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OBSERVATION-DRIVEN AI FRAMEWORK FOR INTEGRATED GEOLOGICAL–HYDRODYNAMIC RESERVOIR MODELLING

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A B S T R A C T

This study presents an observation-driven approach for integrated geological and hydrodynamic reservoir modelling using multi-source data. Reservoir systems are complex due to heterogeneous structures, nonlinear flow behaviour, and limited direct access to subsurface information. These factors make accurate modelling a challenging task in reservoir engineering. Conventional modelling approaches usually follow a sequential workflow from geological interpretation to numerical simulation. This often increases computational cost and introduces uncertainty in model construction. To address these limitations, the study explores the use of artificial intelligence methods together with physics-informed and hybrid modelling concepts. In the proposed framework, geological, petrophysical, and production data are combined in a unified processing scheme. A simple encoder–decoder structure is used to extract latent features that describe reservoir behaviour. A bridge mechanism is introduced to connect these features with physically meaningful reservoir properties such as connectivity, flow capacity, and pressure response. The method does not replace traditional reservoir simulation but aims to support it by improving data integration and reducing computational effort. A synthetic validation study shows that the proposed approach can reproduce main reservoir behaviour trends with reasonable accuracy. Overall, the results suggest that data-driven methods, when guided by physical understanding, can be a useful complement to classical reservoir modelling workflows.

Keywords: reservoir modelling; artificial intelligence; data integration; physics-informed methods; hybrid modelling; surrogate models.

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Introduction

Oil and gas reservoir modelling requires a reliable understanding of subsurface geological structures and fluid flow behaviour. In practice, this process is challenging due to reservoir heterogeneity, nonlinear flow mechanisms, and limited availability of direct measurements from subsurface formations [1-3].

Reservoir properties such as porosity, permeability, pressure distribution, and fluid saturation cannot be measured directly. They are usually estimated using indirect data sources, including seismic surveys, well logs, core analysis, and production history [4, 5]. This makes reservoir modelling highly dependent on data interpretation and introduces uncertainty at different stages of the workflow.

Traditional reservoir engineering approaches follow a sequential modelling strategy. First, a geological model is constructed using seismic and petrophysical data. Then, a numerical reservoir simulator is applied to predict fluid flow and production performance [1, 3]. Although this approach is well established, it often requires significant computational resources and may propagate uncertainties from geological interpretation to dynamic simulation results [6, 7].

In recent years, artificial intelligence methods have been introduced to support different stages of reservoir modelling, including seismic interpretation, reservoir property estimation, production forecasting, and history matching. These methods are effective in extracting patterns from large datasets and reducing manual interpretation effort. However, in many cases, AI is still applied as a separate tool rather than being fully integrated into the reservoir modelling workflow [8, 9].

More recent research focuses on combining physics-based models with machine learning approaches, such as physics-informed neural networks and hybrid reservoir modelling frameworks. These approaches aim to maintain physical consistency while improving computational efficiency and flexibility in modelling complex reservoir systems.

This study proposes an observation-driven framework for integrated geological and hydrodynamic reservoir modelling. The main idea is to integrate multi-source data into a unified representation of reservoir behaviour rather than relying only on predefined static parameters. In this framework, artificial intelligence methods are used to support

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feature extraction and data integration, while physical constraints from reservoir engineering are preserved through model design.

The objective of this work is to improve consistency and efficiency in reservoir modelling by combining geological, petrophysical, and dynamic data within a single modelling structure. The proposed approach is intended to complement classical reservoir simulation methods rather than replace them, with the aim of reducing uncertainty and improving decision-making in reservoir engineering practice [1, 6, 10].

Artificial intelligence in geological modelling

Geological modelling is the first stage of reservoir characterization and plays an important role in describing subsurface structures and reservoir distribution [4, 11]. It is based on seismic interpretation, well log analysis, and laboratory measurements.

Seismic data provide indirect information about subsurface structures through reflected wave analysis. They are used to identify faults, stratigraphic boundaries, and reservoir geometry [5, 7]. However, manual interpretation is often time-consuming and may introduce subjectivity into the process .

Machine learning methods can help improve seismic interpretation by automatically detecting patterns in seismic images and classifying geological features. In addition, well log data are widely used to estimate reservoir properties such as porosity and lithology using data-driven approaches [12-14].

Artificial intelligence in hydrodynamic modelling

Hydrodynamic modelling focuses on the flow of fluids in porous reservoir rocks and the prediction of production performance during field development. These models are based on physical conservation laws describing multiphase flow in porous media and are solved using numerical simulation methods [15, 16].

Reservoir simulation usually uses finite difference or finite element methods to divide the reservoir into a grid of cells [4, 15]. For each cell, flow equations are solved to calculate pressure, fluid saturation, and production over time [17, 18].

Although this approach is reliable, it requires many input parameters and significant computational resources. For large reservoirs with many grid cells, a single simulation can take a long time to complete [4, 15].

To address this, artificial intelligence methods are increasingly used in hydrodynamic modelling. One main application is production forecasting. Machine learning models learn from historical production data and help predict future production trends [19, 20].

Recurrent neural networks, especially LSTM models, are widely used for time-series production forecasting [12, 21].

Another important application is history matching. This process adjusts model parameters so that simulation results match real production data. Traditional methods rely on repeated simulations and manual tuning, which is slow and computationally expensive [15].

To improve this process, optimization methods such as genetic algorithms, particle swarm optimization, and Bayesian optimization are used. These methods help find parameter sets that reduce the difference between simulated and observed data [10, 22].

AI methods are also used in reservoir development planning. For example, they can test different well placement and injection strategies to estimate their effect on production. This helps engineers choose better development options and improve field performance [4, 11].

Multi-source data fusion for reservoir modelling

Modern reservoir characterization relies on large amounts of heterogeneous data collected during exploration and field development. These data include seismic surveys, well logging measurements, core analysis results, and dynamic production data.

Each data type provides partial information about the subsurface system. However, none of them alone is sufficient to fully describe reservoir structure and dynamic behaviour [7, 23].

One of the main challenges in reservoir modelling is the integration of these different datasets into a unified framework. In traditional workflows, geological and dynamic data are usually processed in sequence. First, a geological model is built using seismic interpretation and well-log data, and then hydrodynamic simulation is applied to predict reservoir behaviour. This sequential approach may sometimes lead to inconsistencies between geological interpretation and production data [6, 11].

Multi-source data fusion provides a systematic way to combine different datasets into a single modelling framework. In this approach, data from different sources are merged to form a more complete view of the reservoir system [3, 4]. Artificial intelligence methods are useful here because they can capture relationships between different types of data [10].

In the proposed framework, input data are grouped into three main categories:

- Geophysical data – seismic attributes and structural interpretation from seismic surveys. These describe reservoir geometry, faults, and stratigraphy.
- Petrophysical data – well logs and laboratory measurements describing rock properties such as porosity, permeability, and lithology.
- Dynamic data – production history, injection rates, and pressure data collected during field operation.

By combining these datasets, the model can consider both static geological features and dynamic reservoir behaviour. Machine learning methods help identify patterns and relationships that are difficult to observe using traditional analysis.

A key advantage of multi-source data fusion is reduced uncertainty in reservoir modelling. When different independent data sources are combined, inconsistencies can be detected and corrected during model development. This improves the reliability of predictions and supports better reservoir management decisions.

The observation-driven AI workflow combining geophysical, petrophysical, and dynamic data is shown in figure 1.

The observation-driven artificial intelligence workflow shown in figure 1 illustrates the integration of multi-source reservoir data within a unified modelling framework. The system receives heterogeneous inputs from geophysical, petrophysical, and dynamic data sources.

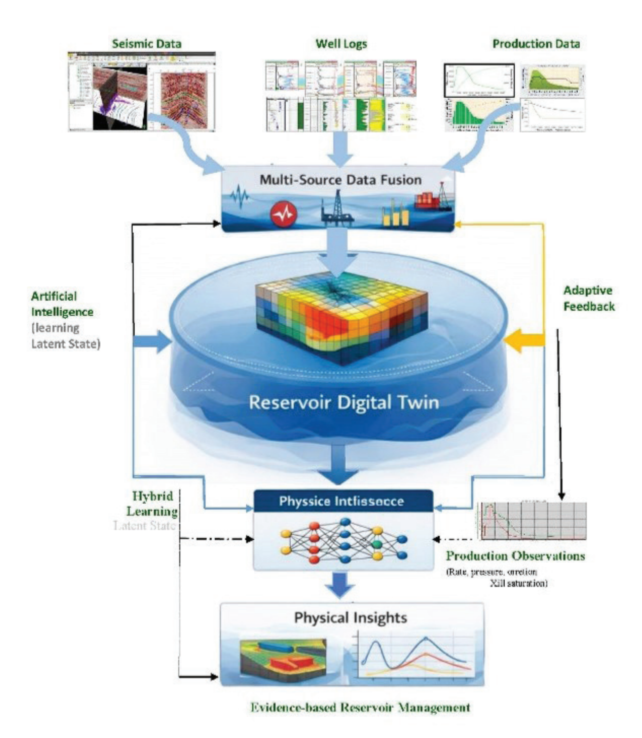

Fig. 1. Observation-driven artificial intelligence workflow for integrated reservoir modelling

These inputs are first pre-processed and organized according to their observational nature. Geophysical and petrophysical data provide structural and static information, while dynamic data describe time-dependent reservoir behaviour during production.

All data streams are then combined within a shared modelling environment, where artificial intelligence methods are used to identify hidden relationships between variables originating from different domains. This integration allows the model to reduce inconsistencies between static geological interpretations and dynamic production responses.

The final output of this workflow is a consistent reservoir representation that can be used for both interpretation and prediction tasks, including production forecasting and reservoir behaviour analysis.

Reservoir information originates from heterogeneous sources with varying levels of reliability and interpretational uncertainty. In the proposed framework, multi-source data fusion is defined not only by data origin but also by the epistemic status of each data category.

The observation set is defined as

$$X = \{X^{(m)}, X^{(s)}, X^{(g)}, X^{(r)}\}$$

$X^{(m)}$ – mandatory, continuous measurements: production rates, injection volumes, time-dependent operational constraints, and well control parameters. These data are unavoidable because they are continuously recorded during field exploitation.

$X^{(s)}$ – sparse and episodic observations: pressure surveys, well tests, buildup data, and other irregular diagnostics. Limited in frequency but highly informative.

$X^{(g)}$ – interpretational geological descriptors: structural interpretations, seismic attributes, stratigraphic segmentation, and petrophysical estimates. This category carries strong modelling subjectivity and interpretational uncertainty.

$X^{(r)}$ – realized dynamic indicators: effective transmissibility evolution, inferred connectivity patterns, displacement-front migration, saturation redistribution trends, and pressure influence contour changes. These replace classical parameters (permeability, porosity) with operationally observable behaviour.

This classification allows reservoir modelling to be grounded in measurable system behaviour rather than predefined geological assumptions.

Latent reservoir representation

Classical modelling and artificial intelligence often operate in different representational spaces. Classical reservoir models rely on physically interpretable parameters, while AI methods typically construct latent representations. When AI outputs remain only in latent form and classical models depend on predefined physical parameters, the integration between the two approaches becomes limited. In such cases, AI is mainly used as a predictive tool, while the reservoir model continues to be adjusted manually as a hypothesis [2, 3, 9].

To address this limitation, a bridge layer is introduced to connect the latent space of AI models with physically interpretable reservoir descriptors.

$$\hat{Y} = f_\theta(X) \tag{1}$$

where: $\hat{Y}$ – predicted output of the model; f_θ – learnable nonlinear mapping function with parameters θ; X – the fused multi-source information. AI constructs a latent reservoir state:

$$Z_\theta = \Phi_\theta(X) \tag{2}$$

where: Z_θ – latent reservoir state representation; Φ_θ – feature extraction operator mapping input data into latent space; X – input observation set.

Z_θ encodes hidden structural and dynamic features. A reconstruction operator produces:

$$\hat{S} = g_\phi(Z_\theta) \tag{3}$$

where: $\hat{S}$ – reconstructed physical descriptors of the reservoir system; g_ϕ – reconstruction (decoder) function with parameters ϕ; Z_θ – AI latent reservoir representation.

The reconstructed descriptor set $\hat{S}$ includes: connectivity indices, effective flow capacities, anisotropy trends, pressure influence geometries, and displacement-front evolution characteristics.

Artificial intelligence systems naturally operate in latent feature spaces [7]. To integrate AI-based modelling with physical interpretation, a bridge layer is introduced between the latent representation and physically interpretable reservoir descriptors [12].

In this framework, the AI model constructs a latent reservoir state (2), where Φ represents an encoder that maps the observation set into a latent space. A reconstruction operator then transforms this latent state into physically interpretable descriptors (3).

These reconstructed descriptors include connectivity indices, effective flow capacity, anisotropy trends, and displacement-front evolution characteristics [8, 13]. The conceptual structure of the proposed modelling system is illustrated in figure 2.

Multi-source reservoir observations (including seismic data, well logs, and production history) are first integrated and processed by an AI encoder. The encoder transforms these heterogeneous inputs into a latent representation that captures the hidden dynamic state of the reservoir, such as connectivity patterns, flow communication between zones, and pressure propagation tendencies.

The decoder then maps this latent state into physically interpretable reservoir descriptors. These descriptors can be directly related to practical engineering concepts such as effective transmissibility between reservoir regions, preferential flow channels, and evolving displacement-front behaviour. In this way, the latent representation acts as an intermediate bridge between raw field data and reservoir engineering parameters used in interpretation and decision-making.

These reconstructed descriptors are subsequently linked to the reservoir simulator. The simulator generates updated dynamic responses, including pressure and production behaviour, which are compared with actual observed field data [7, 12].

If mismatches between simulated and observed behaviour are detected, the AI system uses this discrepancy as feedback. This feedback is not only used for numerical correction but also for updating structural assumptions, such as connectivity strength, anisotropy patterns, and flow pathway distribution within the reservoir model [15, 18].

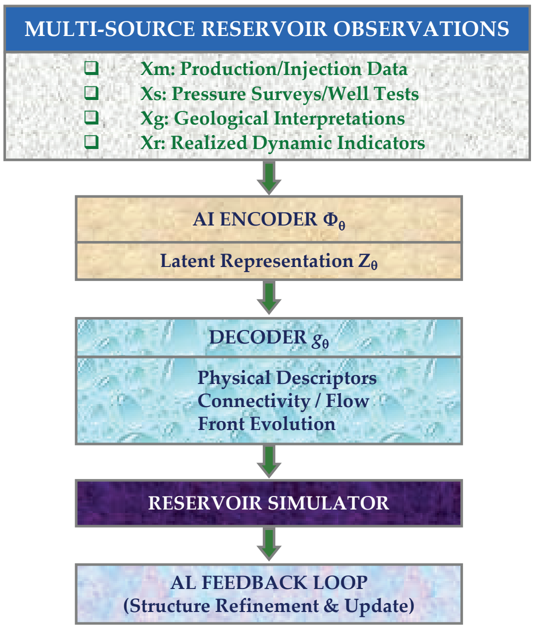

Fig. 2. The conceptual structure of the proposed modelling system

Computational implementation

The proposed modelling framework is implemented using an encoder–decoder neural network architecture. This architecture is well suited for learning latent representations from high-dimensional reservoir data because it separates feature extraction from output reconstruction.

The encoder network takes fused multi-source reservoir observations as input and maps them into a latent reservoir representation. In this process, the encoder learns nonlinear relationships that capture dependencies between geological, petrophysical, and dynamic variables.

The decoder network then reconstructs physically meaningful reservoir descriptors from the latent representation. These descriptors include effective transmissibility indicators, connectivity patterns between reservoir zones, and other flow-related properties [4, 11, 15].

Model training is based on an objective function that balances data fitting and physical consistency. The proposed model uses a composite loss function defined as:

$$L = L_{data} + \lambda L_{physics} + \mu L_{consistency} \tag{4}$$

where: L_{data} – represents the mismatch between predicted and observed production data; $L_{physics}$ – enforces simplified physical constraints derived from reservoir flow equations; $L_{consistency}$ – penalizes inconsistencies between reconstructed structural descriptors and observed reservoir behaviour.

The coefficients λ and μ control the relative importance of physical constraints and structural consistency during training.

The model is trained using stochastic gradient optimization methods. During training, the artificial intelligence system gradually learns latent representations that minimize prediction errors while satisfying physical consistency conditions. This approach allows the model to capture complex reservoir dynamics without relying solely on predefined geological parameters.

Surrogate models for reservoir simulation

Reservoir simulation is one of the most computationally intensive tasks in petroleum engineering. High-resolution reservoir models may contain thousands or even millions of grid cells, and solving flow equations for such systems requires significant computational time.

To reduce this computational burden, surrogate modelling techniques are widely used to approximate the behaviour of full numerical simulators. A surrogate model is a simplified model that reproduces the input–output relationship of a detailed simulator with much lower computational cost.

Artificial intelligence methods provide effective tools for building such surrogate models. Neural networks, Gaussian process regression, and other machine learning methods can learn relationships between reservoir parameters and production responses using data generated from numerical simulations [13, 16, 24].

The process of constructing a surrogate model generally includes three steps:

1. Reservoir simulations are run to generate training data under different geological and operational conditions.
2. A machine learning model is trained to learn the relationship between input parameters and simulation outputs.
3. The trained model is then used to predict new scenarios without running full simulations.

After training, surrogate models can provide results within seconds, while full reservoir simulations may take hours or even days. This speed advantage is especially useful for optimization studies and scenario analysis.

Surrogate models can also be integrated into broader AI-based reservoir management workflows [10, 25]. For example, they can speed up history matching or evaluate different well placement and injection strategies. When combined with optimization algorithms, they allow efficient exploration of a large number of development scenarios.

Synthetic validation study

To evaluate the feasibility of the proposed observation-driven artificial intelligence framework, a synthetic reservoir case study was constructed under controlled heterogeneity conditions. Synthetic datasets are widely used in reservoir engineering because they allow controlled testing of modelling approaches while avoiding uncertainties associated with real field data [4, 11, 16].

The synthetic reservoir model represents a heterogeneous porous medium with spatial variations in permeability and porosity. Production and injection wells were placed within the model domain to reproduce realistic reservoir development conditions. Reservoir responses, including oil production rate, water production rate, and pressure evolution, were generated using a conventional numerical reservoir simulator.

To mimic realistic field data conditions, different types of observations were introduced. Continuous production data were assumed to be available over time, while pressure measurements were included at discrete intervals through simulated well testing. Geological information was represented using synthetic seismic attributes and well-log data derived from the reservoir model.

The proposed artificial intelligence framework was trained on this fused multi-source dataset. The encoder learns a latent representation of reservoir behaviour directly from observational data, while the decoder reconstructs physically interpretable reservoir descriptors that describe dynamic flow behaviour [10, 12].

Model performance was evaluated by comparing predicted outputs with reference simulation results [11, 15]. The evaluation included production prediction error, pressure matching accuracy, and consistency of reconstructed structural patterns.

The results indicate that the framework is able to capture the main dynamic behaviour of the reservoir system. In particular, the latent representation is capable of identifying connectivity relationships between different reservoir regions and reproducing displacement-front evolution during production.

Compared with conventional parameter-based history matching, the proposed approach reduces structural uncertainty while maintaining stable predictive performance. This suggests that observation-driven modelling can serve as a complementary approach to traditional reservoir simulation workflows.

From a methodological perspective, the key advantage of the proposed system is not only prediction accuracy, but also continuous consistency checking between assumed reservoir structure and observed behaviour. For example, the model can indicate whether unexpected well interference implies stronger connectivity, or whether displacement-front behaviour suggests missing flow channels in the model.

This shifts the modelling strategy from manual parameter tuning toward data-driven structural adjustment guided by observations.

As an illustrative example, boundary movement dynamics can be represented using a tensor formulation, where the simulator receives feedback corrections based on mismatch between predicted and observed behaviour.

Example: Contact Motion Tensor and Feedback via K-Tensor As an example, boundary movements are modelled as a tensor, and the simulator receives feedback (advice):

- Contact surface Γ parameterized by exploitation vector $\xi=(t, Np, Gp, W_{inj}, \ldots)$
- Displacement vector $u(\xi)$ and deformation tensor $F(\xi)=\nabla u(\xi)$
- Tensor interacts with flow laws and transmissibility tensor K: $F(\xi) \sim K\nabla p$
- If simulator's boundary motion disagrees with observations, AI provides advice to update K anisotropy and structure

where: Γ – contact surface; ξ – operational vector $\xi=(t, Np, Gp, W_{inj}, \ldots)$; $u(\xi)$ – displacement vector; $F(\xi)$ – deformation tensor; K – transmissibility tensor; p – pressure field.

Discussion

The integration of artificial intelligence into reservoir modelling workflows provides several advantages compared with traditional approaches. One of the main benefits is the ability to process large volumes of heterogeneous data in a unified way. Modern oilfield development generates data from multiple sources, including seismic surveys, well logs, production monitoring systems, and laboratory experiments. Artificial intelligence methods can integrate these datasets and capture relationships between variables that are difficult to identify using conventional techniques.

Another important advantage is the potential reduction in computational cost. Traditional reservoir simulation and history-matching workflows often require multiple simulation runs and significant manual parameter adjustment. By learning compact representations of reservoir behaviour, artificial intelligence models can reduce the need for repeated full-physics simulations and speed up scenario evaluation.

The proposed observation-driven framework also offers an alternative perspective on reservoir characterization. Instead of relying only on predefined geological parameters, the modelling process is guided by observable system behaviour. This allows more direct use of dynamic production data and reduces dependence on uncertain geological assumptions.

At the same time, several limitations should be considered. One key challenge is the availability and quality of training data. Machine learning models require consistent and sufficiently large datasets, and noise or missing data can affect model stability and accuracy.

Another important issue is interpretability. Although latent representations are effective for modelling complex systems, their direct physical interpretation is not always straightforward. The bridge layer introduced in this work aims to partially address this limitation by linking latent features with physically meaningful reservoir descriptors.

Future work should focus on validation using real field data and integration with full-physics reservoir simulators. In addition, incorporation of additional observational sources such as time-lapse seismic and distributed sensing data may further improve model robustness and predictive capability.

Conclusions

This study presents an observation-driven artificial intelligence framework for integrated geological and hydrodynamic reservoir modelling. The proposed approach combines multi-source data fusion with machine learning techniques to improve reservoir characterization and modelling efficiency.

The main contributions of this work can be summarized as follows:

- A unified framework for integrating geological and hydrodynamic modelling using artificial intelligence.
- A multi-source data fusion strategy combining geophysical, petrophysical, and dynamic production data.
- A latent reservoir representation that captures hidden structural and dynamic features of reservoir systems.
- An encoder–decoder architecture for reconstructing physically interpretable reservoir descriptors.
- Application of surrogate modelling concepts to reduce computational cost in reservoir simulation workflows.

Synthetic validation results indicate that the proposed framework can reproduce key reservoir dynamics while reducing structural uncertainty and computational effort under controlled conditions. However, the results should be interpreted within the limitations of synthetic data-based validation.

Overall, the proposed approach provides a promising direction for integrating artificial intelligence with classical reservoir engineering workflows and may support more efficient decision-making in petroleum engineering, subject to further validation on real field datasets.

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