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Multiphase flow meter correction using AI: a case Study of tiguentourine oil field in In-Amenas

Presented by:

Hamadou Abdelalim

Yahyawi Ahmed

President	Dr. GHERBI Mohammed tahar	University of El-Oued
Examiner	Dr. Megdoud Soufiane	University of El-Oued
Supervisor	Dr. ATIA Abdelmalek	University of El-Oued
Co-Supervisor	Dr. ZOBIRI Oussama	University of El-Oued

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Dedication

To my parents,

To my family,

To my friends

List of functions

Nomenclature

Symbol	Description
α	Material Thermal Expansion α or αcone, αpipe (alpha)($°R^{-1}$)
β	Beta Ratio
C_D	Flowmeter Coefficient
d	Cone Outside Diameter (mm)
D	Pipe Inside Diameter (mm)
ΔP	Differential Pressure (DP) (mbar)
ΔP_{max}	Maximum Differential Pressure on Sizing
F_a	Material Thermal Expansion Factor
k	Gas Isentropic Exponent
k_1	
k_2	Simplified Liquid Flow Constant ($\sqrt{\frac{Kg.m^3}{S^2.mbar}}$)
μ	Viscosity (cP)
P	Operating Pressure (barA)
P_b	Base Pressure (barA)
Q	Actual Volume Flow (m^3 /s)
Q_{max}	Maximum Flowrate on Sizing
Q_{STD}	Standard Gas Volume Flow (Nm^3 /s)
Re	Reynolds Number
ρ	Flowing Density (rho) (999.012 kg/m^3)
ρ_{water}	Water Density
S_g	Specific Gravity of the Gas
S_L	Specific Gravity of the Liquid
T	Operating Temperature (K)
T_b	Base Temperature (K)
T_d	Deviation from Standard Temperature (°R)(T_d = T - 527.67)
U_1	Unit Conversion (0.001 barA/mbar)
U_2	Unit Conversion (1,000,000 mm^2 /m^2)

U_3	Unit Conversion (100 kg/m s^2 mbar)
U_4	Unit Conversion
U_5	Unit Conversion (348.338 K kg/m^3 barA)
v	Velocity (m/s)
Y	Gas Expansion Factor
Z	Gas Compressibility
Z_b	Base Gas Compressibility

General Introduction

General Introduction

Oil and gas flow rates in petroleum wells are important and pose a significant challenge for oil companies. It is a top priority for operators to maintain high production rates, and many crucial decisions within the company are based on these data, such as improving productivity, increasing investment, or withdrawing from the project.

The flow rate from the well is measured after the shared processing facility, where the products are separated. This process involves measuring each component using single-phase meters. To determine the well's flow, it is connected to a well testing operation, and the total output of the field is divided by the individual well's production. However, this method's performance is weak as there is a time difference between each measurement operation and the wells are not measured during production but individually during testing.

There is a method for calculating flow rates in natural conditions and online, which involves using a multiphase flow meter. However, this solution still has performance limitations as it has a 5% error rate and requires recalibration with changing operating conditions.

This study will present a multiphase flow meter from the Ain Amenas Tigantourine field and improve available data. We will analyze this data using a machine learning algorithm based on statistical and mathematical methods for simulating multiphase flow.

There are few commercially available solutions for this if they existed and there is a growing interest in their development [1]. The success primarily depends on the availability of devices and data, improved machine learning tools, and an increased number of practitioners. Additionally, with the decline in oil and gas profit margins, there is a search for more efficient solutions with lower costs.

We think that this solution may provide a resolution for companies as it meets their requirements and is an expandable field. It relies on data and only requires monitoring the flow rate for calibration, unlike the mechanical model, which is challenging to maintain due to its complexity.

However, implementing this solution requires trained employees experienced in multiphase flow metering and production allocation [2].

The researchers took the well data on the surface of the pressure, temperature, oil to gas ratio, and built a neural network algorithm, which gave very satisfactory results and reduced the error rate by a large percentage

Other researchers predicted the flow of the well through the surface data and gave their results so that they could dispense with the periodic measurement operations of the well [1-3]

Another study was presented of three possible scenarios for the development of artificial intelligence in the oil and gas industry and the possibility of developing it in the coming years [4, 5]

A study was presented in which 55 wells were modelled and studied, and the results gave a decrease in the step rate up to 50 % [6, 7]

Chapter I: Generality of Multiphase flow meter

I.1. Notion fundamental of Multiphase flow meter

The flow rates of two or more phases (such as gas, liquid, and solid) through a pipeline can be measured with multiphase flow meters. Here are some basic ideas about multiphase flow meters:

1. Flow Regimes: Stratified flow, annular flow, slug flow, and scattered flow are just a few examples of the several flow regimes that multiphase flow may display. For correct metering, it is essential to understand the flow regime.

2. Phase Fraction: The volumetric fraction of each phase in the mixture is referred to as the phase fraction. Phase fractions are frequently needed in multiphase flow meters in order to precisely compute the flow rates.

3. Phase Velocity: Phase velocity is a measure of how quickly each phase moves through the pipe. For accurate metering, the velocity of each phase must be measured or estimated.

4. Phase Distribution: Multiphase flow meters must describe how the various phases are distributed spatially inside the pipe. This data aids in identifying the flow pattern and allocating the proper measuring method.

5. Measurement Techniques: Multiphase flow meters use a variety of measurement techniques, such as nuclear-based methods, electromagnetic methods, acoustic methods, and methods based on differential pressure. Each method has its benefits, drawbacks, and applicability for certain applications.

6. Calibration: Multiphase flow meters need to be calibrated in order to create a connection between readings from the meters and real flow rates. To achieve precise measurement, this calibration procedure uses established phase fractions and reference flow rates.

7. Uncertainty: To evaluate the precision and dependability of the data, uncertainty analysis is essential for multiphase flow meters. It is easier to assess the overall measurement quality when you are aware of the measuring technique and flow conditions uncertainties [3].

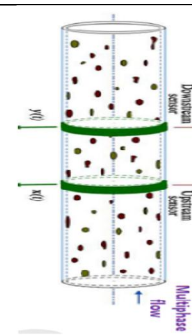
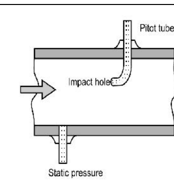
I.2. Definition

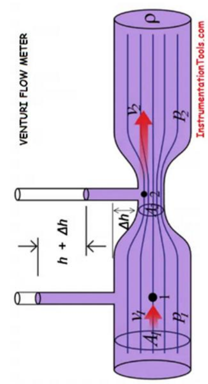
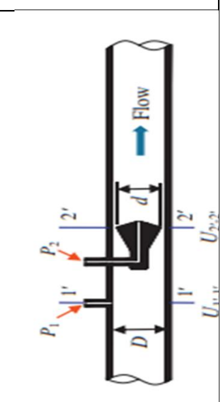
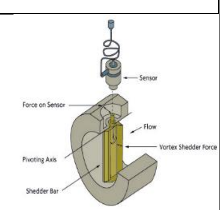
A multiphase flow meter is a device that is used to measure the flow rates of many phases (such as gas, liquid, and solid) concurrently in a pipeline or process. This may be accomplished by measuring the flow rates of a multiphase flow meter. It is intended to handle mixtures that contain multiple phases and correctly estimate the specific flow rates of each phase that is contained within the mixture.

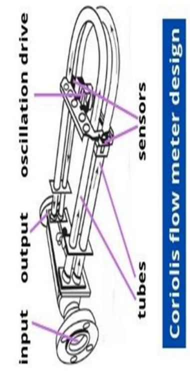
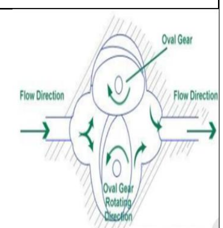
The simultaneous measurement of many phases is crucial for the process optimization, production monitoring, and allocation objectives served by multiphase flow meters, which are utilized in a variety of sectors, including the production of oil and gas, the processing of chemicals, and mining. Multiphase flow meters are utilized in these industries [3].

To capture the flow characteristics of each phase, these meters use a variety of measuring concepts and technologies, which are distinct from one another. The following table 1 are some examples of typical types of multiphase flow meters:

Table 1: MPFMs with their respective advantage and disadvantage[8]

Technology	Advantages	Disadvantages	Figure
Cross Correlation	- Can be non-invasive and not intrusive (i.e. using acoustic sensors - Do not cause pressure loss - Can accurately determine the flow rate over an extremely wide range of Reynolds number	- not accurate in case of a steady flow - The placement of the two sensors may not be adequate for all types of flows	 Figure 1: Cross Correlation
Pitot Tube	- Very less pressure drop - Mature technique with several commercially available probes	- Not accurate enough, especially for low flow rates - Uncertainty increases with the decrease of Reynolds number Re	 Figure 2:Pitot Tube

Venturi meter	- Causes less pressure drop than orifice plate and provide reasonable accuracy - Suitable for medium and large diameter pipes (>2" diameter pipes)	- Relatively low turn down ratio (1:10) - Do not handle unsteady state flow - Not accurate for low flow rates - Uncertainty increases with the decrease of Reynolds number Re. and with the decrease of the liquid phase fraction - Not adequate for small diameter pipes(<2"pipes)	 Figure 3: Venturi meter
V-cone meter	- More accurate than the Venturi meter for wet gas measurement - Wide turndown, short straight length. and stable signals	- Not standardized flow meter. Lack of independent measurements.	 Figure 4: Venturi meter
Vortex flow meter	- Accurate meter for gas steam - Simple design of the transmitter	- The accuracy may be altered by the external pipe vibrations especially for low flow rates	 Figure 5: Vortex flow meter

Coriolis flow meter	- Can measure both the density and mass flow rate of the fluid - May be used for custody transfer metering of pure crude oil	- For custody oil transfer, dissolved gas may cause significant uncertainties on the actual mass of the pure oil. - Relatively fragile to operate in harsh environment (e.g. Multiphase flow with sand) - Not adequate for liquid-gas multiphase flow - Relatively costly and cumbersome - Operate at relatively low pressure: Not adequate for downhole measurement	 Figure 6: Coriolis flow meter
Positive Displacement flow meter	- Accurate for custody transfer of oil -Mature technology	- Comprises mechanical parts - Factory calibration of the meter for oil viscosity is required	 Figure 7: Positive Displacement flow meter

I.3. Case stady

A study of the multiphase flow meter used in this study, which is the approved multiphase flow meter for measuring the flow of wells in In-Amenas.

McCrometer offers two types of V-Cone primary elements: the precision tube V-Cone and the Wafer-Cone. Precision tube V-Cones figure 7 range in line sizes from ½ to 150 and larger and Wafer-Cones figure 8 range from 1 to 6.

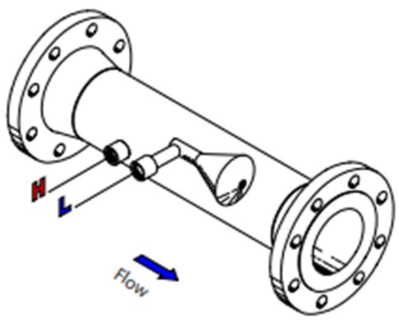


Figure 8: Precision Tube V-Cone

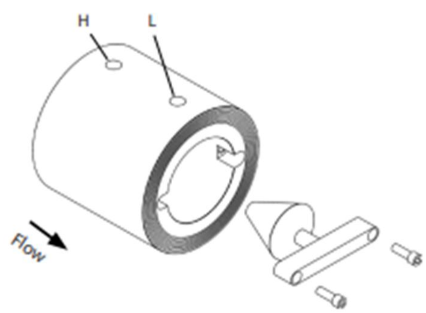


Figure 9: Wafer-Cone

I.3.1. Flow Calculations

In table 2 we present all the equations used in this multiphase flow meter

Table 2: General Flow Calculations

Number of function	Tag	Name of function	Functions
3.1	3.2.1	V-Cone Beta Ratio	$\beta = \sqrt{1 - \frac{d^2}{D^2}}$
3.2	3.2.2	Flow Constant	$k_1 = \frac{\pi * \sqrt{2U3}}{4U2} * \frac{D^2 * \beta^2}{\sqrt{1-\beta^4}}$

3.3	3.2.3	Material Thermal Expansion Factor(note 1)	$Fa=1+2*\alpha*T_d$
3.4	3.2.4	Material Thermal Expansion Factor if cone and main pipe are made of different materials(note 1)	$Fa=\frac{D^2-d^2}{[(1-a\ pipe*Td)*D]^2-[(1-a\ cone*Td)*d]^2}$
3.5	3.2.5	Pipeline Velocity	$v=\frac{4*U2*Q}{P*D^2}$
3.6	3.2.6	Reynolds Number	$Re=U4\frac{v*D*r}{u}$
3.7	3.2.7	V-Cone Gas Expansion Factor	$Y=1-(0.649+0.696*B^4)\ \frac{U1*\Delta P}{k*P}$
3.8	3.2.8	Wafer Gas Expansion Factor	$Y=1-(0.755+6.78*\beta^8)\ \frac{U1*\Delta P}{k*P}$
3.9	3.2.9	Liquid Density	$\rho = \rho_{água} \cdot S_L$
3.10	3.2.10	Gas Density	$\rho=U_5*\frac{Sg*P}{Z*T}$
3.11	3.2.11	Actual Volume Flowrate(notes 2, 3 & 5)	$Q=F_a*C_D*Y*k_1*\sqrt{\frac{\Delta P}{\rho}}$
3.12	3.2.12	Standard Gas Volume Flowrate	$Q_{STD}=Q*[\frac{P*Tb*Zb}{Pb*T*Z}]$

Note:

Material Thermal Expansion – The thermal expansion equations correct for dimensional changes which occur as the operating temperature deviates from the base temperature of 68° F (see 3.2.3 and 3.2.4) The F_a factor can be excluded from the flow equation if the operating temperature is:

< 100° Fahrenheit, < 559.67° Rankine, < 37.78° Celsius, < 310.93 K.

If the F_a factor is significant and the operating temperature is stable then a constant Fa value can be used.

If the F_a factor is significant and the temperature varies then a F_a factor should be calculated prior to every flow calculation.

2. Discharge Coefficient – Discharge coefficients can be implemented in the flow equations via several different methods. Typical methods are average CD, CD look up table, or CD fitted data. If a CD look up table or fitted data is utilized additional calculations must be made based on the Reynolds number (see example process 3d and 5b).

3. Liquid – Typical Calculation Process

a. Given: D, β, ρ, C_D, and input of ΔP

Calculate: 3.2.2, 3.2.11

b. Given: D, β, ρ, C_D, and input of ΔP, T

Calculate: 3.2.2, 3.2.3 or 3.2.4 if req., 3.2.11

c. Given: D, β, S_l , C_D, and input of ΔP, T

Calculate: 3.2.2, 3.2.3 or 3.2.4 if req., 3.2.9, 3.2.11

d. Given: D, β, μ, ρ, C_D look up, and input of ΔP

Calculate: initially set CD = 0.8, 3.2.2, 3.2.3 or 3.2.4 if req., 3.2.11

3.2.5 → 3.2.6 → Look up C_D → 3.2.11

Iterate until flowrate is <0.01% different from last calculation

4. Simplified Liquid Calculation – The simplified liquid calculation can be used if the operating temperature is stable and the CD is constant. The simplified flow constant (k_2) can be calculated from equation 3.3.1 using the V-Cone Application Sizing sheet. The flowrate can then be calculated using equation 3.3.2. Units of measure will be the same as those listed on the V-Cone Application Sizing sheet.

5. Gases and steam – Typical Calculation Process:

a. Given: D, β, μ, S_g , Z, k, C_D, and inputs of ΔP, P, T

Calculate: 3.2.2, 3.2.3 or 3.2.4 if req., 3.2.7 or 3.2.8, 3.2.10, 3.2.11

b. Given: D, β, μ, S_g, Z, k, C_D look up, and inputs of ΔP, P, T

Calculate: initially set C_D=0.8, 3.2.2, 3.2.3 or 3.2.4 if req., 3.2.7 or 3.2.8, 3.2.10, 3.2.11

3.2.5 → 3.2.6 → Look up C_D → 3.2.11

Iterate until flowrate is <0.01% different from last calculation

6. Fluid Properties – Fluid properties such as velocity, compressibility and isentropic exponent vary with temperature and to some extent pressure. The viscosity in the calculations above could affect the selected CD value, the compressibility directly effects the density and the isentropic exponent effects the Y factor, although to a small degree. The instrumentation industry uses many different approaches to calculate flow. McCrometer application engineering and the customer must determine which fluid properties are calculated at each set of flow conditions and which properties are constant

Chapter II: The Intelligent Artificial and using in oil and gas

II.1. Definition of AI

Artificial intelligence (AI) is the fourth revolution, there is no constant definition of the field, so it is defined as a domain that is concerned with developing computers capable of engaging in human-like thinking operations such as learning, inference, and self-learning and is also defined as the improvement of machines that are usually believed to be like human think like Learning, adapting and self-correction is also defined as the extension of human intelligence through the use of computers, or more precisely is to improve the use of computers more effectively through improved programming techniques and all the definitions change over time because the field of artificial intelligence is still developing rapidly.

As for the oldest definition of artificial intelligence, which is the definition by Alan Turing, it is the ability of a computer to answer human questions without the power of a person to differentiate whether the respondent is a human or a computer [11].

II.2. The algorithms using AI

Machine Learning relies on different algorithms to solve data problems. Data scientists like to point out that there's no single one-size-fits-all type of algorithm that is best to solve a problem. The kind of algorithm employed depends on the kind of problem you wish to solve, the number of variables, the kind of model that would suit it best and so on. Here's a quick look at some of the commonly used algorithms in machine learning (ML) [12]**.**

II.2.1. Supervised Learning

Supervised learning uses example input-output pairs to learn a function that maps input to output. Labelled training examples are used to infer a function. Supervised machine learning algorithms require support. Train and test datasets are input. Predict or classify the train dataset output variable. All algorithms use training dataset patterns to predict or classify test datasets. Supervised machine learning workflow is shown below. Here are the most popular supervised machine learning algorithms[9].

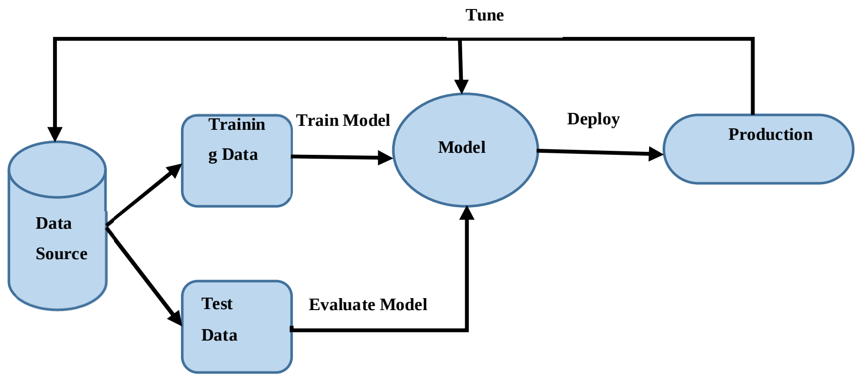


Figure 10: Supervised Learning Workflow

II.2.1.1. Decision Tree

Decision trees show choices and their outcomes as a tree. The edges represent decision rules while the nodes represent events or choices. Trees have nodes and branches. Each node represents attributes in a group to be categorised and each branch represents a value for the node[9].

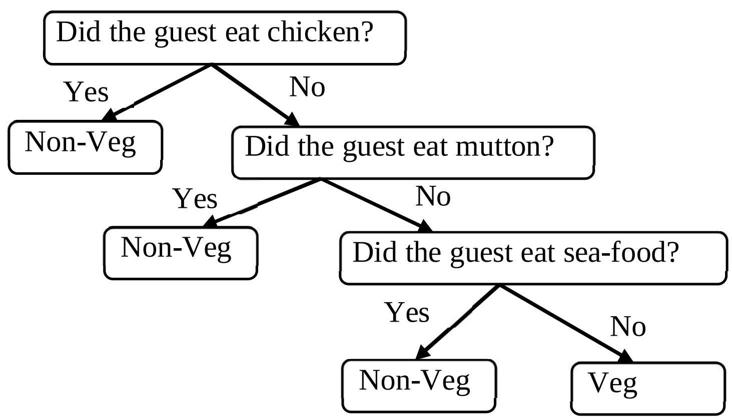


Figure 11: Decision Tree

II.2.1.2. Navie Bayes

Bayes Theorem-based categorization assumes predictor independence. A Naive Bayes classifier posits that the presence of a feature in a class is independent to any other feature. Naïve Bayes targets text classification companies. Clustering and classification based on conditional probability are its principal uses[9].

II.2.2.3 Support Vector Machine

SVM is another popular modern machine learning method. Support-vector machines analyse classification and regression data in machine learning. The kernel trick implicitly maps inputs into high-dimensional feature spaces, allowing SVMs to efficiently perform non-linear classification. It divides classes. The margins are drawn to maximise the distance between them and the classes, minimising classification error[12].

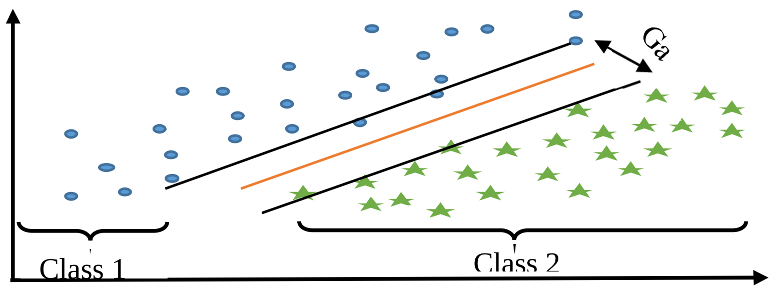


Figure 12: Support Vector Machine

II.2.2.Unsupervised Learning

Unsupervised learning has no proper answers or teacher. Algorithms find and present data structure. Unsupervised learning methods learn minimal data features. It classifies fresh data using previously learned features. Mainly used for clustering and feature reduction[9].

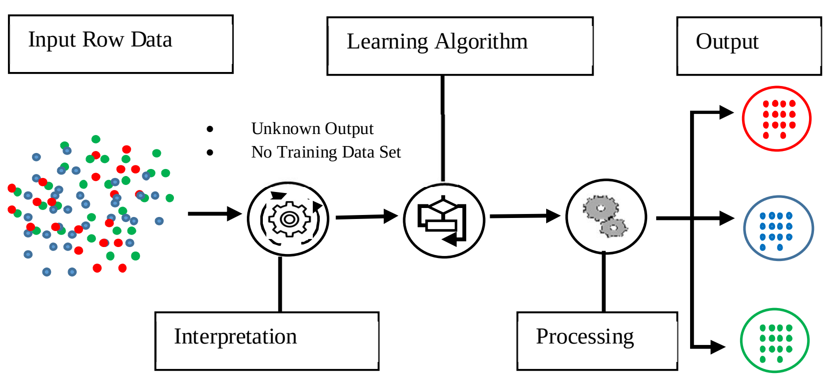


Figure 13: Unsupervised Learning

II.2.2.1K-Means Clustering

One of the easiest unsupervised learning algorithms for clustering is K-means. The approach uses a simple clustering method to classify a data set. Define k cluster centres. Because location affects results, these centres should be strategically situated. Thus, placing them far apart is best.

Next, assign each data set point to the nearest centre. The first step and early group age are done while no point is pending. Recalculate k new centroids as bray centres of the clusters from the previous phase [12].

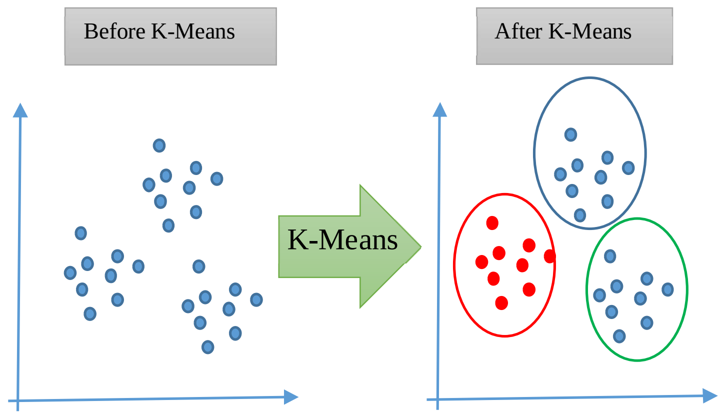


Figure 14: K-Means Clustering [9]

II.2.2.2Principal Component Analysis

Principle component analysis is a statistical method that applies an orthogonal transformation to turn observations of possibly correlated variables into values of linearly uncorrelated variables called principal components. To simplify computations, data dimensions are lowered. Linear combinations of variables explain their variance-covariance structure. It often reduces dimensionality[9]

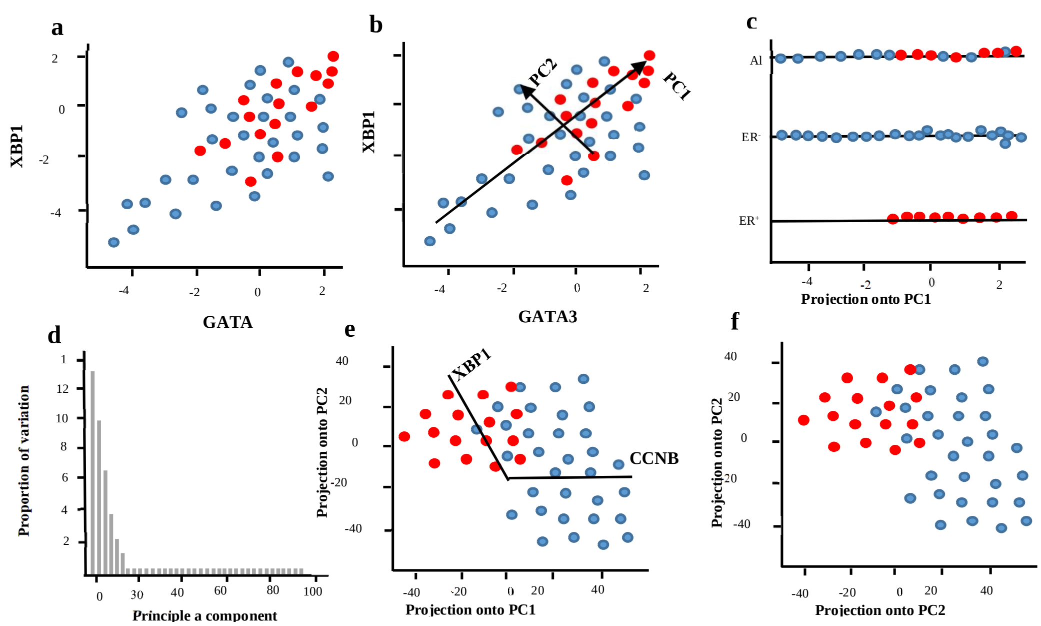


Figure 15: Principal Component Analysis [12]

II.2.3.Semi Supervise Learning

Semi-supervised machine learning is supervised and unsupervised. It can be useful in machine learning and data mining where unlabelled data is already present and labelling it is cumbersome. In supervised machine learning, you train an algorithm using a "labelled" dataset with outcome information. Below are some semi supervised learning algorithms[9].

II.2.3.1Transudative SVM

Semi supervised learning with transudative support vector machines (TSVM) is common. Due of a lack of generalisation, it has been shrouded in mystery. It labels unlabelled data to maximise the margin. TSVM precise solution is NPhard[9].

II.2.3.2. Generative Models

Generative models generate data. It models features and class (full data). P(x,y) techniques are generative because I can utilise this probability distribution to generate data points. One labelled example per component confirms mixed distribution[9].

II.2.3.3. Self-Training

A classifier self-trains with labelled data. The classifier receives unlabelled data. The training set combines unlabelled and anticipated labels. Repetition follows. The classifier is self-training[9].

II.2.4. Reinforcement Learning

Reinforcement learning focuses on how software agents should operate in an environment to maximise cumulative reward. Reinforcement learning is one of three machine learning paradigms: supervised, unsupervised, and reinforcement[9].

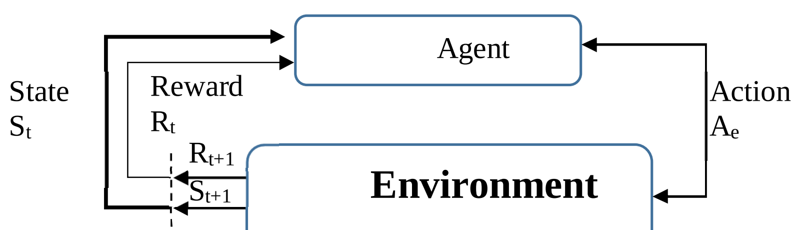


Figure 16: Reinforcement Learning [12]

II.2.5.Multitask Learning

Multi-Task Learning, a subfield of Machine Learning, uses similarities between tasks to solve numerous tasks at once. This enhances learning and regularises. Formally, Multi-Task

Learning (MTL) improves model learning by using the knowledge in all n tasks (conventional deep learning approaches aim to solve just 1 task using 1 model) [9].

II.2.6. Ensemble Learning

Ensemble learning involves intentionally generating and combining classifiers or experts to tackle a computer intelligence challenge. Ensemble learning is used to improve model performance or lessen the risk of selecting a bad one. Ensemble learning can also be used for model confidence, data fusion, incremental learning, nonstationary learning, error correction, and feature selection[9].

II.2.6.1. Boosting

Boosting algorithms turn weak learners into strong learners. Boosting reduces bias and variation in ensemble learning. Kearns and Valliant’s "Can a set of weak learners create a single strong learner?"

Inspired boosting. A weak learner is a classifier, while a strong learner is arbitrarily well-correlated with the true classification[9].

II.2.6.2. Bagging

Bagging or bootstrap aggregating improves machine learning algorithm accuracy and stability. For categorization and regression. Bagging reduces variation and overfitting[9].

II.2.7. Instance-Based Learning

Instance-based learning is a family of classification and regression methods that classify queries based on their resemblance to their nearest neighbours in the training set. Instance-based learning algorithms do not abstract from instances, unlike decision trees and neural networks. They save all the data and use the nearest neighbor(s) to answer requests[9].

II.2.7.1. K-Nearest Neighbor

The basic, supervised k-nearest neighbours (KNN) technique helps tackle classification and regression problems. It's simple[9].

II.2.8. Neural Networks

A neural network is a set of algorithms that mimics the brain to find hidden links in data. Neural networks are biological or artificial neuron systems. Neural networks adapt to changing input and produce the optimum result without changing output criteria. Trading platforms are increasingly using artificial intelligence-based neural networks[9].

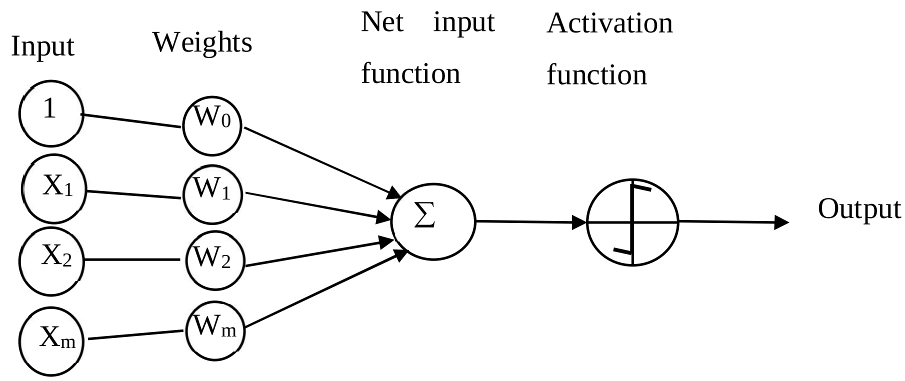


Figure 17: Neural Networks

Artificial neural networks behave similarly. It's three-layered. It receives input. Hidden layers process input. Finally, the output layer provides calculated output[9].

II.2.8.1 Supervised Neural Network

The input output is known in the supervised neural network. The neural network's output is compared against its prediction. The neural network is fed again after changing the parameters based on the error. Feed forward neural network uses supervised neural network[9].

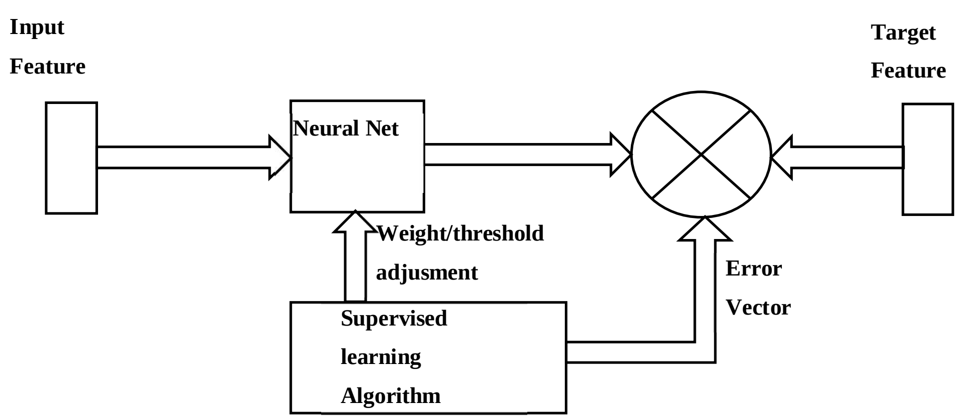


Figure 18: Supervised Neural Network [12]

II.2.8.2 Unsupervised Neural Network

The neural network doesn't know the input's output. The network sorts data by similarity. Neural networks aggregate inputs by correlation[9].

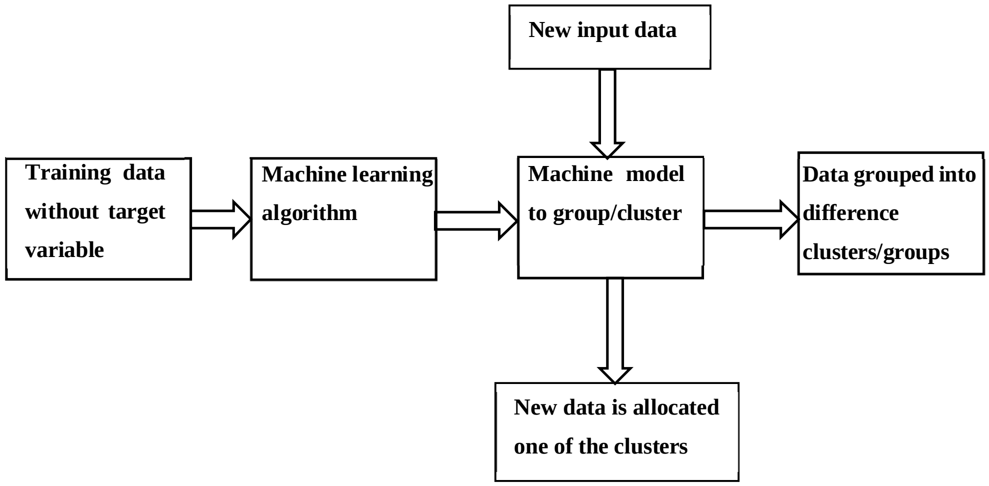


Figure 19: Unsupervised Neural Network

II.2.8.3. Reinforced Neural Network

Reinforcement learning algorithms train to achieve a complex goal or maximise along a dimension over many steps, such as maximising game points over several moves. They may start from scratch and perform superhumanly under certain conditions. These algorithms are reinforced by spankings and candy, like children[9].

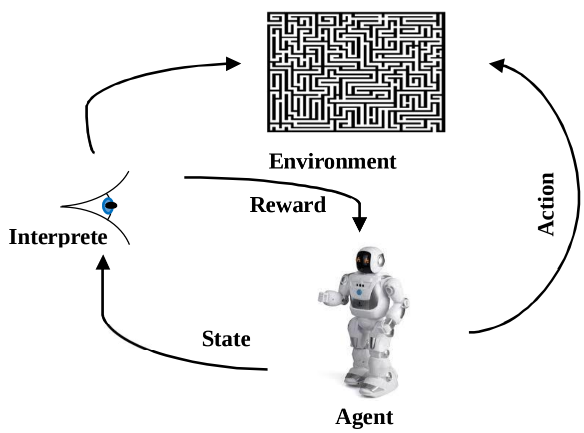


Figure 20: Reinforced Neural Network [12]

II.2.8.3. Artificial neural network (ANN)

Machine learning includes deep learning. Deep learning uses Artificial Neural Networks to understand data. ML models data using neural networks. Deep learning algorithms in the oil and gas industry process massive amounts of data and optimize performance. Automatically selected features. Deep learning algorithms execute complex operations while machine learning algorithms cannot. Neurons process inputs. ANN solves complex issues via machine learning.

Nonlinear and difficult problems in oil and gas sectors are tackled with ANN. FF-ANN forwards hidden neuron information[10].

Neural networks can increase seismic pattern recognition, drill bit diagnosis, gas well production, sandstone lithofacies identification, well performance prediction, and optimization[11].

ANN models assist operators assess and anticipate pipeline conditions. ANN and other algorithms predict pipe failure and mechanical dependability[12].

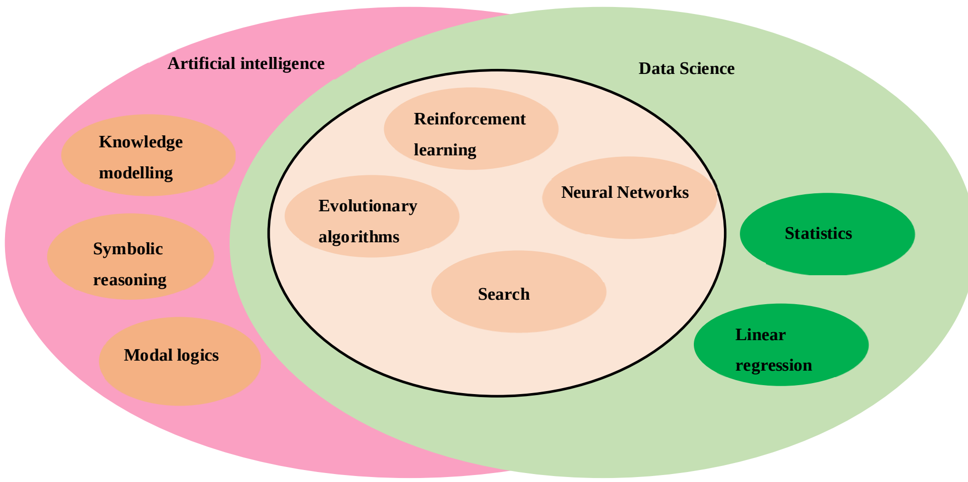


Figure 21: The relationship between diversified fields of Artificial Intelligence [16]

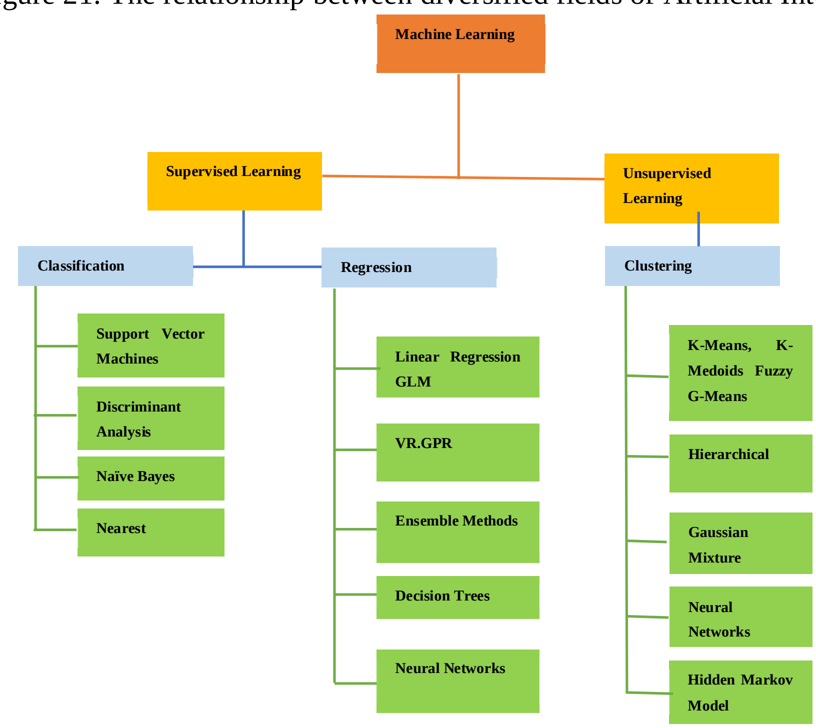


Figure 22: Steps involved in Machine Learning Problems

II.3 Machine learning in upstream

Data processing improves device performance. Oil and gas producers and explorers should leverage computational power[13].

II.3.1 Exploration

Hydrocarbon exploration is risky. Drilling and hydrocarbon extraction require accurate subsurface prospect identification. Subsurface mapping and limited 2D seismic data were used to locate drilling sites in the early 21st century. Success was 1:7 due to risk. More data was collected in each exploration lease over time. With advances in seismic and well data gathering, processing, and interpretation, big data was stored in Terabytes. Machine learning analysed these enormous data. Big data and machine learning enhance signal-to-noise ratios during acquisition and processing. Strong algorithms interpreted 2D, 3D, and 4D seismic data from clean data. An interpreter used well logging and accurate subsurface horizon mapping to create subsurface volume maps and amplitude, porosity, and saturation maps. Inversion was used to comprehend subsurface model data parameters[14].

Machine learning techniques helped identify horizon and window-based sweet spots. Machine learning produced coherency, edge map, spectral decomposition, and relief map. Understanding fault polygons, complex fault structures, and facies mapping using striatal slicing increased subsurface prospect understanding. Machine learning algorithms converted prospects into drillable prospects and increased success to 1:3. 4D or repeat seismic assisted interpreters understand hydrocarbon flow following drilling[15].

Heuristic and artificial neural network methods are currently used to refine target prospects, size, and hydrocarbon volume Figure 23**.** Monte Carlo simulation and evolutionary programming are used to estimate the subsurface's stochastic hydrocarbon range and how much can be extracted. Machine learning changed the exploration and production regime in India and the world[15].

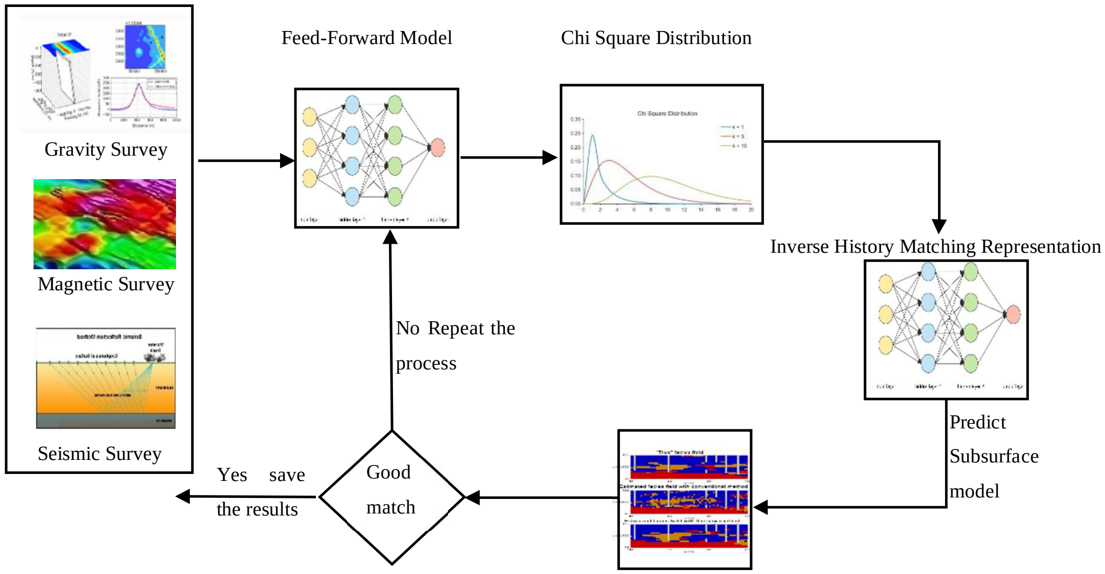


Figure 23: Exploration outline for data processing and interpetation using learning technique

II.3.2 Reservoir engineering

ANN has long estimated reservoir parameters including permeability and porosity. KNN, SVR, KRR, Adaptive Boosting, and Collaborative Filtering can predict reservoir fluid characteristics[16].

Optimization algorithm to maximize oil production. The parametric study compares machine learning methods to estimate permeability, seismic characteristics, and wireline data. SVM outperformed alternative permeability prediction approaches[17]. developed an intelligent model using Extreme Gradient Boosting to forecast reservoir reaction from injector wells[18]. Selected five cases: homogeneous reservoir water flood, channelized reservoir flood, 20-model ensemble water flood, and CO2 flood in heterogeneous reservoir with complex terrain. Figure 24 shows reservoir attributes adjustment with AI-assisted history matching[13].

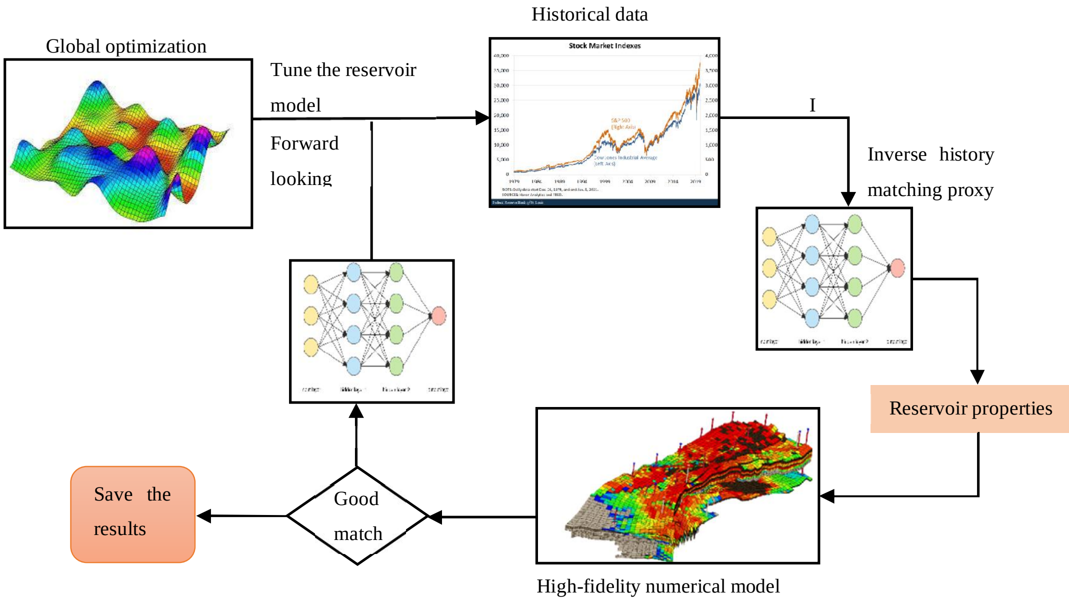


Figure 24: Reservoir modelling outline using artificial neural network

II.3.3 Production engineering

Advanced machine learning technologies streamline engineers' job. Oil and gas production engineering uses machine learning in several ways. For decision-making, analyzing huge data quickly is difficult. Machine learning can recognize manufacturing pattern data[19].

Data patterns help the ANN model forecast closing pressure. To reduce mistake, output data are compared to actual results[20].

Table 3 represents some of the studies conducted with the help of artificial intelligence for production of oil and gas.

Table 3: Used of Artificial intelligence in oil and gas production

Method	Input parameters	Output parameters
Artificial neural network	GDP growth rate, footage drilled, wells drilled, annual depletion, gas prices and other resources are all factors to consider	Production of gas

Back propagation	Temperature, heat, superficial gas velocity, and superficial liquid velocity are all factors to consider	Liquid holdup
Graph neural network þ Improved particle swami optimization	capacity to produce liquids	Water content
Back propagation	Number of open injection wells, newly opened production wells, and old wells with efficient treatment; 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 and liquid producing capacity
Principal component analysis + Adaptive particle swarm optimization þ Least squares support vector machine	Number of open wells, open injection wells, newly opened production wells, and old wells with efficient treatment; injection production ratio; water content; newly opened production wells, and old wells with efficient treatment	Oil production
Artificial neural network	horizontal permeability; porosity; velocity	Oil production
Back propagation	diagenesis; deep; GR log; neutron log; density log; sonic log; deep resistivity log	Porosity; permeability

Multi-layer perceptron neural network	regular flowing time; distributed temperature sensing; distributed acoustic sensing	Gas production
Artificial neural network + Adaptive network-based fuzzy inference system	calliper; porosity; gamma ray; density; neutron; three separate resistivities; gamma ray; density; neutron	Water saturation

Chapter III: Multiphase flow meter correction using Machine learning technics

III.1. Data description

A multiphase flow measurement test is performed to ensure proper well performance after workover (repair of an existing well). This work measured the dataset in real time using the commercial MPFM type V-con. The studied well is located in the gas field in In Amenas Tigantourine.

The dataset contains 20000 samples, and each selection includes temperature, wellhead pressure, flowline pressure and wet gas flow rate of the multiphase flow.

The data points are recorded at 1-hour intervals. Figure 25 shows variations in temperature, wellhead pressure, flowline pressure, gas allocation, LPG allocation, condensate allocation water allocation and wet gas flow rate over time measured in the experiments.

The statistical description of the dataset is presented in Table 5, which includes the count, mean, standard deviation, minimum, first quartile , median or second quartile, third quartile, and maximum values

For building a machine learning model is carried out in several stages:

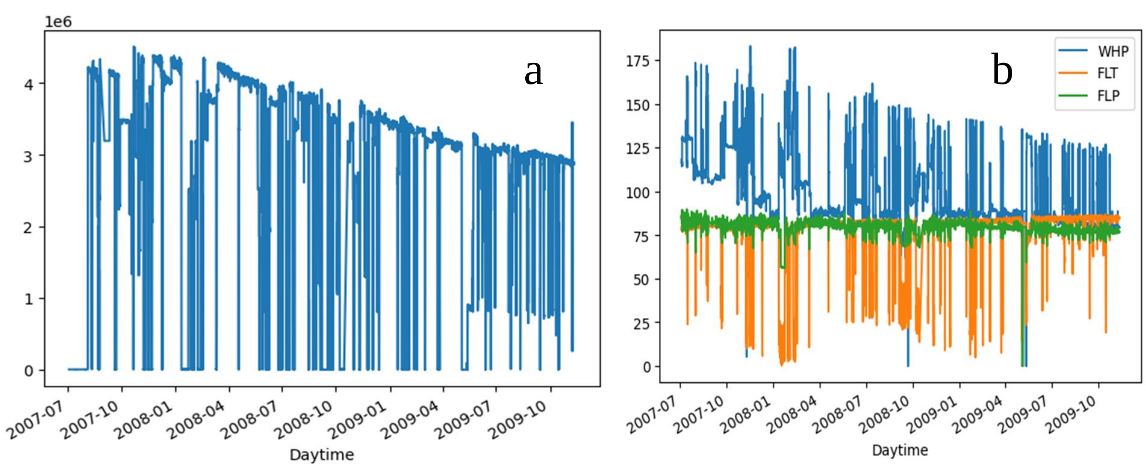


Figure 25: (a) gas flow rate, pressure (WHP, FLP) and (b) temperature

III.2. Data analysis

- Download the data from Excel format to Python, and there are many library in Python that help us in this process, including Numby, Pandas, Mathplothlib, and we show the first five lines of the data to know how to appear in the table as in the first table

Table 4: Data download from Excel to Python

Daytime	Unnamed: 0	Wet Gas Rate [SmÂ³/d]	all-gas	all-con	all-lpg	all-water	Choke Value	WHP	FLT	FLP
7/4/2007 0:00	NaN	4230.2	3640.476	0.731602	0.648285	0.03803	NaN	118.2	78.6	85.9
7/4/2007 1:00	NaN	4244.6	3652.868	0.734093	0.650492	0.038159	NaN	117.9	78.5	85.5
7/4/2007 2:00	NaN	4254.6	3661.474	0.735822	0.652024	0.038249	NaN	117.9	78.7	85.2
7/4/2007 3:00	NaN	4261.7	3667.585	0.73705	0.653112	0.038313	NaN	117.7	78.7	84.9
7/4/2007 4:00	NaN	4269.3	3674.125	0.738364	0.654277	0.038381	NaN	117.7	78.6	84.7

- Understand the data and its type, whether it is digital, date, or category, and define it according to its type, so that we know each type and how to deal with it.

- Try to deeply understand the data and exploit it through a set of operations, including knowing the missing data and recognizing its nature to fill it in, and if we cannot, we drop it. Then we change the data type as per the requirements and group the homogeneous data into groups to see the overall impact on the data.

- Description of the data and knowledge of the highest, lowest and average values, data orientation, the first quarter, the last quarter and the number of data as in the table

Table 5: Statistics the data

	count	mean	std	min	25%	50%	75%	max
WetGasRate	20000	2.83E+06	1.35E+06	0	2694877	3196553	3775009	4504774
WHP	20000	9.90E+01	2.13E+01	0	85.8	88.8	109.6	183.1
FLT	20000	7.63E+01	1.72E+01	0.2	79.7	82.1	83.5	87
FLP	20000	7.91E+01	4.89E+00	0	77.7	79.8	81.5	89.9

- 1.6 Extracting the correlation between the data, as in the figure 26 and figure 27 to find out what data has a high correlation, which are affected by each other, and the value of the effect. In this case, we use the equation:

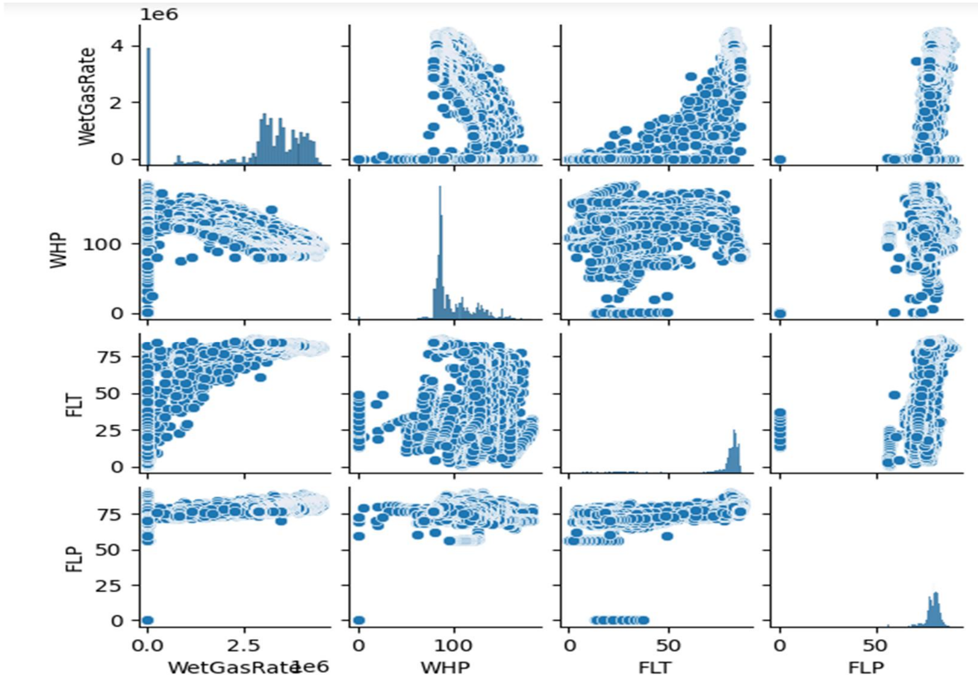


Figure 26: Pairwise correlation in the dataset

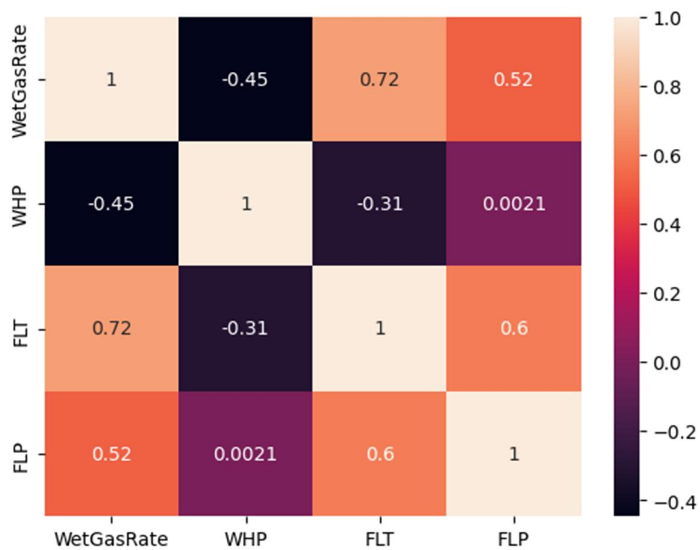


Figure 27: Heatmap plot of Pearson’s correlation coefficient.

III.3. Data training

- ✓ model structure type ANN, we use in this case two hidden layers and use rule for activation function, see the summery of model in Figure 28:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 Dense (Dense)               (None, 100)               84100

 Dense_1 (Dense)             (None, 20)                2020

=================================================================
Total params: 86,120
Trainable params: 86,120
Non-trainable params: 0
```

Figure 28: model summar

- ✓ Divided the data for 70% to training and 30% to test before that put the data in the model and start model training

III.4. Resalt and validation

Compared between test data and predict date we use MSE (main squire error) for know how the model is good or not

Finally, the model gave predict wet gas value is under the actual value around 20% not good value but bater then actual values

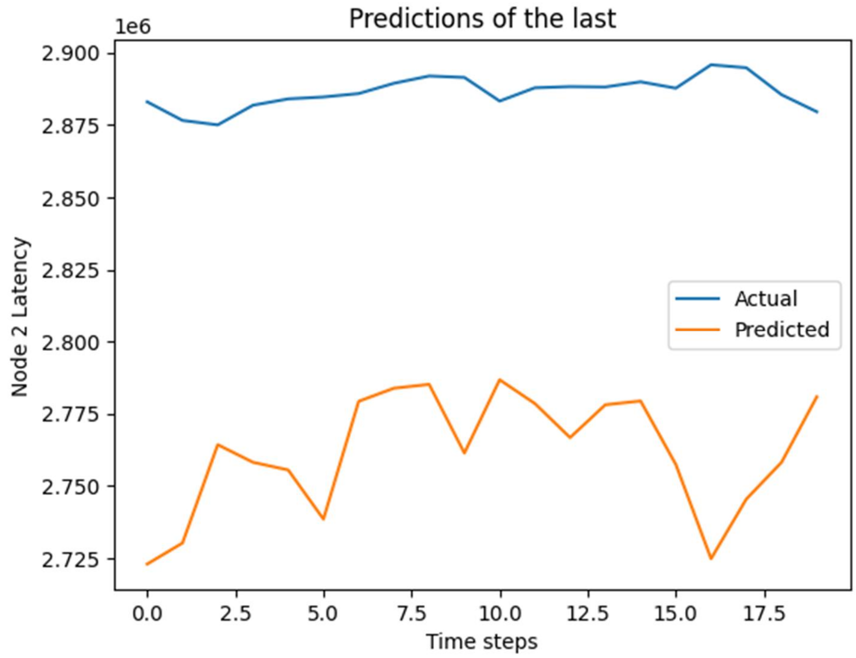


Figure 29: Predict Vs actual flow

Conclusion

In order to apply artificial intelligence in calculating the flow, we need data that are correct to some extent, and the more the data is complete and correct, the more effective the program is. To improve the ability of the modal to learn and expect good results, we will need to provide data, analyze it, and expect new results. This method gave an improvement in reading without reference. To the traditional methods of changing the meter completely or conducting the well

General Conclusion

General Conclusion

According to this study that we have done, we conclude that we can replace the periodic well measurement operations with algorithms that can be learned and improved over time, and this solution reduces the costs of operating the well and we do not need to close the well. Through our study, we concluded that there are several factors affecting the flow calculation, and these factors still pose a challenge to the algorithms for Analyzing and integrating it into computer programs, however, the algorithm provided us with a decrease in the error rate, which is a good indicator for the completion of research in this field.

Recommendations

Despite the good results of the study of machine learning in the field of oil and gas, the field is still wide for further study and in-depth, and the effectiveness of the field increases with the increase of participants and contributors to it and the increase in interest

Artificial intelligence models can be used to reduce costs and increase productivity, and the greater the investment in artificial intelligence, the greater the effectiveness

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Abstract

Thesis title: Multiphase flow meter correction using AI: a case Study of tiguentourine oil field in In-Amenas

Master: Energitic

Authors: Hamadou Abdelalim/Yahyawi Ahmed

Keywords: V cone meter, Multiphase flow meter, Intelligent artificial.

Determining the flow of the multiphase gas well is a very important information, as crucial decisions in the company are based on it, such as increasing investment, improving the performance of the wells, or withdrawing from the project permanently. Several methods are used in calculating the well flow, including the use of multiphase meters, the use of simulation programs, or the well test operation is monthly routine measurements. By a company that specializes in measuring the flow of wells with its own equipment, and all these methods lead to great risks and great losses income for the company, and the accuracy in measurement is weak because we prepare the devices within specific conditions, but when working we put it in real conditions, which are often different from the test conditions. Our solution to the problem depends on the use of artificial intelligence, and that is by suggesting that the conditions measured in it at the beginning of the operation are reference data, and we use that data in order to train the algorithm of artificial intelligence, and it predicts for us the new flow in case the measurement conditions change, and to reach the algorithm we need real data brought from a gas field in In Amnas Tigantourine, and we used data analysis methods, and to reach the most accurate data, we took the part that we assumed was correct and divided it into two parts, 70% for training the algorithm and 30% for testing the algorithm, and we used MSE main squire errore, which is a measure to calculate the accuracy of the algorithm's prediction of the data. The obtaines result was not with the required strength due to several factors that are still under study. However, it is good that it predicted for us that the real value of the flow is below the value measured in the traditional way.

Résumé

La détermination du débit du puits de gaz multiphase est une information très importante, car des décisions cruciales dans l'entreprise sont basées sur celle-ci, telles que l'augmentation des investissements, l'amélioration des performances des puits ou le retrait définitif du projet. Plusieurs méthodes sont utilisées pour calculer le débit du puits, y compris l'utilisation de compteurs multiphases, l'utilisation de programmes de simulation, ou l'opération d'essai du puits consiste en des mesures de routine mensuelles. Par une entreprise spécialisée dans la mesure du débit des puits avec son propre équipement, et toutes ces méthodes entraînent de grands risques et de grandes pertes de revenus pour l'entreprise, et la précision de la mesure est faible car nous préparons les appareils dans des conditions spécifiques, mais lorsque travaillant nous le mettons dans des conditions réelles, qui sont souvent différentes des conditions de test

Notre solution au problème dépend de l'utilisation de l'intelligence artificielle, c'est-à-dire en suggérant que les conditions qui y sont mesurées au début de l'opération sont des données de référence, et nous utilisons ces données pour former l'algorithme de l'intelligence artificielle, et il prédit pour nous le nouveau débit en cas de changement des conditions de mesure, et pour atteindre l'algorithme, nous avons besoin de données réelles provenant d'un gisement de gaz à In Amnas Tigantourine, et nous avons utilisé des méthodes d'analyse de données, et pour atteindre les données les plus précises, nous avons pris la partie que nous avons supposée correcte et l'avons divisée en deux parties, 70 % pour la formation de l'algorithme et 30 % pour tester l'algorithme, et nous avons utilisé MSE main squire errore, qui est une mesure pour calculer la précision de la prédiction de l'algorithme de la données. Le résultat obtenu n'a pas été à la hauteur requise en raison de plusieurs facteurs qui sont encore à l'étude. Cependant, il est bon qu'il nous prédise que la valeur réelle du débit est inférieure à la valeur mesurée de manière traditionnelle.

Mots clés : V Cone meter, Débitmètre multiphase, Artificiel intelligent.

الملخص

يعد تحديد تدفق البئر من الغاز متعدد الاطوار معلومة بالغة الاهمية حيث يبنى عليه قرارات مصيرية في الشركة من زيادة الاستثمار وتحسين اداء الابار او الانسحاب من المشروع نهائيا ويستخدم في حساب تدفق البئر عدة طرق منها استخدام عدادات متعددة الاطوار او استخدام برامج محاكات او باجراء قياسات روتينية شهرية بواسطة شركة متخصصة في قياسات تدفق الابار وبمعداتها الخاصة وكل هدو الطرق تنمو عن مخاطر كبيرة وخسائر كبيرة للشركة و الدقة في القياس ضعيفة لانه نقوم بتجهيز الاجهزة ضمن شروط محددة ولاكن عند العمل نضعه في شروط حقيقية وهي غالبا مختلفة عن شروط الاختبار

حلنا للمشكل يعتمد على استعمال الدكاء الاصطناعي ودلك باقتراح ان الشروط المقاس فيها في بداية التشغيل هي بيانات مرجعية ونستعمل تلك البيانات من اجل تدريب خورزمية دكاء اصطناعي وهي من تتنبأ لنا بالتدفق الجديد في حالة تغير شروط القياس وللوصول الى الخورزمية نحتاج الى بيانات حقيقية تم احضارها من حقل غازي باين امناس تقنتورين واستعملنا طرق تحليل البيانات وللوصول الى البيانات الاكثر دقة اخدنا الجزئ الدي افترضنا انه صحيح وقسمناه الى جزئين 70 % لتدريب الخورزمية و 30 % لاختبار الخورزمية واستخدمنا MSE وهو مقياس لحساب مدى دقة تنبئ الخورزمية بالبيانات . في هذه الدراسة، النتيجة المتحصل عليها لم تكن بالقوة المطلوبة نضرا لعدة عوامل لاتزال تحت الدراسة و مع ذلك من الجيد انه تنبأ لنا ان القيمة الحقيقية للتدفق اقل من القيمة المقاسة بالطريقة التقليدية .

الكلمات المفتاحية: مقياس البئر المخروطي , مقياس التدفق متعدد الاطوار, الدكاء الاصطناعي