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A Critical Review of Surrogate Reservoir Modelling for Uncertainty Quantification in Thin Oil Rim Reservoirs

Yetunde M. ALADEITAN[1*], Damilola V. ABRAHAM[2], Abdulmojeed O. OLUOGUN[3], Abdulwasiu ABDURRAHMAN[4]

[1*,4]Department of Chemical Engineering, University of Abuja, Abuja, Nigeria
[2]Department of Petroleum and Gas Engineering, Baze University, Abuja, Nigeria
[3]Department of Petroleum and Gas Engineering, Nile University of Nigeria, Abuja, Nigeria

[1*]yetunde.aladeitan@uniabuja.edu.ng, [2]damilola.abraham@bazeuniversity.edu.ng, [3]moluogun.olawale@nileuniversity.edu.ng, [4]abdulwasiu.abdurrahman@uniabuja.edu.ng

Abstract
The Surrogate Reservoir Models are becoming popular as a computationally efficient alternative to performing full-field numerical simulations for problems of complex reservoir models where uncertainty analysis is extensive. The low recovery factors for thin oil rim reservoirs (40 percent or less) with oil columns between large water and gas caps is a challenge that must be addressed during development. This review presents the methodology, application and validation of Surrogate Reservoir Models for uncertainty quantification in thin oil rim reservoirs from the basic studies in the Niger Delta to the recent development of machine learning-based proxy modelling up to 2026. The paper critically reviews the use of Surrogate Reservoir Models and shows how experimental design, response surface methodology and Monte Carlo simulation are combined to prioritize uncertain parameters and provide a production forecast, which is probabilistic. Key findings include the fact that the horizontal well length is the largest uncertainty factor and that horizontal well placement just above the oil-water contact had the best results than in the mid-rim or gas-oil contact. The review highlights some key challenges such as the lack of standard protocols for validation, the limited scale of physics-informed neural networks being adopted in industry, and the lack of a real-time updating framework. The best modelling strategy is the response surface methodology used to optimize the model in initial screening followed by Monte Carlo simulation for probabilistic modelling validation, with correlation greater than 0.99 when compared with history matched field data.

Keywords: *Surrogate reservoir modelling; Uncertainty quantification; Thin oil rim; Proxy models; Monte Carlo simulation; Physics-informed neural networks.*

1.0 Introduction

1.1 Background and Problem Statement

The thin oil rim reservoir is one of the most demanding and difficult reservoirs to produce in the petroleum industry. These reservoirs generally have a very thin gas cap, usually less than 80 feet, and are underlain by a very thick aquifer. Average recovery factors for such reservoirs vary from 10 to 20 percent on a global basis, mainly because of the occurrence of coning phenomena when pressure drawdown is too large, resulting in early water and gas influx [1].

The Niger Delta basin has many thin oil rim reservoirs with significant volumes of hydrocarbons, estimated to be around 1.2 billion stock tank barrels [2]. Typical production characteristics from these formations have yielded recovery factors in the past of 2 to 11 percent and total cumulative production per well of 0.8 to 4.6 million stock tank barrels. The economic consequences of water production are serious: the 75 million barrels per day of oil production worldwide can be paralleled with the water production of 300-400 million barrels per day, which also imposes comparable or higher energy requirements for water lifting and disposal [3].

For the development of thin oil rim reservoirs, the technical challenges are the handling of the complex uncertainties in the subsurface. Some of the parameters that remain uncertain are size of gas cap, strength of the aquifer, vertical to horizontal permeability anisotropy, oil viscosity, and the exact location of fluid contacts [4]. The evaluation of these uncertainties has been strongly depended on a traditional way of employing full-field numerical simulation. These simulations are time consuming and expensive as the number of grid cells increases to millions and when many geological realizations are needed to adequately cover the uncertainty [5]. The computational needs increase even more with the increasing use of techniques from artificial intelligence, which require a large amount of training data.

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1.2 The Need for Surrogate Modelling

For the need of quick and accurate production forecasts, Surrogate Reservoir Models have been designed. A Surrogate Reservoir Model is an approximation of a full, numerical reservoir simulation that is run at much less cost. Unlike solving of complex partial differential equations that describe multiphase flow on fine grid systems, Surrogate Reservoir Models use statistical or machine learning methods to model the input-output relationship for the reservoir system [6].

The need for Surrogate Reservoir Models becomes even more critical if multiple geological realizations are needed to adequately represent inherent reservoir heterogeneities. Heath et al. [7] showed that the size of the problem to define a reservoir characterization problem grows with the number of realizations needed to get a meaningful quantification of uncertainty. This correlation highlights the limitation of the traditional simulation methods.

1.3 Recent Advances in Artificial Intelligence for Reservoir Simulation

In recent years, the application of AI techniques has been increasing rapidly in the reservoir simulation field of the petroleum industry. In recent years, deep learning architectures, transformer-based models, and physics-informed neural networks have shown exceptional potential in approximating complex physical systems. Magalhães et al. [8] proposed a cell-level deep learning approach as a proxy model for reservoir simulation, which accurately reproduced the reservoir behavior with more than 80 percent accuracy in all test cases and up to 99.9 percent in some, and required less than a second to predict the reservoir behavior. Canchumuni et al. [9] developed a transformer-based proxy model with reservoir specific features, which yielded average SMAPE errors less than 7 percent for a variety of test reservoirs such as UNISIM, Olympus, and Buzios.

1.4 Aim and Scope of this Review

This review is to critically examine the methodology, application and validation of Surrogate Reservoir Models for uncertainty quantification of thin oil rim reservoirs. The paper reviews and summarizes the basic work on the Niger Delta reservoirs and the recent research in machine learning (ML)-based proxy modelling up to 2026.
Specific objectives include:

a) Evaluating the application of water quality models to the development of the Surrogate Reservoir Model.
b) Evaluating the uncertainty quantification methods, focusing on Monte Carlo simulation and new methods.
c) Critically evaluating a range of validation strategies within studies.
d) Stating where gaps are and what needs to be done.

The review builds on previous work by summarizing and critically analyzing all the works to expose inconsistencies in the validation protocols and suggest directions for future development incorporating physics-informed neural networks with traditional response surface methods.

2.0 Methodological Framework for Surrogate Reservoir Model Development

2.1 Fundamental Concepts and Definitions

A Surrogate Reservoir Model is a model that is an approximation of a full field reservoir simulation model which accurately simulates the necessary input-output relationships with reasonable computation expense [10]. The development stages involve a sequence of steps: data collection and quality control; selection of suitable grid systems; model initialization; sensitivity analysis to determine influential parameters; experimental design for efficient sampling; proxy model development based on response surface methods; and model validation by comparing with the simulation results of the full field.

In Figure 1, the schematic workflow for Surrogate Reservoir Model development is shown. This workflow starts from data acquisition and quality assessment, next follows the parameter screening to select the most important parameters. Experimental design methods ensure the most efficient sampling strategy and then the response surface models are developed and validated. Then the validated surrogate model can be used for uncertainty quantification and production forecasting.

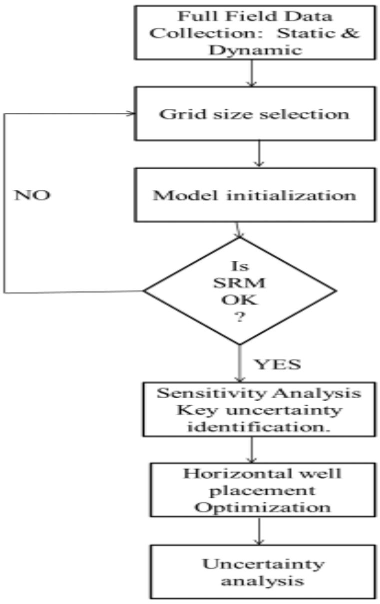

Figure 1: Schematic workflow for Surrogate Reservoir Model development

2.2 Parameter Screening and Sensitivity Analysis

One of the most important first steps in the Surrogate Reservoir Model development process is the identification of "heavy hitters" which are influential parameters. Parameter Screening is done using regular two-level experimental designs. In the foundational study seven uncertainty parameters were studied: oil rim height, horizontal permeability, oil viscosity, bottom hole pressure, vertical to horizontal permeability anisotropy (kv/kh), horizontal well length and gas cap size (m factor). The values that were explored for each uncertainty parameter are given in Table 1.

Table 1: Model Uncertainty Parameters and Their Range of Values

Parameter	**Low**	**Mid**	**High**	**Unit**
Oil Rim Height	30	55	80	feet
Horizontal Permeability	500	1000	1500	millidarcy
Oil Viscosity	0.5	1.25	2.0	centipoise
Bottom Hole Pressure	600	900	1200	pounds per square inch
kv/kh Anisotropy	0.001	0.036	0.070	dimensionless
Well Length	600	650	800	feet
Gas Cap Size (m factor)	0.5	2.25	4.0	dimensionless
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Source: Adapted from [11]

These parameters have been recently confirmed by new investigations. Using Plackett-Burman experimental design study in Niger Delta oil rim reservoirs, gas cap size (m factor) showed strong negative correlation with recovery factor ($r = -0.64$) while oil column height showed strong positive correlation ($r = 0.50$) [12]. The permeability anisotropy ratio showed moderate negative correlation ($r = -0.33$), and this confirmed that increasing the anisotropy results in a decrease in recovery, because the coning tendencies increase as the anisotropy increases.

The Pareto Chart (Figure 2) represents the effect of the parameters on oil recovery. It is apparent from the chart that the horizontal well length and horizontal permeability are the most significant parameters followed by the height of the oil rim and size of the gas cap. Knowing the relative contributions allows for more efficient experimental design and resource allocation.

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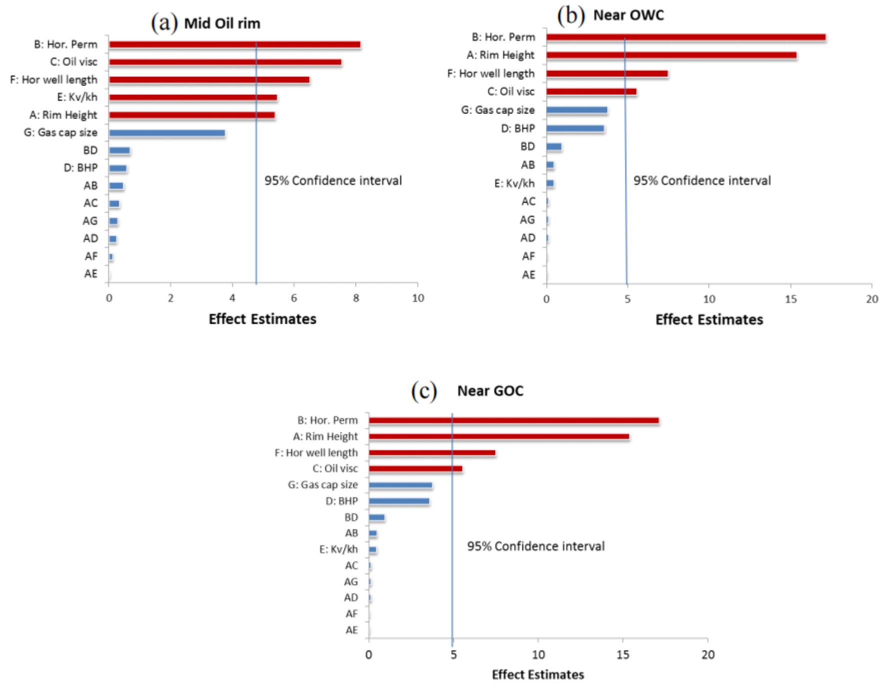

Figure 2: Pareto chart showing the impact of parameters on oil recovery

2.3 Response Surface Model Development

After the screening of the parameters, response surface methodology was used to obtain mathematical equations that correlated the independent variables with the dependent variables (cumulative production and recovery factor). The model F-values for weak aquifer and strong aquifer cases were 369 and 7971 respectively, which signifies the model to be significant. Probability values of less than 0.05 were regarded as the significant level of the model terms.

The final response surface equation for the weak aquifer case is presented as Equation (1):

$$\text{Recovery} = -34.302 + 0.861A + 0.018B - 0.027C + 0.016D + 37.934E + 0.034F - 1.314G - 5.266\text{E-}3AB + 0.017AC - 5.695\text{E-}04AD - 3.25\text{E-}04AF + 0.013AG - 1.287\text{E-}05BD + 4.250\text{E-}07ABD \quad (1)$$

where:

A = oil rim height
B = horizontal permeability
C = oil viscosity
D = bottom hole pressure
E = kv/kh anisotropy
F = horizontal well length
G = gas cap size (m factor)

2.4 Recent Advancements in Proxy Modelling

There has been significant progress in machine learning approaches in the recent years to response surface methodologies. Magalhães et al. [8] suggested a cell-level deep learning model as a proxy model of reservoir simulation and prediction. They used deep neural networks as well as Design of Experiments (DoE) to attain an accuracy of more than 80 percent in all test scenarios and more than 99.9 percent in selected scenarios. The computational efficiency enhancement was astounding: inference time in seconds versus hours for standard simulation.

Canchumuni et al. [9] presented a transformer-based proxy model for three-phase flow simulation, which is modelled on BERT with reservoir-specific features. They have tested their model across several reservoirs such as UNISIM, Olympus and Buzios with average SMAPE error less than 7%, and inference times of seconds, depending on the availability of GPUs.

The use of physics-informed neural networks in convection equations has been shown by Liu et al. [13] for polymer flooding reservoir applications. They found that PINN-based methods performed well in estimating water saturation distribution, and that a single network performed better than separate networks for coupled variables.

3.0 Uncertainty Quantification Techniques

3.1 Monte Carlo Simulation Framework

Monte Carlo simulation is a powerful tool for modelling the impacts of risk and uncertainty on reservoir forecasting. The method creates probability sets for output parameters, based on probability sets for input parameters. The Monte Carlo method was used to synthesize uncertain attributes and to generate the values of the input variables of the model in the basic study. The number of iterations was 1 million, with uniform distribution of input parameters.

The recovery forecasts and parameter sensitivity are shown for both weak and strong aquifer scenarios in Figure 3. The figure shows both scenarios with their respective probability distributions of recovery factors, highlighting the importance of aquifer strength in the recovery outcomes. For the strong aquifer case, the higher the probability, the higher the recovery.

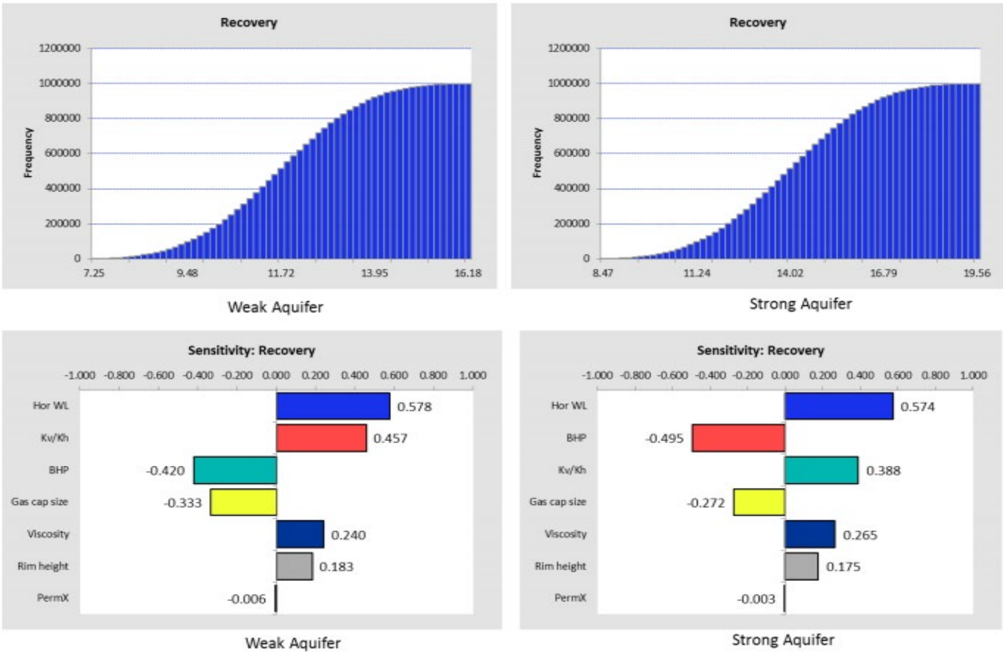

Figure 3: Recovery forecast and parameter sensitivity for weak and strong aquifer cases

3.2 Probabilistic Production Forecasts

The production forecast distribution at different probability levels is given in Table 2. Results show that aquifer strength is an important parameter in recovering oil from thin column reservoirs. The strong aquifer case always has a higher recovery value at all probabilities and the P50 value increases 20 percent when compared to the weak aquifer case.

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Table 2: Production Forecast Distribution

Probability Level	Weak Aquifer Forecast (MMBBL)	Strong Aquifer Forecast (MMBBL)
P10	9.59	11.38
P50	11.72	14.03
P90	13.83	16.64

Source: Adapted from [14]

3.3 Other Uncertainty Quantification Approaches

In recent years, besides Monte Carlo simulation, there are several other approaches that have become popular. Bayesian uncertainty quantification offers a mathematically sound approach to the problem of updating prior beliefs with the data obtained, and produces posterior probability distributions. Probabilistic inversion methods allow the estimation of uncertain parameters through the matching of observed production data, taking into

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account the model's uncertainties and errors in measurement. The Ensemble Kalman Filter (EnKF) is a successful technique for data assimilation used for sequential updates of reservoir models as new production data is received.

Canchumuni et al. [9] introduced uncertainty quantification into their transformer-based proxy model with ensemble predictions that allow to assess the prediction confidence. Xiaoyin et al. [15] used a proxy model based on a CWGAN-GP with high accuracy of spatial structure for pressure fields, which not only gave accurate uncertainty quantification but also ensured physical consistency.

3.4 Well Placement Optimization Through Surrogate Modelling

The surrogate model was also used to test the strategies for optimal well placement. Three placing positions were tested; near gas-oil contact, near oil-water contact, and between gas-oil contact and oil-water contact.

Performance of horizontal wells (based on oil recovery) is shown in figure 4 for various oil rim heights. An 80-foot oil rim proved to be a good depth for which to target recovery and they estimated total recovery of about 17 million stock tank barrels from a horizontal well near the oil-water contact, about 15 million stock tank barrels from a horizontal well in the middle of the oil rim, and about 12 million stock tank barrels from a horizontal well near the gas-oil contact. Oil-water contact placement is superior due to more distance from gas cap, allowing for delayed gas breakthrough and strategic placement to allow for natural water drive and manage coning of water by drawdown.

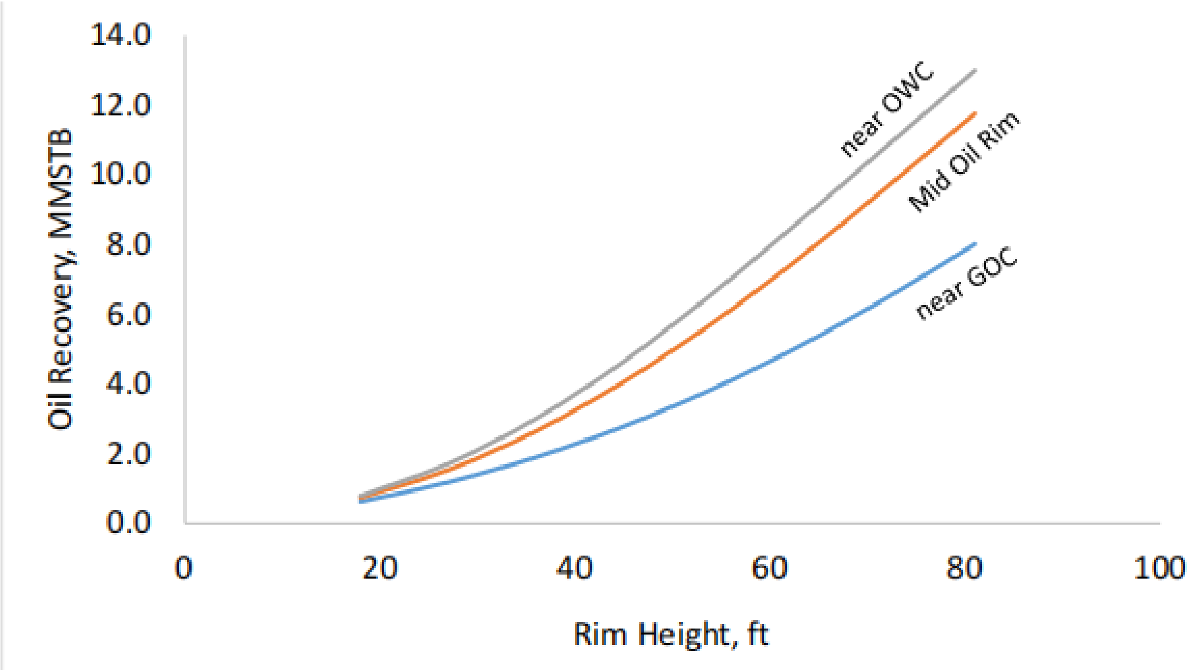

Figure 4: Performance of horizontal wells based on oil recovery at different oil rim heights

4.0 Validation and Comparative Performance

4.1 Validation Against History Matched Field Data

Validation of surrogate models is critical to ensure credibility and usefulness for practical applications when compared to history matched field data. The estimates from the response surface models were compared with the recovery from a history matched Niger Delta oil rim reservoir (termed Reservoir A) in the foundational study. The thickness of reservoir A ranged from 10 to 80 ft, while the horizontal permeability ranged from 100 to 2000 millidarcies and the gas cap size (m factor) ranged from 0.2 to 5.

The results of the oil recovery from model A are compared with the oil recovery from the actual Reservoir A in figure 5. The developed mathematical models were used to model the oil recovery in the field, the results showed good correlation with the field data (R2: 0.998 and 1.000 for weak and strong aquifer models respectively). This high correlation demonstrates the validity of surrogate modelling method for the reservoir conditions studied.

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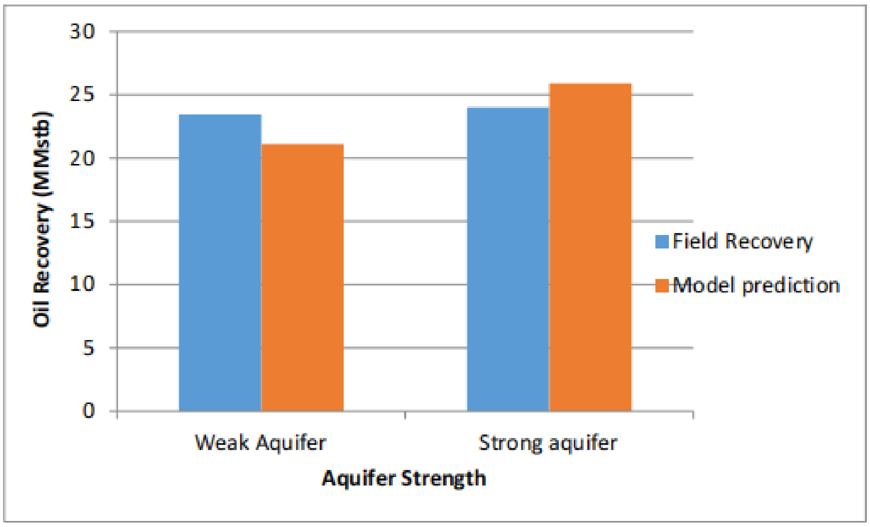

Figure 5: Comparison of oil recovery from actual Reservoir A and surrogate model prediction

4.2 Critical Comparison of Validation Approaches Across Studies

An analysis of the literature on validation, conducted at the outset of the study, shows that there are marked inconsistencies with regard to validation practice. Cross-validation is used in many studies instead of independent field validation. Magalhães et al. [8] validated using k-fold cross validation in synthetic data sets, and Canchumuni et al. [9] validated their transformer model with several benchmark cases and compared with field data, but did not compare with other field cases. The basic study conducted by Aladeitan [14] was, on the other hand, validated against the actual production data obtained from the field and gave more evidence of applicability in practice.

A proxy model based on a CWGAN-GP was introduced by Xiaoyin et al. [15] to accurately recover the spatial pressure field structure with the computational efficiency of two to three orders of magnitude higher than numerical simulation. They were validated against high fidelity simulation, and against benchmark performance metrics.

To overcome the issue of accurate representation of wells, Zhang et al. [16] proposed the WellPINN workflow. In this workflow, several PINN models are trained sequentially, the first PINN model is trained to predict the fluid pressure in the whole reservoir domain, and the second is trained to predict the fluid pressure around the wells, which is then used to correct the prediction results of the first model. This is the first PINN based method that is able to predict pressure over the whole injection duration. Zhang et al. [17] also added the Darcy's law-based seepage equations as physical constraints to a deep learning framework. They found PINN to be well suited for reservoirs with low numbers of wells and high reservoir heterogeneity because it achieves decent prediction accuracy using a small number of training samples.

4.3 Benchmarking Surrogate Model Performance

Comparative study of various surrogate modelling methods shows the balance between accuracy, computational efficiency and generalizability. Table 3 provides a summary of the performance properties of the different surrogate modelling techniques used in the reservoir simulation problems.

Table 3: Comparative Performance of Surrogate Modelling Approaches

Approach	**Accuracy**	**Computational Speed**	**Generalizability**	**Data Requirements**
Response Surface Methodology	High ($R^2 > 0.95$)	Very Fast	Limited to design space	Moderate
Deep Neural Networks	Very High (RMSE < 5%)	Fast	Moderate	Extensive
Transformer-based Models	High (SMAPE < 7%)	Very Fast	Good	Extensive
Physics-Informed Neural Networks	High with physical constraints	Fast	Excellent with physics	Moderate
Ensemble Methods	High with uncertainty bounds	Moderate	Good	Moderate
Approach	Accuracy	Computational Speed	Generalizability	Data Requirements

Source: Compiled from [8], [9], [13], [15], [17]

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5.0 Research Gaps and Future Directions

5.1 Current Limitations and Critical Analysis

Based on literature research, a number of significant limitations are seen for the modelling of surrogate reservoirs in thin oil rim reservoirs.

Lack of consistent Validation Protocols: There is a significant lack of uniformity in the validation protocols used in various studies. Some researchers compare their results with historical data from the field while others compare only with the data within the training set, based on the cross-validation method. The lack of consistency makes it challenging to compare model performance between studies and to evaluate predictive power. The field validation methodology shown by Aladeitan [14] should be a minimum requirement.

Limited Transferability: Not enough evidence of transferability of surrogate models between reservoirs. Niger Delta reservoir models may not be effective in other geologically different areas. This reduces the generalizability of published models, and the need for case-specific development.

Absence of Dynamic Updating: Typically, there are no dynamic updating procedures or algorithms to take new production data as it becomes available. This is a big constraint for any real-time reservoir management application, where production data keeps coming out and production decisions have to be made in a timely fashion.

Advanced Methods' Computational Requirements: Physics-informed neural networks and transformer-based approaches have great potential, but they are still a heavy burden when it comes to computing during training. The balance of development effort with operational benefit needs to be considered for resource constrained operators.

5.2 Future Directions and Opportunities

This review of the literature highlights several promising avenues of research.

Physics-Informed Neural Networks with Traditional Methods: There is great potential to combine physics-informed neural network and traditional response surface methods to gain more physical consistency while keeping computational efficiency in mind. Some early success has been achieved by Liu et al. [13] and Zhang et al. [17] for the initial integration, but there is a lack of systematic integration with existing workflows in the context of thin oil rim reservoirs.

Surrogate Modelling through AutoML Techniques: Making surrogate modelling workflows more accessible to practising engineers by using AutoML techniques. The skill needed for successful surrogate model development may be greatly reduced by automated feature selection, hyperparameter optimization and model selection.

Digital Twin Development for Real-Time Reservoir Management: The development of digital twins with the ability to utilize the surrogate modelling is an important area of further investigation. These would allow for a real-time management of the reservoir, incorporating new production information and updating forecasts on an ongoing basis.

Standardized Validation Frameworks: Establishment of standardized validation frameworks, including benchmark datasets and acceptance criteria, would greatly enhance the credibility and comparability of surrogate modelling studies. Such frameworks might be built and sustained by international collaborative efforts.

Well representation in physics-informed neural network approaches: As shown by Zhang et al. [16], well representation is still a challenge for physics-informed neural network approaches. More research on the efficient and accurate modelling of wells in the framework of PINN would make these methods more useful.

6.0 Conclusions

For this critical review, the use of Surrogate Reservoir Modelling for uncertainty quantification in thin oil rim reservoirs has been explored. The following conclusions are drawn:

a) Surrogate Reservoir Models provide a significantly more computationally efficient alternative to full-field numerical simulation for uncertainty quantification and have been shown to be highly correlated with the full-field numerical simulation in cases where they have been history matched with field data (correlation coefficient > 0.99). The best modelling technique is a mixture of response surface method for screening and Monte Carlo simulation for probabilistic forecasting.
b) In thin oil rim reservoirs, the most important uncertainty parameters are horizontal permeability, horizontal well length, oil rim thickness, oil viscosity and gas cap size. Well length in the horizontal direction is the most significant factor and the need to optimize well design becomes apparent.
c) The location of wells is critical to oil recovery; the best cumulative oil recovery occurs if wells are located directly over the oil-water contact. This placement strategy helps minimize risk of gas breakthrough and will allow for control of water coning.
d) Surrogate modelling has significantly advanced over the past few years, leading to the introduction of physics-informed neural networks and transformer-based architectures, which have demonstrated

enhanced accuracy and physical consistency. But these advanced techniques come with their own set of difficulties, such as the need for more data and computational training.

e) There are still some key research gaps to be addressed such as the lack of standardized validation protocols, limited evidence of transferability across reservoirs, the absence of dynamic updating procedures and low industrial use of physics-informed neural networks.

f) The proposed future research advances include physics-informed neural networks to combine with traditional response surface methods, automated workflows by applying AutoML, standardized validation procedures, and digital twin applications for real-time reservoir management.

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