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Modelling and Optimization Techniques for Gas Hydrate Formation in Pipeline: A Review

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Abstract: *In order to increase production and satisfy customer demands, engineers working in the oil and gas sectors are continuously faced with challenges pertaining to monitoring and improving pipeline flow processes. Considering the decrease in production costs resulting from obstructions caused by various flow assurance problems. In order to establish the simulation framework that has been widely used to improve hydrate formation prediction over the past few years, this paper provides guidance on justifiable hydrate formation prediction methodologies. This report evaluates papers on hydrate formation prediction and modeling from previous years using a systematic literature review process. This paper discusses a classification system for hydrate modeling techniques and their subcategories, including kinetic techniques, thermodynamic techniques, machine learning techniques, and simulation techniques. According to the results, computational and numerical methods are used because of the sustainable formation forecast of the hydrate scheme, even if a rising pattern is seen in the usage of simulation frameworks in conjunction with artificial intelligence approaches. Due to their propensity to handle ambiguity and uncertain data sets more effectively than numerical techniques, simulation and integrated frameworks are in high demand. However, numerical methods do a good job of handling deterministic data sets. Thus, this review helps researchers identify current flaws arising from flow optimization modeling. Finally, current shortcomings in flow optimization modeling were taken into consideration, opening up new research directions.*

Keywords: Hydrate, optimization, simulation, modelling, literature review

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INTRODUCTION

Gas hydrates are non-stoichiometric crystal compounds in the form of ice which are primarily formed by small light gas molecules for example Methane (CH_4) and ethane (C_2H_6) carbon dioxide (CO_2), as entrapped particles captured in voids created by liquid particles known as carrier molecules at extreme pressure as well as low temperature levels (Gharaibah et al. 2015; Hassan et al. 2019). Anytime a system of natural gas and water molecules exists at specific conditions, mostly when the pressure is high and temperature is low then, hydrate may likely form. However, at milder environmental conditions hydrate can still form, mostly when the concentrations of the guest molecules, for instance carbon-dioxide, methane are high in the surrounding or specific chemical interactions are involved.

Properties and structure of Gas Hydrates

Studies on Hydrate require expanse knowledge about hydrate elements and configuration. When hydrate forms, H_2O particles connects with hydrogen to produce polyhedral enclosures, containing the hydrate main cellular structure (Aregbe, 2014). Gas particles are stuck in the cavities with water molecules by van-der Waals forces, forming Gas clathrates Natural gas typically made of Methane gas when burnt in air produces water, CO_2 and energy, shown in Equation (1)

$$CH_4 + O_2 \rightarrow CO_2 + H_2O + Energy \uparrow \quad (1)$$

This process generates energy that can be used for diverse purposes,CO_2 is produced as more energy is given out. Figure 1 is the gas hydrate structure, displaying CH_4 gas as the middle accommodator in green, while water molecule is in (pink) (Aregbe, 2014).

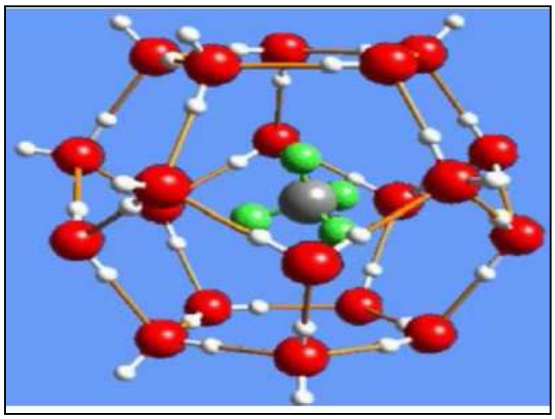

Figure I: Cage-like gas hydrate structure (Aregbe, 2014).

The Cubic structure 1 (S1), which comprises visitor molecules such as CH_4 gas C_2H_6, CO_2 and H_2S, cubic structure 11 (S11) in which Nitrogen (N_2) and small molecules such as hydrogen and natural gases form shape (II) as single guests and the hexagonal structure H (SH) are the three

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crystal structures of hydrate are the three arrangements of hydrate in the crystal structure of H_2O molecules (Al-Saadi and Zhai, 2015; Jai, et al 2021). Clathrate structures as well as its different clathrate cages are presented in figure 1. Structure 1 includes two variants: a small cage with 5^{12} pentagonal faces and a larger version $5^{12}6^2$ cages. While the large cage, signified $5^{12}6^4$ structure S11 also contains the small 5^{12} cages. Structure H has 5^{12} enclosures, a medium $4^35^66^3$ cage having 3 square, 6 pentagonal and 3 hexagonal faces, and a wide $5^{12}6^8$ cage which have 12 pentagonal and 8 hexagonal faces. The structure is a function of the extent of the absorbed molecule (Lu, et al. 2007; Hester, et al., 2007). For hydrates to form, water and secrets must be present, the secrets provide a base or starter for the hydrates to grow from. Hydrate formation in pipelines increases pressure drop (ΔP) and loss in functionality of components. The crude oil consists of diverse components, such as methane which is light so it is accountable for solid hydrate nucleation caused at an intense pressure and cold temperature whereas dense liquids like long alkanes and Iso-paraffins tends to alter state at frigid temperature in both fine and Coarse solids crystals Theyab, (2018). The Natural gas hydrate crystal comprising water molecules covered in a hard lattice with hydrogen. Interaction between the liquid and the visitors is highly inadequate, however complete interplay with the accommodating structure is exceptionally potent (Al-Saadi and Zhai, 2015). In literature over 130 cathartic compounds with water molecules are revealed there is an increased focus on SI and SII hydrate because they have higher weight Hassan, et al., (2019) The (SH) structure is explicit (Dendy, et al., 2007).

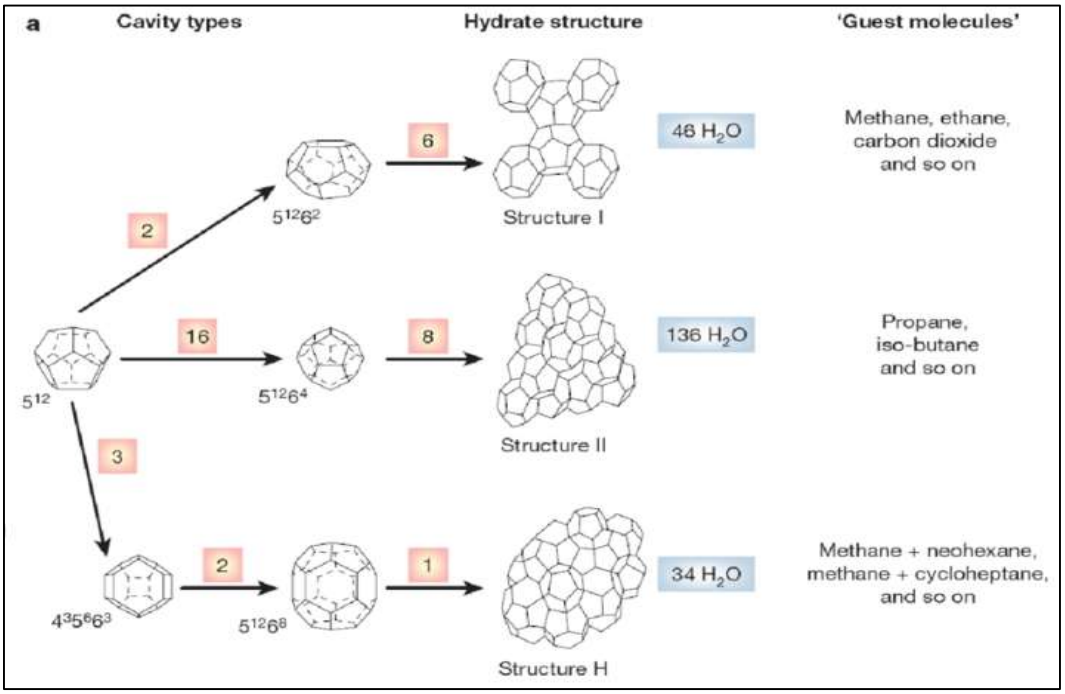

Figure II: Hydrate Crystals structures(a) SI type, (b) SII type, (c) SH type (Jai *et al.* 2021)

Table I. Comparison of the physical characteristics of hydrates, liquid water, and ice

S/No.	Physical property	Water	Ice	Hydrate (S1)	Hydrate (S11)	References
1	Bulk Modulus (B) [GPa]	0.015	9.09(50bar, 273K)	8.41(50bar, 273K)	8.482(304-916 bar, 258-288K; $C_1 - C_2$)	Helgerud, et al.,2003; Mork, et al., 2000)
2	Thermal conductivity (ג) $[WmK]$	0.52 (283K)	2.21 (283K)	0.57(263K)	0.51(261K)	(Lide and Baysinger, 2019;
3	Compressional wave velocity (v) [km/s]	1.5	3.87(50bar, 273K)	3.77(50bar, 273K)	3.821(304-916bar,258-288K; $C_1 - C_2$)	Udachin, et al., 2007)
4	Density	999.7 (283K)	917 (273K)	929(263K)	971 (273K), 940c, $C_1 - C_2 - C_3$)	Waite, et al., 2007)
5	Thermal diffusivity (k) $[m^2/s]$	1.38× 10^{-7}	11.7× 10^{-7}	3.35× 10^{-7}	3.60× 10^{-7}	Hassan, et al., (2019) Waite, et al., 2009)
6	Linear thermal expansion (α) 20K		56×10^{-6}	77× 10^{-6}	52×10^{-6}	Koh, et al., 2011)
7	Shear wave velocity (vs) [Km/s]	0	1.94(50bar, 273K)	1.96(50Bar, 273K)	2.001(266-621 Bar, 258-288K; $C_1 - C_2$)	Waite, et al., 2007)
8	Heat Capacity (C_p)[J/kgK]	4192(283K)	2052 (270K)	2031 (263K)	2020 (261K)	Bahman et al. (2008)
9	Shear Modulus G [GPa]	0	3.46(50bar, 273K)	3.54(50bar, 273K)	3.666 (304-916 bar, 258-288K; $C_1 - C_2$)	Helgerud, et al., 2009; Mork, et al., 2000)

Gas hydrates have attracted huge interest in scientific and practical studies because of the wide variety of potential applications. Hydrate is seen as a major source of energy in the 21st century (Song, et al. 2018).It can store gas nearly 170-times its volume so, can be used in gas storage and transportation and carbon sequestration. Hydrates is used for desalination since dissolved salt is left out during hydrate formation, because it is only free water that is involved in hydrate structures formation (Xu *et al.*2021). Hydrates can also be used for gas separation by using selective

partitioning of different gases in the hydrate and gas phases (Eslamimanesh *et al.* 2012b). Delahaye *et al.* (2008) said hydrate slurries can act as an effective cooling fluid in refrigeration applications. However, one of the most common failures that the gas hydrates within oil and gas pipelines could lead to is pipeline blockage, which could cause economic losses and safety issues (Sloan *et al.* 2007). Furthermore, it can plug pipelines, risers, subsea well- heads and cause a well-control risk (Skogdalen and Vinnem, 2012). These blockage issues lead to reduced production output, increased energy input, and increased pump power consumption hence, the need for hydrate suppression, which can be provided by adding anti-freezing materials and other optimisation techniques (Chen *et al*. 2021).

Problems and economic losses caused by hydrate formation in pipelines

Hydrate formation in oil and gas pipelines is an unwanted situation which challenges the flow assurance plans as well as posing threat to the personnel and equipment (Sloan 2008). Hydrate plugs clusters to block tubing, flow lines and facilities, apart from blockage of pipeline another challenge hydrate poses is the movement of hydrate plugs in the pipeline at high velocity which can cause rupture in the pipeline (Ninalowo and Tohidi 2024). Hydrate formation in oil pipeline causes production downtime (Udayakantha et al 2022). The hydrate just released from the pipe wall along the length may migrate downstream and deposit at sagging sections of the pipeline to cause the blockage (Song et al. 2019).Hydrate blockage on pipelines causes infrastructural damage to the facility (Arya, 2022). Blockage resulting from hydrate formation causes increased operating expenses (Jai, et al 2021). Hydrate plugs in a deepwater gas pipeline in the Gulf of Mexico caused 5 days total shot down of facility and caused a production loss of about $ 20 million, remediation and repair cost of $ 2 million as well as an environmental management loss of $ 500,000 (Ke, et al., 2022). Hydrate remediation and emergency intervention as well as mechanical evacuation gulps millions of dollars per year (Onyegiri *et al.* 2020). Sometimes hydrate obstructions in crude oil and gas transportation lines could result from the failure of the chemical injection system, unplanned shutdowns at the host platforms, or insufficient inhibitor treatment during well start up (Ninalowo and Tohidi 2024). The cost of battling hydrates, working blockages, putting in place pipeline impairment as well as handling safety and environmental hazards can majorly impact on profitability of operators of the pipelines mostly in intricate and inaccessible environments, even a short-term interruption in production can cost the operator millions of dollars (Chen, et al. 2021).

Significance

The best way of tackling hydrate-related flow assurance problems is prevention (Ninalowo and Tohidi 2024). But some operational conditions like offshore operations usually guarantees hydrates formation in pipelines (Chen *et al*. 2021). This is attributed to the twin conditions of low temperature and high pressure frequently encountered offshore (Hong *et al*., 2006). One of the most practical ways of initiating gas hydrates dissociation is either depressurization or thermal dissociation (Okoli *et al*., 2024). Depressurization involves opening of valves to release pipeline pressure, while thermal dissociation involves application of heat. These are usually done simply to move the prevalent conditions outside the hydrates stability region through either decrease in

pressure or increase in temperature. Although depressurization is usually preferred due to its associated low-cost, but it presents considerable hydrates reformation risks due to possibility of Joule-Thompson cooling (Eyankware *et al*., 2021). This unwanted cooling ends up worsening the hydrates problem and can even lead to formation of ice. The above demerits of the depressurization informed the choice of hydrates dissociation by thermal dissociation, as it is believed that sustained supply of heat would significantly decrease the chances of dissociated hydrates reforming. Other means are the use of optimization algorithms, machine learning algorithms and software (Arya, 2022).

Particle Swarm Algorithm (PSA) has least calculation time and has a higher converging time, it has more advantages in solution time and optimization efficiency, high computation efficiency as well as good in handling discrete variables over classical deterministic optimization Algorithms (Liu et al. 2020). Viscometry technique has inherent shortcomings and should not be used solely for flow assurance issue characterization except with other methods (Mahmoud et al. 2021) GPR model succeeds by its inherent flexibility in capturing complex nonlinear relationships and dependencies within a dataset (Aleem *et al.* 2024). Computational and numerical methods are good for their sustainable formation forecast of the hydrate scheme (Abbasi et al. 2022).Whereas, the use of software for simulation and artificial intelligence approaches are used due to their propensity to handle ambiguity and uncertain data sets effectively (Yin, et al., 2016).The use of software for the optimization of hydrate stems from the user-friendly environment which includes GUIs that makes it easier to apply as against manual coding that is experience with algorithms (Wang, et al. 2019). Software has built in thermodynamic models, hydrate phase equilibrium data bases contrary to external data integration and validation, which is time-consuming and error-prone as with algorithms (Sayani *et al.* 2021).

FORMATION MECHANISMS

Zhang et al. (2016) claimed that hydrate nucleation and production depend on a number of factors such as, agitation, existence of free water, and nucleation positions, nucleation positions spurs formation of hydrate crystals from the liquid phase. Temperature, pressure, concentration of guest molecules, interfacial tension, super saturation, presence of nucleation sites are key elements involved in hydrate nucleation processes (Al-Qaisi, et al. 2018). Researchers have explored nucleation theories through various initiating factors and these factors are incorporated into established correlations (Kashchiev and Firoozabadi, 2002).Characteristic hydrate generators are H_2S, N_2, CH_4, C_2H_4, C_3H_8, CO_2 though, some larger hydrocarbons can also form hydrates with these light gases (Al-Saadi and Zhai, 2015). Hydrate cage needs about 85% of water to form, hydrate formation is influenced by the quantity of water, undoubtedly, thermodynamically, in the absence of free water hydrate could possibly nucleate (Ke, et al. 2018). Hydrate most likely forms under a mild temperature with extreme-pressure which depends on the gas-oil configuration and has to form above (0^oC). Distinctively seafloor has temperatures of 4°C, firmly in hydrate nucleation for some vapor, expressly at elevated pressures. On land scenario could repeatedly get

to likely temperatures during cold season in many countries. Hydrate forms in numerous natural gases at 4^{o}C and below 10 bars whereas 100 bars some typical gases precipitates at room temperatures (Al-Saadi and Zhai, 2015).When the gas molecules occupy certain number of cavities, the crystalline structure becomes stable, then solid hydrates may be produced at temperatures above 0^{o}C. However, many heavy hydrocarbons for example benzene, cyclohexane, cyclopropane, methylcyclopentane, methylcyclohexane, isopentane and 2,3-dimethylbutane have been discovered in recent studies as hydrate formers (Ke *et al.* 2020). Considerable conceptual and experimental researches have been carried out on gas hydrate. At present, over fifteen societies and industries are connected doing research on hydrate issues, serious energies are deployed into acquiring deep knowledge of hydrate blockage on flow lines (Sun, et al., 2011).

Kinetic models of gas hydrate growth

The formation of gas hydrates typically occurs after nucleation and is an energy-releasing process that results in multiphase experiments across different investigation stages, and it is seen as a complex interfacial phenomenon (Zare, 2022). Analyzing the conditions of kinetic models necessitates an understanding of heat and mass transfer, flow, and natural phase transitions (Partoon*et al*., 2020). At a fundamental level, the kinetics of hydrate formation predominantly relies on the rates of gas absorption. The calculation of gas hydrates can be conducted at a microscopic scale by examining the mass transfer of water and gases to the hydrate surface during growth, the transport of heat generated by crystals during gas formation, as well as the inherent kinetics of hydrate development; all these factors shape the composition of gas hydrates (Sayani *et al.* 2021).

As a result, a kinetic model can be formulated based on the assumed controlling mechanisms, which include (i) mass transfer; (ii) intrinsic kinetics; (iii) heat transfer, or a combination thereof. Hydrate formation is typically regarded as an interfacial process (Partoon et al., 2020). Englezos et al. (1987) created a fundamental kinetic model for the formation of methane and ethane gas hydrates using a single adjustable variable. This model was created based on crystallization theory, while the intermediary mass transfer model was established using two-film theory. The results indicated that the formation rate was proportional to the difference between the volatility of the dissolved gas and the escape tendency at the triple point for the experimental temperature. This distinctiveness highlights factors like the effects of pressure. Additionally, the gas intake was associated with the second moment of the particle size distribution, and the rate constants demonstrated very low thermal stability. Hussain et al. (2006) detailed a study on the kinetics and morphology of ethane hydrate production conducted in a batch reactor, with temperatures ranging from 270K to 280K and pressures between 0.883 MPa and 1.67 MPa. They found that the kinetics of formation were affected by factors such as temperature, pressure, degree of sub cooling, and stirring rate. Hong et al. (2012) conducted gas intake measurements and in-situ Raman spectroscopic analysis from both macroscopic and microscopic perspectives in a semi-batch stirred tank reactor under constant temperature and pressure to fully comprehend the influence of the kinetic inhibitor poly-N-Vinylcaprolactam (PVCap) on the formation of methane hydrate.

Understanding the behavior of guest molecules is a crucial aspect of hydrate research. Nevertheless, capturing real-time characteristics of cage variation under stable temperature and pressure conditions in a stirring system remains a challenge.Amar, (2021) reviewed the kinetic models for hydrate separation and oil tank simulants and identified distinct relationships among several kinetic approaches depending on their catalyst devices outlining new advancements in respective kinetic approaches.

Hong et al. (2012) investigated the behavior of guest molecules by utilizing in-situ Raman spectroscopy during hydrate formation in a transient system, contrasting with a static system, which provided essential insights into the time-dependent kinetic behavior of hydrates. According to their results, the presence of PVCap reduces the rate of encapsulation of larger cavities during the early stages of hydrate formation.Hydrate formation process was observed by Liu et al., (2015) using kinetic model analysis based on which they provided a prediction model. They also observed that the gas hydrate formation is influenced by the composition of gas and the free water concentration alongside the temperature and pressure. The anticipated outcome of the new gas hydrate kinetics prediction model was near to the observed result, signifying that the prediction approach may accurately replicate hydrate development.Hassanpouryouzband et al., (2019) Performed investigation on kinetics of integrated methane recovery and carbon capture by injection of flue gas into permafrost methane hydrate reservoirs. The results revealed that the kinetics of methane released from methane hydrate and CO_2 retrieved from flue gas are highly shaped by the temperature of the hydrate reservoir. the experiment at 261.2 K resulted in the capture of 81.9%of the carbon available in the injected flue gas, as well as an increase in the CH_4 concentration in the gas phase of up to 60.7 mol percent, 93.3 mol percent, and 98.2 mol percent at optimal pressures after depressurizing the system to dissociate CH_4 hydrate and after depressurizing the system to CO_2 hydrate dissociation point concurrently. This is higher than the maximum efficiency mentioned in the literature for both CO_2 sequestration and methane recovery through flue gas injection, demonstrating the economic feasibility of direct flue gas injection into permafrost hydrate reservoirs for methane recovery and geological CO_2 capture and storage. Lastly, the temperature stability of the preserved CO_2 was checked by heating the system and the result showed that the incidence of N_2 in the injection gas provides an additional safety factor for the stored CO_2 in an instance of a temperature variance. Sun et al. (2019) reported the effects of flow rate and temperature on the thickness and wax content of deposition layer of crude oil of Northeast China. By establishing a kinetic calculation model for the thickness and wax content of deposition layer in a heat insulated crude oil pipeline based on the principle of molecular diffusion, aging and shear energy. The result presented that wax deposition thickness decreases and the wax content increases with increasing flow rate and ambient temperature. The values gotten from the experiment and the calculated from the model are in agreement. This model predicted the wax deposition thickness of a heat insulated pipeline in different seasons and time of operation and this was expected to form a scientific basis for formulating the wax removal cycle of the pipeline. the results showed that the thickness of the wax deposition layer increases first and later decreases along the pipeline.

Thermodynamics models for gas hydrate development

Successfully forecasting hydrate phase equilibrium is key in preventing gas hydrate formation According to Willard et al., (1941) the K- Values was the pioneer model for calculating hydrate formation conditions. This work reported the experimental determination of equilibrium temperatures and pressures of hydrate forming up to 27.58Mpa for three natural gases. This enabled the calculation of the equilibrium between propane-rich fluid, water-rich fluid and crystalline hydrate, it also discussed phase interactions and vapour-solid equilibria. Subsequently Mohamadi-Baghmolaei et al., (2018) reported that Barrer and Stuart performed experiments in 1957 to find the characteristics of gas hydrate using a mathematical thermodynamic model. Partoon et al., (2020) reported that in 1959 Van der Waals and Platteuw developed a mathematical thermodynamic model used for hydrate phase equilibria, using a similar techniques and knowledge of hydrate crystal structure.Mansourpoor et al. (2018) developed a multi-Solid thermodynamic model to predict wax disappearance temperature (WDT) using PR EOS and tested with 56 data points of the ternary system, Paraffinic–naphthenic–aromatic analysis was carried out and they introduced two correlations for fusion properties of the species. Also, the WDT of 12 Iranian crude oil and condensate samples collected from Kharg oil terminal and south pars gasrefineries, Bushehr, Iran.were measured using viscometry and differential scanning calorimetry (DSC) techniques. It was observed that measured WDT by viscometry method is higher compared to DSC. Statistics analysis shows that DSC technique has lower average absolute relative error (AARE) and standard uncertainty compared to viscometry. AARE of the model for ternary systems is 0.52% which is lower among the previous developed thermodynamic models. Also, AARE of the new model for 68 data was about 0.23%, and *R*-square of model prediction was 0.97. The cumulative distribution function also shows that P50 values are almost the same for model and experimental data. These results implies that the model has a good accuracy, the accuracy of model increases as the average carbon number of oil mixtures increases. Finally, it was found that PNA analysis and distribution of each component in its sub-fractions have a considerable effect on the model accuracy.

Hamied et al. (2023) Investigated the effect of temperature, pressure drop, and pipe diameter on the flow rate of Iraqi heavy crude oil of API = 20 from the East Baghdad Oil Field. They also, checked the total discharge and energy losses in order to demonstrate the improvements possibly achievable by using solar heating method replacing pipe, and adjusting the value of the initial pressure difference. Using pipelines sections connecting the separator unit to the storage tank operating at a temperature of 25°C–100°C, pressure drop of 3, 4, 5, and 6 kg/cm^{2,} and with pipe diameter of 4, 6, and 8 inches. The results show that when the temperature and/or the pressure drop was increased, the flow rate increases, thereby raising the total energy of pumping as the pipe size increase, whereas, energy losses increase from the last separator to the storage tank in the field. Increasing pipe size can lead to total pumping energy or energy losses increase. The results of the present analysis propose that employing an optimal temperature of 50°C, is needed to ensure good performance.Parrish and Prausnitz (1972), reported that the first thermodynamic model used for

the analysis of hydrate formation was developed and utilized based on van der Waals and Platteeuw statistical method. Javanmardi and Moshfeghian, (2000) also developed a thermodynamic model that was used to predict hydrate formation conditions in electrolyte solutions also, Nasrifar et al. (1998) developed a thermodynamic model that could be used to analyze hydrate formation condition of both electrolyte and alcohol solutions. Nasrifar and Moshfeghian (2001) also developed a thermodynamic model that wasused to predict the hydrate formation conditions. Du and Guo (1990)developed a thermodynamic model that predicted the hydrate-formation conditions for systems of alcohol solutions.

Table II: Comparison between thermodynamic modelling and kinetic modeling of hydrate

Concern	**Thermodynamic techniques**	**Kinetic techniques**
Principal emphasis	Predicts Equilibrium conditions, such as pressure, composition and temperature	It depends on time to predict the rate of formation and dissociation(Sayani et al. 2021)
Computational complexity	Moderately low	high
capacity for prediction	forecasts stability and equilibrium points	forecasts formation and dissociation rates
Range of application	Very useful for steady-state equilibrium conditions	Useful for momentary conditions, dynamic systems
Data requirements	Needs fewer data	Involves elaborate experimental data (Jai, et al 2021).
flexibility	Unyielding with non-equilibrium conditions	More adaptable with changing operation variables
Top for inhibition	Outstanding for recognizing flash points	Outstanding for handling momentary risks and dynamic control

RESEARCH METHODOLOGY

A Systematic Literature Review (SR) of peer-reviewed scholarly literature that relate to and align with pertinent subjects of hydrate precipitation prediction and optimization models within oilfield pipelines, both conceptually and practically, was used in this work. The procedure is used to find, pick, and assess studies that answer the research questions. This study uses the five ways for SRs development that were introduced by Aghil et al. (2019) and Denyer and Tranfield (2009). In essence, creating inquiry questions and locating study resources are the two key tasks of these stages of conducting an SR. publication compilation and critique, investigation, article fusion, use, and dissemination of the results.

This study attempts to review and classify hydrate formation prediction and optimization techniques so as to correctly cluster the approaches and underscore the Commonalities and dissimilarities between them. However, hydrate remediation techniques are excluded from this study. The review discloses that, the established hydrate formation prediction and optimization model is grouped into predictable, stochastic and Hybrid frameworks. Therefore, this paper answers the investigative question: What are the predominant methods used for prediction, modeling, simulation and optimization of hydrate in the oil field production? A systematic literature review (SRs) is used in providing solutions to the question by reviewing articles available on the content. The determination of (SRs) is the recognition, assortment, and evaluation of articles in order to address the study question. The research suggests a structure for categorizing prevailing studies on hydrate formation and optimization techniques. The ensuing segment explains the research approach adopted to describe the methodology of the (SRs).

This article is split into the following sections. Firstly, the introduction which gives a brief of the background of the study; secondly the hydrate formation mechanisms which explains the conditions under which hydrate nucleates and form thirdly, the methodology section which provides details on the framework use to identify and select eligible articles, and fourthly, the outcome the study, this section elaborates on the findings from the literature and finally, the conclusion of the findings.

Optimisation and modeling Hydrate

Optimisation

Flow optimization focuses on enhancing the efficiency and effectiveness of fluid movement in systems such as pipelines, networks, or processes. This entails analyzing and adjusting parameters to reduce resistance, decrease energy consumption, and improve overall performance Bekibayev et al. 2022).It is anticipated that optimization will notably lower the design and operational costs involved with oil field products networks (Udayakantha et al 2022). Within the context of gas or crude oil pipeline optimization, the primary objective is to maximize a specific economic metric while conforming to the performance equations that describe the system's physical behavior and any established constraints (Arya, 2022). To achieve this, researchers have created different models to analyze and enhance these hydrate formation prediction and optimization Chen et al. 2020). In this research framework, modelling involves the creation of a model that serves as a depiction of either a conceptual or real-world process (Jai, et al 2021). Simulating a complete flowline could aid in the accurate analysis of flow parameters within core frontiers, before, an executive scheme would perform well using the techniques (Balakin, et al, 2011). To cut the cost of transportation and enhance flow without pressure loss hinderance, several other approaches are utilized they are, increased fluidity, mixing and preheating are adopted to enhance the heavy flow through pipelines to achieve desired output (Munoz and Ancheyta, 2022; Ke, et al., 2022). It is distinct from simulation, which involves using a framework to assess the behavior of a conceptual

or real scheme in feedback to varying controls or parameters (Jai, et al 2021). The past decades, have recorded the release of numerous articles focusing on predicting hydrate formation and optimization related techniques, as well as inhibition approaches. These studies encompass the advancement of both deterministic, stochastic and hybrid models. Several conceptual researches have been conducted by means of simulation utilizing packages like ASPEN HYSYS and PVTSIM; OLGA and PIPESIM (Ekwe et al. 2020; Onyegiri, et al. *2020*). However, the use of these tools has not sufficiently shown good accuracy of hydrate predictions (Ozi, et al. 2020).
Similarly, Abbasi et al. (2022) reviewed the essential philosophies of hydrate development and suggested that using a hybrid AI model in forecasting methane hydrate creation could be an effective tool for addressing flow assurance issues in deepwater gas pipelines.

This study attempts to review and classify hydrate formation prediction and optimization techniques so as to correctly cluster the approaches and underscore the Commonalities and dissimilarities between them. However, hydrate remediation techniques are excluded from this study. The review discloses that, the established hydrate formation prediction and optimization model is grouped into predictable, stochastic and Hybrid frameworks. Therefore, this paper answers the investigative question: What are the predominant methods used for prediction, modeling, simulation and optimization of hydrate in the oil field production? A systematic literature review (SRs) is used in providing solutions to the question by reviewing articles available on the content. The determination of (SRs) is the recognition, assortment, and evaluation of articles in order to address the study question. The research suggests a structure for categorizing prevailing studies on hydrate formation and optimization techniques. The ensuing segment explains the research approach adopted to describe the methodology of the (SRs). This article is split into the following sections. Firstly, the introduction which gives a brief of the background of the study; secondly the hydrate formation mechanisms which explains the conditions under which hydrate nucleates and form thirdly, the methodology section which provides details on the framework use to identify and select eligible articles, and fourthly, the outcome the study, this section elaborates on the findings from the literature and finally, the conclusion of the findings.

Modeling

Mathematical models are quantitative representations that illustrate conceptual or real-world scenario by making use ofnumerical principles like equations andvariablesthatis subsequently analyzed and resolved and examined using various elements inside the frameworkto forecast the behavior of systems (Aghil, et al. 2019)
Additionally, numerous researchers have suggested different modeling techniques that incorporate theoretical approaches along with advanced simulation methods namely CFD, and ANN (Jai, et al. 2021; Toyin and Chukwuemeka, 2019). Sayani, et al., (2021) conducted a review on the comprehensive overview of different modeling techniques for gas hydrates, they begin with a discussion of the Heat characteristics as well as rate characteristics of hydrates. Additionally, they cover key areas of Heat characteristics techniques, rate characteristics approaches, and arithmetic

approaches. They also highlighted techniques formulated by means of CFD, algorithms in addition with ANN methods.

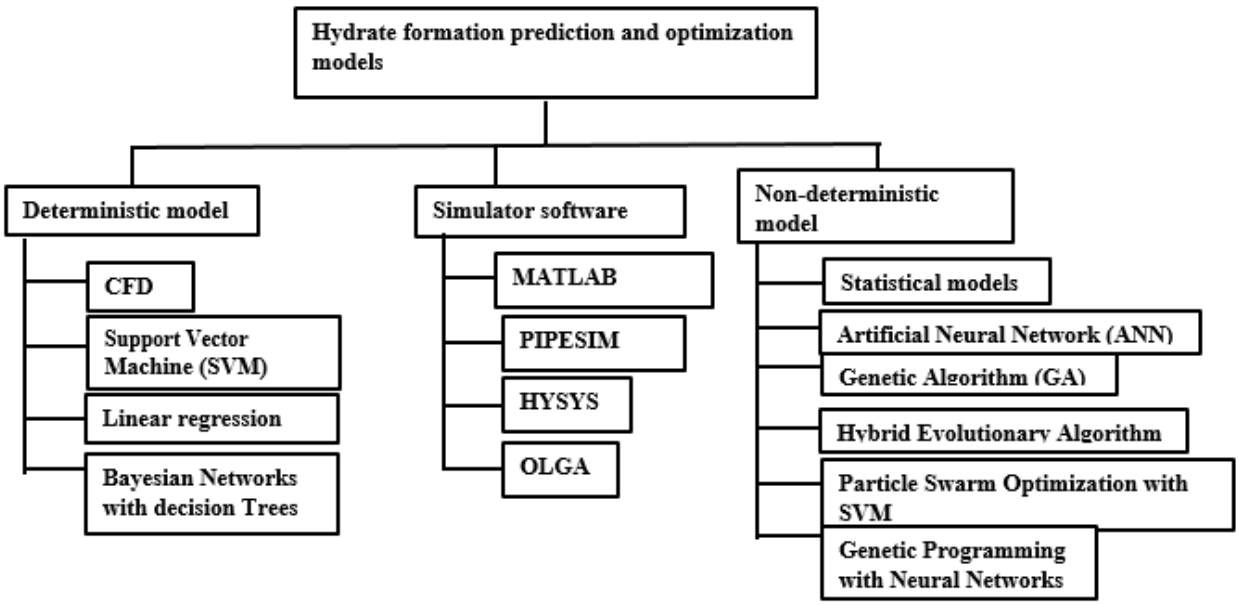

Figure III. Classifications and subcategories of hydrate optimization models

Numerous reduction and preventive measures are used to address gas hydrate concerns in pipelines. Nonetheless, it holds equal importance to forecast the hydrate buildup and disintegration conditions of hydrate. Due to the reason that experimental investigation is not always sustainable. Thus, a dependable forecast modelling approach is needed for it.
This paper attempts to look at the following approaches among other various models used in addressing hydrate formation in pipelines in the industries.

i. Statistical Models
ii. CFD models, and
iii. ANN Models

Statistical Modelling

Correlations for HFT and HFP

Fattah, (2004), first used the gravity method and it has been of immense help to oil field production. Numerous correlations are available for gas gravity technique for computing Clathrate nucleation

like Hammerschmidt, Motiee, Berge and Sloan correlations. According to Hammerschmidt (1934) equation (2) is used to find hydrate formation temperature

$$T = 8.9 \times P^{0.285} \quad (2)$$

Modifying equation (2) to pressure form gives equation for initial pressure calculation given in equation (3)

$$P = \left(\frac{T}{8.9}\right)^{3.509} \quad (3)$$

Where P is the system operating pressure (Psia) and T is the temperature (^{o}F). Various models have been presented to enhance hydrate prediction, Balakin, et al. (2010) and Davies, et al. (2009) presented the model in equation (4) in the method fifteen coefficients that would correlate temperature, pressure and specific gravity were determined. This was fit in temperature range of 34 ^{o}F to 60^{o}F and pressure range of 65 psi to 1500 Psi, while the gas gravity ranges from 0.552 to 0.9 and the equations are as stated in equation (4)

$$HFT = \frac{1}{\begin{matrix} c_1+c_2(lnp)+c_3(lnY)+c_4(lnP)^2++c_5(lnp)(lnY)+c_6(lnY)^2+c_7(lnP)^3+ \\ +c_8(lnY)(lnP)^2++c_9(lnY)^2(lnY)+c_{10}(lnY)^3+c_{11}(lnP)^4+c_{12}(lnY)(lnP)^3 \\ +c_{13}(lnY)^2(lnP)^2++c_{14}(lnY)^3(lnP)+c_{15}(lnY)^4 \end{matrix}} \quad (4)$$

The Berge correlation

The Berge method uses the following equations presented in equations (5) and (6) to predict hydrate formation temperature. They are used directly for given pressure and specific gravity (Amar, 2021).

For $0.555 \leq \gamma_g < 0.58$

$$\text{HFT} = -96.03 + 23.37 \times lnP - 0.64 \times (lnP)^2 + \frac{\gamma_{g-0.555}}{0.025} \times \left[\frac{80.61\times P+1.16\times 10^4}{(P+596.16)} - (-96.03 + 23.37 \times lnP - 0.64 \times (lnP)^2)\right] \quad (5)$$

For $0.58 \leq \gamma_g < 1$

$$\text{HFT} = \frac{\left\{80.61\times P-2.1\times 10^4-1.22\times\frac{10^3}{1}(\gamma_g-0.535)-\left[1.23\times 10^4+1.71\times\frac{10^3}{(\gamma_g-0.509)}\right]\right\}}{\left[P-\left(-260.42-5.18/(\gamma_g-0.535)\right)\right]} \quad (6)$$

where, $\gamma_g$is specific gravity of gas, P is the pressure, and T is the calculated temperature (Amar, 2021).Bavoh et al. (2018) Motiee correlation presented in equation (7) gives a better embrace in hydrate forecasting

$$HTF = K_1 + K_2 log(P) + K_3 log(P)^2 + K_4\gamma_g + K_5\gamma_g^2 + K_6\gamma_g log(P) \quad (7)$$

The Motiee correlation

This is a regression technique developed which aided in determining six constants used to relate temperatures, pressure as well as specific gravity. It is stated in equation (8)

$$\log(P) = a_1 + a_2 T + a_3 T^2 + a_4\gamma_g + a_5{\gamma^2}_g + a_6 T\gamma_g \quad (8)$$

$$T = b_1 + b_2 log(P) + b_3\big(log(P)\big)^2 + b_4\gamma_g + b_5\gamma_g^2 + b_6\gamma_g log(P) \quad (9)$$

Bekibayev, et al (2022) said Carson and Katz in 1942, studied hydrate formation temperature and they developed the k-factor method presented in equation (10) wherein the hydrate temperature isforecastedby means of equilibrium constants (k-factor)method

$$\sum_i^n = 1\frac{y_i}{k_i} = 1 \quad (10)$$

where y*i* is the fraction of composition *i* in vapour in liquid-free basis, and K*i* is gas–solid equilibrium for composition *i*, while n designates number of compositions. Chen, et al (2021) proposed the model presented in equation (11) model and used it to analyse the hydrate nucleation temperature in line with specific gravity and system pressure.

T=13.47ln (P)+34.27ln(γg)−1.675[ln(P)×ln(γg)] −20.35 (11)

W$here T$ = °F, $and P = psia$, γg= specific gravity of gas

The Van der Waals and Platteeuw model, assumed two stages for hydrate crystallization. Stage one, defines the vacant hydrate structure which formed through water, the second stage is the voids occupied by guest particles. Then statistical thermodynamics approach is used to calculate the Chemical Stability of Hydrate Structures (μw_H)

$$\mu w_H = \mu w_B + RT\sum_i n_{ci} ln\big(1 - \sum_j \theta_{ji}\big) \quad (12)$$

Where μw_B = chemical potential in voided hydrate structure

$n_{ci} = type\ i$ number of cavities in a water molecule in basic structure

θ_{ji} = fractional habitation of type I cavity by type j molecule

Table III. Brief important statistical models used for gas hydrate evaluation studies

S/N	Authors/(Models)	Research attention	disadvantages	references
1	Motiee	HFT	narrowed to specific gravity of gas between 0.5 – 1	Amar, (2021)
2	Hammerschmidt	HFT	It is contradicted, and the gas gravity approach is suggested subsequently	Hammerschmidt (1934); Amar, (2021)
3	Ostergaard	HFT	formulated with formation. Not explored sufficiently	Ostergaard et al., (2000)
4	Katz	HFT	Graphical method for forecasting. Established reliability with conditional accuracy for mixed gases	Berge, (1986)
5	Zahedi	HFT	Highly complicated as 11 Variables are considered	Kamari and Oyarhossein (2012)
6	Van der Waals Platteeuw	HFT	Statistical thermodynamics studies the water molecule interactions with gas molecule framework	Jai et al. (2021)
7	Berge	HFT	Streamlined gas specific between 0.5 – 1	Saito et al., (1964)
8	Kobayashi and Sloan	HFT	narrowed to specific gravity of gas between 0.65 – 1	Saito et al., (1964)
9	Bahadori	HFT	Restricted to sweet natural gases	Bahadori and Vuthaluru (2009)

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Machine Learning Methods

A substantial change with computation is triggered with the onset of fast technologies and robust data handling tools which reduced the reliance on the traditional approach for the measurement of gas hydrate growth condition. Significant advancements in soft computing techniques for example ANN, Genetic Algorithm, large data analysis techniques surfaced and modified research.
Yu et al. (2019) used a Neural Network (NN) to model a real temperature and pressure response system as against solving complex model equations. The NN is trained and built by pipeline history data obtained from the Supervisory Control and Data Acquisition (SCADA) system. For Rizhao–Yizheng digital long crude oil pipeline in China, real-time operating parameters like pressure and temperature are predicted by the NN once the inputs are given. A back propagation neural network (BPNN), radial basis function neural network (RBFNN), and general regression neural network (GRNN) were utilized for comparison to show their error-control abilities. The variables are sent to particle swarm optimization and differential evolution (PSO-DE) optimization units for the costs analysis. Experiments show that all the NNs have similar prediction accuracies, while RBFNN and GRNN have better prediction stability than BPNN. Most of the prediction errors of the flow, outlet pressure, and inlet temperature can be controlled below $50\,m^3/h$, 0.1 MPa, and 0.1°C, respectively, and the optimization is realizable. The maximum reduction of the total energy cost is 10.75%, and the saving effect is significant. Aleem et al. (2024) reported on a comprehensive and novel comparative analysis of nine distinct machine learning models for accurate prediction of methane hydrate formation temperatures. By applying major machine learning (ML) algorithms such as multiple linear regression (MLR), gradient process regression (GPR), long short-term memory (LSTM), radial basis function (RBF), support vector machine (SVM), gradient boosting regression (GBR), random forest (RF), and K-nearest neighbor (KNN), artificial neural network (ANN). The model accuracy was validated against 1000 dataset obtained from Qatif oil field in Peninsula with varied range of salt concentrations the model accuracies were compared by means of indicators like $R^{2,}$ ARD, and AARD. The results from the experiment showed that KNN algorithm converged faster, accurately and consistent over the complete range of data points with an R^2 value of 0.975 and AARD of 0.385%. These results help accurate and efficient temperature forecasting through ML algorithms in multiple hydrate-associated procedures.

Haghighi, et al. (2009)said recently the ANN systems is predominantly used for automated preliminary detection of pipeline blockage as a result of hydrate formation and other flow assurance issues within the oilfield process production. For quick detection, nucleation of hydrates, Artificial Neural Network is valuable because it reports clog. In general, artificial neural network (ANN) is an effective and practical approach used for multivariable groupings**.**ANN computes and analyses dosage of KH inhibitors, AA and salts concurrently. ANN is trial based training and neither needs an equation nor underlining knowledge of physical association (Bahman, et al. 2008). ANN helps to achieve an innovative method for LDHIs Elgibaly and Elkamel, (1998).
Al-Qaisi et al. (2018)employed ANFIS, LSSVM, and RBF-ANN frameworks in forecasting the temperature of a gas hydrate by means of choking and found out that the model were viable for predicting parameters accurately up to $R^2 > 0.99$ and AARD% < 0.5. Nonetheless the forecast

from RBF-ANN were precise compared to other deterministic models. Amar, (2021) performed an investigation into finding the Hydrate Formation Temperature of different gases, like acid gas, sour gas and sweet gas blends by utilizing the GEP model, and the outcome was good with an AARE value of 0.1397% which could be used to predict the hydrate temperature for diverse schemes. Lim *et al.* (2021) gathered more than 3000 data sets for the investigation of effect of Luvicap 55W as a KHI 0wt% to 3 wt% in water on CH_4 hydrate nucleation at 12Mpa operational pressure with automated lag time apparatuses (HPS-ALTA) and discovered that adding KHI to the sample repeated the induction times for the same sample signaling a reduction in methane behaviour in the system. Though, the initial development frequency reduced by five times for the samples. Glycol ether was also checked with gas hydrate using Luvicap 55W at 4^{o}C and 95 bar. It was observed that glycol ether did not alter the induction time but rather decreases the rate of hydrate nucleation using a stirred reactor. Mesbah et al. (2020) and Al-Qaisi et al. (2018) used the LSSVM algorithm to check the temperature hydrate will precipitate (HFT) using vapour that has diverse elements and structures. This model was expansive and it had an R^2 value of 0.9918, and it showed a high precision in contrast to standard correlations and established thermodynamic models. Ghiasi, et al., (2021)carried out methane hydrate separation in contact with different salts in liquids state with sulfates anions, dicyanamide, tetrafluoroborate, and halides using LSSVM, ANFIS, and CART with different input parameters like pressure and temperature and the result showed that LSSVM model has higher accuracy compared to ANFIS, and classification and regression tree (CART). The accuracy was 0.08, 0.31 and 0.10 AARD% for LSSVM, CART and ANFIS respectively. Mehrizadeh, (2021) utilized ANFIS, LSSVM, and RBF-ANN to forecast the start temperature of a gas system, and the models predicted the initial temperature variable accurately having R^2 value above 0.99 with AARD% $<$ 0.5, a more precise value was recorded for RBF-ANN model. Pelalak, et al. (2021) utilized GEP model to forecast HFT for gas system blends like sour gas, acid gas, as well as sweet gas, 279 experimental data was used for this analysis, and the GEP model had a good result that could correctly compute HFT having an AARE of 0.1397%**.**

Mehrizadeh, (2021)used two clever models, for example ANN and ANFIS, in predicting HFP for different gases. He learnt that the performance of ANFIS was higher and in accord with that of the experiment than ANN, time for commencement is a serious variable for hydrate precipitation, thus, KHI insertion in flowlines shifts the formation, thereby surging the initiation time. Thus, forecasting proper initiation time is advisable (Mahmoud, et al., 2021). Saberi, et al., (2021) posited that sub-cooling and molecular weight of blends are key factors in nucleation and growth. Hosseini and Leonenko,(2024); Dendy et al. (2007)said three clear associations based on machine learning methods, and GEP with predefined frameworks were created for forecasting the methane HFT in pure H_2O and saline solutions. The error analysis indicated a satisfactory correlation with the experimental data. Among the models, the correlation based on GEP demonstrated peak performance of R^2 and AARD having 0.8860 and 0.087%, correspondingly. Amar, (2021)said Machine learning methods particularly artificial intelligence (AI), is a very useful techniques to aid in modeling and predicting hydrate nucleation potentials and transport via pipelines. Qin et al. (2019) used 4500 sets of data from a pilot-scale flow loop set-up alongside field data, to run various

AI tools like SVM algorithm and NN. The techniques utilized hydrate fraction and the likelihood of hydrate blockage as outputs. Input parameters included water cut, interfacial tension, gas-oil ratio, cohesive force of hydrate particles, fluid velocity, specific gravity, and time. It was concluded from the results that the machine learning could be used for hydrate risk prediction in the field.

Yarveicy and Ghiasi (2017); Bahman, et al. (2008) used Extra Trees (ET) and LSSVM to calculate HFT and duration for dissociation of gas, salt and alcohol systems. The result showed that the models can be used to regulate objective variables with R^2> 96%. Thus, these models could be used for the forecast with good precision.LS-SVM was utilized in determining hydrates equilibrium conditions, along with the flow rate of monoethylene glycol (MEG) in different settings like, gas/MEG/water, the results proved that the AARE estimated HFT and flowrate, of MEG as 0.15, 0.58, and 7.17 correspondingly, it is a testament that LSSVM has a result consistent with the experiment (Zare, 2022).Rebai et al. (2016)used both ANN and ANFIS in the forecast of thermodynamic properties like viscosity. Five AI tools (MLR, K-Nearest Neighbor, SVR, RF and GBR) were deployed in this study, while 702 data set from 1951 to 2020 for this course was collected. Salt conc. of 29.2 wt%, pressure of 200Mpa was considered. GBR have best results of R^2 of 0.998 AARD of 0.074%. According to Xu, et al. (2021) GBR can be used to forecasting the nucleation conditions of methane hydrates in brine.

Table IV. Summary of Various Artificial intelligence (AI) models used on hydrate prediction study.

S/No.	AI MODEL	part considered	References
1	ANN	THIs and KHIs	Yang, et al., (2012)
2	ANN	Conc. of thermal retardants/KHI/AA and salts using electro conductive properties, sound velocity and temperature	Jassim, et al (2008)
3	ANN-MLP	Temperature under which hydrate forms	Zahedi, et al., (2009)
4	ANN	Triple phase Equilibrium forecasting in Gas	Amar, (2021)
5	ANN	forecasting Hydrate Impasses in Oil, vapour and liquid-based Systems	Zerpa, et al., (2012)
6	ANN	Performance of LDHI	Bahman, et al., (2008)
7	ANN	Comparing the capacity of an (ANN) and the CSMHYD algorithm for the Forecast of HFP in binary mixes	Babakhani, et al., (2015)
8	MATLAB, GA, PSA, ICA	HFT forecasting	Hesami, et al., (2017)
9	ANN	Hydrate formation temperature prediction	Elgibaly and Elkamel, (1998)

Table V. The results of some studies on intelligent algorithms in current years

S/N	Algorithm name	Optimization object	Results and conclusion	reference
	SA, PSO and GA	Energy requirements in subsea pipelines	The method cut down energy usage in like pipelines by 33.77%	(Balakin et al 2010)
	BPNN, GRNN and RBFNN	Optimization of energy consumption in heated oil pipelines	Lower energy related to simulated pipeline usage by 10.75%	(Zhang et al 2020)
	Ant colony optimization (ACO)	Enhancement of natural gas transportation pipeline system	ACO an attractive approach for system optimization use on pipeline flow.	(Chebouba et al 2009)
	A heuristic algorithm	Energy use optimization in natural gas pipelines processes	The process substantially diminishes the optimization duration and the computation are accurate	(Liu et al 2019)
	Tabu search algorithm	optimization of Energy in subsea pipelines	The proposed optimization strategy significantly lowers the energy intake of the offshore pipelines	Peng et al (2019)
	Genetic algorithm (GA)	optimization of Energy use in liquid pipe flow	The likely optimum plan can cut the energy flow process by 5%-9%	(Liu et al 2015; Dendy, et al 2007)
	GA-BPNN	Assessment of the superficial viscidness of crude oil	The GA-BPNN model is relevant to use for the Superficial viscidness forecasting of countless oils	Zhang et al 2019
	GSAHA	optimization of gas distribution	The algorithm is highly suitable for optimizing gas supply provision	(Qiao et al 2019)
	MC-GPSO, MC-LPSO, MCFIPSO, and MC-SLPSO	Optimal design of subsea oil Pipe lines.	MC-SLPSO is shown to be better suited for the analysis of subsea flow optimization complications	(Zhang et al 2017)

Computational Fluid Dynamics models

CFD analysis uses the fluid flow theory and utilizes computational approaches and algorithms in solving issues related to liquid flow (Fattah, 2004).A pertinent procedure and variables of hydrate crystal formation can be analyzed and enumerated using CFD (Yin, et al. 2016).

Onyegiri, *et al.,* (2020) undertook optimization analysis of multiphase flow with the aid of PIPESIM on waxy crude oil pipeline of length 10.2km from wellhead to separator, with special

attention given to pipe size, flow rates and insulation material. The results favoured pipe internal diameter of 0.29m, with 3280m^3/d, poly-urethane foam PIP insulation, using the Carson and Katz correlation$\sum\left(\frac{y}{k}\right)=1$ they forecasted the HFT and WAT to be 26^{o}C with an optimum process pressure of 11 bar.

Ozi, et al., (2020) modeled offshore pipeline in Nigeria having length 64, 000m with dual segments of 23,000m, of 0.56 meters Internal Diameter and 41,000m, of 0.69 meters ID, with insulation thickness 0.003m polyethene of subsea oil field operating at base condition of 114 barg and 18.7 MMSCfd using PIPESIM. A pressure loss of 13.8 barg was recorded during the simulation. For the sensitivity analysis, three flow rates (3, 12, and 18.7 MMSCFd) were tested at the respective inlet pressures of 57barg, 114barg, and 171 barg, and six varying pipe diameters. This setup produced 81 unique data combinations that were used to develop a pressure drop correlation through LINEST regression analysis in Microsoft Excel. The result showed that pressure dropped with larger pipe sizes, under a constant flow rate the developed correlation yield a good result with R^2 value of 0.8025 and it is reliable and can serve as an estimation tool. Marfo *et al.* (2019) designed a subsea pipeline network using PIPESIM to study flow assurance problems on Ghana's Jubilee and TEN Fields, a condensate gas pipeline of 16 inches Internal Diameter of 44 km length and proposed a parallel 12 inches pipe of Internal Diameter placement. This parallel pipeline increased the designed flow rate by almost 4.7 times (705 MMSCFD). The alternate design employs 18 in. and 20 in. Internal Diameter pipes for flowlines 1 and 2 respectively It was observed that Hydrate formation temperature and pressure was 72.5^{o}F and 3000 Psig respectively, but with insulation thickness of 1.5 inches and 2 inches the hydrate formation for flowlines 1 and 2 were curbed. This study proposed 12inches and 14 inches pipe sizes for flowlines 1 and 2 respectively. The maximum designed flow rate was achieved at 150 MMSCFD. Peters et al. (2022) reported the result of a parametric analysis carried out using PIPESIM Software on the pipeline of the Gulf of Guinea, a Subsea data was gotten from Schlumberger bearing input parameters from the Wellhead to the Separator to meet the discharge pressure, discharge temperature and the erosional velocity ratio. By varying 202.74mm, 254.46mmand 304.74mm pipe sizes against the flow rates of 0.01472m^3/s, 0.02576m^3/s, and 0.02944m^3/s. After the analysis, 254.46mm and 304.74mm pipe were selected. The 254.46mm pipe delivered at flowrate of 0.02944m^3/s and at the required discharge temperature and pressure of 65.56°C, 7,909KN/m^2, while 304.74mm delivered at temperature and pressure of 64.61°C and respectively 7,986KN/m^2 Both at Erosional Velocity Ratio <1. Marfo, et al. (2018) used PIPESIM software for the design and analysis of a subsea pipeline for natural gas transportation from Gazelle Field in Cote d'Ivoire to a platform 30 km away. The design comprised of two risers and one flowline; hydrate was predicted to form at 65°F for an arrival pressure of 800 psia. The result showed that, for optimal operation, the insulation thickness for the flowline was determined to be 0.75 inches with specific pipe size of 10 inches to satisfy the arrival pressure condition. At Jinzhou in China in 1993 a 50,000m pipeline was obstructed by hydrate, in 8 days this blockage was eliminated using methanol injection (Babakhani

et al, 2015). Liu et al. (2020) reported that MATLAB programming software was used to establish a corresponding mathematical model of oil pipeline energy consumption of the Qingtie Fourth-line crude oil pipeline in China and the result shows that among the genetic algorithm, particle swarm optimization, and simulated annealing algorithms used for solving the optimization model, the particle swarm optimization algorithm has fast convergence speed, short optimization time obtains the most optimal scheme, and can reduce energy consumption by 7.84%, which proves the practicability and creativity of the optimization model. Tamzor, et al. (2023) utilized computational fluid dynamics model for the simulation of fluid parameters (pressure, temperature and flow-rate) along a crude oil pipeline in Nigeria in MATLAB domain. PIPESIM software was then utilized to compare the simulated results obtained. 9,875.52m, 0.228m/s, 289.51K and 68.95 bar at a constant flow rate and fluid density of 1000 STB/d and 828.5 kg/m^3. The results showed that both pressure and temperature decreased along the length of the pipe, indicating frictional losses and obstructions from scales and potential hydrate formation. although, the predicted pressures and temperatures by PIPESIM were rather higher than the values computed by the model but was a better correlation giving a RMSE value computed between the software and the model are 0.15823and 0.025995 for predicted pressure and temperature, respectively the result reveals that both techniques can be used to study hydrate formation in crude oil transmission pipelines.

Liang et al. (2016) utilized Euler tool and CFD-PBM model in the simulation of gas-oil-liquid during the underwater transport of gas hydrates, the results from the CFD-PBM model showed that both the vapour and solid concentrated toward the core of the pipe, although this concentration was not clearly defined as it is in the Euler model. So, the velocity differential within the circular axis was less marked compared to the Euler techniques. Thus, the flow conditions showed that CFD-PBM model has better effectiveness than the Euler model. Sultan et al. (2019) simulated the behavior of three -phase flow by replicating a system primarily influenced by gas than liquid, and predicted the imminent location and state of Clathrate hydrate nucleation in the multiple-phase flowline system with CFD simulations to ensure comprehensive assurance. A routine CFD model was developed to discern the characteristics that govern hydrate nucleation in subsea flow lines analyzing the effects of methane mass transfer from vapour to liquid as well as the conversion of dissolved methane reactions using water volume percentage of 20% (low) and 40% (high).He recorded that water has volume fraction of 97.53% and 99.33% for inlet water volume proportions both low and high at the bottom of the flow line in both cases respectively (Neto, 2016). Zi, et al. (2016) used EECFDM in the forecast of the agglomeration of Freon R11 hydrate particles in a disturbed liquid flow, a flow loop data was used in the validation of the model. Al-Qaisi et al (2018) presented in their study that Monoethyleneglycol in 20wt% concentration added to a hydrate ridden pipeline suppressed the deposition of hydrate, the preparatory reboot gas tests in this flow loop gave clear evidence of hydrate nucleation with a gas velocity less than 0.26 ft/s. Song et al., (2019) simulated the response of hydrate growth using FLUENT 14.5. the major parameters of interest were frequency of collision, frequency of accumulation, frequency of dissociation and the size of distribution of particles of hydrate. A log-normal analysis was used to determine the particle sizes of hydrate, and was observed that flow rate has much impact on

pressure differential. Naseer and Brandst (2011)utilized UDF integrated FLUENT in enhancing comprehension of processes involved in vapor droplet formation and the ensuing settlement of water in the lower sections of a gas pipeline, the temperature distribution of the flowline and water vapour droplet formation on the walls, hydrate nucleation as well as the flow behaviour of hydrate paste were examined. The results showed that moisture uptake and hydrate formation take place at the steep side of the flowline. Yang et al., (2019)utilized ANSYS in a CFD analysis in creating a meshed geometry of flowlines, designed pyramidal cells with incremental mesh and orthogonal quality, and the result showed that blockage diameter and length of pipe significantly affects pressure drop. Al-Qaisi, et al (2018) used an extreme-pressure DSC to check hydrate crystallization of the formers and observed that for hydrate nucleation to occur, a sub-cooling temperature of about 30K should be kept.

Table VI. Summary of computational Fluid Dynamics Models used in gas hydrate prediction studies

S/N	Software used	Area considered	References
1	Theoretical particle size distribution Sensors	Methane hydrate formation process using real-time particle sizing	Herri, et al., (1999)
2	FLUENT	Predictive modeling of methane hydrate decomposition in sandstone formations	Nazridoust and Ahmadi (2007)
3	FLUENT	A CFD-Based Model for the Detection of flow Restriction-triggered Cutting-edge strategy for exploring hydrate deposition in gas pipelines	Jassim, et al., (2008)
4	STAR-CD	merged CFD/ Computational modeling of hydrate cluster generation in pipelines using a population balance approach/ Experimental investigations of hydrate flow dynamics in complex pipeline configurations and Computational modeling of hydrate particle generation in pipelines using chaotic liquid movement CFD-PBM simulation of cluster and settlements in oilfield	Balakin, et al., 2010; Balakin, et al., 2010; Balakin, et al., 2016)

5	HydrateResSim	Simulation and mathematical modeling of methane generation processes in hydrate reservoirs	Gamwo and Liu, (2010)
6	ANSYS	Advanced CFD-PBM technique with refined drag modeling for gas-liquid interactions in bubble columns	Liang et al., (2016)
7	ANSYS	Predictive CFD approach for estimating hydrate formation in underwater pipelines	Neto, (2016)
8	ANSYS	Validation of CFD simulations for vapour-liquid-solid multiphase flow in lateral pipes	Sultan, et al., (2019)
10	FLUENT	Population dynamics-based numerical simulation of hydrate Study of natural gas hydrate formation characteristics during the decomposition process and numerical modeling of hydrate particle distribution and sedimentation in pipeline systems	Song, et al., (2019)Song et al., (2018)
11	CFD—UDF	Numerical simulation of Hydrate decomposition in a 90^{o} bend using CFD model approach	Jozian and Vafajoo (2018)
12	FLUENT	Examination of multiphase flow properties in natural gas hydrate pipeline systems	Chen, et al., (2020)
	COMSOL	Computational simulation of fluid flow for predicting hydrate buildup in the Ilam gas refinery pipeline	Aghil, et al., (2019)

Table VII: Comparison **of advantages and disadvantages of different hydrate formation modeling techniques**

between statistical modelling and CFD modeling of hydrate

	Merits	**Demerits**
Statistical techniques	Requires data for analysis	Needs huge amount of data sets
	Can absorb complex, irregular relationships	Hidden nature, difficult to interpret
	Complex and adjustable	Liability of excessive fitting
CFD	Comprehensive live flow and hydrate formation forecasting	High cost of computation
	It treats multiphase flow and complex structures	demands high quality input data
	delivers visual feedback for easier understanding and analysis	Intricate set up and prolonged simulation periods

CONCLUSION

An integral component of the oil and gas sector is pipeline optimization. In every phase, from exploration to production and distribution, as well as in market research and policy formation, optimizing oil and gas demand provides vital data for accurate and well-informed decision-making. Based on the available data and the unique characteristics of the oil field, various strategies have been investigated for optimizing single-phase and multiphase flow, each with unique advantages and disadvantages. In extreme pressures, no particular modeling is used for agents or suppressors with different vapor blends; nonetheless, many modeling approaches have been used for various gases and gas mixes. Successfully estimating the equations that could resolve situations with advanced gas specific gravity is crucial. Furthermore, it is essential to have equations that can solve a variety of mixed flow schemes. Although computational fluid dynamic simulation techniques have been applied to various blends, agents and hydrate suppressants with the various vapour blends at high pressures have not been simulated using a specific framework. It should be mentioned that artificial neural networks, which are also used in kinetics and effectiveness analysis, make up the majority of the AI modeling techniques included in the review. Viscometry technique has inherent shortcomings and should not be used solely for wax characterization. The solution based on particle swarm optimization was better. Particle swarm algorithm had the least calculation time, and the convergence algebra was similar to the genetic algorithm, particle swarm optimization algorithm has more advantages in solution time and optimization efficiency. Has advantages of handling discrete variables and of high computation

efficiency over classical deterministic optimization algorithms simulated. It is also, clear that annealing algorithm has a higher converging time. The GPR model outperformed several other established models, such as MLR, LSTM, RBF, SVM, ANN. GPR succeeds by its inherent flexibility in capturing complex nonlinear relationships and dependencies within the dataset. The GBR model showed superior performance in contrast to MLR, LSTM, RBF, SVM, and ANN models, as indicated by its lower overall RMSE of 2.990. The GBR model's success can be ascribed to handling non-linear relationships and dependencies. Its collective method of combining weak prediction models, permits it to optimize predictions and handle diverse data types effectively. The RF model have a relatively low overall RMSE of 1.457. This performed better than established approaches like MLR, LSTM, RBF, SVM, ANN, GBR, and GPR. The high coefficient of determination (0.963) further confirms the RF model's accuracy in capturing the underlying patterns. The KNN algorithm shows great result to predict gas hydrate formation temperature. The KNN model performed better than many other models, including MLR, LSTM, RBF, SVM, ANN, GBR, GPR, and RF, accomplishing an overall RSME of 1.331.But in addition to the experimental research, further research into creating effective prediction and dissociation models will speed up the development of gas hydrate solutions and enhance flow assurance in the oil and gas sector.

Future work

The key to the overall success of hydrate mitigation is a full integration of a good front end-design, comprehensive deployment plan and an effective monitoring program. Practical or experimental methods can be used alongside other modeling algorithms and machine learning approaches like Particle Swarm Algorithm, Support Vector Machine, Genetic Algorithm, Artificial Neural Network etc. Despite the fact that different dissociation models for pipeline hydrate plug remediation provide insightful information about hydrate behavior and remediation tactics, their use is faced with difficulties, including complex thermodynamic processes, complex heat distribution issues, the influence of flow regimes, and safety and financial limitations. For effective remediation, these gaps must be filled using integrated methodologies that combine dissociation models and simulation, to overcome this menace.

NOMENCLATURE

CFD	Computational fluid dynamics
CSMHyK	Colorado School of Mines Hydrate Kinetic Model
AA	Anti-Agglomeration
GA	Genetic Algorithm
LDHI	Low dosage hydrate inhibitor
ANN	Artificial Neural Network
THI	Thermodynamic hydrate inhibitor
vdWP	Van der Waals and Platteeuw

HFT	Hydrate Formation Temperature
HTP	Hydrate Formation Pressure
KHI	Kinetic Hydrate Inhibitor
PSA	Particle Swarm Algorithm
WAT	Wax Appearance Temperature
WDT	Wax deposition temperature
SVM	Support vector machine
MEG	Mono Ethylene Glycol
AI	Artificial Intelligence
LSSVM	Least Squares support vector machine
EECFDM	Eulerian–Eulerian Computational Fluid Dynamics model
BPNN	Back Propagation Neural Network
ACO	Ant colony optimization
ANFIS	Adaptive Neuro-Fuzzy Inference System
RBF	Radial Basis Function
GEP	Gene expression programming
ICA	Imperialist competitive algorithm
CART	Classification and Regression Tree
AARE	Average Absolute Relative Error

Symbol

T	Temperature, K
P	Pressure, Mpa
R	Universal gas constant, 8.314J/(mol K)
γ_g	Gas gravity

Declarations

The authors declare that there is no conflict of interest in this research

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