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A Critical Review for Application of Artificial Intelligence in Predicting Sand Production.

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Abstract

Sand production is a worldwide issue for all oil and gas wells are producing from sandstone reservoirs. Along past century many of authors and companies worked on putting suitable solutions for this situation that causing many problems as decreasing of fluid production reach to well shutdown. In present paper many published manuscripts that dealt with employment artificial intelligent approaches in predicting the onset of sand production are reviewed. The reviewed artificial intelligent approached are developed to perform one main target: the sand onset production prediction. This main target is detected by employment different ways such as artificial neural networks, generalized regression neural network, feedforward neural network, genetic algorithm, particle swarm optimization and support vector machine. Many influencing parameters on sand production initiation are used as inputs for these models likewise: total vertical depth, transit time, gas and water flowrates, formation cohesive strength, bottom-hole shut-in and flowing pressures, drawdown, critical drawdown pressure, effective overburden vertical stress, interval length, perforation density, and sand free production duration in years. The models results were in many terms including predicted critical drawdown pressure for sanding onset, or for making sand production probability in term of numbers (minus one, zero or positive one). The main conclusion from this review, the accurate artificial intelligent approach for sand onset production need to accurate and large data set as well as the results accuracy proportional to progress and development in artificial intelligent tools.

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1. Introduction

Sand production is the flow of sand particles with produced fluids under specific conditions [1], Sand production begins with the loss of rock cohesiveness around wellbores and perforations, followed by the movement of failed rock particles through fluid production, and transit of these bits into wellbore, wellhead, and surface facilities with produced fluids [2, 3]. Around 60% of middle east oil and gas wells produced from sandstone reservoirs [4] but this percentage raises to 70% if counting all worldwide fields [5, 6, 7, 8, 9].

Based on fields observations sand production classified to three types: (a) Transient sand production: due to acidizing, clean up after perforation and water breakthrough, it declines with time under same production conditions, (b) Continues sand production: sand accumulate inside the wellbore and increases the hold-up depth. Depending on the sand concentration and the lifting capacity of the fluid flow, the producing interval may eventually be blocked. Sometimes, it is continuing in acceptable amounts depend upon operational limitations regarding erosion, capacity of separators, sand depositions, artificial lift, well location and etc., and (c) Catastrophic high rate of sand influx according to sudden shut in/open well, its classified into two failure scenarios once as sand slug that creating bridge of sand in tubing or chokes according to shut in operation and other massive sand influx that filling bottom of well [4, 10].

The completion engineer must be aware of the conditions under which sand may produce before implementing any method for controlling its production [11], therefore the decision to perform or does not any one of sand controlling methods need to predict onset of sand production [12].

Optimum sand management need to complete comprehension about causing factors of sand problem so can be developing different validated methods and tools for predicting sand onset production and controlling [13]. Where sand production onset is according to produce from weak formation, increasing of water cut from brittle to moderate unconsolidated reservoirs, consolidated hard formation pressure depletion, high lateral abnormally tectonic forces of nearly strong reservoirs, sudden open shut in to flow or high producing rate [14. 15], not appropriate shot density, high permeability, perforation cavity and geometry, high fluid viscosity [16], in situ stresses values and variations, changing of fluids saturations, strength factors represented by (materials strength, internal fraction of particles, sanding arch and capillary forces), likewise some of operational parameters as drilling/completion strategies [17], difference of temperature between wellbore and formation, and coefficient of thermal elastic also have an effect on increasing or decreasing sand production [18].

Sand production prediction studies begun as a study of sand arching stability in laboratory famous Tap-Door experiment introduced by Terzaghi [19, 20], but before that [21] mentioned to sand production as one of problems connected to produce from unconsolidated formations. With the development that has occurred in the oil and gas industry, many scientific methods have been presented to predict sand production, and the latest advanced method is the use of artificial intelligence.

The objective of present paper is reviewing numbers of artificial intelligent approaches that adopted for sand production prediction by using different data sets and types for many oil fields in the world.

2. Theory

Over the last few decades, a great deal of time and effort has been spent by many authors in identifying and developing models for predicting sand production as a function of rock formation stress, reservoir pressure, production rate, formation and drop characteristics, fluid type and properties, and other influencing factors. These models support well completion design optimization as well as field operations including production control and sand management [22]. The application of artificial intelligent (*AI*) in prediction of sand production started at the end of the last century [23]. The *AI* used in the reviewed literature will be defined and discussed in the next sections, followed by a description of how to use them and what data was used in the next main parts.

2.1. Artificial Neural Network

An artificial neural network (*ANN*) processes an information system with unique performance characteristics, and its function is analogous to biological neural networks [24], *ANN* categorized due to connection among nods, how to determine connections weight (training and learning algorithm) and activation function [25]. Mohaghegh in 2000 [26] mentioned to first research on *ANN* that introduced by McCulloch and Pitts in 1943 [27] for discussing various applications of the calculus. Consequently, Rosenblatt in 1958 invented the perceptron to develop a weight vector that separates the classes so more than layer structure had been structured to overcomes of simple perceptron limitations [28]. A new *ANN* called Adeline developed by [29]. As shown previously, the application of *ANN* in oil and gas industry approximately begun at last decade of twentieth century as in exploration [30, 31], drilling [32], production [33] and reservoirs [34, 35]. Alkinani et al. in 2019 on their review paper cited many of literatures on history of *ANN* and its application in oil and gas industry and set forth [36], a summary flowchart of successfully steps on how to apply *ANN* in petroleum and gas industry as clearing in the following **Fig.1**:

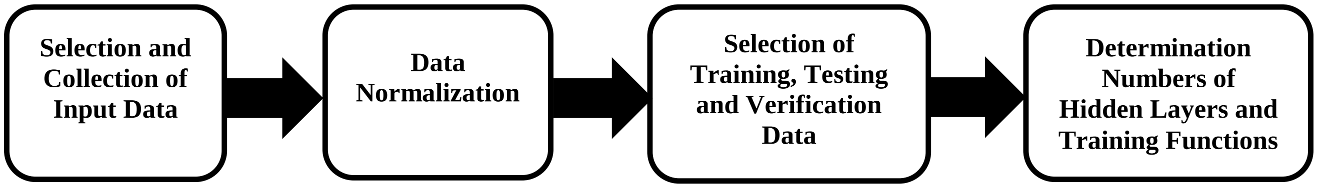

Figure 1: Flowchart of successfully applying of ANNs in petroleum and gas industry steps.

Many ANN types reviewed and will explain in next for prediction sand production must exhibit:

2.1.1. Generalized Regression Neural Network

A generalized regression neural network (*GRNN*) was introduced to deal with the challenge of developing a unique equation for statistical scattering plots from simple regression analysis. The GRNN's results are realized based on the probability density of the data function rather than a guess function [37]. It is consisting from four layers input layer, pattern layer, half nods of input layer as summation layer and output layer [38]. The *GRNN* is used for the estimation of continuous variables, as in standard regression techniques and **Fig.2** show example of *GRNN* structure [39]:

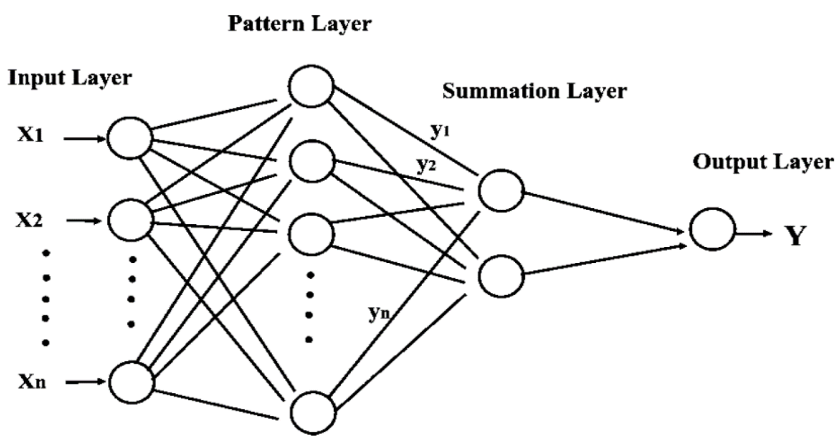

Figure 2: *GRNN* structure example [39].

2.1.2. Feedforward Neural Network

A feedforward neural network (*FNN*) is a simple type of artificial neural network wherein information goes away in one direction toward hidden layers and exist from output layer without any cyclic loop [40]. There are two types of *FNN*: Single-layer perceptron that is consisting from input and output layers, and multi layers with input, hidden and output layers [41]. Backpropagation is a generalized of least mean square algorithm for minimizing mean square errors that is describing as supervised learning algorithm applying on nonlinear multi layers feedforward nod's structure [23]. Back propagation is directing results in two ways, a feedforward as showed above and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and feedforward outputs [42]. **Fig.3** illustrates example of feedforward backpropagation (*FFBP*) neural network [43].

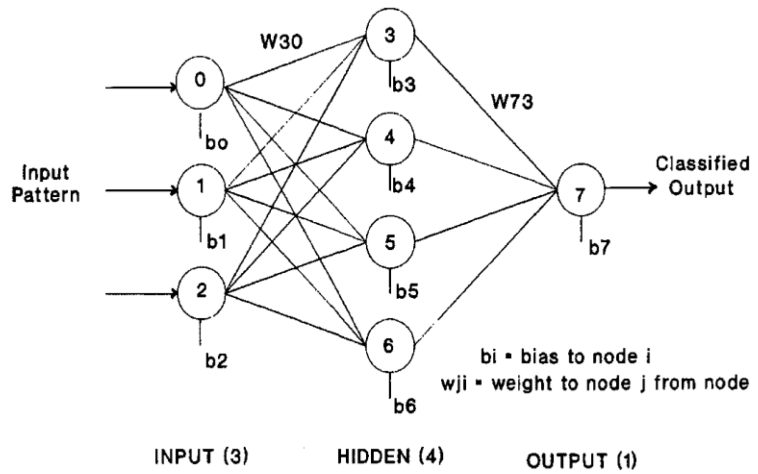

Figure 3: *FFBP* neural network structure example [43].

2.2. Genetic Algorithm

A genetic algorithm (*GA*): is a stochastic method for solving and optimization of constrained and free problems based on randomly populations of Gaussian random distribution. The multiple solution of GA is inspired by represent chromosomes of individuals. Each chromosome has a set of variables, which simulates the genes. Selection initially based on roulette wheel that one from other selection methods as boltzmann, tournament, rank, steady state, truncation, local, fuzzy, fitness uniform, proportional, linear rank and Steady-state reproduction, so work flow chart of *GA* stating in **Fig.4** [44]:

Figure 4: *GA* flow chart.

2.3. Particle Swarm Optimization

Particle swarm optimization (*PSO*) algorithm introduced by [45] as a method based on population search for continuous nonlinear function optimization. Each population called swarm with number of particles that may have solution of problem and move in special velocity with ability to adjust its position with respect to other particles and flaying experience until have best position (personal best) that will use in solution, **Fig.5** is showing *PSO* example [46].

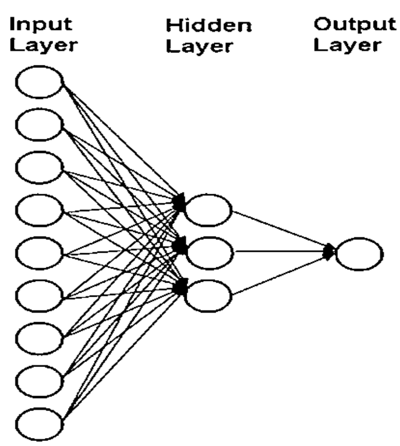

Figure 5: Schematic of *PSO* structure example [46].

2.4. Support Vector Machine

Support vector machine (*SVM*) is a non-probabilistic binary linear classifier utilizing regression analysis. It is supervised learning algorithm for pattern recognizing and data analysis has been studied extensively for both classification and regression analysis [47]. Least square support vector machine (*LSSVM*) introduced by Suykens et al. in 1999 as a modification for *SVM* to increase speed based on solution obtained by solving a linear set of equations, instead of solving a quadratic programming problem involved by standard *SVM* [48].

3. Application of Artificial Intelligent Approaches in Sand Production Prediction

Many authors are utilized the above explained AI methods for sand production prediction such as Ketmalee and Bandyopadhyay in 2018. The first artificial neural networks (*ANNs*) were constructed for sand onset prediction in 1999 by Kanj and Abousleiman, they used two kinds of *ANNs*: *FFBP* and *GRNN* topologies. The data are used for predicting sand initiation related to twenty-three sand problematic wells and eight sand free gas wells of the Northern Adriatic Basin. The considered influencing factors in *ANNs* construction of the problematic wells included: total vertical depth, transit time, gas and water flowrates, formation cohesive strength, bottom-hole shut-in and flowing pressures, drawdown, critical drawdown pressure, effective overburden vertical stress, interval length, perforation density, and sand free production duration in years, same factors of problematic twenty three wells considered in sand free wells except of replacing the critical total drawdown by the total drawdown of the well, and well's sand free production period is replaced by its life span in years. Before constructing two *ANNs* some efforts had been done as: (1) Rocks formation strength estimation based on well logs data, (2) Analog between underestimating and overestimating sand problem wells, (3) Correlating sand problem in term of gas flow rate plot with depth that showed very erratic and no apparent systematic distribution, (4) Analyzing of gas flow rate per perforation with depth that led to same conclusions of prior step, (5) Interpretation of relations of plot drawdown, gas flow rate and total drawdown with depth that showed no direct relation of drawdown with sand particles flow and no real effect of water cut on sanding initiation, despite of past literatures concluded contrast that, (6) Also, three zones of sand as danger, risk and free showed by plot of total pressure drawdown versus depth and likewise strength of rocks correlated with critical drawdown pressure [23].

Results appeared one from four possibilities: (1) Boolean classifier sand onset prediction as 0 indicate to no sand production problem, (2) 1 to sand production problem existing, (3) problematic-year that showed the probable life of well without sand production, and (4) sanding potential for accounting time periods of sand production problem, total and critical drawdown pressure determinations. Using of two *ANNs* for purpose of accounting effect of network structure and testing patterns.

The importance of unconfined compressive strength (*UCS*) for predicting real time sanding potential and critical drawdown pressure (*CDDP*) calculations emphasized in 2013 by Dong, et al [49]. This confirmation led to build *ANN* by Oluyemi et al. in 2010 in term of supervised *FFPB* learning algorithms by using C^{++} code with reporting mechanical property as rock compressibility, failure inducing property as stress path, petrophysical/textural property as porosity, median grain size and sorting. All reported data derived from logging while drilling and measurement while drilling divided into three parts for objectives of training, cross validation and testing of the *ANN* [50]. Date is transformed to close normal distribution because of existing some of outliers and nonlinearity where this process will be making *ANN* better and faster [50, 51]. Sensitivity analysis to many affecting parameters on *ANN* performance had been done where performance increased with least error as increasing of learning rate to 0.75, and numbers of neurons in hidden layers and decreasing of hidden layers. As a final result, predicted *UCS* validated with measured so depths of sand problem onset were determined.

The comparison study for calculating of *CDDP* by two shear failures, tensile failure and *ANN* models is accomplished in 2011 by Azad et al. Main topic to explain is utilizing *ANN* method in this study. Selected data were from three oil fields located in south of Iran, its production from three reservoirs Asmari, Ilam, and Sarvak that each one divided to five, three and seven subdivision zones respectively. Important influencing factors of sand production prediction divided into: (1) Formation and strength properties, (2) Reservoir and production properties as well as (3) Completion character. When first two factors took in consideration in *ANN* while the last is neglected so, *ANN* model with one hidden layer is constructed by adopting following data to input layer: reservoir parameters as critical drawdown pressure and reservoir pressure, formation factors as *UCS*, overburden and horizontal stresses, critical depths, and transit time. Input influencing parameters sources as *UCS* is calculated from corresponding empirical correlation and core samples, other data derived from compressional and shear sonic logs data with considering perforation depth and high porosity zones as a sources of sand production initiation. A thirty-eight data set divided to twenty-four set for training, seven for validation and seven for testing. Training sets had coefficient factor equal to 0.73 used for *FFBP* to achieve testing set that had coefficient factor of 0.77. results of comparison among four sources of *CDDP* demonstrated *ANN* gave best results and that expected because *ANN* can be overcoming on high data complexity and putting appropriate solutions in comparison with other three methods that need to accurate measurements and determination of rocks mechanics parameters, but one condition is determine the accuracy of *ANN* method is an availability of accurate data of input layer [52].

The same data that collected from twenty-three wells from North Adriatic Sea field and studied by Kanj and Abousleiman in 1999 [23] reused by Khamehchi et al. in 2014 where multiple linear regression (*MLR*), genetic algorithm evolved *MLR* (*GA-MLR*), *FFBP*, and *PSO* are constructed to determine the causes parameters of sand production. *FFBP* three layered *ANN* with same variables used in *ANNs* of Kanj and Abousleiman in 1999 [23] is built as a third method for predicting *CDDP* with sequence of reading of specific input and detecting belong to outputs: (1) accounting if error present between output results and measured is acceptable so stop and if no, (2) *FFBP* will be used to improve *ANN* weights of interconnection nodes. Likewise, *PSO* used for optimizing continuously non-linear functions of last *FFBP*. Results of both two methods referred to enhancing performance of *FFBP* from coefficient factor equal to 0.987 to *PSO* with 0.994 in training set while *FFBP* coefficient factor equal to 0.979 to *PSO* of 0.995 in testing set so performance observed of *PSO* is better than *FFBP* in the training, testing and all phases. As a summery simple linear regression showed a meaningful relation between *CDDP* and mentioned variables in Kanj and Abousleiman study, *MLR* gave a clear equation for *CDDP* calculation and *GA* showed ability to improve *MLR* as wells as *FFBP* constructed a complex relation among *CDDP* as output nodes and used in literatures variables, *PSO* had been enhanced *FFBP* performance [46].

The different artificial intelligent approaches: *SVM* and *LSSVM* methods are used by Gharagheizi et al. in 2016 [53] for predicting sand production onset for the same data founded in study of Morrica et al. in 1994 [54] that utilized in above mentioned studies that cited as [23, 46]. Same influencing factors of past two studies utilized for present two methods. Separating hyper-surface in the input space performed to build *SVM* in two steps nonlinear mapping to higher dimensional feature space for input pattern maps and building a separated hyper-plane with maximum margin. *SVM* outputs enhanced by *LSSVM*. Results appeared as (1) referred to observing sand and (-1) was indicating to no sand observation. Classification of quality was evaluated by confusion matrix in term of: *FP* is the number of errors made by prediction referred to sand problem while field observation is free sand and, *FN* is the errors number due to predicting a case being free sand while field observation is problematic of sand. Results of sand prediction relating to field observation explained that *LSSVM* was a powerful tool for sand production prediction that gave accurate results helping completion design engineer for making decision for sand controlling time and appropriate tools [53].

As discussed for three previous above studies that cited as [23, 46, 53] were used same data for predicting sand production onset, each study used different path than others but the target was one with some of differences. All three studies used same influencing parameters for constructing *ANNs*. Kanj and Abousleiman in 1999 used *FFBN* and *GRNN* for predicting sand onset in term of sand indictors as (1) referred to problematic and (0) free sand and simple relation between *CCDP* and cohesive strength correlated, problematic year determined, sand potential concluded as well as *CDDP* comparison among measured [23], field case study by Azienda Generale Italiana Petroli (AGIP [54]. Khamehchi et al. in 2014 utilized four mentioned methods for just calculating *CDDP* that validated with *AGIP* results [46], while last study of Gharagheizi et al. in 2016 [53] adopted *SVM* and *LSSVM* for finding probability of sanding existing (1) or free sand (-1). Based on comparisons among these three studies, Gharagheizi et al. in 2016 [53] were the best according to high accuracy results that identical in 100% with field observations that shows full set data of Morrica et al. in 1994 study [54] with last column of *LSSVM* results.

Olatunji and Micheal in 2017 worked same study of [53] on oil and gas reservoirs in Niger Delta region. Hypered algorithm of Nelder-Mead simplex simulated annealing (*SSA*) is utilized to deal with the demerits and shortcomings associated with single implementation of either the simulated annealing procedure or the Nelder-

Mead algorithm where it is combined between simple form of Nelder-Mead and annealing simulation. Many direct and indirect influencing parameters on sand onset entered to system: measured depth, Azimuth, total oil and gas rate, thick walled cylinder, shot per foot, pressure at mid perforation, water and gas viscosities, *UCS*, porosity, permeability, residual and connate oil and water saturations oil, perforation thickness, wellbore radius, solution oil gas ratio, oil and gas density, and formation volume factor of oil and water. Predicted results were identically of the observes field data that proofing hypered algorithm method very accurate way for sand production onset prediction [55].

The *ANN* applied for three wells from Bongkot field by Ketmalee and Bandyopadhyay in 2018 for determining absence sonic and density logs where wells *A* and *C* had no sonic data and well *B* had no sonic and density data. *ANN* cleared results better than sonic and density found from equations of synthetic density, synthetic depth and synthetic porosity. Measured Gama ray, neutron and resistivity of three wells used with sonic and density of nearby wells as nodes of input layers. When sonic and density calculated accurately, sand can be managed and interval depths of three wells analyzed with detecting sand problematic depths and free sand depths. *ANN* method had been solved important issues where before used it, analog methods are utilized for data predicting and that did not accurate in contrast [56].

Sulaimon and Teng in 2019 are employment *ANN* that performed by *MATLAB* for making a validation for sand production prediction by *MPL* empirical method and geomechanical modeling (*GM*). *MPL* validated by *ANN* for values of shear modulus to rock compressibility ratio for sand onset prediction while *GM* validation by *ANN* in term of predicted *CDDP*. *ANN* structured based on calculated mechanical properties that validated with core measurements that used as input layer nodes of system. It built to give outputs appropriate for two mentioned methods for validation them results. 70% of data were utilized for training while 15% for validation and last 15% for testing. *ANN* here played as a testing for validity where results of validation showed *GM* best than *MPL* method for sand production prediction [57].

The comparison between two utilized *ANN* with *FFBP* and *SVM* approaches for sand production prediction of Niger Delta as a case for studying had been made by Ngwashi and Ogbe in 2021 on his master thesis and published paper [58, 59]. *FFBP* and *SVM* are built by entered eleven influencing factors on input layer. Two methods validated with calculated and concluded data in study of Udebhulu and Ogbe in 2015 [60]. By using Python library, results appeared as (1) referred to free sand and (0) as a sand problem existing. Two algorithms evaluated based on (Shin 2020) criteria as classification accuracy represented by: (1) Prediction accuracy to total prediction, (2) Confusion matrix that tells us about performance and if prediction corrected or no, (3) Precision of true positive to summation of true and false positive where results between zero and one, (4) Recall of true positive to ratio of true positives and false negatives, also its results between zero and one, (5) F1–Score as a harmonic mean of both precision and recall, (6) Cohen kappa that measured rate's reliability, and (6) Loss function as a mean squared error. Sand problem are evaluated based on confusion matrix as explained in above study of Gharagheizi et al in 2016 [46]. Two methods comparison criteria with different sets of testing sizes showed *SVN* is better than *FFBP* especially for binary subdivisions with sparse training data sets. The confusion matrix of both two methods is referring to well numbers in term of problematic and free sand in both statuses of predicted and actual. 30% testing rate of *SVM* was the best that representing the actual states as five wells problematic on actual and predicting and three wells free sand in actual and predicting [58, 59].

4. Comparison of Artificial Intelligent Approaches in Sand Production Prediction

Table 1. is summarizing and comparing among all *AI* discussed approaches for sand production prediction and according to studies above, *AI* approaches for sand production prediction can be using to: (1) Find probability of sand onset or no, (2) Prediction sand production by determination of *CDDP*, and (3) *AI* approaches for comparisons and giving a permission for validity of using conventional methods for sand production controlling.

Table (1): Summarizing and comparison among (*AI*) studies for sand production prediction.

Reference	*AI* Method	Area of Study	Main Targets	Notes
Kanj and Abousleiman 1999	FFBP and GRNN	Thirty-three gas wells from the Northern Adriatic Basin.	• Boolean Classifier. • Problematic-Year. • Sanding Potential. • Total Drawdown.	• Some conclusions as no effect of gas rate and pressure drawdown cleared initially at first analysis before making ANNs.
Oluyem et al. 2010	FFPB code by C++	Offshore field in Niger Delta.	• Sand potential determination.	• UCS is an indication for weak zones as well as sanding onset.
Azad et al. 2011	FANN and FFBP	Three oilfields located in the southeast of Iran are producing from Asmari, Ilam, and Sarvak formations.	• CDDP calculation by using from two shear failure, tensile failure and ANN models comparison.	• ANN is powerful method rather than others if large data existing
Khamehchi et al. 2014	MLR, GA, FFBP and PSO	Thirty-three gas wells from the Northern Adriatic Basin.	• Determination of CDDP by four methods.	• Confirmation of Kanj and Abousleiman conclusions about no effect of water cut on sand onset due to weak formation type. • PSO was the best method and accurate.
Gharagheizi et al. 2016	Modifying SVM results by LSSVM	Thirty-three gas wells from the Northern Adriatic Basin.	• Sand onset prediction in term of 1 and -1.	• Ability to modify got results from SVM by LSSVM by accounting classification model quality as well as validation by many statical parameters based on confusion matrix results.

Olatunji and Micheal 2017	Modifying SVM results by LSSVM	Niger Delta	• Sand onset prediction in term of 1 and -1.	• Many of direct and indirect influencing factors considered because at any time minor factors will affect at any way to initiate sand production.
Ketmalee and Bandyopadhyay 2018	ANN	Three wells from Bongkot field	• Sonic transient time. • Rock density. • Sanding prediction.	• Accurate determination of sonic and density data means best sand prediction.
Sulaimon and Teng, 2019	ANN by MATLAB	Field X, in Sabah, Malaysia, and Field Y, in Shimokita, Japan.	• Validation of MPL and GM sand onset prediction.	• Another purpose of ANN as permitting validity for sanding prediction methods.
Ngwashi and Ogbe 2021 and Ngwashi et al. 2021	ANN with FFBP and SVM by Python.	Niger Delta	• Comparison between ANN and SVM.	• New comparison criteria in term of (Shin 2020). • Different way for sanding indicating by confusion matrix.

5. Conclusions

The application of *AI* approaches in sand production prediction are very excellent and providing a good result as explained in the text, so from the critical review of the sand production prediction by *AI* approaches, the following points had been concluded:

1. The main parameter that effect on *AI* approaches results accuracy is the availability large extent of information.
2. Different *AI* approaches could be using for sand onset problem prediction either by *CDDP* determination or by sand onset possibility significance numbers such as zero one or minus plus one.
3. Different *AI* approaches could be utilizing either for comparisons among the provided results with measured values to select the best one or for detecting conventional sand production prediction methods validity.
4. There are many affecting parameters on sanding problem must be taken in consideration in *AI* model but the limitations of using it is the availability.

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