay NPs, barite and bentonite NPs on the rheological, filtration and shale inhibition properties of the water based drilling fluids at harsh well like conditions [82-84].

In 2022, a combination of inorganic nanomaterials with organic macromolecules were used to formulate and test a potential filtrate loss reducer and rheology modifier called PAASM-$CaCO_3$. PV, AV, and YP were measured at ambient temperature and atmospheric pressure while the filtrate loss was recorded at temperatures up to 180 °C and pressures up to 3.5 MPa. PAASM-$CaCO_3$ was capable of increasing the PV and AV and reduce the volume of filtration compared to the base fluid [85]. Furthermore, a hybrid of NPs can significantly reduce the filtration volume in HTHP fluid loss and particle plugging tests at differential pressures up to 1,000 Psi [86].

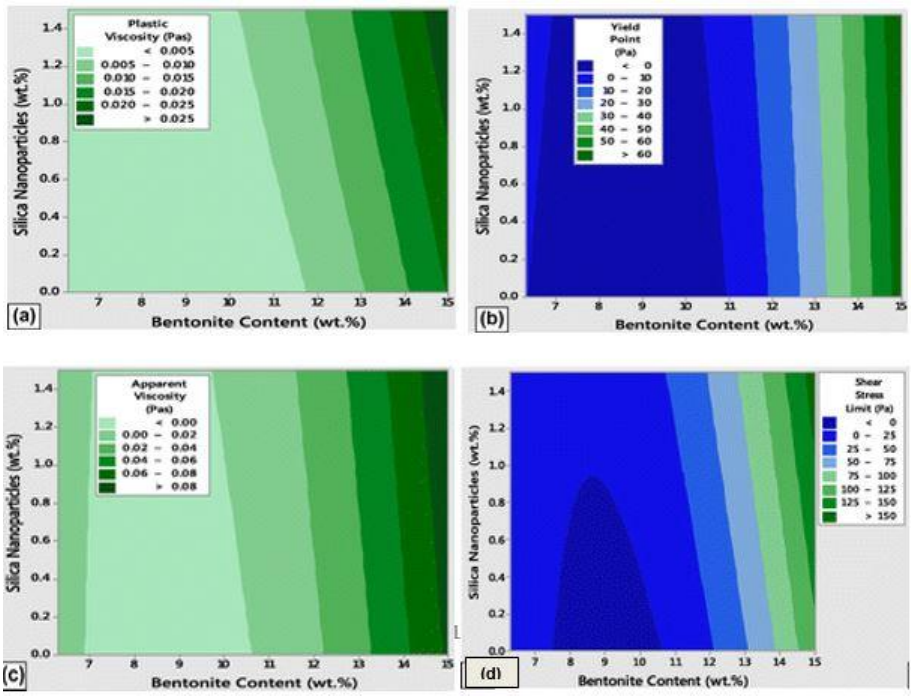

Figure 7 Overlaid contour plots of: (a) PV, (b) YP, (c) AV, and (d) shear stress limit [79].

Table 1 Elemental analysis of the local bentonite collected from South Hamam, Egypt using X-ray florescence [81].

Element	**SiO_2**	**TiO_2**	**Al_2O_3**	**Fe_2O_3**	**Na_2O**	**K_2O**	**P_2O_5**	**Cl**
Wt. %	54.91	1.53	17.01	9.31	2.75	1.03	0.16	1.20

Further, glass beads were investigated in various sizes of 90 - 150 and 250 - 425 µm as rheological property modifiers as well as drilling fluid lubricators [31]. For this aim, different samples were prepared with different sizes and concentrations of the glass beads. It was found that an optimum concentration of 4 ppb of glass beads reduces the coefficient of friction by 28 % compared to the base mud. In addition, increasing concentration of the glass beds increased the PV and the increase above 8 ppb increased the YP significantly. On the other hand, the increase of glass beads concentration from 2 to 6 ppb decreased the GS while at high concentrations of 6 to 12 ppb the GS slightly increased [31].

Adewle and Najimu [87] investigated the mutation in WBM performance on the addition of date seed based. Moreover, they investigated rheological/filtration properties, density, and thermal stability of WBM on the addition date-seed and the influence of particle size, date-pit fat content, and date-pit loading on the drilling fluids. It was revealed that particles with size less than 75 nm enhanced both the rheological and filtration properties of the WBM. However, the best performance was determined to be achieved on the dispersion of 15 to 20 wt. % date-pit to the base WBM. **Figure 8** shows images of the date-pit processing (upper) and the effect of the date-pit loading on the shear thinning behavior (lower-left) and the AV and GS (lower-right) of the drilling fluid [87].

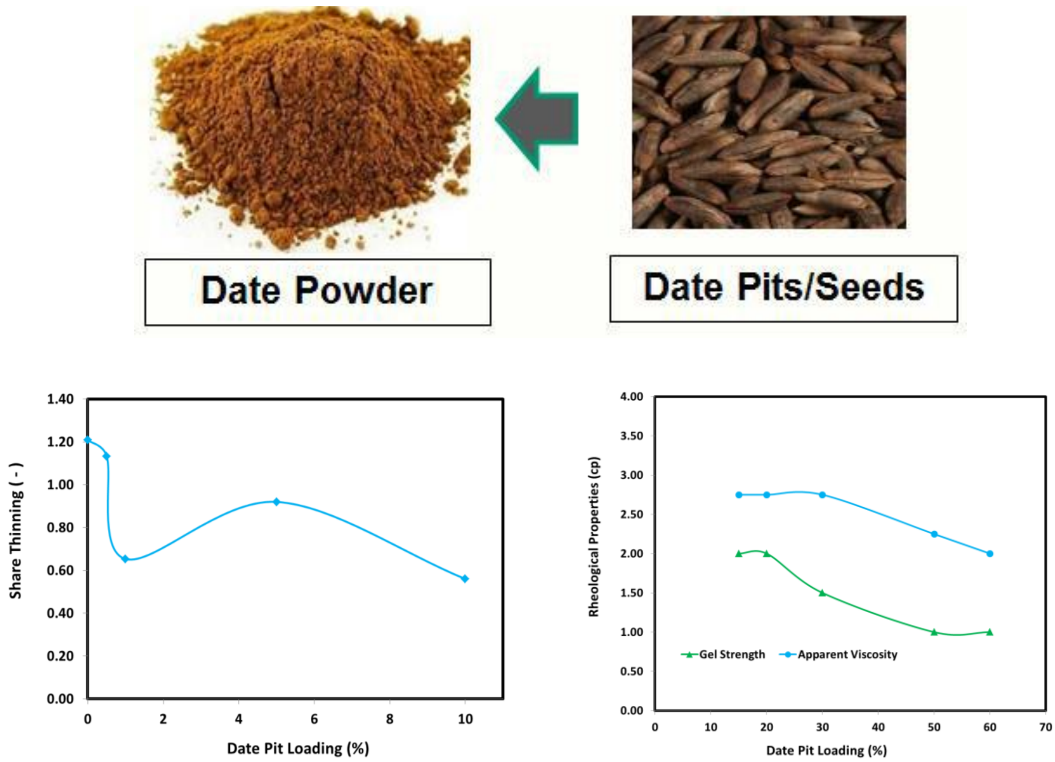

Figure 8 (Upper) date-pit processing, (Lower) effect of date-pit loading on the rheological performance of the drilling fluid [87].

In 2020, Ismail *et al.* [88] explored the feasibility of applying henna-leaf extracts and hibiscus-leaf extracts as ecological being products in WBM, which might minimize the environmental hazards. Rheological and filtration characterizations were carried out at 78 and 300 °F. The results of the low viscosity polyanionic cellulose were compared to plant extracts results. It was revealed that the volume of filtrate was dramatically decreased between 62 - 76 % on the addition of henna-leaf extracts and hibiscus-leaf extracts as well as significant improvement in the mud cake and rheological characteristics of the WBM. Furthermore, the viscosity and inhibition properties of WBM were both progressed when using both extracts as promising additives. Further, compatibility test data confirmed that the green additives are compatible with the other base fluid additives. The swelling behavior of sodium bentonite verified that the green plants are effective in inhibiting bentonite swelling. **Figure 9** shows images of the leaf extracts and powder after processing henna (upper-left) and hibiscus (upper-right), and mud cake filter cakes (lower) for different test fluids [88].

Figure 9 (Upper) Leaf extracts and powder after processing henna and hibiscus, (Lower) mud cake filter cakes for different test fluids [88].

Khan *et al.* [89] examined the combination of hydrophobic ionic liquid (Trihexyltetradecyl phosphonium bis (2,4,4-trimethyl pentyl) phosphinate) - (Tpb-P) and cationic gemini surfactant (GB) as a WBM additive for clay swelling inhibition. Different concentrations of the combined ionic liquid and gemini surfactant were used to prepare the drilling fluids ranging from (0.1 to 0.5 wt. %), and their performances were compared with the base drilling fluid. The wettability results showed that novel drilling fluid having 0.1 % Tpb-P - 0.5 % GB wt. % concentration has a maximum contact angle indicating the highly hydrophobic surface. The linear swelling test yielded the least swelling of bentonite at a concentration of 0.1 % Tpb-P - 0.5 % GB wt. % combined solution. Furthermore, the results of the capillary suction test (CST) also suggested improved performance of the combined solution at 0.1 % Tpb-P - 0.1 % GB concentration [89].

The application of okra mucilage for the prevention of shale swelling was the objective of several studies [90,91]. Okra mucilage (hibiscus esculents) was extracted from the okra plant and used – as an alternate green additive – at 3 different concentrations (5, 10 and 20) vol. % for linear swell test at atmospheric conditions for 24 h on bentonite wafers. Further zeta potential, particles size and capillary suction timer test (CST) were conducted. An experimental study revealed that okra mucilage reduced the swelling of bentonite. For instance, 10 and 20 vol. % of okra mucilage solutions reduced the swelling by 36.8 and 50.5 %, respectively. Also, the Okra mucilage decreased the zeta potential of clay and increased its particle size. CST time decreased initially at low concentration and increased with concentration [90]. In the second study [91], the composition of okra powder was diagnosed by X-ray fluorescence (XRF) and Fourier-transform infrared spectroscopy (FTIR), and its thermal stability was tested using thermal gravimetric analysis (TGA). Then the okra powder was mixed in various concentrations (1, 2 and 3 g) in 350ml of WBM and its performance was compared with starch-based drilling fluid. The addition of okra reduced fluid loss in different proportions at different concentrations. For instance, drilling fluid with 3g okra concentration had 42 % lower fluid loss as compared to the base fluid. The cake thickness was reduced upon the addition of okra. The addition of okra powder also increased the viscosity and GS of the WBM. TGA analysis of okra powder showed that it has strong thermal stability as compared to starch [91]. Later in 2022, the okra mucilage showed comparable performance to the commonly used clay stabilizer (KCl) used in the industry [92]. It was observed that okra mucilage reduced the fluid loss and provided a thin filter cake. The rheological properties were improved with the addition of okra mucilage. The increase in clay particles and reduction in zeta potential showed the inhibition properties of the okra mucilage. In addition, okra mucilage reduced friction and provided lubricity, which suggests that okra mucilage could be a green and environmentally friendly alternative clay swelling inhibitor [90-93]. **Figure 10** showed the scanning electron (SEM) micrograph images of filter cakes of the base mud and those of the base mud modified with 10 % okra mucilage [92].

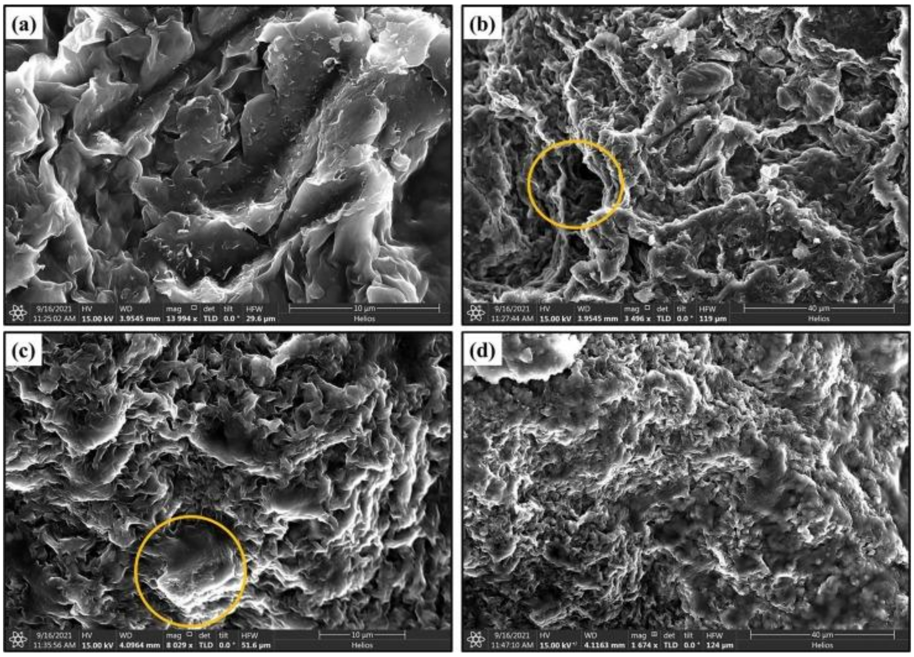

Figure 10 Scanning electron micrograph images of filter cakes (a,b) base mud and (c,d) base mud modified with 10 % okra mucilage [92].

The formulation of a drilling fluid modified with a combination of NPs with their unique properties and cost-effective biodegradable materials (pomegranate peel powder, and *Prosopis farcta* plant powder) was the aim of another study [94]. The drilling fluids were identified and recognized using scanning electron microscopy (SEM), X-ray diffraction (XRD), and Fourier transform infrared spectroscopy (FTIR) techniques. Furthermore, experimental tests were conducted to investigate the performance of the newly formulated drilling fluid in improving fluid loss characteristics. The results showed that adding 0.3 wt. % of pomegranate peel powder to the reference (base) drilling fluid reduces the filter loss volume to 7.9 mL compared to the reference fluid (11.6 mL). As the optimal concentration of TiO_2 was mixed with 0.3 wt. % of pomegranate peel powder then added to the reference fluid, the filter loss volume was reduced to 8.6 mL [94].

Yang *et al.* [95] used styrene, butyl acrylate, acrylamide, and 2-acrylamide-2-methylpropanesulfonic acid as the main raw materials to synthesize a polymer nanolatex (SBAA) employing a conventional emulsion polymerization approach (one-pot method). SEM, TEM, and PSD experiments demonstrated that SBAA is a NP with a particle size of around 150 nm and a distinct core-shell structure. The TGA analysis revealed that SBAA had a decomposition temperature of 296 °C. The experimental results showed that SBAA could reduce the medium pressure filtration loss by around 33 % compared with the basic bentonite fluid, and the reduction rate after aging at 200 °C is around 41 %. Moreover, it can reduce the filtrate loss velocity of WBM in heterogeneous pores, and the effects of filtration reduction and mud cake quality enhancement outperform those of commercial nanosilica particles [95].

Rambutan waste, one of Malaysia's most produced fruit wastes, was regarded for the first time as a filtering additive in WBM [96]. Rambutan peel contains cellulose fibers that act as rheological modifiers. Rambutan fiber increases the pressure on the crack of the plug and reduces the loss of liquids. Low, medium, and high concentrations of rambutan waste (0.01, 0.1 and 0.5 g) were used to prepare samples of mud to compare the rheological and filtration properties of WBM. The results showed that by increasing the concentration of rambutan waste samples, the properties such as PV, YP, and GS are gradually increased. Furthermore, rambutan additives significantly improved the filtering performance by reducing the loss of filters and the thickness of mud cakes. It was observed that 0.01 g of raw rambutan peel reduced filtrate loss from 9 to 4 mL compared to 9 mL of base liquid. In addition, the lowest concentration of rambutan additive produced the thinnest mud cake of 1.09 mm compared to 2.82 mm of base liquid, respectively [96]. **Figure 11** reveals a schematic illustration for the preparation of rambutan waste WBM, and the influence of different concentrations of rambutan waste on the drilling fluid properties.

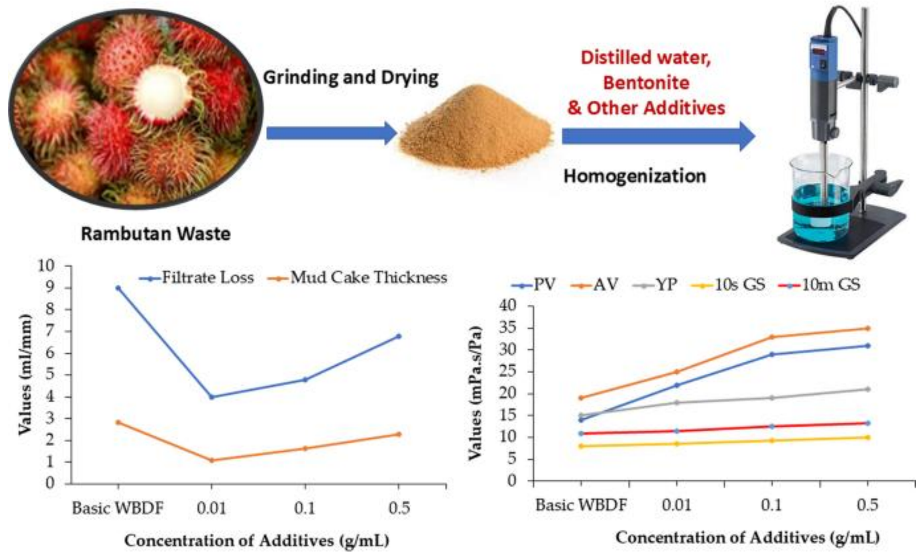

Figure 11 (Upper) the preparation of rambutan waste WBM, (Lower) the effect of different concentrations of rambutan waste on the drilling fluid properties [96].

Fadairo and Oni [97] reported an examination of eggshell NPs (ESN) to enhance the efficiency of WBM at elevated temperature. The study was based on previous reported literature which revealed that ESN can withstand a lot of heat and at the same time retain their properties under extreme conditions. ESN was added at various weighted amounts to the petroleum industry's approved mud composition for an elevated temperature well to design eggshell-boosted WBM samples. Filtration and rheological tests were conducted under HTHP conditions. The results showed that ESN helps WBM to withstand drilling operations in elevated temperature formations by delaying thermal degradation up to 270 °C. Specifically, the Fluid sample with 5 lb/bbl of ESN exhibited an 8 % reduction in HTHP filtrate volume when compared with an equal volume of commercial calcium carbonate (CCC), while a larger quantity of ESN (6 lb/bbl) yielded a 17 % reduction. Additionally, the inclusion of 5 lb./bbl of ESN was observed to be more effective than an equal quantity of CCC at 250 °C as it yielded a 28 % increase in 10 min GS. However, the rheological properties of 5 lb./bbl of ESN were not as effective as CCC at LTLP conditions which may be due to the presence of organic matter as a constituent of ESN at any temperatures below 200 °C [97].

A novel biosynthesized nanofluid system integrated with a natural surfactant was developed to tackle biological challenges and reduce the damage to hydrocarbon formations [98]. This innovative approach combines biosurfactants and NPs systems in WBM to minimize formation damage during hydrocarbon extraction while prioritizing environmental sustainability. Rheological measurements revealed that the PV and YP increased to 67.9 cP and 29.71 Pa, respectively, at a concentration of 0.1 wt. % zinc oxide NPs. The biosurfactant (Chuback) enhanced wettability by reducing the contact angle. This reduction, a crucial factor in wettability, led to a decrease of 51.53 % in the contact angle of WBM on sandstone slabs and 52.32 % on carbonate slabs, compared to more hydrophilic surfaces [98]. The research findings indicate that the optimized fluid obtained through Design of Experiments can significantly enhance the operational efficiency of drilling and production by minimizing the negative impacts on reservoir permeability. Finally, images taken before and after the flood using Computed Tomography Scans (CT-Scan) showed that the green additives proposed in the WBM have improved the factors that reduce formation damage.

Based on the articles reviewed in this work, 17 % of the additives used in the drilling fluids investigations contained silica while 16 % of the literature used iron to test its effect on the drilling fluids. Only 2 % used MgO NPs to enhance the properties of the bentonite WBM while 10 % used uncommon additives like yttrium oxide

NPs and Nano ATR **Figure 12**. A compressive summary for the reviewed paper, the type of the investigated drilling fluids, the additives used, the experimental conditions, and the investigated parameters are listed in **Table 2**.

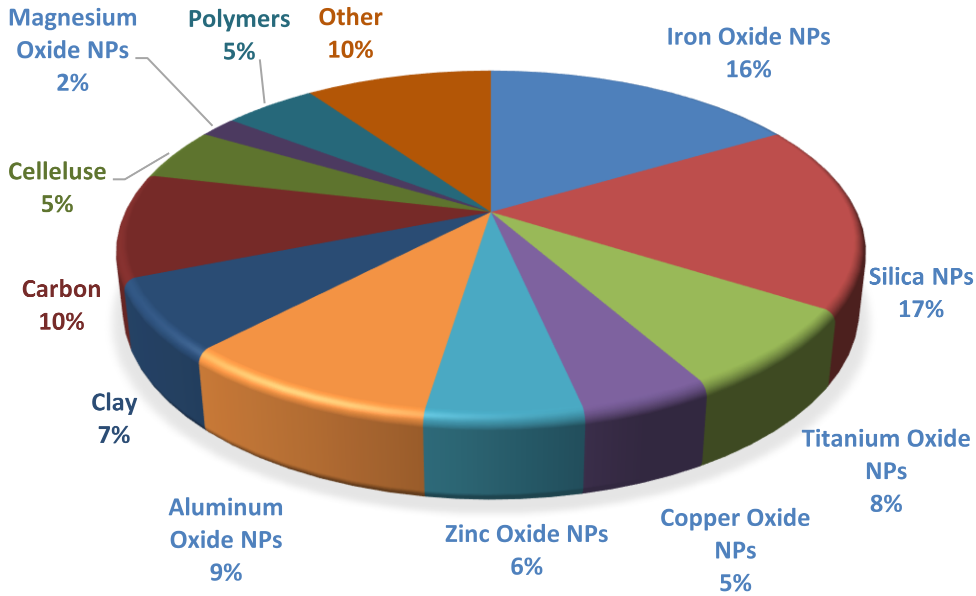

Figure 12 Comparison between the usage percentages of different additives.

Table 2 Summary of the presented papers in this review.

Year	Drilling fluid(s)	Additive(s)	Pressure(s)	Temperature(s)	Investigated parameter(s)	Reference
2011	Bentonite WBM	Iron oxide NPs	1 to 100 atm (R)* API (F)**	20 to 200 °C (R)	Rheology, Filtration	[21]
2011	Bentonite WBM	Nano ATR	Ambient	Ambient	Rheology, Filtration, and Lubricity	[22]
2012	Fresh WBM Saline WBM	Graphene oxide NPs	API	20 °C	Stability of GO in saline environments, and Filtration	[47]
2013	Polymer WBM	–	Ambient (R) 300 Psi (F)	120 °F (R) 225 °F (F)	Rheology, Filtration, and Filter cake properties	[2]
2014	Ester-based drilling fluids WBM	Multi-walled carbon nanotubes	API and HTHP (F)	80, 200, 250 °F (R)	Rheology, and Filtration	[29]
2014	Bentonite WBM	Acrylamide polymer	Ambient	Ambient	Rheology, and Modeling	[75]
2015	Bentonite WBM	Silica NPs Iron Oxide NPs	Ambient (R) 100 and 300 Psi (F)	78 to 140 °F (R) 78 and 250 °F (F)	Rheology, and Filtration	[23]
2015	Low solid content bentonite fluids	Fe_2O_3 NPs Iron-oxide clay hybrid Aluminosilicate clay hybrid	6.9 and 70 bar	25 and 200 °C	Rheology and Filtration	[27]
2015	Salt Polymer WBM	Nano graphene	HTHP	HTHP	Lubricity, Thermal stability, Shale swelling, and Rheology	[48]
2015	-	Ball-milled functionalized – COOH carbon NPs	Ambient	5 to 75 °C	Thermal conductivity Viscosity	[76]
2016	Bentonite WBM	Fe_3O_4 NPs	Ambient (R) 100 and 300 Psi (F)	78 to 158 °F (R) 78 and 250 °F (F)	Rheology, and Filtration	[24]

Year	Drilling fluid(s)	Additive(s)	Pressure(s)	Temperature(s)	Investigated parameter(s)	Reference
2016	Bentonite WBM	Fe_3O_4 NPs Fe_2O_3 NPs	Ambient (R) 100 and 300 Psi (F)	78 to 140 °F (R) 78 and 250 °F (F)	Rheology, Filtration, and Degree of thixotropy	[25]
2016	KCl-Polymer WBM	Multi-walled carbon nanotube, Nano silica Glass beads	Ambient (R) API (F)	Ambient	Rheology, Filtration, and Lubricity	[31]
2016	KCl-Polymer WBM	Zinc oxide NPs-acrylamide composite	Ambient (R) 100 and 500 Psi (F)	80 and 150 °F (R) 80 and 250 °F (F)	Rheology, Shale swelling, Lubricity, and Filtration	[33]
2016	Bentonite WBM	Ferric Oxide NPs Silica NPs	Ambient (R) 200 to 500 Psi (F)	120 to 200 °F (R) 175 to 350 °F (F)	Rheology, and Filtration	[38]
2016	Low and High Ph bentonite WBM	SiO_2 NPs	Ambient	Ambient	ECD, Rheology, and Filtration	[52]
2016	Polyethylene Glycol WBM Polyvinylpyrrolidoe WBM	CuO NPs ZnO NPs	Ambient	Ambient	Thermal properties, Electrical properties, and Filtration	[63]
2016	Bentonite WBM	A mixture of: Poly vinyl alcohol &N-vinyl-2-pyrrolidone &Diethylene glycol di methacrylate	Ambient (R) API F	60 to 200 °F (R) Ambient (F)	Rheology, and Filtration	[81]
2016	KCl- polymer WBM	TiO_2-bentonite nanocomposite	80 and 150 °F (R) API and HTHP (F)	80 and 150 °F (R) API and HTHP (F)	Rheology, and Filtration	[34]
2017	High pH bentonite WBM	Nano silica Nano titanium Nano aluminum	Ambient (R) API (F)	Ambient	Rheology, Filtration, and Hydraulic properties	[7]
2017	Bentonite WBM	Magnetic Fe_3O_4 NPs	Ambient	25 °C	Rheology	[26]
2017	KCl- polymer WBM	Partial hydrolytic polyacrylamide Graphene nanoplatelet Nano silica multi-walled carbon nano tube	Ambient (R) API and 500 Psi (F)	Ambient (R) 250 °F (F)	Rheology, Lubricity, Shale inhibition, and Filtration	[30]
2017	Sarapar-based mud Saraline-based mud	Multi-walled carbon nanotube	Ambient (R) API (F)	80 to 350 °F (R)	Rheology, Filtration, Effect of hot rolling	[32]
2017	Calcium bentonite WBM	Ferric oxide NPs Silica NPs	Ambient (R) 200 to 500 Psi (F)	120 to 200 °F (R) 175 and 350 °F (F)	Rheology, and Static and Dynamic Filtration	[35]
2017	Bentonite WBM	Silica NPs	Ambient	Ambient	Rheology, and Modeling	[81]
2017	WBM	Henna leaf extracts Hibiscus leaf extracts	Ambient (R) 100 to 500 Psi (F)	78 and 300 °F (R) & (F)	Rheology, Filtration, and Shale swelling	[88]
2018	Calcium bentonite WBM	Ferric oxide NPs	Ambient (R) 300 to 500 Psi (F)	140 °F (R) 250 to 350 °F (F)	Rheology, Filtration, and Filter cake properties	[36]
2018	Calcium bentonite WBM	Fe_3O_4 NPs Fe_2O_3 NPs SiO_2 NPs ZnO NPs	300 Psi	250 °F	Filtration, Filter cake properties, Formation damage analysis	[40]

Year	Drilling fluid(s)	Additive(s)	Pressure(s)	Temperature(s)	Investigated parameter(s)	Reference
2018	Bentonite WBM	Aluminum oxide NPs Copper oxide NPs Magnesium oxide NPs	Ambient (R) 100 and 500 Psi (F)	Ambient to 120 °F (R) Ambient to 250 °F (F)	Rheology, Filtration	[41]
2018	Bentonite WBM	Aluminum oxide and Silica NPs	14.7 to 500 Psi	23 to 120 °C	Rheology, Filtration, and post-dynamic ageing effect	[42]
2018	KCl-Polymer WBM	Yttrium Oxide NPs	Ambient to 10,000 Psi	75 to 300 °F	Rheology	[44]
2018	Salt-Polymer WBM	Carbon NPs ZnO NPs	Ambient (R) API (F)	20 to 85 °C (R)	Rheology, Sagging effect, and Filtration	[45]
2018	Bentonite WBM	Nano clay	Ambient (R) 100 Psi (F)	25 to 85 °C (R) 25 and 85 °C (F)	Rheology Filtration Modeling Electrical resistivity	[78]
2018	KCl- polymer WBM	SiO_2 Clay NPs	Ambient (R) 100 Psi (F)	25 and 90 °C	Rheology, Filtration, and Thermal stability	[83]
2019	Sodium bentonite WBM	Fe_3O_4 NPs SiO_2 NPs custom-made bare Fe_3O_4 NPs Citric acid coated Fe_3O_4 NPs	Ambient	20 to 60 °C	Rheology	[28]
2019	Salt-polymer WBM	Aluminum oxide NPs	Ambient	30, 60, and 80 °C	Rheology, and Filtration	[43]
2019	Bentonite WBM	SiO_2 NPs Graphene Oxide nanoplatelets	Ambient (R) 100 to 500 Psi (F)	Ambient (R) 77 to 250 °F (F)	Rheology, Filtration, and Shale inhibition	[46]
2019	WBM	Organophilic clay, Associative polymer Synthesized Gemini surfactant	300 Psi	100, 150, 200 °F	Rheology, Filtration, and Shale inhibition	[82]
2020	Bentonite and KCl-based drilling fluids	Fe_2O_3 NPs	Ambient	22, 50, 80 °C	Rheological properties, Viscoelastic properties, Lubricity, and Filtration	[37]
2020	Bentonite WBM	Aluminum oxide NPs Titanium oxide NPs Copper oxide NPs Magnesium oxide NPs	Ambient	Ambient	Rheology Hole cleaning efficiency	[53]
2020	Bentonite WBM	Dual-functionalized cellulose nanocrystals	Ambient (R) API (F)	25, 40, 60, and 80 °F (R)	Rheology, Toxicity, Thermal tolerance, and Filtration	[56]
2020	KCl-Polymer WBM	TiO_2/bentonite nanocomposite	Ambient 100 and 500 Psi (F)	299 and 338K Ambient to 394K (F)	Lubricity, Filter cake properties, Shale and clay inhibition	[57]
2020	Polyamine-based non-damaging mud Bentonite-based drilling fluids	Silica oxide NPs Copper oxide NPs	Ambient (R) 200 Psi (F)	Ambient	Rheology, and Filtration	[62]
2020	Polymer WBM	Barite NPs Bentonite NPs CLOISITE5 NPs TiO_2 NPs SiO_2 NPs	Ambient (R) 100 and 500 Psi (F)	Ambient (R) 75 and 200 °F (F)	Rheology, and Filtration	[84]

Year	Drilling fluid(s)	Additive(s)	Pressure(s)	Temperature(s)	Investigated parameter(s)	Reference
2021	Bentonite WBM	SiO_2 NPs	Ambient	Ambient	Rheology, Energy saving, and Modeling	[39]
2021	Low bentonite content WBM	Cellulose nanofibers, and Cellulose nanocrystals	Ambient	Ambient	Rheology, and Cuttings transport	[54]
2021	Bentonite WBM	ZnO NPs Associative polymer	Ambient (R) API (F)	25 °C (R& F)	Rheology, Filtration, and Shale inhibition	[58]
2021	KCl-Polymer WBM	Aluminum oxide NPs Copper oxide NPs	Ambient (R) API (F)	120 °F (R)	Rheology, Filtration, Filter cake properties	[59]
2021	KCl-Polymer WBM	ZnO NPs	Ambient (R) API (F)	40 and 80 °C (R)	Rheology, and Filtration	[60]
2021	ethyl octanoate ester-based drilling fluid	Aluminum oxide nanorods	Ambient (R) API (F)	2.6, 26.8, 70 °C (R) Ambient (F)	Rheology, and Filtration	[64]
2021	Polymer WBM	α-MnO_2 NPs	Ambient (R) API and 500 Psi (F)	25 °C (R) Ambient to 150 °C (F)	Rheology, Electrical conductivity, Filtration, and Heat tolerance	[77]
2022	OBM	Silicon oxide NPs	Ambient (R) API (F)	40 °C Density Ambient (R&F)	Rheology, Filtration, and Colloidal stability	[49]
2022	KCl-polymer WBM	Titania NPs Alumina NPs Silica NPs	–	–	Specific heat capacity, and Rheology	[51]
2022	Low bentonite content WBM	Cellulose nanofibers, and Cellulose nanocrystals	Ambient	Ambient	Rheology, and Cutting transport	[55]
2022	Fresh WBM Saline WBM	Hybrid NPs	Ambient (R) 300 to1000 Psi (F)	120 °F (R) 180 to 300 °F (F)	Rheology, Filtration, and Effect of hot rolling	[86]
2022	Sodium bentonite WBM	PAASM-$CaCO_3$	Ambient (R) API and 3.5 MPa (F)	Ambient (R) 180 °C (F)	Rheology, Filtration, and Effect of hot rolling	[85]
2022	WBM	Okra mucilage	Ambient	Ambient	Rheology, Filtration, Lubricity, and Shale swelling	[92]
2023	Bentonite WBM Polymer WBM	SiO_2 NPs Al_2O_3 NPs	Ambient	25, 40, 55, and 80 °C (R)	Rheology	[50]
2023	WBM	modified polystyrene micro-nano spheres (MPS)	API (F)	Ambient	Filtration, Shale inhibition, and contact angle	[65]
2023	WBM	copper oxide NPs and multiwalled carbon nanotubes (MWCNTs)	Ambient (R) API (F)	Ambient	Rheology, Filtration	[66]
2023	WBM	silica NPs coated with AEAPTS ([3-(2-Aminoethylamino) propyl] trimethoxy silane)	Ambient (R) API (F)	After aging at 105 °C for 16 h and measured at 30 °C and 60 °C (R) Ambient (F)	Rheology, Filtration	[69]
2023	WBM	silica NPs modified by Hexadecyltrimethylammonium bromide (CTAB) cationic surfactant	–	149 to 232 °C	Rheology, Filtration	[70]
2023	WBM	TiO2 NPs, pomegranate peel	Ambient	Ambient	Filtration	[94]

Year	Drilling fluid(s)	Additive(s)	Pressure(s)	Temperature(s)	Investigated parameter(s)	Reference
		powder, and Prosopis farcta plant powder				
2023	WBM	synthesize a polymer nanolatex	0.69 MPa and 3.5 MPa (R)	120 °C (R)	Filtration, Thermal stability	[95]
2024	WBM	Biogenic CuO NPs synthesized using a natural extract from Colocasia esculenta leaves	Ambient	Ambient	Rheology, Filtration, and Lubricity	[71]
2024	WBM	Synthesized SiO2/g-C3N4 NPs hybrid	before hot rolling (BHR) and after hot rolling (AHR))	before hot rolling (BHR) and after hot rolling (AHR)	Rheology, Filtration, and Thermal stability	[72]
2024	WBM	hydrophobic nanosilica (HNS)	LTLP and HTHP filter press (F)	25, 50 and 75 °C (R)	Rheology, Filtration, and Shale swelling	[73]
2024	WBM	Mesoporous Nano-Silica (MNS)	Ambient (R) 100 psi and 500 psi (F)	hot rolling at 180 °C at 100 psi pressure for 16 h measured at 25 and 70 °C (R) 150 °C (F)	Rheology, Filtration,	[74]
2024	WBM	Rambutan waste	Ambient	Ambient	Rheology, and Filtration	[96]
2024	Industry-standardized WBM	Eggshell NPs	Ambient (R) 100 psi and 400 psi (F)	100, 150, 200, and 250 °C (R) 100 and 270 °C (F)	Rheology, and Filtration	[97]
2025	WBM	Synthesized ZnO NPs + biosurfactant (Chuback)	Ambient	Ambient	Rheology, Core flooding (filtration and formation damage), and Contact angle	[98]

(R)*: Rheological measurements; (F)**: Filtration measurements; API: room temperature and 100 psi

Machine learning and artificial intelligence applications

AI can be defined as the teaching of computers to perform an action or series of actions that usually require human intelligence to be done. AI can use either explicit approaches like writing a code or implicit techniques like using ML algorithm. On the other hand, ML is teaching the computers how to do a certain task without telling it how to perform this task, instead you provide it with appropriate number of exemplars [99]. Hence, ML is located within the domain of AI, while AI is located within the computer science (CS) domain which has a common domain with data science domain as shown in **Figure 13**. The petroleum filed like a lot of the other fields has grown an interest in utilizing AI and ML techniques to optimize the several operations[11].

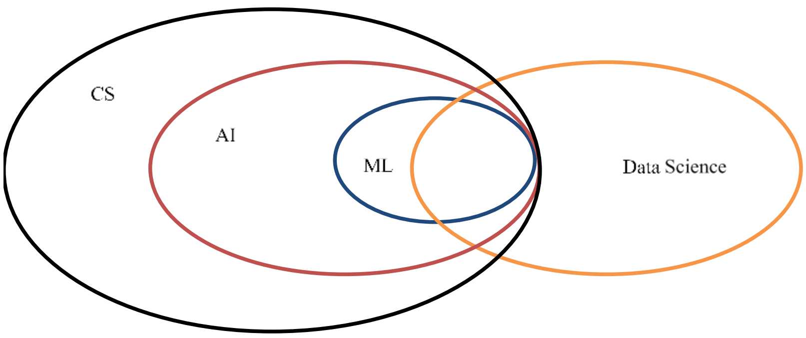

Figure 13 Different domains of computer science branches.

ANN is one of the widely used algorithms in the petroleum field especially in the drilling fluids applications with over 54 % [13]. ANN is a powerful tool that can simulate the human brain learning process through creating networks of artificial neurons. The ANN can learn and train by experience with appropriate learning examples just as people do (i.e. they build their awareness by detecting the relationships and patterns in the data) [100]. Neurons are fully connected and, in a network, shaped form. Neurons act like messengers sending and receiving impulse. However, each neuron can have multiple inputs, it will generate only one output then pass it to the neurons in the next layer which results as an intelligent artificial brain capable of predicting, learning, and recognizing patterns (**Figure 14**). Artificial neurons can also be referred to as processing elements (PEs), single units and/or simply neurons. An ANN is usually created by from hundreds of PEs which are entirely connected with weights (coefficients). PEs construct the structure of ANN as they are marshaled in the input layer, the hidden layer(s) and the output layer (**Figure 14**). The power of neural computations comes from connecting neurons in a network. Each PE has weighted input, activation function, and one output. The combination of the weighted inputs controls the activation of the neuron. Each layer has a bias which is the value that combination of the weighted inputs must exceed to activate the neurons and pass the signal to next layer. If the signal is activated, it passes through the transfer function to produce a single output of the neuron that proceeds to neurons in the next layer. The performance and the behavior of ANN is based on the network's architecture, number of PEs, activation functions of its PEs, and learning rule [100,102].

Indeed, the problems of predicting, classifying, and controlling neural networks are being faced. This sweeping success can be attributed to a few key factors. Most conventional modeling techniques seek a presumed mathematical formula for the modeling to be efficient. However, on the other hand, ANN models are considered soft models as they don't demand an exciting mathematical function beforehand and suitable of multivariant calibration modelling [103]. Usually, the presence of clear and unnoisy data sets is very challenging. ANN has the capability and flexibility to safeguard its performance even in the presence of considerable amount of noise in the input data.

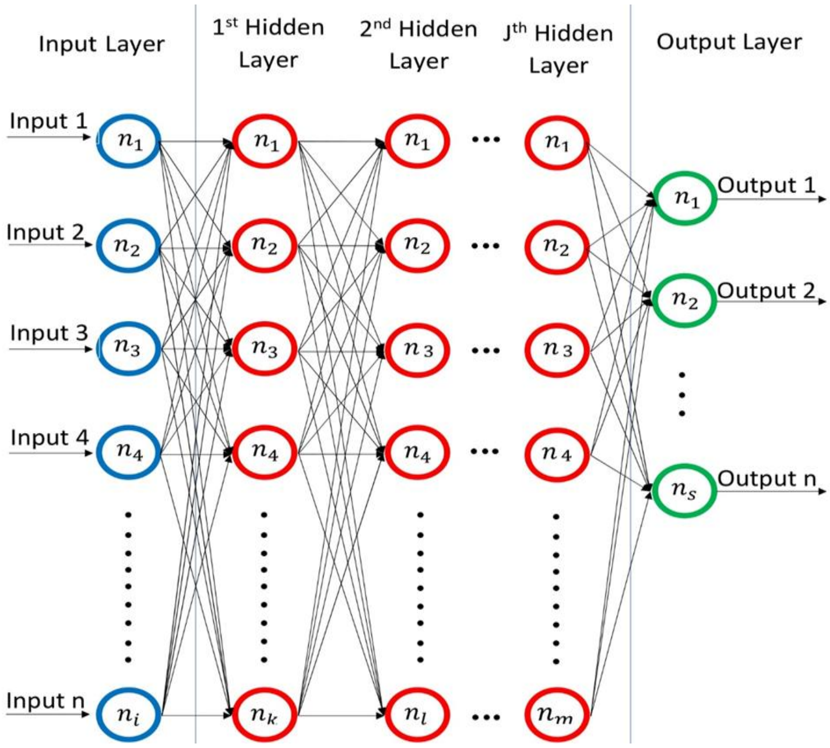

Figure 14 ANN general architecture. ANN consists of 3 or more layers; an input layer, an output layer, and one or more hidden layer(s). Each layer consists of number of neurons and are fully connected with weights [101].

ML is a subset of AI around the idea that we should feed the machines with data and let them learn for themselves. If programming is automated, then ML automates the process of automation. In traditional programming, data and program are both run on the computing machine to compute the output but in ML; both data and output are run on the computer together to develop a program. This program can be used in traditional programming [104]. This concept is visualized in **Figure 15**.

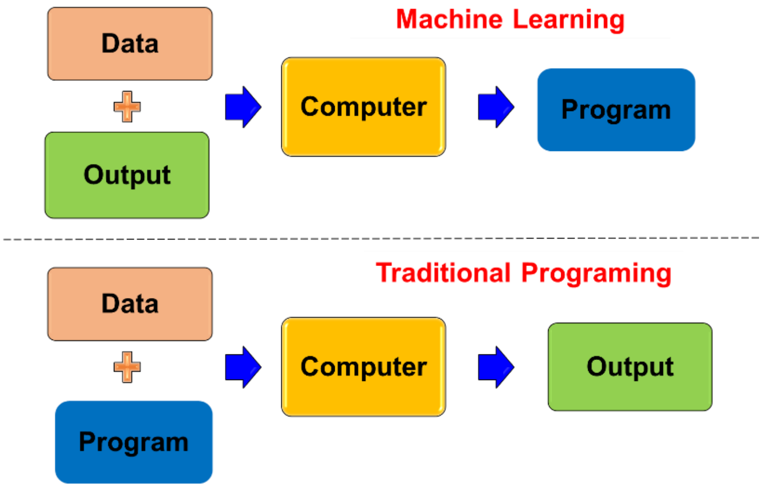

Figure 15 Traditional programming versus machine learning [104].

Every ML algorithm has 3 stages during the process of building the automated model; **Representation:** The algorithm used to represent the data pattern knowledge. Examples include regressors, classifiers, support vector machines (SVM), model ensembles and others. **Evaluation:** The way to evaluate the chosen algorithms' performance. Examples include accuracy, precision, recall, mean squared error, cost function, etc. **Optimization:** The process of adjusting the model hyper-parameters to improve performance [105].

There are different styles in ML problems [106]; **Supervised Learning:** Algorithms in which when given a sample of data and its desired outputs, the algorithm approximates a function that maps inputs to outputs. A model is developed through a training phase where prediction is made and then corrected when they proved wrong. The training phase remains until the model reaches to a desired accuracy level on the training data. **Unsupervised Learning:** Algorithms in which the given sample of data does not contain the desired output. The algorithm learns the inherent pattern of the data without using explicitly provided labels. A model is prepared by inferring structures hidden in the input data. **Semi-Supervised Learning:** The input data is a mixture of labelled and unlabeled examples, aims to label unlabeled data points using knowledge learned from the labelled data points. The model must learn the structures to organize the data as well as make predictions. **Reinforcement Learning:** It works the following way, there is a presence of an agent and environment. The agent would be able to take some action on the environment, based on which it would be rewarded or punished.

To build ML model, the appropriate package should be selected for scientific computing, performing different operations, data manipulation and analysis, and data visualization. In addition to having good data, you need to make sure that it is in a useful scale, format and even that meaningful features are included. Steps of building a ML model are [105]; **Data Gathering:** Different data sets should be collected from many wells and/or fields. **Data Pre-Processing:** Is a long and burdensome process to get unseen knowledge. Pre-processing of data refers to the transformations applied to the data before feeding it to the algorithm (i.e., cleaning data to have homogeneity by deal with *Missing Values and Detecting Outliers*). **Feature Engineering:** Is the process of incorporating domain knowledge to identify attributes from raw data. Relevancy of features to the output varies from one feature to another, so to make the proposed model more accurate, it is mandatory to investigate all the dataset features and assess their importance and focus on features with high relevancy to the output. **Algorithm Selection and Training:** The field of ML includes an enormous number of algorithms, some of which are easy to use, while some others necessitate more difficult understanding of the algorithms. Predictive modeling is the method of developing a model using historical data to make a prediction on new data where we do not have the answer. It can be described as a mathematical problem of approximating a mapping function (f) from input variables (x) to output variables (y). **Table 3** shows a list of the ML algorithms that were duly applied in this research with their advantages and disadvantages [105].

Model Training and Evaluation: Typically, when dataset is separated into a training set and testing set, most of the data are used for training, and a smaller portion of the data are used for testing. Splitting data is an important stage of model evaluation and determining the performance of the model when it is used in real life. Testing model performance on held-out data is the best way to evaluate model accuracy. The most common split of data is 70 % training and 30 % testing parts [107]. This action identifies the precision in the selected algorithm depending on result. A better way to check the accuracy of the model is to see it performs well on data which was not used during training. It's worth mentioning that diversity of data (not necessarily huge dataset) is a significant factor that enhances the model's performance and enables model generalization (i.e., model is efficient in forecasting or classifying unseen datasets). For better generalization, cross validation is required during training phase to ensure all portions of dataset are exploited. The nature of ML algorithm and model complexity also play an obvious role in model generalization.

Table 3 The advantages and disadvantages of different ML algorithms [105].

ML Algorithm	Advantages	Disadvantages
Logistic Regression (LR)	• It is used extensively because of its efficiency, high interpretability, and no scaling or tuning required. • Logistic regression has higher efficiency when irrelevant and correlated features removed.	• Other algorithms will outperform Logistic regression in case of similar or correlated variables.
Decision Trees (DT)	• Easier data preparation during preprocessing phase. • Decision tree does not prerequisite data normalization or scaling. • Missing values in the data also doesn't affect the process of building decision tree to any considerable extent. • The decision tree model can be easily explained because it is very intuitive.	• Instability of models can result from any minor change in data. • Long time of model training.
Random Forest (RF)	• It can handle large number of features (dimensions). • It can calculate the contribution of each feature. • Less training time.	• Difficult interpretation of some random forest models. • For very large datasets, the size of the trees can take up a lot of memory.
Support Vector Machines (SVM)	• Higher accuracy in case of having classes with clear separation margin. • SVM shows more efficiency in case of high dimensional spaces.	• The presence of noise in data badly affects SVM performance.
K-Nearest Neighbors (KNN)	• Simple and easy to interpret. • It can be directly implemented in non-linear cases because it doesn't include any assumption.	• Model speed decreases with increasing number of data points increases. • Not memory efficient. • Sensitive to outliers.

ML Algorithm	Advantages	Disadvantages
Stochastic Gradient Descent (SGD)	• Efficiency and ease of implementation.	• Requiring several hyper parameters and being sensitive to feature scaling.
Adaptive Boosting (AdaBoost)	• Simple to implement. • Few Parameters.	• Sensitive to noisy data and outliers.
Naïve Bayes	• Better performance compared to other models in case of independent predictors. • It performs well in case of categorical input variables compared to numerical variables.	• It is almost impossible that we get a set of predictors which are completely independent.
Quadratic Discriminant Analysis (QDA)	• More efficient compared to other models like logistic regression in case of having more than 2 non-ordinal classes. • More stable than other models in case of well-separated classes.	• Performance severely declines as the number of predictor variables approaches sample size.
ANN	• Good performance with linear and nonlinear data • Capable to learn from the analyzed data and reprogramming not required	• Needs a large and diverse training data for real-life applications. • In many cases, referred to as "black box" as it offers little insights.

AI and ML have been introduced and used thoroughly to generate more reliable models and correlations in different petroleum engineering aspects. AI and ML have been used for drill bit diagnosis, well-log analysis, surveillance of major drilling and completion activities, and reservoir simulation, encompassing seismic pattern identification, history matching, and reservoir characterization, prediction of permeability and porosity, pressure-volume-temperature (PVT) analysis, production optimization, and well performance evaluation [105,108-125]. **Figure 16** shows better summarization of ML applications in the oil and gas industry [105]. In the following lines, we briefly present some of those AI and ML journeys in the field of drilling fluid property prediction.

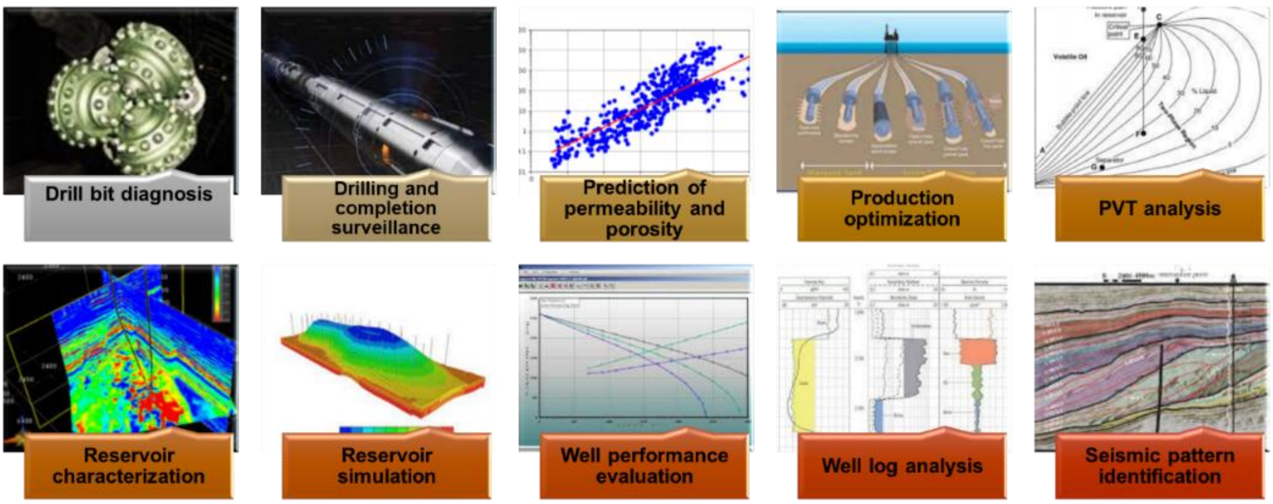

Figure 16 Applications of AI and ML in oil and gas industry [105].

In 2016, almost 9,000 data points of invert emulsion mud were used as the modeling and testing layer to convert ANN black box to a white box to obtain visible mathematical equation of its rheological properties [126]. The developed ANN can be used to easily predict the dial readings at 600 and 300 rpm, which can then be used to obtain the values of AV, PV, YP as well as the consistency index (*k*) and the flow behavior index (*n*) as shown in **Table 3**. In those equations, x represents the input parameter, j is the number of input variables, N is the number of neurons which was optimized to be 12 for one hidden layer, b_1 is bias of the hidden layer, and b_2 is bias of the output layer, w_1 is weight of hidden layer, w_2 is weight of the output layer. About 70 % of the data were used to train and obtain the mathematical equation [126].

After modeling, 30 % of the data was used to test the developed equations, which showed good values of the average absolute percentage error (AAPE) and the coefficient of correlation (R). The models constructed for the dial readings at 300 and 600 rpm, AV, PV, YP, *k*, and *n* gave AAPE of 3.48, 3.7, 3.7, 5, 3, 4.2, and 1.2 %, respectively. In addition, they gave correlation coefficients (R) of 0.898, 0.92, 0.91, 0.91, 0.90, 0.92, and 0.954 for models constructed for the same parameters, respectively. The developed ANN models can save huge times if one knows that AV, PV, YP of the drilling fluids are measured twice a day on the rig in the petroleum fields, while Marsh funnel viscosity, solid content, and density are measured every 10 - 20 min [126,127]. Correlations to predict fluid rheological properties using ANN visible mathematical model are shown in **Table 4**.

Table 4 Correlations to predict drilling fluid rheological properties using ANN visible mathematical model [126].

Rheological Parameter	ANN Correlation
Plastic Viscosity	$PV = \left[\sum_{i=1}^{N} w_{2i} tansig\left(\sum_{j=1}^{J} w_{1i,j} x_j + b_{1i}\right)\right] + b2$
Yield Point	$Yp = \left[\sum_{i=1}^{N} w_{2i} tansig\left(\sum_{j=1}^{J} w_{1i,j} x_j + b_{1i}\right)\right] + b2$
Herschel-Bulkley Consistency Index	$k = \left[\sum_{i=1}^{N} w_{2i} tansig\left(\sum_{j=1}^{J} w_{1i,j} x_j + b_{1i}\right)\right] + b2$
Herschel-Bulkley Flow Behavior Index	$n = \left[\sum_{i=1}^{N} w_{2i} tansig\left(\sum_{j=1}^{J} w_{1i,j} x_j + b_{1i}\right)\right] + b2$

Using the same concepts, Gowida *et al.* [128] used the ANN to developed mathematical correlations of the rheological properties of the high-bentonite WBM and OBM [129] by knowing only the marsh funnel viscosity and the mud density. While developing their model, 200 data points for WBM were gathered and divided into 2 datasets with 70 % of the data being used for training while the rest were used for testing. The developed model used one hidden layer with 20 neurons processed by Levenberg-Marquardt algorithm as training rate and Tan-sigmoidal as a transfer function. The new ANN was then tested by evaluating the AAPE and R, which were less than 6 % and more than 0.9, respectively, which shows higher accuracy compared to the other already used models in the petroleum industry [128]. While 522 data points were collected for OBM to predict PV, YP, AV and Herschel-Bulkley flow behavior index. The model has R of 0.94, 0.92, 0.92, and 0.95 for the abovementioned parameters, respectively [129].

In order to better understand the rheology of the drilling fluids, Jondahl and Viumdal [130] in used ML and AI for frequent monitoring their properties like density, viscosity, and GS. For that, Non-invasive ultrasonic measurement techniques and ANN have been used at 3 different levels of ultrasonic frequencies on the WBM to create an atomized sensor. This sensor is aimed at predicting the drilling fluid density, viscosity, and GS depending on the time of flight, signal amplitude, and the distance between receiver and transmitter. A setup was built for ultrasonic measurements, and 11 different types of drilling fluids were tested. The gathered experimental data were then used in training, validating, and testing the ANN model. Compared to the actual experimental data, the developed model gave promising accuracy with 0.84 to 95 % mean absolute percentage error (MAPE) for density, challenging values of 4.4 to 7 % and not accurate values of 15 to 19 % for PV and GS, respectively [130].

Ahmadi *et al.* [131] suggested a rigorous predictive model for estimating drilling fluid density (g/cm^3) at wellbore conditions utilizing a couple of particle swarm optimization (PSO) and artificial neural network (ANN) was utilized. Moreover, 2 competitive ML models including fuzzy inference system (FIS) model and a hybrid of genetic algorithm (GA) and FIS (called GA-FIS) method were employed. To construct and examine the predictive models the data samples of the open literature were used. Based on the statistical criteria the PSO-ANN model has reasonable performance in comparison with other intelligent methods used in this study.

Agwu *et al.* [132] developed an ANN model to predict the density of OBM under varying conditions of pressure and temperature. Drilling fluid density is a very important parameter during the drilling operation to determine the hydrostatic pressure of the mud column. This property is highly affected by the pressure and temperature, especially in the deep wells. For this purpose, several data points of OBM were collected, 60 % of those data were used for the ANN training, 20 % were used for the ANN testing, and the last 20 % were used in validation. R, mean square error (MSE), root mean square error (RMSE), residual sum of squares (RSS), mean absolute error (MAE), and MAPE of the developed models were very satisfactory with values of 0.9999, 0.000477, 0.022, 0.056, 0.017, and 0.127, respectively [132]. The relative importance of independent variables in the ANN model was also sensitively studied using the connection weights algorithm to Determine the contribution of each input variable to the prediction of the dependent variable. **Figure 17** reveals that increases in initial mud density and downhole pressure would lead to increased downhole mud density (positive sign). However, the negative sign for the temperature indicates that increasing the downhole temperature would surely lead to decreased downhole mud density.

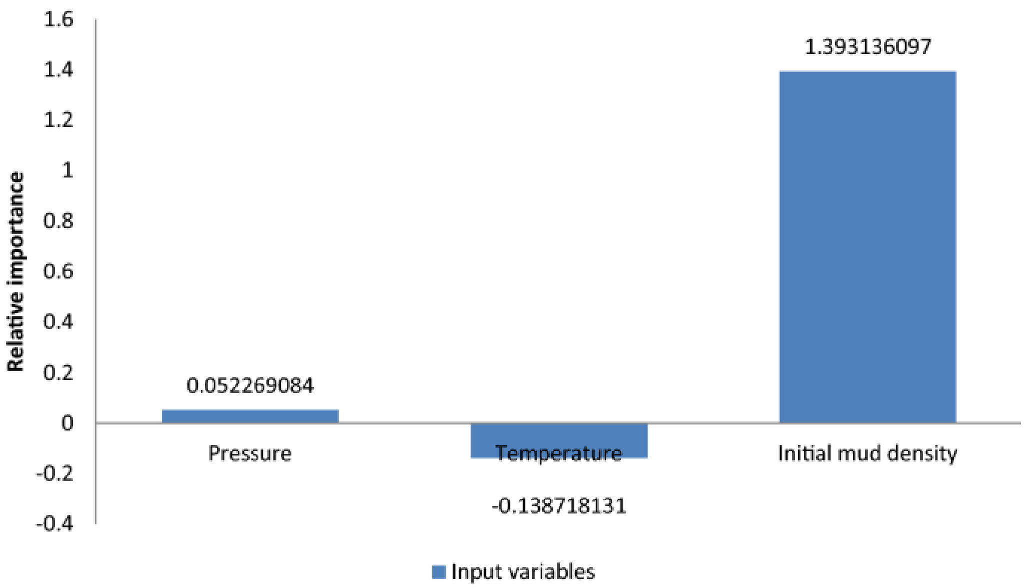

Figure 17 Relative importance of input variables in the ANN model [132].

In 2019, 2 ECD models were constructed using ANN and adaptive neuro-fuzzy inference system (ANFIS) algorithms. The model used 16,64 data points for training and another 712 for testing the model. Mud weight, ROP, and surface drill pipe pressure are the factors taken into consideration as input parameters for the model. The models results showed an AAPE of 0.2252 % for training and 0.2237 % for testing dataset while R for the ANN model were 0.9971 and 0.9982 for training and testing datasets, respectively [133] . Later in 2021, using a similar approach ECD of the drilling fluids was estimated using ANN and ANFIS based on 3,570 data points. While developing the model, more input parameters were considered like standpipe pressure, weight on bit (WOB), rate of penetration (ROP), flow rate, revolution per min (RPM), and torque. The proposed models have an efficiency of R = 0.98 for ANN model and 0.96 for ANIFS model [134].

Different AI algorithms like linear regression, polynomial regression, hybrid regression, ensemble method, and ANN were used to determine the shear dial reading at 600, 300, 200, 100, 6, 3, gel-10 s, and gel-10 min at elevated temperatures[135]. Seventeen selected features were used as input parameters at ambient temperature in addition to the field temperature as feed to the models. A total of 8 features related to the composition of the drilling fluid, 6 components for the rheological properties at ambient temperature, 2 features for gel-10 s and gel-10 min, and one feature describes the field temperature. Ensemble method had the best performance with MAPE of 1.88 % while the rest of the models had 13.22, 8.75, 7.26, and 6.18 for linear regression, ANN, polynomial regression, and hybrid regarrison models [135].

Later in 2020, The volume of filtration for WBM and OBM was predicted using, random forest (RF), XGBoost, support vector machine (SVM), ANN, and multi-linear regression algorithms. For this aim, 1,298 clay and polymer-based mud, 1,786 KCl-polymer WBM, and 105 OBM data points were collected and used to train and test the models. The input parameters for the WBM models were PV, YP, mud density, and temperature while AV, mud density, electrical stability, and water content were the input parameters for OBM models. The relative importance of each input parameter was evaluated, and the results showed that PV has the highest impact in WBM models while the water content had the highest importance in OBM models [136]. In 2022, Linear regression, ANN, and ERT decision tree were used to predict PV, YP, gel 10 s, gel 10 min, pH, and the filtration volume of WBM. A dataset containing 6878 data points were used in developing the models. The accuracy of the models was evaluated using MAE for the models which was 1.17 for linear regression, 0.74 for ANN, and 0.27 for ERT decision tree [137].

Golsefatan and Shahbazi [138] presented one of the trails of applying ANN in predicting the properties of drilling fluid. In this study, the authors developed ANN that can predict the effect of NPs if used as additives to modify the characteristics of the drilling fluids according to what’s needed in drilling operation. The authors collected about 1003 data points from the literature and used them to develop the model, which can then be used in predicting the filtration volume of KCl-polymer WBM. Different parameters were taken into consideration in this model, especially the type and concentration of NPs, KCl concentration, temperature, pressure, rate of penetration, and time. The developed ANN model was made of 3 layers, 2 of them are hidden layers (**Figure 18**). Almost 803 data points were used in developing and training while the other 200 were used for testing the developed model. After that several statistical tests were made to indicate the accuracy of the constructed model, which showed that the model can describe and predict the filtrate volume efficiently and precisely. Furthermore, this study showed that the volume of filtrate is very sensitive to the concentration of NPs as shown in **Figure 19** [138]. In 2021, a similar approach has been used to predict the volume of filtrate using ANN and SVM algorithms were used considering the same aforementioned input parameters for 1,003 data point [139].

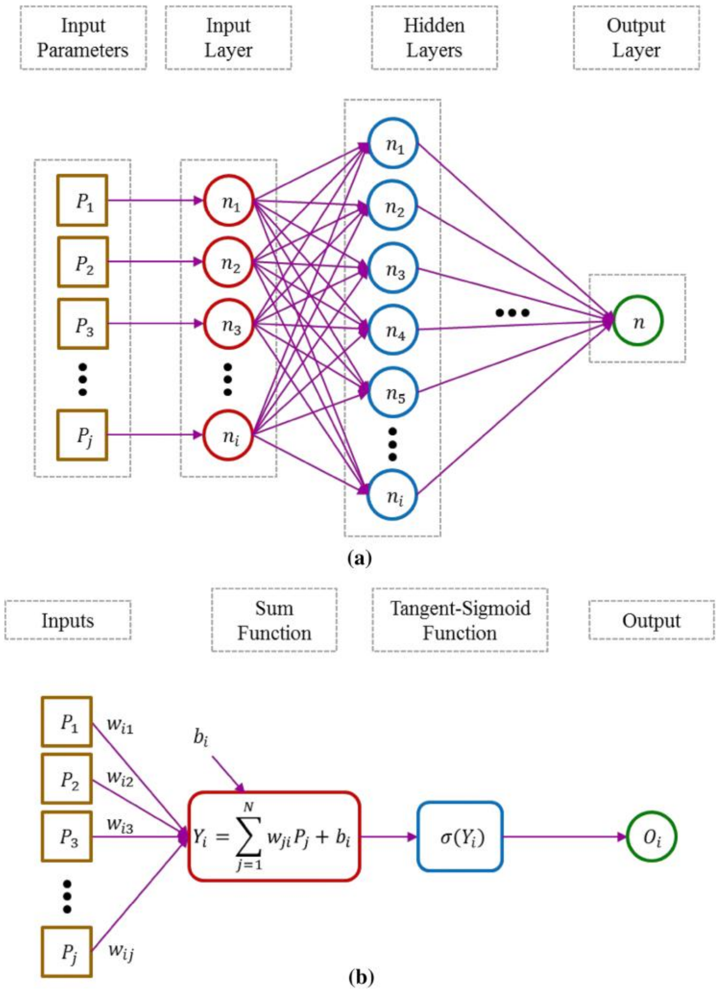

Figure 18 General architecture of an ANN model (a), and a neuron structure (b) [138].

As above-mentioned, ANN was applied to predict the density and rheological properties of drilling fluids that have no NPs [126,128,130,132] in addition to predicting the filtration characteristics of NPs-based drilling fluids [138]. A novel application of ANN to predict the rheological properties of NPs-based drilling fluids is introduced by Gasser *et al.* [140]. In this study, promising ANN models were developed to predict the 4 viscosity-related parameters that are usually measured and optimized (AV, PV, YP, gel-10 s, and gel-10 min) for a nano-based drilling fluid.

Experimental data were collected and used to feed the ANN. Four types of NPs with different sizes and characteristics were used in those experiments: Al_2O_3, SiO_2, TiO_2, and CuO NPs. The experimental data was collected for 3 different types of NPs-based drilling fluids (KCl-polymer, low solid non-dispersed, and bentonite-based mud). The data was then divided into 70 % for training, 15 % for validating, and 15 % for testing. MATLAB–ANN tool was used to develop the models. N-encoded method was used to convert the categorical data of the NPs, and the drilling fluid types into numerical data. The input used to construct the models were: 1) the drilling fluid type, 2) the NPs' type, 3) NPs' concentration, 4) NPs' size, and 5) NPs' molecular weight. The targets (outputs) of the models were the rheological parameters. Statistical description of the data for different NPs-based drilling fluids is shown in **Table 5** [140].

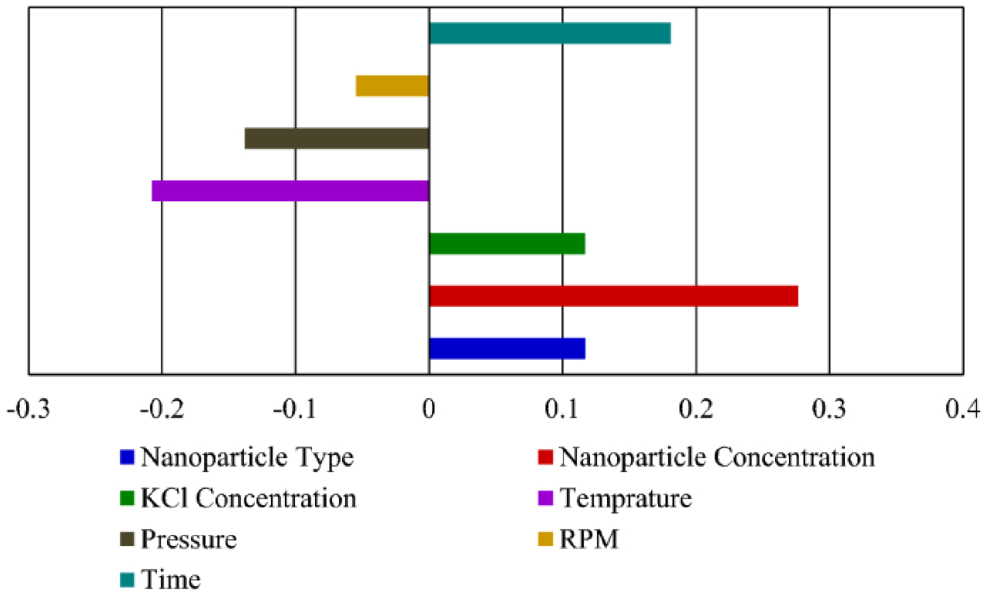

Figure 19 Sensitivity analysis of filtration volume [138]. Figure shows that in modeling the filtration volume, the most sensitive parameter is NPs concentration, and the least sensitive parameter is RPM.

Table 5 Statistical description of the data sets for different NPs-based drilling fluids [140].

	KCl-polymer mud				**Low solid non-dispersed mud**				**Bentonite-based mud**			
Parameter	**Min.**	**Max.**	**Avg.**	**SD**	**Min.**	**Max.**	**Avg.**	**SD**	**Min.**	**Max.**	**Avg.**	**SD**
NPs' Type	Aluminum oxide (Al_2O_3), silica oxide (SiO_2), titanium oxide (TiO_2), copper oxide (CuO)											
NPs' Concentration (wt. %)	0	1	0.5	–	0	1	0.5	–	0	1	0.5	–
NP's Size (nm)	15	40	27.5	–	15	40	27.5	–	15	40	27.5	–
NPs' Molecular Weight	60.08	101.96	81.02	–	60.08	101.96	81.02	–	60.08	101.96	81.02	–
PV (cP)	1	14	8.03	2.99	4	8	6.11	1.07	6	15	12.03	2.25
AV (cP)	6.5	13.5	9.09	2.09	8.5	25	16.9	3.16	7.5	17.5	13.17	2.66
YP (lb/100 ft^2)	8	19	11.8	3.14	8	21	14.3	3.42	8	21	14.3	3.42
Gel-10 s (lb/100 ft^2)	2	7	4.11	1.27	4	21	15.65	3.18	2	10	5.23	1.9
Gel-10 min. (lb/100 ft^2)	3	29	7.92	6.36	5	24	17.8	3.57	4	46	24	9.9
Temperature (˚F)	120											
Pressure (atm)	1											

Statistical tests were conducted to evaluate the performance of the newly developed models. The R was used to measure the fitness of the curve. The deviation of the predicted and the actual values for each point are determined using the relative deviation (RD), while the standard deviation of the predicted and real values are obtained by the standard deviation (SD). The mean difference between the predicted and the actual data with respect to the actual data is calculated using the average relative error (ARE) and average absolute relative error (AARE). The MSE was originally used in constructing and evaluating the model at the training phase. The accuracy of the developed ANN-model showed promising results. The overall R were 0.975, 0.987, 0.962, 0.997 and 0.991 for the developed PV, AP, YP, gel-10 s, and gel-10 min models, respectively. The overall MSE were 0.257, 0.208, 1.476, 0.08, and 0.81 for the aforementioned rheological properties, respectively, while the overall AARE were 5.425, 0.566, 5.869, 5.553, and 6.437, respectively [140].

In 2022, the filtration volume for 3 types of WBM was predicted for nano-based drilling fluids using ANN. A MATLAB script was developed to conduct 6,750 different combinations of different parameters like transfer function of the hidden layer, transfer function of the output layer, number of neurons of the hidden layer, the number of hidden layers, and the training function [141]. The categorical data were converted into numerical data using N-encoded method with a total of 2,863 data points. The developed model predicts the filtration volume based on the composition (drilling fluid type, NPs type, concentration, size, molecular weight, temperature, pressure, and time). The input parameters were normalized to be ranging between 0 and 1 while the filtration volume was transformed to have more normal distribution like curve. The overall accuracy of the model was measured using R, RMSE, ARE, RD, SD, and AARE which were found to be 0.9941, 0.5838, 0.0042, 0.3408, 0.1855, and 0.0515, respectively [141]. Later in 2023, the authors extended the ANN model to predict the extent of filtrate invasion under various operational conditions. The model is trained using experimental data from laboratory tests on nanoparticle-enhanced drilling fluids as well as from literature (**Table 6**) [101]. The model's ability to predict filtrate invasion provides a valuable tool for engineers to optimize drilling fluid formulations in real-time, reducing the risks of formation damage and improving the overall efficiency of drilling operations. **Figure 20** shows a comparison between the proposed model and the Golsefatan and Shahbazi model [138] based on R, RMSE, ARE, MSE, SD, and AARE. The model's ability to predict filtrate invasion provides a valuable tool for engineers to optimize drilling fluid formulations in real-time, reducing the risks of formation damage and improving the overall efficiency of drilling operations [101].

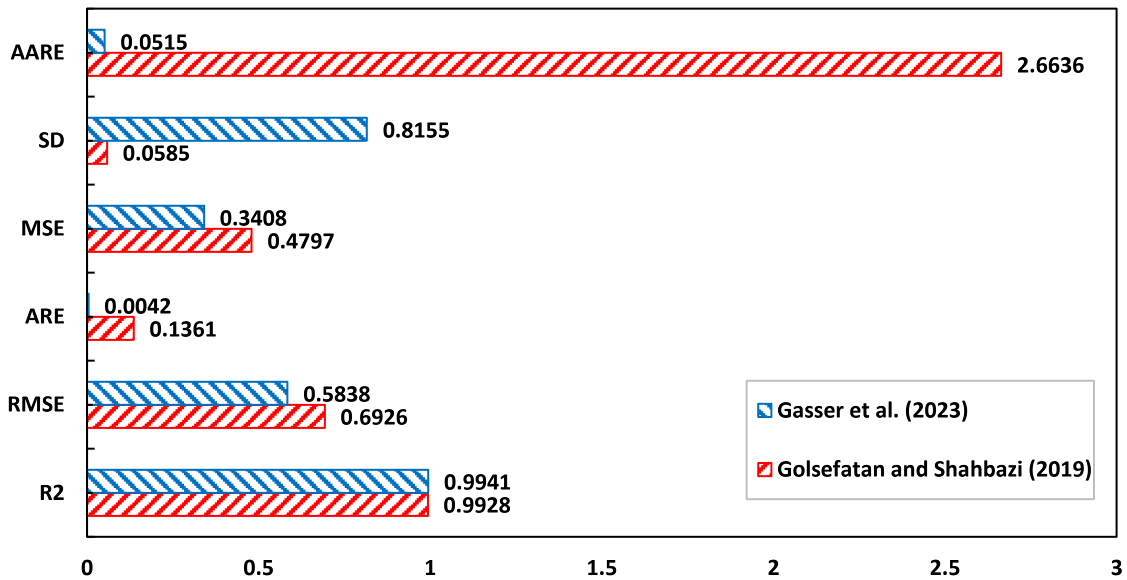

Figure 20 Comparison between the proposed model and the Golsefatan and Shahbazi model [138] based on R2, RMSE, ARE, MSE, SD, and AARE. The statistical parameters confirm the better accuracy of the newly developed model [101].

Table 6 Statistical description of the data sets for different NPs-based drilling fluids [101].

Parameter	Maximum	Minimum	Mean	Median	Mode	SD	Skewness
Drilling Fluid Type	Salt-Polymer WBM, low solid non-dispersed mud (LSNDM), And bentonite water-based mud (BWBM)						
NPs' Type	Ferric oxide (Fe_2O_3), aluminum oxide (Al_2O_3), silica oxide (SiO_2), titanium oxide (TiO_2), copper oxide (CuO), magnesium oxide (MgO), and zinc oxide (ZnO)						
NPs' Concentration (wt %)	2.5	0.001	0.627	0.5	0.5	0.569	1.597
NPs' Molecular Weight (g/mol)	159.69	40.3044	80.757	79.866	60.08	47.289	0.239
NPs' Size (nm)	100	3	34.454	30	50	29.982	0.974
Temperature (°F)	350	77	121.419	80	80	75.787	1.408
Pressure (Psi)	500	100	157.692	100	100	114.435	1.929
Time (s)	5,400	10	1,044.025	900	1,800	935.568	2.105
Filtrate Volume (mL)	140	0.1	8.473	7.5	9	7.671	6.426

Davoodi *et al.* [142] predicted the rheological and filtration characteristics of WBM using a field dataset of 1,160 records collected from 14 wells in 2 oil and gas fields in southwest Iran. The target properties for prediction include PV, YP, and filtrate volume (FV). Six different models were tested, and the study found that the Multilayer Extreme Learning Machine (MELM) hybridized with the Cuckoo Optimization Algorithm (COA) delivered the best predictions for PV, YP, and FV. The model demonstrated the ability to generate reliable predictions using more readily available variables such as flow density, mud filtrate volume, and solids content, which are typically easier to measure during drilling operations. MELM-COA provides the best PV, YP, and FV predictions. It achieves RMSE values of 0.6357 mL (FV), 0.6086 cP (PV), and 0.6796 lb/100 ft ^{2} (YP). MELM-COA proved to be a rapid and accurate method for predicting drilling fluid properties, offering a real-time alternative to time-consuming laboratory tests for filtration and rheological properties.

Al-Rubaii *et al.* [143] presented 2 novel models to predict ECD and mud weight using surface drilling parameters, including standpipe pressure, rate of penetration, drill string rotation, and mud properties. The study employed ANN and SVM to predict ECD with an impressive correlation coefficient of 0.9947 and an AAPE of 0.23 %. For predicting mud weight, a decision tree (DT) model was used, achieving a correlation coefficient of 0.9353 and an AAPE of 1.66 %. The results demonstrated that these 2 novel models outperformed other AI techniques when compared to values obtained from pressure-while-drilling tools. The models showed greater accuracy and offer a cost-effective alternative to traditional methods.

Kandil *et al.* [144] predicted ECD using 3 ML algorithms: ANN, K Neighbors Regressor (KNN), and Passive Aggressive Regressor (PAR). These models are based on 14 critical operational parameters, such as annular pressure, annular temperature, and rate of penetration, provided by downhole sensors during drilling operations. Almost 4,663 data points, with 80 - 85 % of the data used for training and validation, while the remaining data is reserved for testing. The ANN model demonstrated exceptional performance, with a R of nearly 0.999 for training, validation, and testing phases. The RMSE values for overall, training, validation, and testing were 0.000211, 0.000253, 0.00293, and 0.00315, respectively.

Other studies addressed the challenge of optimizing fracture fluid viscosity in high-salinity mediums like seawater and produced water. A series of rheology experiments were conducted using an Anton Paar rheometer to gather viscosity data across varying conditions, including different polymer types and concentrations, crosslinkers, chelating agents, water salinities, shear rates, temperatures, pressures, and mixing orders [145]. The experiment resulted in 645 data points from 86 tests, which were then input into several ML models, including fully connected neural networks (FCNN), gradient boosting (GB), adaptive gradient boosting (AdaBoost), extreme gradient boosting (XGB), RF, and DT. The models' hyperparameters were optimized using a grid search technique during the training phase, and their performance was further enhanced using K-fold cross-validation. The model accuracy was evaluated using metrics like RMSE, R, AAPE, and cross-plots. Among all the models tested, the FCNN model outperformed the others, yielding a 95 % accuracy in predicting the viscosity of fracturing fluids, with significantly lower error rates. Furthermore, the study used particle swarm optimization (PSO) to maximize fracturing fluid viscosity by optimizing input parameters where the FCNN model was trained. This methodology offers a promising approach to predict fracturing fluid viscosity and potentially minimize the experimental costs associated with measuring fluid rheology [145].

Two data-driven ML approaches were proposed for predicting the rheology and filtration properties of nano-SiO_2 WBM, which are ANN and least-square-support-vector-machine (LSSVM) [146]. Parameters involved for the prediction of shear stress were SiO_2 NPs concentration, temperature, and shear rate, whereas SiO_2 NPs concentration, temperature, and time were the inputs to simulate filtration volume. A feed-forward multilayer perceptron was constructed and optimized using the Levenberg–Marquardt learning algorithm. The parameters for the LSSVM were optimized using Couple Simulated Annealing. The performance of each model is evaluated based on several statistical parameters. The predicted results achieved R value higher than 0.99 and MAE and MAPE values below 7 % for both the models [146]. The developed models were further validated with experimental data that reveals an excellent agreement between predicted and experimental data. **Figure 21** shows the general workflow to develop the ML models.

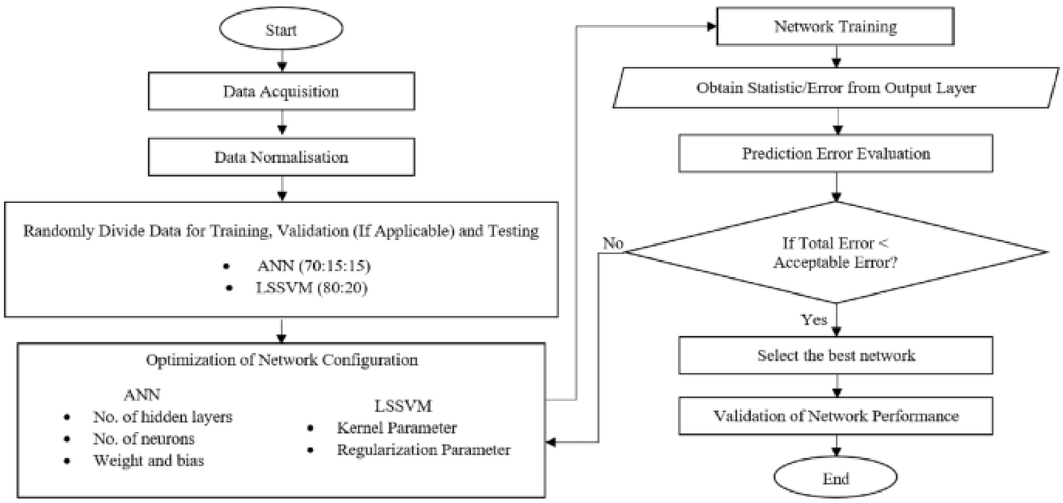

Figure 21 General workflow to develop the ML models [146].

Gasser *et al.* [147] studied the effects of MgO and ZnO NPs on the rheological properties of KCl-polymer WBM. The results showed that the MgO improves the rheological properties of the drilling fluids when added at a high concentration of 0.7 wt %, while ZnO has shown a significant improvement at low concentration of 0.1 wt %. In addition, 5 ANN models were constructed to predict the rheological properties (at 120 °F and atmospheric pressure) of the nano-modified drilling fluids based on their composition. The effect of NPs' type, size, concentration, and drilling fluid formulations were considered. The 5 models showed good accuracy with an overall correlation coefficient of 0.9017, 0.941, 0.878, 0.961, and 0.9, for PV, AV, YP, gel-10 s, and gel-10 min, respectively.

ML-based methodology for optimal hyperparameter determination and prediction of the drilling fluid rheological behavior at HTHP was proposed [148]. The dataset used in this study was obtained from extensive rheometric tests of WBM and olefin-based drilling fluid in steady-state flow curves. The optimal hyperparameters were guided by performance metrics and compared with alternative models such as Power-law and Herschel-Bulkley rheological models. Different configurations with different hidden layers, using neuron sequences of 16, 32, and 64, learning rates of 0.001 and 0.01, and the

ReLU activation function were used to improve the model's performance. Additionally, the work delved into the impact of the number of training epochs on the accuracy of shear stress predictions. Finding this equilibrium was identified as a crucial factor in achieving precise results. The neural network model demonstrated remarkable accuracy when using the ML-C3 configuration, with MAE value of 0.535 and *R* of 0.987 in predicting the steady-state flow curves of drilling fluids, establishing itself as a powerful tool for forecasting the rheological behavior of these fluids under diverse operational conditions [148]. **Figure 22** illustrates the process flowchart and the methodology implemented with each step followed in developing the ANN to predict steady-state flow curve data.

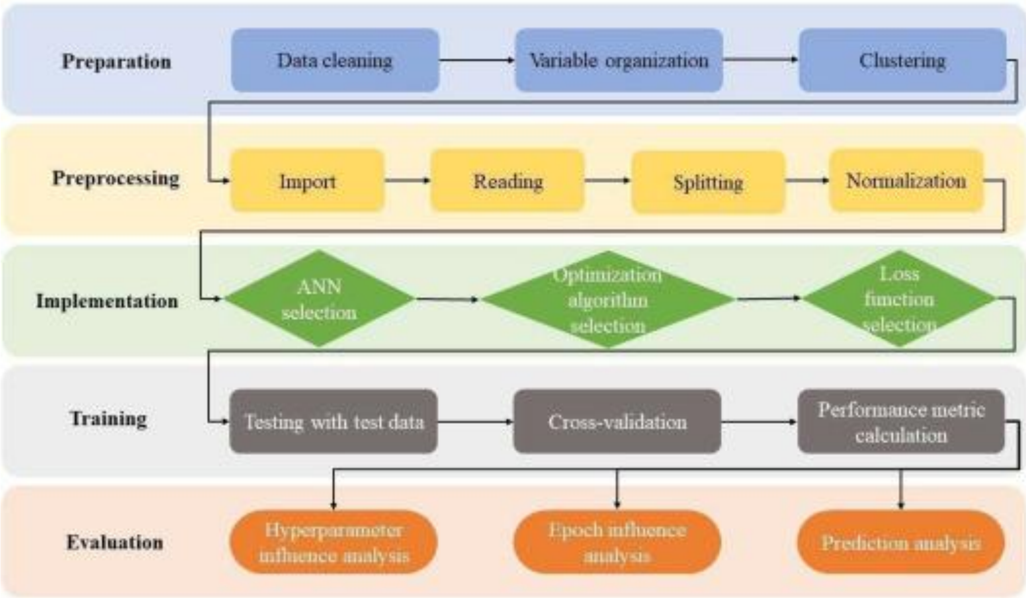

Figure 22 Prediction process flowchart. The methodology implemented with each step followed in developing the ANN to predict steady-state flow curve data [148].

Based on the articles reviewed in this paper, ANN is by far the most common AI algorithm in predicting the properties of drilling fluids. **Figure 23**. Shows a comparison of the number of existing models for each drilling fluids property. A summary of the reviewed articles is presented in **Table 7**.

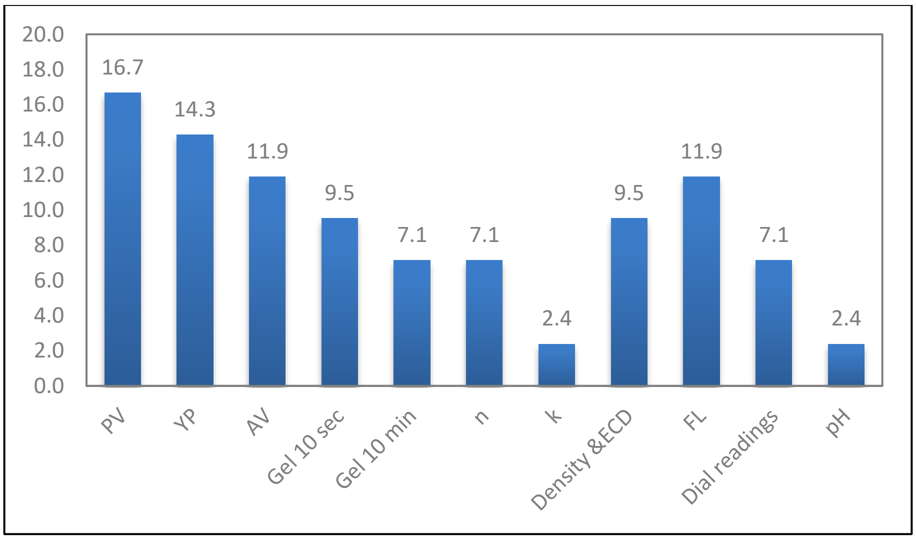

Figure 23 The number of existing models for drilling fluids parameters.

Table 7 A compressive summary for the AI and ML studies on drilling fluids.

Year	Used algorithm(s)	Target parameter(s)	Input parameter(s)	Accuracy	Number of data	Reference(s)
2016	ANN	R300 R600 *n* PV AV *k* YP	Marsh funnel viscosity Solid content Density	R = 0.8981, 0.9235, 0.954, 0.917, 0.9235, 0.9205 ABE = 3	9,000	[126]
2018	ANN	Density Viscosity Gel strength	Distance between receiver and transmitter Amplitude Time of flight	MAPE = 0.84 - 0.95, 4.4 - 7, 15 - 19 %	700 - 800	[130]
2018	ANN, PSO	Mud density	Initial fluid density Pressure Temperature	R = 0.9964 MSE = 0.0001374	664	[131]
2019	ANN	PV YP AV *n* R300 R600	Mud density Marsh funnel viscosity Solid percent	R = 0.95, 0.93, 0.96, 0.92	1,029	[127]
2019	ANN Adaptive neuro-fuzzy inference system	ECD	Mud weight Surface drill pipe pressure Rate of penetration	R = 0.9971	2,376	[133]
2020	ANN	YP PV AV	Marsh funnel viscosity Density	R = 0.94, 0.95, 0.98	200	[128]
2020	ANN	Downhole density	Downhole pressure Downhole temperature Initial mud density Final mud density	R = 0.9999	117	[132]
2020	Linear regression polynomial regression Hybrid regression Ensemble method ANN	All at elevated temperature: Shear reading at 600 RPM Shear reading at 300 RPM Shear reading at 200 RPM Shear reading at 100 RPM Shear reading at 6 RPM Shear reading at 3 RPM Gel-10 s Gel-10 min	All at ambient temperature: 8 features for the composition 6 features for the rheology Gel 10 s Gel 10 min ________________ Field temperature	MAPE = 13.22, 7.26, 6.18, 1.88, 8.75 %	–	[141]
2020	RF XGBoost SVM ANN multi-linear regression	Filtration	WBM: PV YP Mud density Temperature ------------------------- OBM: AV Mud density Electrical stability Water content	R = 0.86, 0.82, 0.83, 0.81, 0.75,	1,298 WBM, 1,786 KCl-polymer WBM, and 105 OBM	[136]

Year	Used algorithm(s)	Target parameter(s)	Input parameter(s)	Accuracy	Number of data	Reference(s)
2020	ANN	Filtration volume of nano-based fluids	NP type NP Conc, KCl Conc. Temperature Pressure RPM Time	R = 0.9928	1,003	[138]
2021	ANN Adaptive neuro-fuzzy inference system	ECD	Standpipe pressure WOB ROP Flow rate RPM Torque	R = 0.98, 0.96	3,570	[134]
2021	SVM and ANN	Filtration of nano-based fluids	NP type NP Conc, KCl Conc. Temperature Pressure RPM Time	R= 0.998, 0.999	1,003	[139]
2021	ANN	For nano-based fluids: PV AV YP Gel 10 s Gel 10 min	Fluid type NPs type NPs Conc. NP molecular weight NPs size	R = 0.978, 0.987, 0.962, 0.997, 0.991	400 - 500	[140]
2022	ANN	PV, YP, AV, and *n*	Mud density Marsh funnel viscosity Solid percent	R = 0.94, 0.92, 0.92, 0.95	522	[129]
2022	Linear regression ANN ERT decision trees	YP PV Gel 10 s Gel 10 min Filtration pH	–	MAE = 1.17, 0.74, 0.27	6,878	[139]
2022	ANN	Filtration of nano-based fluids	Fluid type NP type NP Concentration NP molecular weight NP size Temperature Pressure Time	R = 0.9942	2,863	[141]
2023	ANN Least-square-support-vector-machine (LSSVM)	Prediction of shear stress/ and Filtration volume	SiO_2 NPs concentration, temperature, and shear rate/ and SiO_2 NPs concentration, temperature, and time	R higher than 0.99 and MAE and MAPE values below 7 % for both the models	254	[146]
2024	ANN	PV AV YP gel-10 s, and gel-10 min	Fluid type NPs type NPs Conc. NP molecular weight NPs size	R = 0.9017, 0.941, 0.878, 0.961, 0.90	-	[147]
2024	ANN	Steady-state flow curves	Fluid type, pressure, temperature, and shear rate	MAE value of 0.535 and *R* of 0.987	-	[148]

Despite the clear benefits of NPs and their significant potential in enhancing the properties of drilling fluids, further research is essential to optimize the types and concentrations of NPs for different drilling conditions [149-151]. Moreover, while laboratory studies under controlled conditions have demonstrated promising results, the performance of nanofluids in real-world field applications remains underexplored. Field studies are crucial to validate the potential of nanofluids, as the actual drilling environment often presents unpredictable variables that could affect their efficacy [152-154]. Moreover, despite the challenges of data cleaning and processing, ANN and ML have proven to be reliable tools for predicting drilling fluid properties [155-158]. Developing hybrid models that integrate these techniques with traditional physical and chemical models could provide even more accurate and robust predictions.

Recommendations and future perspectives

As NPs have shown significant potential in enhancing the properties of drilling fluids, further research should explore the optimal types and concentrations of NPs for various drilling conditions. Additionally, the interaction mechanisms between NPs and other fluid components should be studied in more detail to fully understand their impact on fluid performance under extreme conditions. While the positive aspects of using NPs in the drilling industry are undeniable, several challenges remain. Another significant challenge is the development of models that can accurately capture the effects of NPs on overall drilling fluid performance, providing reliable predictions under varying conditions. Other recommendations and future research perspectives are:

1) One of the primary challenges is the efficient synthesis and large-scale production of NPs. Despite the promising potential of NPs, their large-scale production remains costly and complex. As a result, it is crucial to develop cost-effective and efficient methods for nanoparticle production.

2) The high cost of NPs is another significant hurdle. However, recent advancements in enhanced synthesis methods have reduced the cost of various types of NPs, making them more affordable compared to several expensive chemicals currently used by oil and gas companies.

3) The development and implementation of a comprehensive methodology for assessing the formation damage caused by NPs-based drilling fluids is crucial for optimizing drilling operations. Accurately evaluating the extent of formation damage helps in understanding how drilling fluids interact with the formation, affecting reservoir permeability, wellbore stability, and overall production efficiency.

4) While NPs and advanced polymers are promising, other emerging additives should also be explored. For instance, bio-based additives or those derived from renewable resources could offer promising alternatives to traditional chemical-based solutions. Research into these alternatives could lead to more sustainable and eco-friendly drilling fluids.

5) Future studies should consider the environmental impact and sustainability of additives, especially NPs, used in drilling fluids. Research into biodegradable and non-toxic alternatives could reduce the ecological footprint of drilling operations. The life cycle analysis of these materials, including their impact on both the environment and the economy, should be prioritized.

6) It is essential to continue developing models that predict and optimize the rheological properties of drilling fluids under harsh conditions, such as high pressure and temperature environments. These models should account for time-dependent changes in fluid behavior and provide strategies for maintaining optimal flow and performance during the entire drilling process.

7) While ANN and ML have proven to be reliable tools for predicting drilling fluid properties, developing hybrid models that integrate these techniques with traditional physical and chemical models could provide even more accurate and robust predictions. This approach could enable better forecasting of fluid behavior under different operational conditions.

8) To improve the reliability of ANN and ML models, continuous data collection during actual drilling operations is necessary. This will help refine the models, ensuring that they adapt to changing fluid characteristics over time and under varying environmental factors. Real-time monitoring systems should be implemented to gather comprehensive data on fluid properties, enabling adaptive control strategies.

9) To validate the predictive capabilities of ANN and ML models, they should be tested across a wide range of reservoir conditions and geographic locations. By ensuring the models' applicability in various real-world scenarios, their adoption can be more widespread in industry.

Conclusions

This paper highlights the significant advancements in the field of drilling fluid optimization, particularly the introduction of NPs and novel polymers, and the growing role of AI methods such as ANN and ML. The use of these advanced techniques enables more precise predictions of drilling fluid behavior, offering improved control over fluid properties and operational efficiency. The integration of ANN and ML models with traditional models can enhance their reliability and provide valuable insights for fluid management under various operational conditions. Furthermore, the ongoing development of new additives and optimization models paves the way for more sustainable and efficient drilling practices. Future research should focus on refining these models and exploring alternative, environmentally friendly additives to further enhance the performance and sustainability of drilling fluids. Based on this review of the previous literature research, the following conclusions can be drawn:

1) The monitoring and optimization of the rheological behavior of drilling fluids are crucial during drilling operations. Continuous control of shear viscosity is essential to ensure efficient fluid performance, especially in non-Newtonian fluids where shear stress significantly impacts viscosity. Effective optimization can improve drilling efficiency and reduce operational costs.

2) The addition of NPs to drilling fluids has shown significant improvements in key rheological properties. Laboratory studies report up to a 20 - 30 % increase in viscosity, 25 - 40 % enhancement in yield stress, and up to 35 % better gel strength when small concentrations of NPs are added. These results suggest that NPs can greatly enhance fluid performance, although field testing is necessary for broader validation.

3) NPs have also been shown to positively impact the filtration properties of drilling fluids. The addition of NPs can reduce fluid loss by up to 15 - 25 % by forming a more stable filter cake that enhances the sealing properties. This helps to minimize fluid loss into porous formations, reducing costs associated with excessive fluid consumption and improving wellbore stability. NPs, particularly those with surface-active characteristics, contribute to better fluid-barrier formation, improving the overall efficiency of the drilling process.

4) Several new materials have shown promising results as drilling fluid additives. Studies on henna-leaf and hibiscus-leaf extracts, glass beads, local bentonites, and date-pits have demonstrated improvements in fluid properties. These materials have provided up to a 15 - 20 % increase in fluid stability and enhanced lubrication, suggesting their potential for use in various drilling conditions.

5) ANN has been shown to provide more accurate predictions of drilling fluid behavior compared to traditional rheological models. ANN-based models can predict fluid viscosity with an accurate improvement of approximately 10 - 15 % over existing models. This increased precision makes ANN a valuable tool for real-time optimization and better decision-making in drilling operations.

6) Despite laboratory successes, further research is required to validate these findings under real-world conditions. The implementation of NPs and novel additives in field applications could result in 10 - 20 % improvement in overall drilling efficiency, depending on the specific material and drilling environment. Moreover, future research should explore the integration of AI models with advanced materials to enhance sustainability and reduce environmental impacts.

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