Compressive Strength and Thickening Time of Cement: A Critical Review of Existing Models

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ABSTRACT

The quality and integrity of a cement job can determine how long a well will be stable and productive before it needs to be repaired. This is primarily determined by the compressive strength of the cementing material. Because of the economic implications of drilling and cementing oil and gas wells, the oil and gas community and academia have maintained an interest in compressive strength and thickening time of cement measurements. Despite the growing number of published articles on this subject, there is no comprehensive critical review, to the best of the authors' knowledge. The goal of this paper is to provide a broad overview of models and modeling techniques used to estimate cement compressive strength and thickening time, as well as to critically evaluate them. The review's findings are presented in tables in a concise manner for clarity and ease of reference. The information for this review was gathered from a variety of sources. This work heavily relied on several key drilling fluid texts for the theoretical pieces related to compressive strength and thickening time of cement in general. The researcher relied on conference proceedings from the Society of Petroleum Engineers for operational and field studies. In order to contextualize the subject in terms of current practices, these sources were supplemented with articles from peer-reviewed journals. This review is interspersed with critiques of the models, as well as areas in need of improvement. Despite massive efforts in this direction, the results of the bibliometric analysis show that there is no universal model for all situations. Furthermore, a broad review of the literature on recent compressive strength and thickening time models reveals that researchers are drawn to the field of artificial intelligence because of the tremendous opportunities it provides. This review is the first critical compilation of models used to predict compressive strength and thickening time of oilfield cements.

1 Introduction

Cements are one of the most widely used and least understood materials. High quality oilfield cement is an essential ingredient in any successful well because it protects the conduits that connect reservoir fluids to the surface where they are used. The quality and integrity of a cement job can determine how long a well will remain stable and productive without requiring repair. (Adamson *et al.,* 1998).

The starting material, cement powder, is obtained by grinding cement clinker. Gypsum (calcium sulfate) is then added to slow the hydration process. The cement powder is composed of multi-size, multi-phase, irregularly shaped particles ranging in size from less than a micrometer to slightly more than one hundred micrometers after the clinker and gypsum are ground. When this starting material is mixed with water, hydration reactions occur, resulting in a rigid porous material that serves as the matrix phase for concrete, a cement paste-sand-rock composite. (Coveney *et al.*, 1996).

Cement's most common use is, of course, in building construction, where it has been used since at least Roman times. The work described here, on the other hand, is concerned with another important application of cement - in the oil industry, where approximately 3% of the world's annual cement output is deployed. After drilling, cement is used to line oil and gas wells by pumping a cement slurry between the well-bore and a steel casing inserted into the well. During the placement process, the cement displaces all of the drilling fluid that was originally present during the drilling operation. The cement then hardens to form a low-permeability annulus that isolates the well's productive hydrocarbon-bearing zones from the rest of the formations, excess water, and the surface.

Because of issues such as samples from the same batch of cement aging differently during storage, well cementing has remained more of a black art than a science until now. Various cement slurry properties, such as compressive strength development, permeability to oil and gas, flow behavior, and thickening time must be specified and controlled while downhole temperatures and pressures are high. The thickening time is an important factor in the formulation of oilfield cement slurries because it determines how long the cement can be pumped (American Petroleum Institute, 2006).

Given the overwhelming complexity of cement hydration, a model that predicts the performance properties of a given cement sample prior to use would be a valuable quality control tool. Because calculating the compressive strength of cement slurry takes a long time (Biswas *et al*., 2021), requires a large amount of material (Ahmad *et al*., 2021), and requires a lot of effort, artificial intelligence (AI) methods, as dynamic, applicable, accurate, and simple-to-use technologies, have been successfully used to overcome these issues (Armaghani and Asteris, 2021). Despite the abundance of models for estimating compressive strength and thickening time of cement, no literature review or critique of these models has been done to date, to the best of my knowledge and the depth of literatures reviewed. Because of the lack of a critical review, cement compressive strength and thickening time models have grown in complexity, over-parameterization, and predictive uncertainty. This is the gap in the literature that this work seeks to fill.

1.2 Objective of the Study

The specific objective of this work is to curate existing models for predicting compressive strength and thickening time of cement with the intent of critiquing them by evaluating their predictive performances as well as their empirical or mechanistic methodologies while keeping their potential field applications in mind. This is what distinguishes this study and contributes significantly to the existing body of knowledge on the subject. Finally, potential issues that may be causing the lack of field applicability of existing prediction models would be identified, and recommendations for future research would be made.

1.3 Existing Approaches to Cement Compressive Strength and Thickening Time Measurements

1.3.1 Compressive Strength

Cement compressive strength is simply the strength of a "set" cement sample measured by the force/load required to crush/crack them. It is expressed in terms of force per unit area. In a compression testing machine as shown in Figure 1, the compressive strength of cement slurry is measured by breaking cylindrical set cement specimens. Compressive strength tests are performed by pouring the cement slurry into 2 inch (5.08 cm) cube moulds according to API Specification 10A. The moulds are then subjected to a curing regime that is appropriate for the simulated well temperature conditions used. However, with a recent trend toward deeper drilling in many parts of the world, which involves bottom hole total pressures significantly greater than 20.7 MPa, the appropriateness of some of these tests for simulating well conditions has been called into question. Because high pressures and high temperatures influence cement reactivity, high-pressure-high-temperature compressive strength tests for cement slurries in very deep wells are required (Liska *et al*., 2019). Ultrasonic cement analyzers (UCAs) are now widely used to continuously and nondestructively assess the compressive strength developed by cement slurries cured under simulated downhole conditions. The existing compressive strength development approaches includes;

i. **Setting-** Refers to changes of cement paste/slurry from a fluid state to rigid state. It is measured using the VICAT apparatus.
ii. **Initial Setting**- This is the time when the cement slurry starts to stiffen.
iii. **Final Setting-** This is the time when the cement slurry gets hardened to limits that it takes some load.

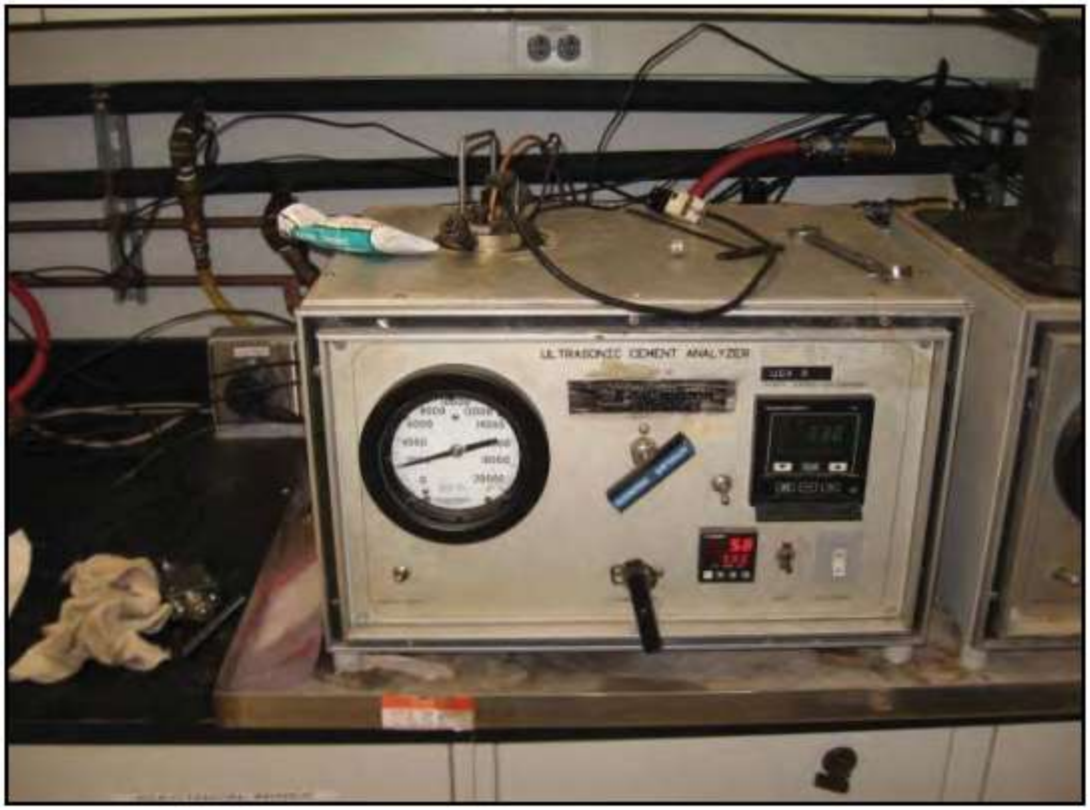

Figure 1: Ultrasonic Cement Analyzer for Compressive Strength Testing
Source: (API, 2006)

1.3.2 Thickening Time

Thickening time is essentially a setting time under controlled temperature and pressure ramps that is intended to simulate conditions for a given well depth. API 10A defines it as the time required for a cement slurry of a given composition to reach a consistence of 100 Bearden units of consistence (Be) using the methods outlined in API Specification 10A. Bearden units are arbitrary and correspond to poise (or Ns/m^2) units. Thickening time is measured using a high-temperature-high-pressure consistometer as shown in Figure 2 (Liska *et al.*, 2019). This is a test machine with a rotating cylindrical slurry container, a stationary paddle assembly, and a pressure chamber.

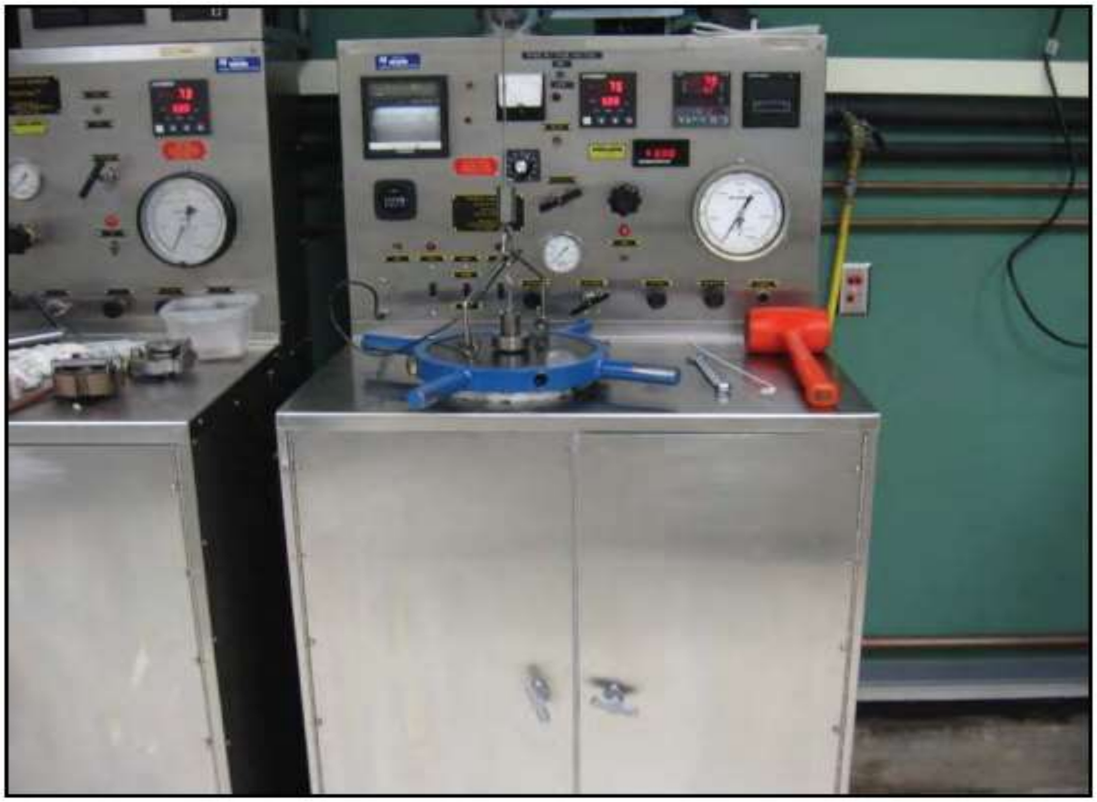

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Figure 2: Chandler Consistometer for Measuring Thickening Time of Cement Slurry. Source: (API, 2006)

2 Review Sequence Adopted

Grigg (2015) noted that a historical perspective is required for important/worthwhile advances in the oil and gas industry, in addition to knowledge of recent advances. As a result, a thorough review of the literatures on cement compressive strength and thickening time is required. This literature search is based on the premise that without extensive empirically based and theoretical knowledge, one may end up only addressing symptoms while ignoring the underlying issues. As a result, this review would take a comprehensive approach, isolating historical research efforts in the area of cement compressive strength and thickening time modeling and extracting the major details of each work in order to highlight its main findings and critique the models. As a result, the investigation would begin with a review of existing review works on cement compressive strength and thickening time modeling. Following that, existing models for cement compressive strength and thickening time prediction would be presented, followed by a summary of data ranges used by researchers for cement compressive strength and thickening time modeling. The researchers' major findings on cement compressive strength and thickening time modeling, as well as a critique of these models, would come next, with the review finding capping off the review. Following this order would help readers understand the work better.

2.1 Highlights of Previous Reviews on Cement Compressive Strength and Thickening Time

Previous review studies on cement compressive strength and thickening time modeling are highlighted in this section. Tables 1 through 4 present the focus of each review as well as the major findings of each review work.

It is clear from the preceding that, while the reviews were comprehensive, they were primarily focused on soft computing techniques, despite the fact that empirical, theoretical, and ensemble modeling techniques abound. A review of only studies from one area of the subject would yield a conclusion that is only applicable to that area in question. On the contrary, a thorough review, such as the one discussed in this paper, that evaluates a wide range of modeling methods would create a new and useful platform from which the model user could make informed decisions about which method offers the most benefits. Furthermore, the review presented in this paper differs significantly from the much more common traditional "review papers," in which the reviewer identifies studies in a specific area, summarizes their findings, and reports a conclusion in narrative form. While beneficial, such reviews are primarily subjective. This work is not intended to replace the already valuable review articles on this subject, such as those in Tables 1 through 4, but rather to provide a complementary perspective with a particular focus on critiques of existing models with the goal of deepening knowledge on the subject; this is what distinguishes this review from others in the existing literature.

Table 1: Summary of Related Works on Modelling Compressive Strength of Cement Slurry

Algorithm Name	Acronyms	Data Set Used	Prediction Properties	Researcher(s)	Waste Material Used
Artificial Neural Network	ANN	180	Compressive Strength	Topcu et al. (2009)	FA
Artificial Neural Network	ANN	300	Compressive Strength	Prasad et al. (2009)	FA
Artificial Neural Network	ANN	80	Compressive Strength	Siddique et al.(2011)	FA
Artificial Neural Network	ANN	368	Compressive Strength	Hakim et al. (2011)	FA
Multivariate adaptive Regression Splines	MARS	87	Compressive Strength and Fracture Characteristics	Yuvaraj et al. (2013)	FA-slag
Factorial Design	FD	16	Compressive Strength	Falode et al. (2013)	FA
Regression Models	RM	95	Compressive Strength	Chopra et al.(2014)	FA
Artificial Neural Network	ANN	169	Compressive Strength	Asteris et al. (2016)	FA, GGBFS,SF
Biogeographical Based Programming	BBP	413	Elastic Modulus	Golafshani and Ashour, (2016)	SF, Slag, FA
Artificial Neural Network	ANN	1000	Compressive Strength & Slump	Ashraf et al. (2016)	Slag, FA
Artificial Neural Network	ANN	114	Compressive Strength	Belalia et al. (2017)	FA
Multivariate Adaptive Regression Spline	M5, MARS	114	Compressive Strength, Slump test, L-box test and V-funnel test	Kaveh et al.(2018)	FA
Artificial Neural Network	ANN	205	Compressive Strength	Asteris and Kolovos (2019)	FA, GGBFS, SF
Random Forest	RF	169	Compressive Strength	Zhag et al. (2019)	FA, GGBFS, SF

Algorithm Name	**Acronyms**	**Data Set Used**	**Prediction Properties**	**Researcher(s)**	**Waste Material Used**
Intelligent Rule-Based Enhanced Multiclass Support Vector Machine and Fuzzy Rules	IREMSVM, FR & RSM	114	Compressive Strength	Selvaraj and Sivaraman (2019)	FA
Multi-Linear Regression	MLR	6	Compressive Strength	Kiambigi et al. (2019)	FA
Support Vector Machine	SVM	115	Slump test L-box test V-Funnel Test Compressive Strength	Saha et al. (2020)	FA
Multivariate Adaptive Regression Spline, Least Squares Support Vector Machine and Genetic Programming	MARS, LSSVM & GP	1030	Compressive Strength	Rahul et al. (2020)	FA
Artificial Neural Network, Support Vector Machine and Gene Expression Programming	ANN, SMV & GEP	300	Compressive Strength	Farooq et al. (2021)	FA
Multivariate Polynomial Regression	MPR	125	Compressive Strength	Imran et al. (2022)	FA
Ensemble Learner Algorithm	ELA	270	Compressive Strength	Barkhordari et al. (2022)	FA
Multivariate Adaptive Regression Spline, Least Squares Support Vector Machine	MARS, ANN, RF SVM, ELM and MnLR	120	Compressive Strength	Dong et al. (2022)	FA, Slag
Ensemble Supervised Machine-Learning	ESML	471	Compressive Strength	Song et al. (2022)	FA

Table 2: Summary of Related Works on Modelling Thickening Time of Cement Slurry

Algorithm Name	Acronyms	Data Set Used	Prediction Properties	Researcher(s)	Waste Material Used
Polynomial Regression Analysis with visual Basic. NET	PRA and VB. NET	58	Thickening Time	Nmegbu et al. (2019)	GBFS
Multiple Regression Analysis	MRA	84	Thickening Time	Mofunlewi et al. (2019)	FA

Table 3: Summary of Recent Studies on Modelling Compressive Strength of Cement Slurry

Author (s)	AI Method	Architecture	Number of input Data	Input parameters	R	R^2	MSE	MAE	RMSE
Ibrahim (1989)	-	-	32	Water-cement ratio, water-solid ratio, density, apparent viscosity, water level	0.7	0.6241	0.2655	-	0.51527
Hakim *et al.* (2011)	ANN	$8-10-6-1$	368	Water, cement, coarse aggregate, fine aggregate, silica fume, fly ash, superplasticizers, granulated graded blast furnace Slag	-	-	-	-	0.001

Author (s)	AI Method	Architecture	Number of input Data	Input parameters	R	R^2	MSE	MAE	RMSE
Riyadh (2012)	RM	-	32	Water-cement ratio, water-solid ratio, density, apparent viscosity, water level	0.9904	0.9809	0.0136	37.4122	0.11662
Palika *et al*. (2014)	RM	-	15	Water-cement ratio, cementitious content, water, workability, curing ages	0.9688	-	-	-	0.0227
Ashraf *et al*. (2016)	ANN	$10-10-3$	1000	Fly ash, water-cement ratio, cement aggregate, superplasticizers	-	-	0.0044	-	0.0663
Akintunde *et al.* (2020)	ANN	$7-10-1$	200	Age, cement content, water, natural coarse, natural fine aggregate, water-cement ratio, fine modulus of cement	0.9387	0.8813	8.0265	6.36	2.8331
Farooq *et al*. (2021)	ANN	$6-13-1$	300	Cement, fly ash, coarse aggregate,	0.9588	0.9193	8.8447	2.326	2.974

Author (s)	**AI Method**	**Architecture**	**Number of input Data**	**Input parameters**	**R**	**R^2**	**MSE**	**MAE**	**RMSE**
				water-binder, fine aggregate, superplasticizers					
Barkhordari *et al.* (2022)	ELA	-	270	Water-cement ratio, days, fine aggregate, coarse aggregate, super plasticizers, water, fly ash, cement	0.9823	0.965	0.0060	-	0.0775
Huang *et al.* (2022)	RF, FA	-	361	Day, sand, fly ash, water-cement ratio, calcium oxide, crushed stone	0.8347	0.6967	-	-	11.6643

Table 4: Summary of Recent Studies on Modelling Cement Thickening Time

Author (s)	AI Method	Architecture	Number of input Data	Input parameters	R	R^2	MSE	MAE	RMSE
Ibrahim (1989)	-	-	32	Water-cement ratio, water-solid ratio, density, apparent viscosity, water level	0.4335	0.1879	-	70.1312	-
Riyadh (2012)	RM	-	30	Water-cement ratio, water-solid ratio, density, apparent viscosity, water level	0.9957	0.9914	0.0136	20.2794	0.11662
Mofunlewi et al. (2019)	RM	-	-	Temperature, pressure	-	0.961	-	-	-
Nmegbu et al. (2019)	LRM	-	-	-	-	0.965	-	-	-

3. Critique of the Reviewed Models

This section examines the models for predicting compressive strength and thickening time of cement slurry properties that have been extracted from the literature. The critique looks at the model's applicability in the field, its replicability, generalizability, sensitivity analysis and computational speed. It should be noted that the purpose of this critique is not to discredit or support any of the works on this subject, nor to question the veracity of their respective outcomes. It is also not intended to pit one researcher against another. Its emphasis, however, is dual:

i. To critically examine the strengths, weaknesses, and scope of each of these models, as well as how the challenges and gaps in each model are shaping the trend in the evolving improvement of cement slurry's properties models, and
ii. To serve as a form of feedback that would help deepen knowledge on the subject.

3.1 Reviews of Conventional Cement Compressive Strength and Thickening Time Models

The integrity and quality of a cement job can impact how long a well remains stable and productive before needing to be fixed. Compressive strength development and thickening time are essential aspects in the formulation of oilfield cement slurries that must be specified and regulated to achieve this goal. Previous research employed methods such as hydraulic cement mortars with heating baths and pressurized consistometers, which are time-consuming, tiresome, and require expensive devices that are limited in locations where real-time decisions are required. These methods do not produce models that are flexible, generalizable, accurate, or robust. These challenges necessitated the development of predictive models. It is to be stated here that, of all the models reviewed, the models were not explicit, hence, did not make the models simple to be incorporated in software applications. Suffice it to say that this work arguably presents the first machine learning based model reviews for cement compressive strength and thickening time estimation.

3.2 Artificial Intelligence Based Models

i. Field Applicability of the Models: One major issue with most existing models for estimating cement slurry rheological properties is the selection of input variables. This problem explains some of the model's field applicability challenges. It is important to note that a greater proportion of AI-based models developed today use solids content as input. The American Petroleum Institute (API) mud retort test is used first to perform a complete compositional analysis of drilling mud. It entails heating a measured sample of the mud until the water and oil vapourize. The liquids are collected in a graduated cylinder while the vapours are cooled in a condenser. The volume percent of water and oil measured with the graduated cylinder are added. The total is then subtracted from 100 and recorded as the volume of solids (Annis and Smith, 1996). Given the length of the procedure, it is obvious that the test would take time, making it less useful for field conditions where information is needed in real time to make decisions. Second, a close examination of the API-developed models reveals that the solid content parameter is conspicuously absent, implying that it is not relevant for field computation of rheological properties. Because engineers prefer to use easily obtained parameters in any engineering calculation (Leal *et al.,* 2013), models with solid content in their models are less appealing for field application. Akintunde *et al*. (2020), Hakim et al. (2011), Farooq *et al*. (2021) and Barkhhodari *et al*. (2022). Finally, because solids content cannot be easily measured because it takes time, models that use it as input would be inefficient. Ibrahim (1989), Riyadh (2012) and Palika *et al.* (2014), on the other hand, used inputs such as water-cement ratio, slurry density, apparent viscosity, water, age, cementitious contents, workability and so on, which all take time to obtain. As a result, their models are less appealing for use in the field. To summarize, due to the time required to conduct the test, it may not be practical to include solids content as an input to cement slurry rheological property models at this time. However, it could be argued that the authors were proactive in including it as an input in their models in the hopes that as technology advances, solids content measurement procedures could be made much easier and results obtained in a much faster manner (say, split seconds), which would then warrant its inclusion as an input into cement slurry rheological property models.

ii. **Replicability of the Models' Results:** One of the major challenges observed in model development using artificial intelligence is the ability to replicate and reproduce the results of some of the ANN models in this work. For example, some studies that used ANN to predict cement slurry rheological properties were insufficient because the necessary model details, such as the network weights and biases that can be used to reproduce the models, were not presented. Some of these studies are those Topcu *et al*. (2009) and Hakim et al. (2011). Other studies, however, included these details in their work. They are Rahul *et al.* (2020), Farooq *et al*. (2021), Imran *et al*. (2022) and Dong *et al*. (2022). Second, most AI tools, such as SVM and ANN, are not user-friendly and cannot be integrated into commercial software due to their black box nature, which does not allow for an explicit mathematical equation relating the input to the output. Little wonder, according to Bikmukhametov and Jaschke (2020), machine learning models are frequently regarded as black-box solutions, which is one of the reasons they are rarely used in process engineering systems. However, gene expression programming (GEP) or multigene genetic programming is a technique that can evolve explicit equations that can be easily associated with commercial software (Rostami and Ebadi, 2017). Finally, while model replicability remains a challenge, the authors agree that the omission of critical model information by researchers for the purposes of copyright or intellectual property protection is justifiable.

iii. **Generalizability of the Models:** While ANN is the most commonly used method in most studies to model cement slurry rheological properties, it should be noted that the method is effective at finding a local optimistic solution but ineffective at finding a global optimistic solution. The works in this review have provided little discussion of how to train the network optimally and why it is critical to perform a sensitivity analysis of the input features in order to create robust ANN models. As a result, this is likely to have a significant impact on the generalizability and robustness of the models developed, particularly for models that were not cross validated. Some studies used a small number of data points to build ANN models and reported training coefficients close to unity. This is despite the well-known guidelines in ANN literature that the ratio of data points to weights in the network should be greater than or equal to 2 in order to avoid overfitting (Kakar, 2018). The unknown variables are the ANN weights, and the training set is the number of equations. As a result, the sum of all the weights in a network must at least equal the number of data points in the training set. For example, in developing an ANN model with two input neurons, nine hidden neurons, and one output neuron, there are a total of [(2 × 9) + (9 × 1)] = 27 unknown variables that must be estimated by the neural network; therefore, 27 data points are required to serve as training data. This was not observed in Siddique *et al.* (2011) work. This may have resulted in network overfitting. Because larger datasets are more representative of the general population, models from these samples are more likely to be generalizable and reduce the likelihood of overfitting, whereas a model's performance can be misleading with a small dataset. This could be the start of a problem caused by a lack of sufficient data, which is worth investigating.

iv. **Sensitivity Analysis of the Developed Models:** Creating a model that predicts correctly solves only one aspect of the problem. The hidden information about the relationships revealed by the modelling technique must also be extracted. For example, it is sometimes useful to determine which, if any, input parameters are relevant by assigning a variable relevance score to each input parameter (Greenwell *et al*., 2018). This can be accomplished through the use of sensitivity analysis. Sensitivity is defined as the relative impact of an input parameter on an output parameter or target variable inside a model. It should be noted that a high sensitivity to a parameter indicates that the system's performance can change dramatically with a little change in the parameter. Similarly, a low sensitivity indicates little change in performance. Despite the availability of models developed in recent past, the models sensitivity analysis was only examined by Farooq *et al*. (2021) and Barkhordari *et al.* (2022).

v. Computational speed of Developed Models: A balance must be struck between the complexity of a model, the time required to make a prediction, and the accuracy of the output parameters (Downton, 2012). Despite their elegance, all of the mud rheological property estimation models were generated using sophisticated software without any discussion of the computational speed of the developed models. Indeed, several ANN architectures for estimating compressive strength and thickening time of cement have been proposed without addressing this, and are thus considered gaps in the literature. The resulting networks in the reviewed studies may be too heavy in terms of memory occupation and processing time, necessitating the use of high-performance computing units. As expected, the required computational power grows in proportion to the network's complexity. As a result, for a given model, a trade-off between model accuracy and memory consumption must be considered. This work thus aligns with the ideas of Kalechofsky (2016), who stated that having a complex model does not imply having good predictions.

vi. Model Performance: Model performance is generally defined as the difference between actual and predicted values, and it can be measured in a variety of ways. As a result, prior to conducting the analysis, the metric of choice should be defined (Scheinost *et al*., 2019). Despite the availability of a large number of statistical metrics in the literature, the performance of some models in the studies reviewed was examined using only one or two performance metrics. Hakim *et al.* (2011), Huang *et al.* (2022) and Ibrahim (1989) used the correlation coefficient (R) and the goodness of fit (R^2), whereas Akintunde et al (2020), Palika (2014), Riyadh (2012) and Barkhordari *et al*. (2021) used three metrics, the R , R^2 and the MSE values. Despite its popularity, the R^2 is not a good model performance metric for nonlinear models (Archontoulis and Miguez, 2015). Furthermore, according to Wallach (2006), the R^2 metric has the limitation of not accounting for the number of parameters. Li (2017) focused in on the same point. He claims that R and R^2, aside from being incorrect and quadratically biased, do not measure a model's accuracy unless the observed and predicted values perfectly match. According to Spiess and Neumeyer (2010), demonstrating the validity of single nonlinear models using only R^2 values is outdated and should be replaced or supplemented with Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) values. Finally, Kelessidis *et al*. (2006) stated that the sum of square errors (SSE) or best index value (BIV) can be used instead of the correlation coefficient to determine the goodness of fit.

vii. **Application of Developed Models in A Well Cementing System:** The majority of the studies concluded that the models they created could be used to automate the measurement of cement slurry rheological properties. Based on the studies reviewed, a design of the cement slurry system demonstrating where the developed models can be incorporated and how it would work is required. However, none of the studies examined took this into account.

3.2 Non-Linear Regression Models

i. **Model Flexibility:** Johnson (2017) defines a model's flexibility as the amount of influence data features has on the behaviour of the model. The critique against the usefulness of these non-linear regression models is linked to the elements causing inflexibility in the models. The cause of the inflexibility is as a result of the fixed form of the models. Another limitation of a non-linear regression model is that it is only valid for the specific data or set of conditions that was used to develop the model. To capture the peculiarities of other conditions, the computations must be repeated.

ii. **Replicability of Model Results:** The ultimate goal of regression analysis is to determine the explicit form of a regression equation. The estimation of the model's parameters is an iterative process. The model's utility would be limited without the numerical coefficients of these parameters and the associated constants. This goal was not met by some PV, YP, apparent viscosity, and gel strength models. Oriji and Dosunmu (2012) developed regression models for PV, YP, and gel strength. These models lacked the regression coefficients, which are an essential component of regression-based models. Furthermore, the models of Ofoche and Noynaert (2020b) were not shown at all. The models' usefulness, applicability, and replicability would be limited if the model coefficients and models themselves were unavailable.

4. Review Findings

i. The avalanche of research on modeling of cement slurry rheological properties is impressive and confirms the subject's continued importance as a research topic.

ii. Since its humble beginnings in 2550 BC, modeling of cement slurry rheological properties has come a long way. Advances in cement slurry rheology modeling have occurred at an astounding rate, owing primarily to the availability of limitless computing techniques and sophisticated methods.

iii. In its most basic form, cement slurry rheology can be described by a model with shear rate and shear stress. While such models have existed for years and capture rheology at its most basic level, it is important to note that they fail to capture mud behavior at either high or low shear rates. This is due to the fact that cement slurry is a mixture of various materials that can exhibit multi-exponential behavior in the face of shear.

iv. While it is tempting to try to make models more comprehensive by incorporating multiple parameters to help capture the rheological complexity of cement slurry, the model can become so cumbersome that the results are no longer transparent and field applicability is nearly impossible.

v. It has been observed that the size of the dataset used to develop the models varies from study to study. Studies that used fewer datasets may have produced more accurate results. However, when exposed to new data, the model may exhibit higher error than those developed from larger databases.

5. Conclusion

This study identified and critically evaluated papers in which models for estimating compressive strength and thickening time of cement slurry were developed. From the existing literature, twenty-eight (28) models for estimating cement slurry physical properties were isolated. There were 25 predictions for compressive strength and four for thickening time. This review differs significantly from the much more common traditional "review papers," in which an author identifies studies on a specific topic, summarizes their findings, and reports a narrative conclusion. In contrast, the review presented in this paper is interspersed with model critiques. The review shows that there have been significant advances in cement slurry properties modeling. As in many other areas of exploration and production, there is an urgent need for in-depth evaluation of existing models as well as comparisons between conventional and cutting-edge models. As drilling muds become more complex due to the harsh environments in which wells are drilled, the use of existing models will be limited, implying a corresponding demand for high fidelity models. Finally, as long as there is no universal model for predicting cement slurry rheological properties, there will be a continuing need for research on the subject.

6. Recommendations for Further Studies

i. Cement slurry rheology modelling is complicated. Many factors contribute to the problem, and they interact in nonlinear ways. Although existing models are statistically elegant, researchers may obtain more robust results by using hybrid models to predict cement slurry rheological properties. This is an open area for investigation.

ii. Another significant gap is the scarcity of models for cement slurry thickening time. The fluidity and pumpability of the cement slurry would be unknown without knowing the thickening time, and the wait on cement (WOC) time would be long. As a result, developing a thickening time of cement slurry model is an area worth investigating.

iii. Various studies have demonstrated the use of AI techniques in a clean, non-noisy dataset. Data generated or measured during drilling is frequently contaminated with noise. This noise could be caused by the measuring equipment or by outside sources. It would be interesting to see how these models perform with noisy data and at what noise level the algorithms begin to fail. To simulate a typical field condition and assess the robustness of developed models, significant random noise must be added to blur the associations in experimental data.

iv. The frequency with which important information has been left out in some studies, resulting in models that are not useful in practice, suggests that future work should be done with greater care.

v. Because the usefulness of a model for predicting cement slurry rheological properties or any other parameter is heavily dependent on the availability of a wide range of data, willing researchers should conduct more and more experiments with wide parameter ranges.

Nomenclature

Abbreviation	**Meaning**
AI	Artificial Intelligence
API	American Petroleum Institute
ANN	Artificial Neural Network
Be	Bearden Units
ELM	Extreme Learning Machines
FA	Fly Ash
PV	Plastic Viscosity
RF	Random Forest
SSE	Sum of Squares Error
SVM	Support Vector Machines
UCAs	Ultrasonic Cement Analysers
WOC	Wait on Cement
YP	Yield Point

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