FUDMA Journal of Engineering and Technology
ISSN: 3092-9385
https://fjet.fudutsinma.edu.ng/index.php/fjet/
Volume 2, Issue 1, 2026, 1025-1032

A Data-Driven Surrogate Framework for Economic Optimization of Thin Oil Rim Developments: A Comprehensive Methodological Review and Niger Delta Application

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Abstract
Reservoirs with a thin oil rim where the hydrocarbon column is in danger of being breached by an active aquifer and gas cap is a long term optimization problem. Sour gas and water coning significantly impact recovery profits, and uncertainty underground makes development decisions challenging. The large number of scenarios and uncertainties involved in a robust field development plan cannot be sufficiently addressed through the traditional simulation-intensive processes. In this paper, a framework of the Surrogate Reservoir Model (SRM) is proposed and consists of three elements: the statistical design, the machine learning proxy modeling, and the economic analysis. The methodology includes the sequential experimental design for parameter screening, high-dimensional response surface and machine learning for proxy construction and Monte Carlo forecasting for probabilistic predictions. For a case study in the Niger delta, the key uncertainties identified are the permeability anisotropy, oil column height, and horizontal permeability. Seven development options have been investigated using a probabilistic analysis and it is found that the one with the greatest technical recovery is not economically best. The framework was able to enable economics-based decision making, such as simultaneous oil and gas production which show the best value of Net Present Value and Internal Rate of Return.

Keywords: *Thin Oil Rim; Surrogate Reservoir Model; Uncertainty Quantification; Experimental Design; Machine Learning; Integrated Reservoir Management.*

1.0 Introduction

Marginal and complex hydrocarbon resources are increasingly important for sustainable global energy supply. Thin oil rim reservoirs, characterized by an oil column typically less than 50-100 feet thick with an overlying gas cap and underlying aquifer, exhibit recovery factors ranging between 10 and 35 percent worldwide [1], [2]. The primary technical challenge involves controlling gas and water coning, where excessive production drawdown causes unwanted penetration of free gas or aquifer water into the wellbore, resulting in high production rates, increased handling costs, and premature well abandonment [3], [4].

Optimal development requires navigating a high-dimensional decision space encompassing well positioning, completion design, depletion strategy (e.g., sequential versus simultaneous production), and pressure maintenance through injection [5], [6]. Additional complexity arises from pervasive subsurface uncertainties including oil column thickness, permeability heterogeneity and anisotropy (Kv/Kh), gas cap size (m-factor), aquifer strength, and fluid properties [7].

Traditional reservoir management typically employs a limited number of deterministic simulation models or analytical correlations that cannot adequately quantify risk, potentially leading to suboptimal investment decisions with high variance [8]. While high-fidelity numerical reservoir simulation remains the industry standard for prediction, it is computationally infeasible to conduct the hundreds or thousands of simulation runs required for rigorous global sensitivity analysis, uncertainty quantification, and strategy screening within project timeframes [9], [10]. This disparity between analytical requirements and computational capability presents a major obstacle to optimal field development planning.

Surrogate Reservoir Models (SRMs), also known as proxy models or meta-models, offer a data-driven approach to bridge this gap [11]. An SRM is a computationally efficient mathematical approximation of a simulation model, trained on strategically selected simulation runs. Recent advances in machine learning and statistical learning have substantially improved SRM capabilities for capturing the complex, nonlinear physics of coning-dominated systems [12], [13].

Although proxy modeling is not new, its implementation as an integrated, end-to-end decision-support solution for thin oil rim development—from uncertainty screening to economic ranking—has not been thoroughly addressed in the literature. Furthermore, limited research demonstrates how such a paradigm reveals that technically optimal recovery strategies are not necessarily economically optimal.

Received: 24/02/2026; Revised: 16/06/2026; Accepted: 22/06/2026; Published: 26/06/2026

To address these gaps, this paper presents a comprehensive methodological framework for constructing and deploying SRMs for thin oil rim optimization. The framework integrates classical experimental design techniques with machine learning-enhanced proxy modeling, probabilistic forecasting, and economic analysis. The methodology is rigorously illustrated through a detailed case study of a representative Niger Delta thin oil rim reservoir. The objectives are threefold: (1) to provide a systematic, repeatable methodology for developing accurate SRMs for coning-dominated systems; (2) to demonstrate SRM application for global sensitivity analysis, uncertainty quantification, and comparative strategy evaluation; and (3) to emphasize the critical integration of economics for identifying true value-optimal development plans.

2.0 Literature Review

2.1. The Thin Oil Rim Conundrum: Technical and Economic Challenges

The technical literature on thin oil rims is large, starting with the early analytical studies of coning critical rates [3] and [14] and continuing through in-depth numerical analysis of advanced completion and management strategies. To reduce the drawdown and delay breakthrough, horizontal and multilateral wells have been used [15, 16]. Other research has focused on progressive depletion techniques such as gas cap blowdown to mobilize the rim [17], co-production of oil and gas for earlier monetization [18] and pressure maintenance and contact stabilization, which include various types of injection (water, gas, or simultaneous water and gas) [19, 20].

One issue that has persisted is with the uneven sweep and coning that has been addressed by the use of smart or intelligent well completions with inflow control devices and interval control valves for zonal management [21, 22]. As recent reviews by Ikomi et al. [23] and Zhang and Gupta [24] highlight, however, many of the more advanced strategies are not easy to implement in practice because of economic considerations and the challenge of de-risking projects completely prior to development. One of the major shortcomings identified is the lack of detailed technical simulation studies that are fully integrated to full economic modeling with uncertainty through the cycle [25].

2.2. The rise of Surrogate and Machine Learning Models in Subsurface Optimization.

This idea of using proxies to approximate complex simulation models is well known in reservoir engineering, having started with simple response surfaces [26]. The new paradigm is based on the recent availability of more computing power and tools of data science and relies on new sophisticated statistical methods and machine learning. Mohaghegh [27] introduced the term "SRM", which uses artificial neural networks to simulate full-field reservoir performance. Many techniques have been used since that time, such as Gaussian Process Regression [28], Support Vector Regression [29] and Random Forests [30].

The joint development of experimental design and ML proxies for uncertainty quantification and optimization have been well-developed [31]. The experimental design gives efficient sampling methods to cover high dimensional input parameter space (e.g. Latin Hypercube Sampling, Sobol sequences); whereas machine learning models build complex input-output mapping. Focus has recently turned to hybrid or physics-aware machine learning models, which combine domain knowledge to enhance extrapolation and decrease data needs [32, 33].

Applications of coning and thin oil rims are growing. Ahmadi et al., [34] optimized the well location in fractured reservoir with thin oil column by a combination of experimental design and artificial neural network. In the same way, Chen et al. [35] used Gaussian process regression based proxies to quickly estimate the uncertainties of simultaneous water and gas injection in a volatile oil rim. All of these studies validate the method but focus on a particular element, such as well location or a specific approach. What is new in the current work is the SRM used as a complete integrated workflow of a field development plan from geology to economic metrics.

3. Methodology: A Hybrid Srm Framework For Development Optimization

The proposed framework comprises a sequential six-stage process designed to maximize learning efficiency and decision quality. The general workflow is depicted in Figure 1.

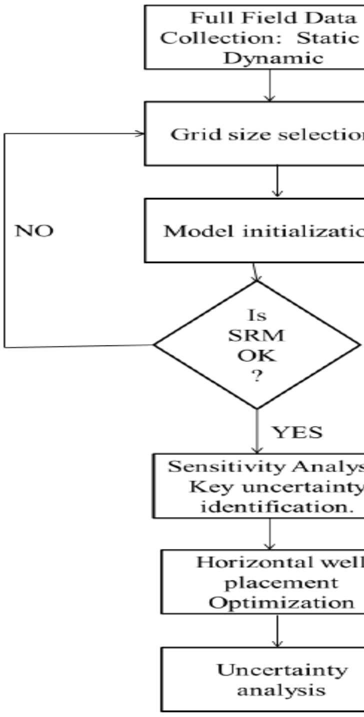

Figure 1: The integrated SRM framework schematic for thin oil rim development optimization

3.1. Stage 1: Definition and Model Construction

This stage will consist of creating a numerical simulation model that is fit for purpose. The model should include the essential physics of the system (black oil or compositional as appropriate) and be sufficiently efficient to execute hundreds of times. Usually a sector model or a simplified full-field model with representative geology, fluid contacts and well controls is used. The model is calibrated and validated to provide a reasonable match of the critical rate and coning behavior observed in a similar field.

3.2. Stage 2: Global Sensitivity and Parametric Screening

This important step helps to identify influential parameters from minor ones. A screening design is used to select the global sensitivity indices, which is also done using the Morris method [36] or a low-resolution fractional factorial design. Many uncertain parameters are characterized such as structural depth, net to gross, porosity and permeability distributions, Kv/Kh, aquifer influx coefficients, fluid PVT properties, relative permeability endpoints, and well length. The base model is used to implement each designed scenario. Sobol indices, Pareto charts or analysis of variance are used to rank the parameters based on a contribution to variance in the key outputs (e.g. 10-year cumulative oil, water breakthrough time). This phase significantly simplifies dimensionality by providing resources to 5-8 factors of most important uncertainties for detailed modelling.

3.3. Stage 3: Experimental Design and High-Fidelity Simulation

The experimental design chosen is a space filling design to sample the reduced uncertainty space for a screened set of key parameters efficiently. Non-linear responses can be dealt with by using OLS or Sobol sequences [37] which have good projective properties. This design includes a finite number of simulation runs (usually 50-200) to maximize the information for training proxy models.

3.4. Stage 4: Proxy Model Construction and Validation

The main part of the SRM is the proxy model. The training data is made up of simulation runs used in Stage 3. In the current study, a comparative approach was used with three model types: Polynomial Response Surface Models for moderately nonlinear responses, Kriging/Gaussian Process Regression for irregular nonlinear interpolation with confidence limits [28] and Artificial Neural Networks for complex nonlinear relationship that would require careful tuning and larger datasets [12].

The Gaussian Process Regression (GPR) model was chosen as the final SRM for this study because of its high R^2 value of 0.98 after validation, as it provided the highest accuracy of interpolation of the models used, which was higher than the other models used in this study, the Polynomial Response Surface Models (PRSM) with $R^2 = 0.95$. Models are developed to forecast important KPIs such as annual cumulative oil, gas and water production and field water cut.

Received: 24/02/2026; Revised: 16/06/2026; Accepted: 22/06/2026; Published: 26/06/2026

Striking validation is essential. A blind test set represents one-fifth of the simulation runs. Model performance is evaluated based on R^2, root mean square error and visual parity plots. The best performing model is chosen to be the functional SRM.

3.5. Stage 5: Strategy Evaluation and Probabilistic Forecasting

The validated SRM that can produce forecasts in millseconds allows for analysis which was previously impossible:

Uncertainty Quantification using Monte Carlo Simulation: Thousands of samples are taken from probability distributions of key input parameters. The SRM calculates a full probability density function for each sample, as well as cumulative distribution functions (e.g., P10, P50, P90) of the reserves and recovery factors.

Multi-Strategy Screening: A number of development concepts are described (Base Depletion, Concurrent Production, Gas Reinjection, Waterflood). Stages 2-4 can be repeated for each concept or a more complex SRM can be created with a categorical input variable for strategy type. This allows for a fast, like-for-like comparison of all possible strategies over the entire uncertainty space generating probabilistic outcomes for every strategy.

3.6. Stage 6: Integrated Economic Analysis for Decision-Making

Technical outputs are translated into an economic value. SRM forecasts are associated with a discounted cash flow model. For each of the strategies and Monte Carlo runs, production profile (oil, gas, water) is converted into cash flows, which is conducted through the use of economic assumptions (commodity prices, capital expenditures for wells and facilities, operating expenditures, fiscal terms, discount rate). This creates the following probability distributions: Net Present Value, Internal Rate of Return and Discounted Payout Period. The economic distributions are analysed using a risk-weighted approach and are used to inform final decision making. Efficient frontier analysis (means and risks of NPVs) or stochastic dominance criteria are useful for selecting the best strategy in terms of company risk-appetite and corporate objectives [38].

4. Case Study: Application to A Niger Delta Thin Oil Rim

4.1. Reservoir Description and Model Setup

The framework was applied to Field Alpha, a well-matured field in the Niger Delta with typical thin oil rim problems. The target reservoir, Sands X, has an average oil column of 75 ft, a very large overlying gas cap (initial m-factor = 2.5) and a moderately strong underlying aquifer. The high fidelity truth case was a history matched three-phase black-oil simulation model. The most important dynamics of the sector were taken as the efficient base model (Table 1) for SRM development, which was simplified while representing important dynamics.

Table 1: Key properties of the Field Alpha sector model used for SRM construction

S/N	Parameter	Value	Unit
1.	STOIIP (Sector)	56	MMSTB
2.	GIIP (Sector)	966	BSCF
3.	Avg. Oil Column Height	75	Ft
4.	Avg. Horizontal Permeability (Permx)	1043	mD
5.	Avg. Vertical Permeability (Permz)	10.4	mD
6.	Kv/Kh Anisotropy Ratio	0.01	-
7.	Porosity (Avg.)	0.27	fraction
8.	Initial Pressure	3976	Psia
9.	Oil Viscosity	0.8	cP
10.	Aquifer Strength	Moderate-Strong	-

4.2. SRM Framework Application

4.2.1. Stage 2: Parameter Screening

A preliminary screening design comprising 12 parameters was executed. The parameters with the most significant impact on 10-year cumulative oil recovery, accounting for more than 85% of outcome variation, were identified as: (1) Oil Rim Height, (2) Horizontal Permeability, (3) Kv/Kh Anisotropy Ratio, and (4) Gas Cap Size (m-factor). Aquifer strength and fluid viscosity were secondary influences.

4.2.2. Stages 3 and 4: Proxy Model Development

Fifty simulation runs were generated using an Optimal Latin Hypercube design for the four key parameters over their realistic ranges. Second-order Polynomial Response Surface and Gaussian Process Regression models were trained. The Gaussian Process Regression model demonstrated superior performance ($R^2 = 0.98$ versus 0.95 for Polynomial Response Surface) and was selected as the primary SRM due to its better interpolation capabilities.

Received: 24/02/2026; Revised: 16/06/2026; Accepted: 22/06/2026; Published: 26/06/2026

4.2.3. Development Strategy Definition

Seven 20-year development strategies were defined for evaluation:

- **S1: Base Depletion** – Horizontal producers only in the oil rim
- **S2: Concurrent Production** – Oil producers plus gas cap producers
- **S3: Sequential Production** – Oil production for 10 years, then gas cap blowdown
- **S4: Gas Reinjection** – Oil producers plus reinjection of produced gas to the gas cap
- **S5: Gas Reinjection with Late Blowdown** – Strategy S4 with injection cessation and cap blowdown during final 5 years
- **S6: Water Injection** – Oil producers plus peripheral water injection
- **S7: Combined Water Injection and Gas Reinjection** – Oil producers, water injection, and produced gas reinjection

Individual SRMs (Gaussian Process Regression proxies) were constructed to capture the unique performance characteristics of each strategy.

4.3. Results and Analysis

4.3.1. Probabilistic Technical Forecasts

Monte Carlo simulations with 10,000 samples were performed for each strategy using the SRMs. Table 2 summarizes probabilistic oil recovery (P10, P50, P90).

Table 2: Probabilistic 20-year cumulative oil recovery for each development strategy

Strategy	P10 (MMSTB)	**P50 (MMSTB)**	**P90 (MMSTB)**	**Mean (MMSTB)**
S1: Base Depletion	14.2	17.5	20.1	17.3
S2: Concurrent	13.8	17.5	20.5	17.4
S3: Sequential	12.1	15.2	17.9	15.1
S4: Gas Reinjection	15.8	18.7	21.2	18.6
S5: GR + Blowdown	15.9	18.7	21.1	18.6
S6: Water Injection	15.0	18.1	20.8	18.0
S7: WI + GR	15.9	18.6	21.0	18.5

Injection-based strategies (S4-S7) demonstrated superior technical performance in mean oil recovery. Strategies S4 and S5 (Gas Reinjection) generated the highest P50 values (approximately 18.7 MMSTB), primarily due to pressure maintenance and gas cap expansion control. The Concurrent strategy (S2) was equivalent to the Base case recovery, indicating that under these conditions, managed gas offtake did not significantly damage the oil rim.

4.3.2. Integrated Economic Analysis

A typical Niger Delta oil and gas economic model was applied (Oil: $65/bbl, Gas: $3.5/MSCF, Discount Rate: 10%). Differentiated capital expenditures were assigned for producers, gas injectors, and water injectors. Table 3 presents the economic indicators.

Table 3: Economic indicators for seven development plans (P50 values)

Strategy	Capital Intensity	**NPV @10% ($MM)**	**IRR (%)**	**Discounted Payout (Years)**
S1: Base Depletion	Low	220	20.0	3.0
S2: Concurrent	Low	335	24.2	2.8
S3: Sequential	Low	160	10.0	6.0
S4: Gas Reinjection	High	287	21.4	3.5
S5: GR + Blowdown	High	270	21.1	3.5
S6: Water Injection	High	219	18.1	4.0
S7: WI + GR	Very High	214	13.2	4.2

The economic analysis revealed a compelling insight. Although S4 (Gas Reinjection) was technically superior, S2 (Concurrent Production) was the undisputed economic leader, providing the highest NPV of $335MM, highest IRR of 24.2%, and shortest payback period. The high incremental capital expenditures and operational complexity of injection facilities (compressors, water treatment plants, injection wells) eroded the value of additional oil recovered in S4-S7. The Base case, despite having the lowest risk, produced substantially lower value. This demonstrates a crucial principle: Maximizing recovery is not equivalent to maximizing value.

Received: 24/02/2026; Revised: 16/06/2026; Accepted: 22/06/2026; Published: 26/06/2026

4.3.3. Decision-Support Template

The SRM-enabled analysis produced a strategy selection matrix based on reservoir characteristics (Table 4), providing a concise reference guide for similar applications.

Table 4: Strategy selection guidelines based on dominant reservoir characteristics

Dominant Reservoir Characteristic	Recommended Strategy	**Primary Rationale**
Very Large Gas Cap (m > 3)	S2: Concurrent Production	Maximizes early gas monetization; oil rim management feasible
Very Strong Aquifer	S2: Concurrent or S6: WI	Aquifer drive provides strong energy; WI may help stabilize OWC
Thick Oil Column (>80 ft)	S4: Gas Reinjection	Higher oil volume justifies injection CAPEX for improved sweep
Poor Vertical Permeability (Low Kv/Kh)	S1: Base Depletion or S2: Concurrent	Coning less severe; advanced injection offers limited benefit
High Oil Value / Scarce Gas Market	S4/S5: Gas Reinjection	Prioritizes oil recovery and conserves gas for later sale/reinjection
Capital Constrained / Fast Payout Required	S2: Concurrent Production	Highest IRR and shortest payout, lower upfront capital

5. Discussion

The SRM framework showed strong potential in the case study for integrated reservoir management. It offers the following contributions:

Efficiency and Comprehensiveness: The framework shortens the months of simulation work to weeks and allows for thorough uncertainty analysis and strategy analysis that was previously not feasible.

a. Deterministic to Probabilistic Thinking: It asks for predictions about a single outcome and allows for a trade-off analysis between risk (P10) and reward (P90).
b. Organizational Integration: Technical and economic models are integrated in one workflow, enabling collaboration between subsurface, facilities and finance teams in making value-driven decisions.
c. Heuristic Reframing: The discovery of a simpler concurrent strategy than the more complex injection strategies is a case in point of how data-driven frameworks can demystify the industry assumptions and uncover non-intuitive optima.

5.1 Limitations and Future Work

The fundamental level of accuracy of the SRM depends on the quality and extent of training data. It can not be used for extrapolation beyond the sampled parameter space. To further improve generalization, future research should include the use of physics-informed neural networks [33]. Furthermore, the model can be extended to dynamic optimization under uncertainty by using the SRM in a closed loop control system or in a reinforcement learning (RL) numerical implementation for the real-time adjustment of the well control [39]. Lastly, the incorporation of environmental measures (e.g., GHG intensity per barrel) into a multi-objective optimization is also a relevant line related to energy transition objectives [40].

6. Conclusion

In this paper, an effective end-to-end Surrogate Reservoir Model framework that can be used for de-risking and optimally developing thin oil rim reservoir is proposed. The method integrates all the necessary tools in a strategic manner: global sensitivity analysis, machine learning based proxy modelling, probabilistic forecasting, and economic valuation, and provides a practical and scalable approach to a classic industry problem.

The framework was applied to an illustrative case study from the Niger Delta and effectively identified a number of key uncertainties at the subsurface level, while enabling a comprehensive evaluation of seven development strategies. The most important result was that the strategy that had the highest technical recovery did not have the highest economic recovery. The economics-based analysis made possible by the computational efficiency of SRM was found to be superior in terms of Net Present Value and Internal Rate of Return for concurrent oil and gas production, demonstrating the inseparability of economics-based analysis and computational efficiency made possible by SRM.

The described framework is not only a process of work but also a philosophy of decision support. It will enable asset teams to go beyond the rudimentary deterministic planning process and to a more holistic, quantitative, value-driven approach to field development planning. The industry is keen to get the most from complex and marginal resources, and for value-accretive and strong investment decisions to be made, these data-driven, integrated frameworks will be key.

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Received: 24/02/2026; Revised: 16/06/2026; Accepted: 22/06/2026; Published: 26/06/2026