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Review

AI/ML Technology for Water Treatment in Oil and Gas Industry: A Review Paper

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Abstract: The opportunities and advantages of implementing Artificial Intelligence (AI) and Machine Learning (ML) to optimize the process control of wastewater treatment in the Oil and Gas industry are discussed in this work. Discussion is centered around five major points: 1) Various types of Oil and Gas wastewater (Sour, Oily, Produced) and industry standards/methods for treatment, including specific case studies and challenges when treating certain wastewater. This section aims at the common types of wastewater in the Oil and Gas industry and how they are generally treated. 2) How AI/ML has been implemented in wastewater treatment in various industries; summary of which AI/ML languages were used along with a brief overview of how they work. This article focused on an understanding of the specific case studies and AI explanations to understand the effectiveness of wastewater treatment using AI/ML. 3) AI that is currently implemented in Oil and Gas such as personal protective equipment (PPE), smartwatches radiofrequency identification etc. This showed that AI/ML already plays a successful role in the Oil and Gas industry and has proven to help optimize many processes and components. Many of these AI/ML implementations are now industry standards and have greatly benefitted the industry. This section demonstrates that the implementation and the use of AI/ML have been proven to be a successful endeavor and that expanding the role of AI/ML would be beneficial. 5) Using the established points from the previous sections the paper outlines why AI/ML is ideal for Oil and Gas wastewater treatment; this argument centers around fit-for-purpose treatment, and the possible uses of the treated water. A determination of the best-suited AI languages, possible implementation scenarios, and how this would shift the way Oil and Gas industries treat and approach wastewater is presented to the reader.

Keywords: artificial intelligence; machine learning; produced water; oil and gas industry

1. Introduction

As a whole, Earth and the people who reside on it require energy to continue sustaining life, especially with a growing population. As technology advances, it has been shown that, as a society, humans are slowly phasing out nonrenewable energy sources such as fossil fuels and moving to more abundant and renewable sources. However, the majority of energy produced in the world still derives from fossil fuels, as of 2019, an immense 84% of the primary total energy produced originates from fossil fuels (Ritchie, et al. 2020). While the global society makes this transition over to a cleaner, renewable energy source, it is critical to use the infrastructure that has already been set up in the form of oil and gas. Certain technological advances have been made to be as efficient and clean as humanly possible (Kamali, et al. 2020). Wastewater treatment is becoming a larger issue (Radelyuk, et al. 2019). This large amount of wastewater is a consequence of modern-day drilling techniques and can be separated into two categories, flow back and produced water (Kondash, et al. 2016). Put simply, flow back is the fluid that returns to the surface of the well after drilling. Well stimulation treatments are then completed after the well is drilled and before recovered oil and gas. These processes, such as hydraulic fracturing or acidizing, add even more fluid and internal water to the well that will later be removed and placed in the second wastewater category. Produced water consists mainly of existing fluids that are already found in geological formations and is known as formation fluid. Unfortunate as it is, wastewater is an integrated part of oil and gas. When crude oil is separated, there is a large amount of water left over (Veil, et al. 2004). This water is toxic and full of heavy minerals such as lead. Due to the nature of the wastewater and drilling techniques, this produced water must be treated (Utvik, et al. 2000).

Produced water is a partially challenging issue because this form of wastewater can have a dangerous compound known as hydrogen sulfide (H_2S), which is well known to have the smell of rotten eggs. Hydrogen sulfide is also poisonous, H_2S corrosive, and flammable (Airgas SDS), making this compound especially hard to handle and dispose of. Hydrogen sulfide is especially dangerous to humans having a threshold limit value short-term exposure limit (TLV/STEL) of only five parts per million (ppm) (Perry, et al. 2014). Companies use evaporation pounds to treat this wastewater, but oftentimes there is still a need for further purification. Additionally, the evaporation pound can easily pollute both the soil and air.

Thus there is a natural need to reduce the amount of wastewater and treat the produced water more effectively. As technology has quickly become more advanced, it has been shown that Artificial Intelligence (AI) can be used in the treatment of produced water. New developing AIs and machine learning (ML) models could be the future for such an intimidating task as produced water treatment (Koroteev, et al. 2020). Moving forward, the industry is looking to implement computers and robotics to keep humans out of harm's way in such a risky but necessary industry. Placing these new technologies out in the field will allow humans to understand the normally unseen better. If disaster strikes, a new form of technology could be the reason for mitigation instead of a person put into harm's way. In the oil and gas industry, there are seasons everywhere in every step of the process that frequently record real-time data (Shah, J. M. et al., 2024). Oftentimes such a large amount of data cannot be processed and iterated by a human. For a computer, however, this is completely possible. ML algorithms have been made the same way a human's brain works with neural networks. These neural networks can take several inputs and produce a number of outputs. As the number of inputs increases, the size and complexity of the neural network do as well. ML can take inputs, analyze, weigh factors, and then produce an output that is optimum extremely fast (Verma, N. et al., 2024). This allows the operating system to be monitored and changed to be in the most optimum conditions for a longer time. ML allows for a cleaner, more effective process, which saves the industry money and reduces the amount of pollution released into the environment. Therefore, the development of AI and ML would allow for a much faster response and more optimum monitoring of potential risks while keeping humans safer. These new technologies in development would allow for a much cleaner and safer future in a hazardous world.

2. Basis of Machine Learning

A basic machine learning system can be used to recognize or classify certain types of patterns known as a model. A model can be used to answer a question and classify similar things (Aamir, M. et al., 2024). For example, if a model was made to classify whisky from wine. A model could be made given the color and the alcohol content known as features. Using just these two features a model could be made to place the drink into a category. A model is made by a process known as training. In ML the goal of training is to develop an accurate model that can answer the question correctly a majority of the time. To train a model a large amount of data must be given to the system to learn from. The first step of ML is obtaining data; this step is exceptionally vital to developing a superior model. The quality and quantity of the data will directly influence the accuracy of the predictive model (Wang, Z. et al., 2024).

A large number of quality data points will produce a more accurate model than a small number of inferior data points. The next step is data preparation occurs when data is logged into the system and prepared or initialized for use in training. Data is assembled then the order is disbursed randomly to ensure the order does not affect how the model learns. The data is then examined to

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ensure there are no data imbalances (Astsauri, T. et al., 2024). If more data was collected for whisky than wine, the model could have a large bias toward classifying a drink as a whisky. Data is then split where a majority is used for training, and a smaller amount is used for evaluation. Different data is used in evaluation to prevent the model from remembering the question. It is at this time the model is picked and training can begin. In this simple case, a linear equation can be used, y=m*x+b. Where y is the output, x is the input, m is the slope of the dividing line between whisky and wine, and b is the y-intercept. The only values that can be adjusted or trained are just m and b, because the only true variables that can change the position of the line x, the input, and y, the output, cannot be adjusted (Riquelme-Dominguez, J. M et al., 2024).

In ML, many values form can be formed into a matrix that is often denoted as w for weights. In the same way, a basis matrix can be formed for the b value. The training process starts by initializing random values for the weight matrix and the basis matrix, then attempting to predict the output with the given values; this is known as a generation or training step. In most cases, the first generation does very poorly. To improve upon the first generation, the model prediction is compared with the output that should have been produced and the values in w and b to gain more accuracy in predictions. The process is repeated several times before the model is evaluated. Finally, is parameter tuning to further improve training in any way (Massidda, L. et al., 2024). There are a few values that are assumed to gain a starting point, these parameters are known as hyper-parameters (Zhao, Y. et al., 2024).

One such hyper-parameter is the learning rate; this parameter adjusts the amount line is shifted during each generation based on the information from the previous one. This can massively affect how long it takes to train a model and how accrue the model can be.

3. Wastewater Treatment in Oil and Gas

To produce the massive amounts of energy the current world needs by refining crude oil, it is at the cost of producing by-products, one of which is wastewater (Pichtel, et al. 2016). The raw petroleum from the ground is a mixture of crude oil, formation water (can be brine or freshwater), and undissolved solids such as hydrocarbons (along with other unwanted compounds/heavy metals) (Varjani et al., 2019). However, most of the composition of raw petroleum is water. When raw petroleum is processed, the separated water from petroleum is commonly referred to as produced water.

Produced water is classified as wastewater because it is difficult to treat/dispose of properly. Discharging produced water into the surroundings as a means of disposal presents environmental challenges. It is wastewater because it has been separated from crude oil to produce a finer quality refined oil. The leftover water typically cannot be used for human consumption/use. There is no exact definition for wastewater because wastewater has a complex composition (Pichtel, et al. 2016). However, one can briefly classify wastewater as organic or inorganic.

There are many classifications for wastewater in the oil industry; some examples include refinery wastewater, petroleum refinery wastewater, produced water, petrochemical wastewater (Fadali & Farrag, et al., 2017), and oil refinery waste effluent (Abdelwahab et al., 2009), etc. A few more commonly produced waters in the petroleum industry are described in greater detail.

3.1. Types of Wastewater in the Oil and Gas Industry

3.1.1. Sour Wastewater

In the gas production sector, the water that is commonly encountered is sour wastewater. This kind of wastewater is high in sulfur and acidity concentrations. The acidity comes from the trapped CO_2 and H_2S gases trapped in the natural gas reservoirs (Olajire, et al. 2020). Sour wastewater is usually dangerous to handle/dispose of because of the elevated levels of H_2S which can be dangerous or fatal if inhaled in large quantities. One of the simplest forms of process control safety in the gas industry would be the implementation of the H_2S meter.

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The meter protects the worker from high concentrations of H_2S through the feedback control system in the meter; the meter alerts the worker with an alarm that automatically detects when the concentration of H_2S is too high. In addition to increased safety risk, sour wastewater is corrosive to iron pipes, causes equipment failure and high fluid velocity can cause stripping of the iron sulfide layer to expose fresh iron and increase corrosion, leading to high-stress fractures in sections of the pipeline (Hatcher et al., 2014). Although all acidic water comes from produced water, not all produced water is sour. The main contaminants are the increased levels of sulfur and acid in the sour wastewater.

3.1.2. Oily Wastewater

This is produced water that contains high levels of complex organic compounds (especially oily sludge wastewater). Distinct types of groups for organic compounds consist of aliphatic, nitrogen sulfur oxygen (NSO), aromatics, and asphaltene-containing organic compounds. These are usually complex hydrocarbons with these groups that increase the amount of dissolved oxygen. Therefore, discharging oily wastewater to the environment increases oxygen consumption by microorganisms. However, the normal aquatic life that depends on these microorganisms can perish if not enough oxygen is available in the water (Padaki et al., 2015).

The biggest risk for environmental contamination would be heavy molecular weight hydrocarbons. It is especially difficult to treat these undissolved and dissolved organic hydrocarbon chains that have been trapped in reservoirs for millions of years. Because their high molecular weight causes a decrease in their solubility (Neff et al., 1992), discharging treated produced water will always leave behind a small amount of these hydrocarbons dissolved in water, increasing the toxicity to wildlife in proximity. Agricultural soil contamination by oily wastewater decreases plant nutrient production, and the germination of seeds is reduced, leading to less food production in farms near oil wells or wastewater treatment regions (Padaki et al., 2015). Because these organic compounds have a high molecular weight, water absorption is highly limited in oily wastewater-contaminated soil (R. R. Sulemanov et al., 2005).

3.1.3. Produced Water (PW)

Produced water is the formation of water from gas or petroleum reservoirs. This wastewater is typically high in the amount of salt concentration (although, in some cases, the formation water is freshwater). Some samples of offshore-produced water contained over 300% of the normal sodium chloride concentration found in seawater. Produced water from offshore wells can have just as high or higher salt concentration compared to the produced water gathered from petroleum wells on land. In addition to increased salt concentration, produced water, like sour and oily wastewater, can contain the contaminants in these types of wastewater, but with ranging concentrations (Neff et al., 1992).

Offshore well-produced water can also contain large organic carbon concentrations from the hydrocarbons trapped in the oil reservoirs. More contaminants present in the hydrocarbon chains are functional groups from organic acids/aromatic ring structures. Metals, too, are present in the extraction of raw petroleum, but depending on geographical age and location will determine what type of chemical species will be in the produced water (Hur et al., 2018).

3.2. Petroleum Wastewater Treatment Methods

After the raw petroleum is processed into refined oil (which can then be converted into other oil products, like gasoline, plastics, lubricants, etc.), most of what remains is water leftover from petroleum processing and can be further treated for recycled use. The composition of crude oil depends on the geographical location where the oil was extracted (Hur et al., 2018). Oil companies typically want water composition in refined oil to be less than 1%. The process of treating wastewater is quite complicated, but if the entire treatment is separated into sections, it becomes simpler to understand. Heavy water treatment is needed to safely reuse the water produced from the oil wells and refineries (Varjani et al., 2019).

A general flowchart for treating petroleum wastewater is shown in Figure 1:

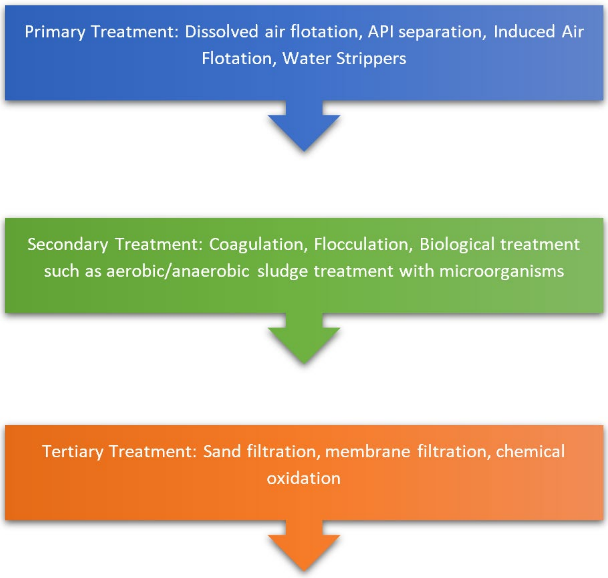

Figure 1. Petroleum wastewater treatment flowchart (Varjani et al., 2019).

On a review of wastewater treatment processes, Table 1 shows different physicochemical wastewater types and their respective treatments and brief results from several researchers. A few processes were chosen to see if A.I./Machine Learning could be used to improve gas/oil production for this study.

Table 1. Examples of various wastewater treatment methods (Al Deen Atallah Aljuboury et al., 2017).

Method Applied	Wastewater Type	Removed Pollutants	Maximum Removal Efficiency (%)	Reference
The physicochemical processes	A refinery wastewater	Total naphthenic acids (NAs) Aromatic naphthenic acids	16 24	Wang et al. (2015)
An immersed membrane process	Petroleum refinery wastewater	Wastewater oil content	69	Al-Malack (2016)
Membrane bioreactor (MBR)	Petrochemical wastewater	Heavy Metals Iron	70 75	Malamis et al., (2015)
Nanocomposite membrane with the multi-walled carbon nanotube (MWCNT) incorporated in Polyvinylidene fluoride (PVDF) matrix	Refinery wastewater	Oil		Moslehyani et al., (2006)
A crossflow membrane bioreactor (CF-MBR)	Petroleum Wastewater	COD	93	Rahman and Al-Malack (2006)

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The hollow-fiber membrane bioreactor (HF-MBR)	Real petroleum refinery wastewater	COD BOD_5 TSS VSS Turbidity	82 89 98 99 98	Razavi and Miri (2015)
Membrane sequencing batch reactor	A synthetic petroleum wastewater	Hydrocarbon pollutants	97	Shariati et al., (2011)
Ultra-filtration (UF) membranes	Refinery wastewater	COD	44	Asatekin and Mayes (2009)
Poly-aluminum chloride and ferric chloride for coagulation treatment	Petroleum wastewater	COD	58	Farajnezhad & Gharrbani (2012)
Poly-zinc silicate (PZSS) and anion polyacrylamide (A-PAM) for coagulation/flocculation treatment	Heavy oil wastewater	Oil	99	Zeng et al. (2007)
Subsequent coagulation/H_2O_2	Petroleum refinery wastewater	COD BOD_5	58 78	Wagner and Nicell (2001)
Coagulation by alum Coagulation by ferric chloride (FeCl3)	Petrochemical wastewater	COD COD	61 52	Altaher et al., (2011)

3.3. Wastewater Treatment Methods

3.3.1. Evaporation Ponds

Depending on the type of wastewater, it is common practice as a form of wastewater treatment to store petroleum wastewater in large ponds, commonly referred to as evaporation ponds. The water can either be evaporated without any other intervention, or the addition of bacteria can further purify the water to a certain acceptable extent. However, this treated water can still be possibly toxic with brine and other unwanted compounds (Ahmed et al., 2000), but after controlled treatment can be reused for other treatments such as crop irrigation (Pichtel, et al. 2016).

Evaporation ponds are typically developed in arid regions where evaporation rates are substantially greater. However, evaporation ponds are one of the cheapest methods for treating heavy brine-produced water compared to desalination plants (Ahmed et al., 2000). Companies need to be cautious as the water from these ponds can be hazardous to health and pollute the soil in the event that the pond collapses/overflows. In an event where an evaporation pond fails (for example, a thunderstorm causing an overflow), the accumulated water that has spilled over contaminates the soil (Pichtel, 2016).

3.3.2. Removal of Naphthenic Acids and Aromatic Naphthenic Acids

In a wastewater treatment plant in North China, a study was done to analyze the effectiveness of physicochemical treatments in petroleum wastewater by removing naphthenic acids (N.A.s) and aromatic N.A.s. The removal of N.A.s was done by treating the water by processes of gravity setting through a designated chamber, a coagulating chamber, filtration through walnut shells, flotation, and aerobic/anaerobic. The composition of N.A.s in the wastewater varied from 2.1-8.8%. An interesting finding is that the removal efficiencies for total N.A.s and aromatic N.A.s were much better in the summer than in the winter after biodegradation, with removal efficiency of 73% and 53%, respectively (Wang et al., 2015).

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Unfortunately, there is no mention of A.I./M.L. in this wastewater treatment plant. However, they could have had an A.I./M.L. system that could have contributed to the separation of N.A.s, such as a fuzzy neural network or a different A.I./M.L. process control system.

3.3.3. Membrane Technology

One of the most effective wastewater treatment methods is the implementation of membrane-separation technology. Membrane technology can vary from filtering water to filtering the very blood from one's body through dialysis. From the point of petroleum wastewater treatment, the wastewater membrane separation processes rely on absorption, sieving, and electrostatic phenomena. Membrane separation technology is especially effective at treating oily wastewater through microfiltration, and nanofiltration, but the most effective method is ultrafiltration (Padaki et al., 2015). Several types of membrane separation materials include organic and inorganic materials such as polymer and ceramic membranes, respectively. The advantage of using membrane technology is that it works without additional chemicals to aid in separation.

4. A.I and Machine Learning Wastewater Treatment

4.1. Implementing the AI and ML to the Wastewater Treatment

According to the USGS.gov, the Earth is made of 71 percent water. We need water for drinking, eating, and transportation. Furthermore, water is the home of about 1.4 to 1.6 million species making it a priority to keep it clean. In water treatment, pollutants such as dyes, heavy metals, and organic compounds can be removed AI's implementation. AI technologies (Zhiping, Xin, Jining, and Jaide, 2018). In addition to wastewater treatment, different AI technologies have been implemented to control the disposal of wastewater. Technologies like the Radial Basic function network, Multilayer Perceptron Neural Network, Scalable Vector Graphic, Genetic Algorithm, and Feedforward Neural Network have been implemented for wastewater treatment (Zhiping, Xin, Jining, and Jaide, 2018).

The efficiency of these machine languages and AI have been tested through numerous experiments. The removal of dyes has been experimentally tested using the Artificial neural network coupled with a genetic algorithm known as GA-ANN. Some setbacks like time-wasting during computations using GA-ANN. However, GA-ANN is highly fast and accurate when giving results. AI and machine learning have also been implemented to remove heavy metals. One of the most famous experiments done was the use of MLPNN and ANFIS for the adsorption of copper (Nag, Mondal, Roy, Bar, and Das, 2018). MLPNN and ANFIS are accurate and are exceptionally good for value estimation. The only issue with these two AI is that they are error-prone, which is not good for results that need to be precise and accurate.

4.2. AI and Machine Languages Implemented

4.2.1. Radial Basis Function Neural (RBFNN)

RBFNN is an algorithm language with three main layers: input, hidden, and output. In the case of water treatment, we use RBFNN for heavy metals. The RBFNN detects the metals by making accurate predictions for each metal (Nag, Mondal, Roy, Bar, and Das, 2018). Also, RBFNN has been implemented in the modeling of coagulants in water treatment. The RBFNN was used to measure the dosage of coagulants. The coagulant dosage rate is non-linear due to conductivity, turbidity, and pH. The conductivity, turbidity, and pH of the coagulant make the coagulation process difficult to control. That is why the RBFNN is implemented in this process to measure the coagulation and the coagulant dosage. Figures 2 and 3 below show the observed and predicted chlorine dosage as the number of samples increases (Nag, A. et al. 2018).

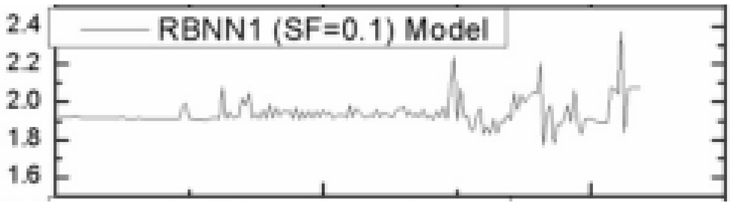

Figure 2. Trial 1 for the observed and predicted chlorine dosage as the number of samples increases (Nag, A. et al. 2018).

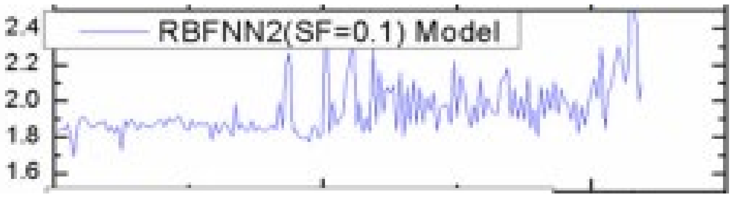

Figure 3. Trial 2 for the observed and predicted chlorine dosage as the number of samples increases (Nag, A. et al. 2018).

4.2.2. Multilayer Perceptron Neural Network (MLPNN)

The Multilayer Perceptron Neural Network is a very efficient algorithm with a fully accurate estimation and forecasting technique. This algorithm is mostly used in weather forecasting, but it can also be applied in water treatment for making coagulants that can be put in water making it drinkable. The Basic Read 46(BR46) and Cu adsorption from an aqueous solution experiment is a good application of this (Nasiri, S., et al., 2017).

This investigation was based on removing copper, which is a heavy metal, through adsorption by combining it with a scale reactor. The input parameters were pH, concentration, time of contact, adsorbent dosage, and Initial BR46 (Basic Read 46) and Copper (II). The neural networks applied were MLPNN and ANFIS. The parameters used were dye, Copper (II), contact time, pH, and adsorbent dosage. By using sawdust from Melia Azedarach Wood, the MLPNN ANFIS model was used to give an accurate prediction model of dye and copper (II). The training dataset, validation datasets, testing datasets, and *R2* values were respectively 38, 6, 6, and 0.99 (Figure 4)(Nasiri, S., et al., 2017).

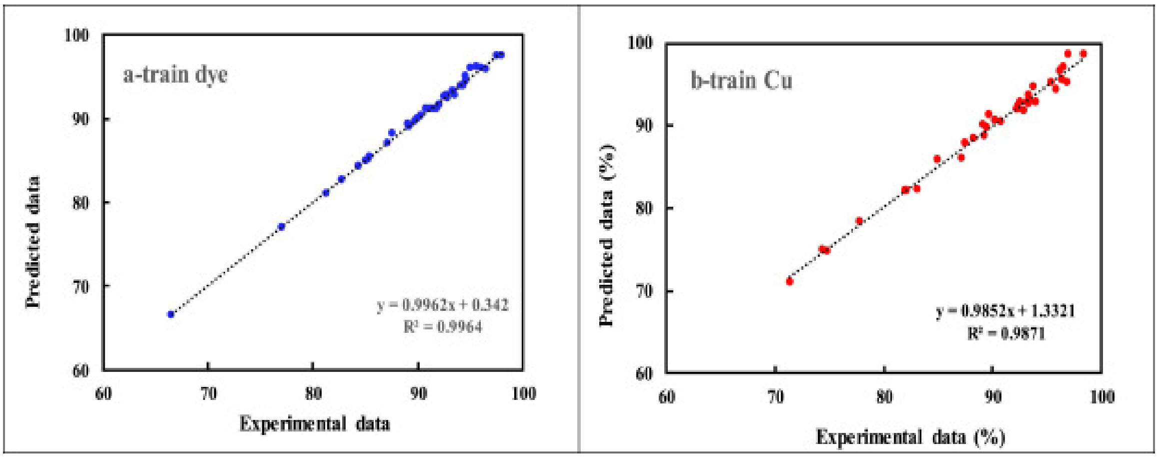

Figure 4. Predicted data for a-train dye and b-train due vs experimental data (Nasiri, S., et al., 2017).

5. Artificial Neural Network Coupled with Genetic Algorithm (GA-ANN)

This neural network is very promising because its high speed and accurate prediction can be used in various applications. ANN network helps us to understand datasets in both ascending and descending order. Furthermore, the ANN network can help us identify the model which has the best fit and it changes based on the environment it is put into(Tavish, 2014). Figure 5 indicates the various stages the ANN neural network goes through in processing data.

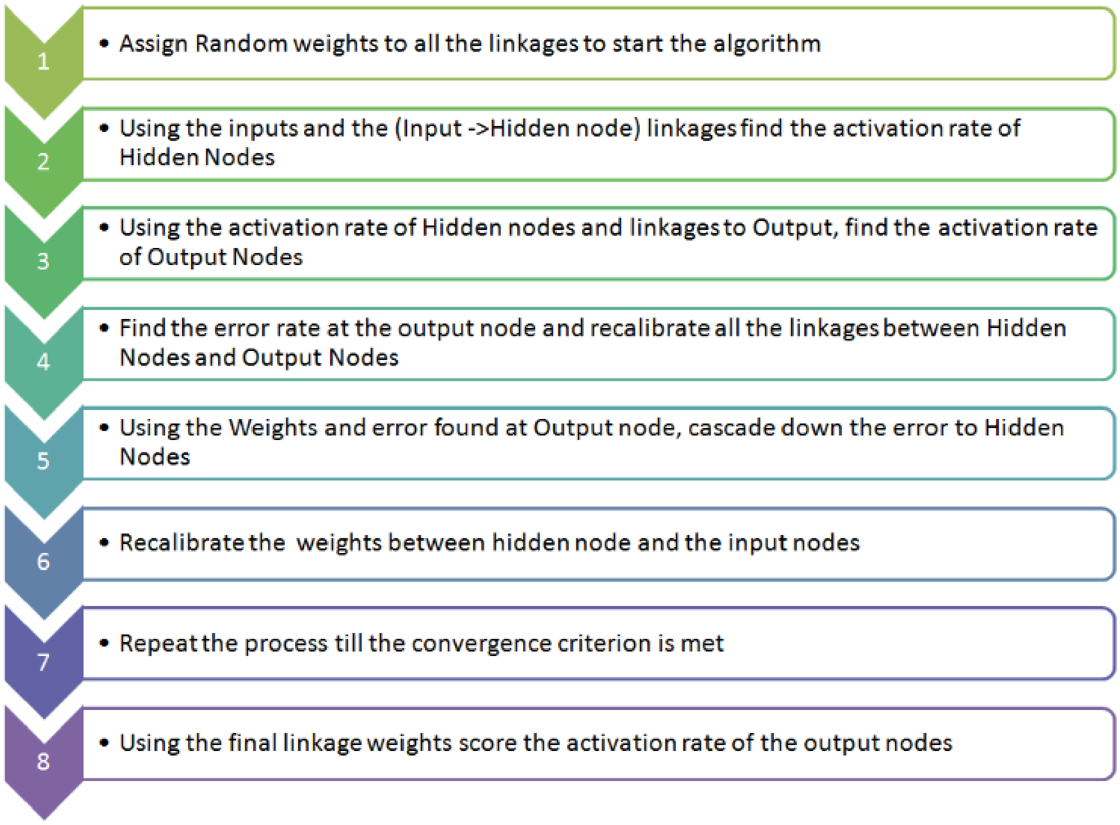

Figure 5. Steps of ANN neural network processing (Tavish, et al., 2014).

For example, in an experiment involving the Bioremediation of Cadmium (II) from an aqueous solution using waste materials, the GA-ANN was used to model a complex sorption process which was used to predict the efficiency of the metal ion removal (Nag, et al., 2018). The training dataset, validation datasets, testing datasets, and R^2 values were respectively 65, 19, 9, and 0.94. The *R2* values obtained showed how efficient the GA-ANN is in predicting heavy metals (Figures 6 and 7)(Nag, et al., 2018).

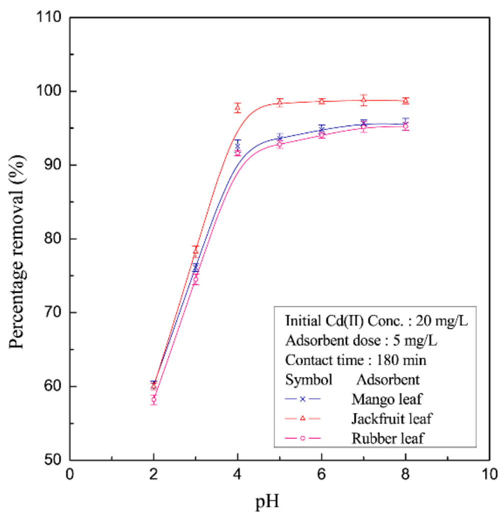

Figure 6. The graph of Ph effect on CO_2 (Nag, et al., 2018).

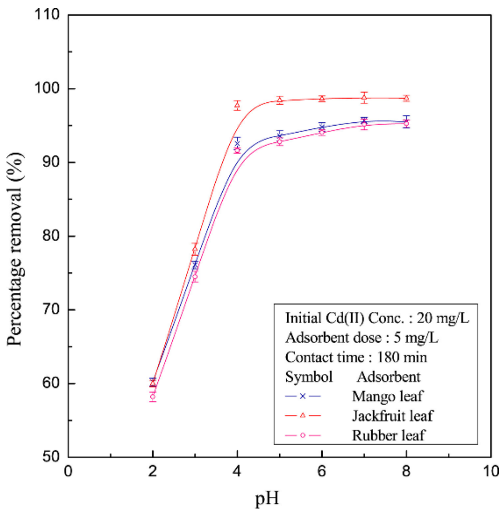

Figure 7. Adsorbent dose effect in Cd (II) (Nag, et al., 2018).

6. Genetic Algorithm (GA)

A genetic algorithm is one of the first built algorithms for counting the population, it applies the principle of Genetics and Natural section for searching (Mirjalil, et al., 2019). The evolutionary biology technique improves the parameters which gives it an extremely high estimation power and can be used to optimize (Mirjalil, 2019). The genetic algorithm is made up of various operators which are encoding, crossover, selection, and mutation. All these operators have various subunits that help in algorithm processing as can be seen in Figure 8 (Katoch, et al., 2021).

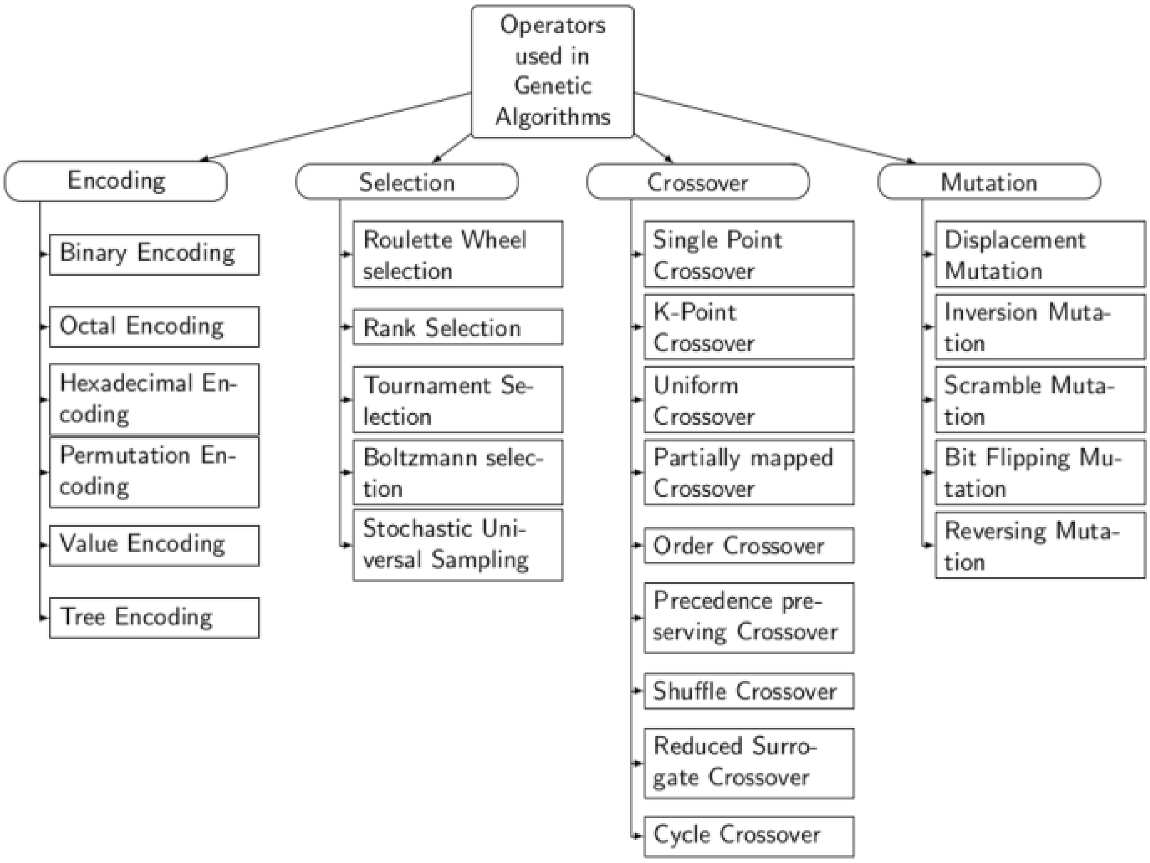

Figure 8. Different operators used in Genetic algorithms (Katoch, et al., 2021).

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6.1. AI Currently in the OGI

Entering a new era of technologies, the implementation of AI is critical for the oil and gas industry to continue to advance. The Internet of Things (IoT) describes a physical object with sensors that collect data and exchange that data with other software and systems (Wanasinghe et al., 2020). IoT applications include wearable watches, smart helmets, and smart glasses to be worn by oil field engineering for safety purposes, communication, and assistance in the oil and gas industry. Drones and robots are used to inspect potential hazardous leakages in pipelines, flare emissions, offshore drilling, inspections, and disaster control to improve efficiency and personnel safety (Ivanov et al., 2018). Smart pipelines are utilized for detecting damages and notifying the control room immediately. Micro and nanotechnologies are commonly implemented to give more accurate and in-depth data. As part of IoT, wireless sensors monitor and oversee operations such as pipeline leakage, rust, and instrumentation in real time (Rahmati et al., 2017).

Radiofrequency identification (RFID) technology is applied to the oil and gas industry for asset and oil rig management, inspections, safety, and security. However, the large amount of data that the sensors collect is often too difficult for human interpretation, so the data is filtered through intelligent systems (Aldhaeebi et al., 2014). Machine learning (ML) in the oil and gas industry aims to analyze and interpret the data to make predictions. ML is useful for drilling objectives, identifying, overseeing, and forecasting so optimization can be determined in real-time at a low cost.

The most common and simplest algorithm used is Artificial Neural Networks (ANN) which has high input parameter requirements in order to operate (Table 2) (El-Abbasy et al. 2014). Supper Vector Machine (SVM) is useful for small-scale instruction and not very suitable for real data (Anifowose et a. 2012). Particle swarm operation (PSO) can disregard the problem information, but the accuracy is low. Fuzzy logic does not need a specific mathematical model but is not very accurate. Deep learning (DL) and Genetic Algorithms (GA) are often combined to improve the accuracy of other ML algorithms; however, GA is complex and requires more programming (Romero et al. 2000). BP neural networks are the most frequent and utilized AI in the oil and gas industry. Overall, choosing a suitable algorithm combination according to the advantages and disadvantages is important. If correctly implemented, the oil and gas industry can perform better at higher speeds (Windarto et al., 2017).

Table 2. Advantages and disadvantages of using common AI algorithms (Li et al. 2021).

Method	Advantages	Disadvantages
ANN	High classification accuracy, strong parallel distributed processing ability, strong distributed storage and learning ability, strong robustness and fault tolerance to noise nerves, full approximation to complex nonlinear relations, associative memory function, etc.	Many parameters are required, such as network topology, initial values of weights and thresholds, output difficult to be interpreted, long training time, etc.
PSO	Free from the problem information, solve problem with real numbers, strong universality, few parameter adjustment, simple theory, easy to achieve, collaborative search, fast convergence	Low accuracy, prone to divergence, has certain dependence on parameters, imperfection of the theory
Fuzzy logics	Precise mathematical models are not required, strong robustness, easy to achieve	Low accuracy, lack of systematic design
SVM	Suitable for small sample machine learning problems; can improve generalization performance, solve high dimensional problems, solve nonlinear problems, and avoid Neural network structure selection and local minimum point problem	Sensitive to missing data, no general solution for nonlinear problems
GA	Fast random search capability unconfined in problem domain, potential parallelism and good robustness, simple process, use probability mechanism to conduct iteration with certain randomness, extensible and easy to be combined with other algorithms	Complex programming, problem decoding is required after the determination of optimal solution, accurate solution requires more training time, etc.

AI can be employed in the oil and gas industry for dynamic production predictions, development plan optimization, identification of oilfield development, fracture detection, oilfield diagnosis, and enhanced oilfield recovery (Li et al., 2021).

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Predictions using AI are some of the fundamental necessities in reservoir engineering and oilfield development. Dynamic predictions are often used to give optimum predictions. The most common method is to combine neural networks with fuzzy logic to obtain optimal accuracy of the production data (Anifowose et al., 2011).

In Table 3, the AI applied to the oilfield development is primarily focused on fluids and water content rather than oil processing speed. However, the combination of AI algorithms has the potential to make dynamic predictions based on the desired result, and there may be a need to perform with many algorithms at once (Li et al., 2021).

Table 3. Dynamic predictions using AI in oilfield development (Li et al. 2021).

Method	Input parameters	Output parameters	Errors
ANN	Gas prices; GDP growth rate; annual depletion; wells drilled; footage drilled and other properties.	Gas production	0.0034 (MSE)
BP	Temperature; pressure; superficial gas velocity; superficial liquid velocity	Liquid holdup	8.544 (SD)
GNN + IPSO	liquid producing capacity	Water content	1.37% (MAPE)
BP	Remaining geological reserves; total number of production wells, monthly injection–production ratio; kernel function; number of open injection wells, newly opened production wells and old wells with efficient treatment	Monthly oil production and liquid producing capacity	2% (MAPE)
PCA + APSO + LSSVM	Remaining geological reserves; injection–production ratio; water content; number of open wells, open injection wells, newly opened production wells and old wells with efficient treatment	Oil production	0.1485 (RMSE)
ANN	Porosity; velocity; horizontal permeability et al.	Oil production cumulative	–
BP	Deep; GR log; neutron log; density log; sonic log; deep resistivity log; dizgenesis	Porosity; permeability	–
MLPNN	Distributed temperature sensing; distributed acoustic sensing; daily flowing time	Gas production	–
ANN + ANFIS	Gamma ray; density; neutron; three different resistivity's; caliper; porosity	Water sateration	0.07 (MSE)

A developing plan for the oilfield development is critical due to the complications involved with the processing. Optimization using AI is mainly applied to improve production considering economic components. The input parameters often widely vary, so adaptable algorithms are used to compensate (Aung et al., 2020).

Below in Table 4, plan optimization using different AI algorithms is shown. The most customary algorithms used are ANN and GA A standard AI system should be utilized for a multi-dimensional study in oilfield development planning.

Table 4. Plan optimization using AI algorithms in the oil and gas industry (Li et al. 2021).

Method	Input parameters	Output parameters
BP	Net present value; profit investment ratio; investment payback period; total investment; average cost; cumulative oil production; oil and gas ratio	Expected value
PNN +GA	Realizable net present value; porosity; permeability; temperature; initial pressure	Gas production
BP	Final recovery; maximum recovery rate; net present value; total profit and internal profitability; annual decline rate; total investment; dynamic payback period and average unit cost	Expected value
NARX	Energy production; energy use; final consumption expenditure; gross domestic product; gdp growth; gold price; oil rent	Predicting oil price movements
QPSO	12 measures and unit price	Annual production; cumulative production ratio
FCM	Fuzzy clustering parameters mainly include porosity, permeability variation coefficient, contained area, residual reserve abundance and water flooding control extent	Oil production; recovery and water content

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Identifying residual oil is a principal matter in oil and gas development. However, before applying the recommended methods in Table 5, more research should be conducted considering the possible applications of other methods applied in other fields, such as rapid identification.

Table 5. Identification of residual oil using AI algorithm methods (Li et al. 2021).

Method	Input parameters	Output parameters
BP	Sand body type, injection–production relationship, connection status between the estimated well and the injection–water well, distance from the injection–water well, and water injection status	The water flooded degree
BP	Net present value, profit investment ratio, investment payback period, total investment, average cost, cumulative oil production, oil and gas ratio	Expectations
BP	Concavity, roundness, aspect ratio, rectangularity, eccentricity, and radius ratio	Island shape, network shape, strip shape, column shape, plug shape, membrane shape

Surface structure, property features, and the categorization of fracture are often studied to detect fractures in the oil and gas industry. It is often a complicated process, and implementing AI is a reliable and easy method. In Table 6, some recommendations for AI are used for fracture detection. The identification accuracy may increase by combining the seismic and logging data and the AI algorithm to attain dynamic identification.

Table 6. Fracture detection using AI (Li et al. 2021).

Method	Input parameters	Output parameters
BP	Orientation, aperture, surface roughness, alteration degree, mineral fillings, and other properties	The conductive state of individual fracture
BP	Neutron porosity, volume density, acoustic time difference, depth and shallow lateral resistivity, natural gamma spectrum	Fracture density in well log interpretation and core description
BP	Reflection intensity, Root Mean Squared amplitude and arc length properties, coherence, curvature, ant body and instantaneous frequency	Fracture density
ML +DBA +SVM	Surface treating pressure, clean and slurry pump-rates, surface and downhole amounts of 100 mesh and 30/50 mesh sand proppants	Automatically classify hydraulic fractures
PSO + LSSVM	Mud body integral number, resistivity differential ratio, induced porosity, density ratio, acoustic time difference ratio and compensated neutron ratio	No filling, argillaceous filling, siliceous filling and the crystallization of filling
CNN	Borehole diameter, acoustic wave, neutron, density, gamma ray, shallow laterolog, deep laterolog	Fracture reservoir types
ANN	Bottom pressure; the regularization parameter	Closure pressure
ANN	weight on bit; rotation per minutes; rate of penetration; mud weight; pore pressure	Fracture pressure

7. How AI/ML Can Be Used to Treat Oil and Gas Wastewater/Produced Water

AI is a tool with expanding uses in many industries to help solve and optimize problems using human-like capabilities. Water is a precious resource on Earth. While abundant most of it is unusable without treatment. AI, specifically artificial neural networks (ANN), can be used as a regression model, and genetic algorithms (GA) as a global optimization technique, have been implemented in multi-purpose applications for the desalinization and treatment of water (Aani, Bonny, Hasan, Hilal 2019). AI has proven to be a reliable tool in handling complex and difficult problems, especially when it comes to optimization modeling. ANN is considered a black box model because of its ability to model any given process without the need for extensive knowledge (Aani, Bonny, Hasan, Hilal 2019).

Essentially numerical equations and detailed information assuming characteristics that help describe the fundamental engineering principles at play are not required for ANN to successfully

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model the process accurately (Aani, Bonny, Hasan, Hilal 2019). GA essentially evaluates all possible solutions for the given engineering or science-based problem by developing a Pareto set that gives the optimum global point and all possible solutions. This technique compares favorably for water desalination to traditional approaches that seek to guess a solution than search for a direction based on the pre-determined transitional rule (Aani, Bonny, Hasan, Hilal). Feedforward ANN has been applied extensively to membrane processes to overcome the flux drop that occurs in these processes with tremendous success compared to traditional modeling methods such as pore blocking and modeling water permeability for reverse osmosis systems. ANN's overall have shown an ability to predict consistently and accurately model different desalination technologies compared to traditional approaches. GA has been applied to optimizing desalination processes to increase the production rate with great success (Aani, et al., 2019).

The Oil and Gas industry is heavily reliant on water throughout many of its processes and could greatly benefit from the growing use of AI/ML. Hydraulic Fracturing (HF), commonly referred to as fracking, is currently the biggest contributor to the shale gas boom. HF requires 4-6 million gallons of water per well (15,000-23,000 m^3/well) pumped below the surface to free trapped hydrocarbons from shale formations (Conrad, Yin, Hanna 2020). The size and scope of this water usage and subsequent wastewater/processed water (PW) treatment would suggest favorable outcomes from the use of AI optimization. The amount of water treatment needed from the wastewater associated with HF depends on many factors, such as the starting point of the water and the intended use of the treated water. There is no shortage of water from reuse/recycling in HF, such as agricultural uses like water for non-consumption plants and even human consumption. Figure 9 illustrates a simple overview of US-produced water (Conrad, et al., 2020).

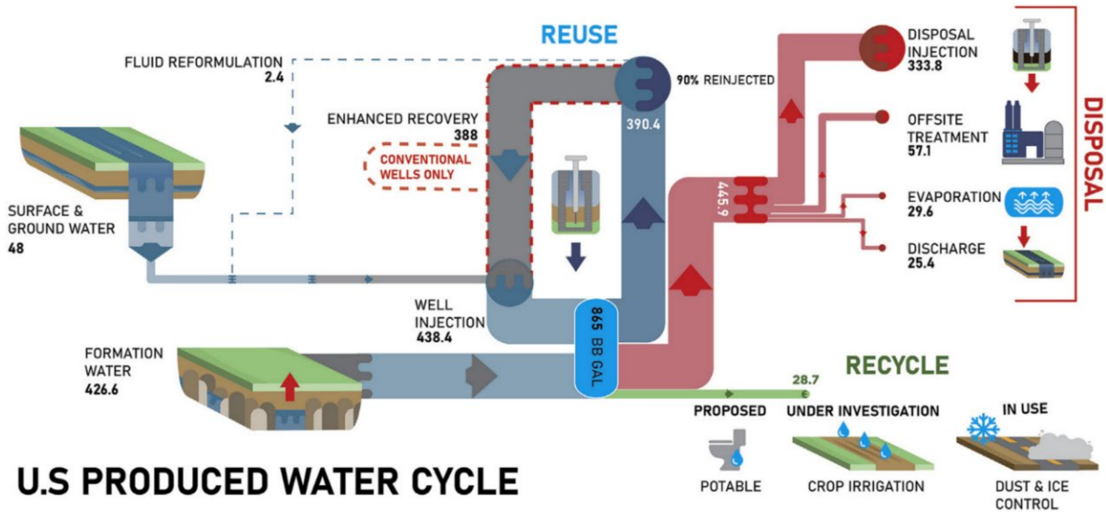

Figure 9. Produced water cycle (Conrad, et al. 2020).

Regulatory and environmental factors play a big role in treating wastewater and PW, but ultimately, cost efficiency dictates which treatments are possible. Ideally, the wastewater is treated to the exact point that is needed for its intended use and not overtreated. Any additional treatment past that point would be an unnecessary waste of money and resources; water treated too much (to the point of distilled) would be detrimental to water non-consumption plants. Currently, the cost to take the wastewater from HF and treat it until it is safe for human consumption on such a massive scale is not cost-efficient or feasible for various reasons. However, non-consumption agricultural applications represent a big opportunity, with the cost of treating the water still being the biggest hurdle. HF water process contains five stages: acquisition, fluid mixing, injection, Incidental release of produced water from HF (U-PW) handling, and end-use application. Figure 10 represents the various stages and subsequent water quality after each treatment stage. Figure 11 contains a graphical representation of the contaminants found after water treatment (Conrad, et al. 2020).

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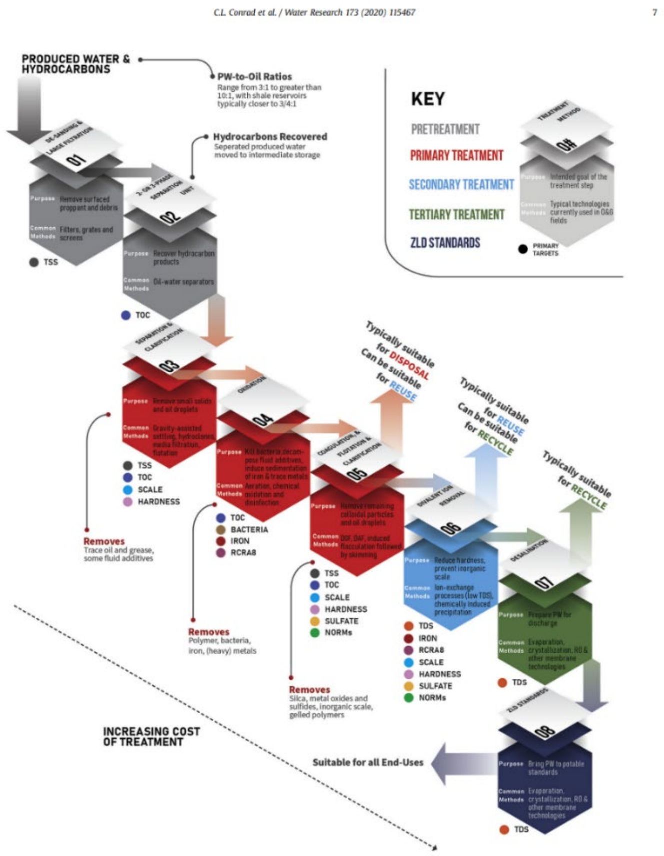

Figure 10. Block diagram of produced water treatments (Conrad, Yin, Hanna 2020).

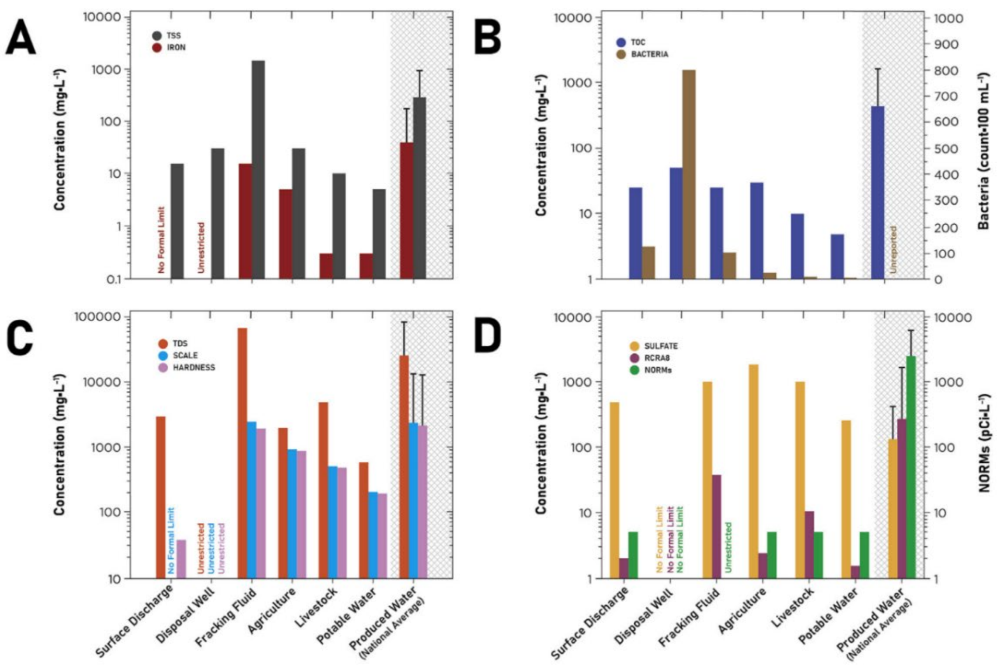

Figure 11. Final treatment goals for disposal, reuse, and recycling of wastewater/P.W. based on ten contamination metrics (Conrad, et al. 2020).

When treating HF wastewater or PW the total dissolved solids and salinity are key factors in determining which treatments are viable and how many treatments are required. When reuse is the

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wastewater's intended goal, the treatment focuses on reducing solids, residual oil and grease, iron, and certain chemical additives; repurposing desalination is usually the focus (Conrad, et al. 2020). The current technologies used for treatment are categorized as primary, secondary, and tertiary treatment (Conrad, et al. 2020).

Primary treatment removes solids, residual oil/grease, iron, HF fluid, and bacteria. Secondary treatment removes ions that can negatively affect the HF process when the wastewater or produced water is reused. Tertiary treatment is the process of removing salts using desalination. Desalination costs are the biggest hurdle limiting the options for wastewater use. Currently, it is more attractive to dispose of wastewater or reuse it to avoid additional treatment and the costs associated with desalination (Conrad, et al. 2020).

Wastewater exceeding 100,000 mg/L TDS is especially difficult to treat cost-effectively, with membrane technology being cited as the best option. However, hurdles such as membrane fouling and membrane degradation limit this as a viable option (Conrad et al. 2018). The recent advances in AI/ML could potentially bridge the technological gap between these processes. AI, such as ANN and GA, has improved and optimized desalination in water treatment. ANN specifically continues to see a huge improvement and uses in the membrane water treatment sector. Using predictive feedforward ANN or GA to optimize the process control of wastewater/P.W. treatment for reuse or ideally repurposing could reduce the cost of the process to the point that is not just environmentally appealing but economically the best route for a company (Conrad, et al. 2018, Zhang, et al. 2019).

There is always a demand for processed water, and as AI continues to develop, water treatment should become more economically attractive. As AI technology becomes more mainstream, the number of applications for AI technology is expected to increase and become more cost-effective. There is then the opportunity to shift the narrative of the wastewater/P.W. industry. AI is expected to continue advancing in its ability to optimize and cost-effectively manage the process controls of wastewater/P.W. and the opportunity to expand into the oil and gas industry, specifically in the field of HF is enormous. (Grace, et al. 2018 Conrad, et al. 2020).

8. Conclusions and Future Works

This review paper looked at wastewater in the oil and gas industry and AI/ML applications in water treatment and their applications in the oil and gas industry. With increasing environmental constraints in the oil and gas industry, recycling water for reuse plays a major role in the future. However, the biggest hurdle for reusing wastewater is the cost of treatment. With recent advancements in AI/ML, especially in water treatment, these costs could be reduced through AI/ML optimization. Wastewater in oil and gas has no exact definition because the nature of the wastewater varies greatly due to many factors such as location; because of this, accurately treating wastewater to the exact desired point for the intended use can be costly and difficult. Certain AI process controls like feedforward ANN have been proven to treat water successfully and efficiently and, therefore, could have direct applications in treating oil and gas wastewater. Millions of gallons of water are used for HF and pulled from the ground in oil and gas, presenting a great opportunity to find ways for this water to be useful and cost-effective on a large scale. AI/ML is used in the oil and gas field to help with optimization for things like production and predictive patterns. There is an opportunity to expand the use of AI/ML into the wastewater treatment sector of oil and gas as the cost and efficiency of this technology improve and the need to reuse wastewater necessitates a shift in how wastewater is handled. The overall goal of expanding AI/ML in produced water/PW treatment is to make the reuse of produced water through treatment cost-effective.

Determining the costs associated with each viable AI/ML process for treating wastewater would be needed to determine which process and strategies to implement for the given wastewater. This initial investment could then be compared to the current methods/costs, analyzed based on the expected improvement of the AI/ML process, and used to determine expected cost efficiency between the current methods versus optimization using AI/ML. Additionally, a study showing the quality and efficiency of each AI/ML process with varying wastewater would allow the industries to determine which AI/ML process they should invest in based on the expected wastewater/PW makeup. With both studies, a critical analysis could and a general conclusion can be drawn on the strengths and weaknesses of the various AI/ML water treatment options. A determination on which AI/ML process would be best suited for the given wastewater/PW based on the intended use of the treated water could be made, and then used to estimate how much better optimized the process of treating the wastewater/PW would be. This information would allow companies to determine if and when these AI/ML implementations would be worth the initial cost of implementation.

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