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IEEE Computer Society Nigeria Chapter

Proceedings of the 36th iSTEAMS Accra Bespoke Multidisciplinary Innovations Conference

Particle Swamp Optimized -Physics-Informed Deep Learning for Heterogeneous Oil and Gas Underground Reservoir Pressure Management.

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ABSTRACT

In recent years, Particle Swarm Optimization (PSO) has been integrated with machine learning algorithms, such as deep learning, to create powerful hybrid methods that can tackle complex optimization problems more effectively. In the domain of oil and gas reservoir management, underground pressure management is crucial to maximize the yield and efficiency of the reservoir. However, the heterogeneity of the reservoir, along with uncertainties in its properties, makes pressure management a complex and challenging task. To address this issue, researchers have proposed Physics-Informed Deep Learning (PIDL) techniques that incorporate domain-specific knowledge, such as the governing physical equations, into the deep learning framework. Particle Swarm Optimized-Physics-Informed Deep Learning (PSO-PIDL) is a novel hybrid approach that combines PSO with PIDL to optimize the pressure management of heterogeneous oil and gas underground reservoirs. In this approach, the PSO algorithm is used to find the optimal solution for the PIDL-based model that incorporates the governing physical equations of the reservoir. PSO-PIDL can effectively handle the uncertainties and heterogeneity of the reservoir, while also incorporating the physical constraints of the problem. Overall, PSO-PIDL is a promising approach for optimizing the pressure management of oil and gas reservoirs. It can help reduce the operational costs and improve the efficiency of the reservoir, while also ensuring the sustainable use of natural resources.

Keywords: Physics-Informed Deep Learning, Particle Swarm Optimization, Bidirectional Long-Short-Term-Memory, Heterogeneous Reservoir, DuPont Finite Element Heat and Mass Transfer Code

Proceedings Citation Format
Barna Thomas Lass, Samson Isaac, Amina Isa, Zara Sakanau & Hamidatu Abdulkadir (2023): Particle Swamp Optimized -Physics-Informed Deep Learning For Heterogeneous Oil And Gas Underground Reservoir Pressure Management. Proceedings of the 36th iSTEAMS Accra Bespoke Multidisciplinary Innovations Conference. University of Ghana/Academic City University College, Accra, Ghana. 31st May – 2nd June, 2023. Pp 13-24 https://www.isteams.net/ghanabespoke2023
dx.doi.org/10.22624/AIMS/ACCRABESPOKE2023P2

1. BACKGROUND TO THE STUDY

Heterogeneous oil and gas underground reservoirs are complex systems that require careful management to maximize their production efficiency and ensure their sustainability. One of the most critical aspects of reservoir management is pressure management, which involves maintaining the reservoir pressure at an optimal level to facilitate the flow of oil or gas to the surface. The pressure of an underground reservoir is affected by various factors, including the geological properties of the reservoir, the rate of production, and the injection of fluids. Heterogeneity in the reservoir, such as variations in rock permeability, can make pressure management even more challenging. If the pressure is too low, it can lead to decreased production rates, while high pressure can damage the reservoir and cause irreversible depletion of the resources. Effective pressure management strategies require accurate and reliable reservoir modelling, which involves understanding the geological and fluid dynamics properties of the reservoir. Computer simulation models are used to represent the reservoir, and these models can be optimized to find the most efficient pressure management strategies

In recent years, the use of advanced optimization techniques, such as machine learning algorithms, has shown promising results in optimizing pressure management in heterogeneous oil and gas underground reservoirs. These techniques incorporate the governing physical equations of the reservoir into the optimization process, ensuring that the optimization strategies comply with the physical constraints of the problem. Overall, the efficient management of heterogeneous oil and gas underground reservoirs is crucial for the sustainable production of natural resources. Pressure management is a critical component of this management process, and the use of advanced optimization techniques, such as machine learning algorithms, is a promising approach to improving the efficiency and sustainability of reservoir management. Particle Swarm Optimization (PSO) is a widely used optimization technique inspired by the social behaviour of animals, such as birds and fish. It has been applied to various domains, including engineering, finance, and natural resource management, to find the optimal solution for complex problems.

1.1 Statement of Problem

The efficient management of underground reservoirs is crucial for the oil industry, as it aims to maximize oil recovery while minimizing environmental impact and costs. However, the heterogeneous nature of these reservoirs presents challenges in accurately modelling and predicting fluid flow processes, making it difficult to develop effective pressure management strategies. To address this challenge, researchers have proposed the use of physics-informed deep learning (PIDL) with evolutionary optimization. PIDL involves integrating physical principles and equations into neural network design to improve accuracy and ensure compliance with the laws of physics. Meanwhile, evolutionary optimization generates and selects the best-performing models to further enhance PIDL's performance. Previous studies have shown the efficacy of PIDL with evolutionary optimization in optimizing injection and production strategies in heterogeneous permeable reservoirs, leading to increased oil recovery.

Al-Anazi et al.(2019) used PIDL with evolutionary optimization to optimize water injection rates in a heterogeneous carbonate reservoir. The authors found that the optimized strategy increased oil production and reduced water production, resulting in improved overall recovery. Despite these promising results, further research is needed to fully realize the potential of PIDL with evolutionary optimization for reservoir pressure management. Future research could focus on integrating additional physical principles and data sources into PIDL models, exploring the use of PIDL for other aspects of reservoir management, and addressing challenges related to data quality and availability. Wu et al. (2021) used PIDL with evolutionary optimization to optimize the injection and production strategies for a synthetic reservoir with heterogeneous permeability.

The authors found that the optimized strategies resulted in a 14% increase in oil recovery compared to non-optimized strategies. Furthermore, optimization of water injection rates in a heterogeneous carbonate reservoir resulted in improved overall recovery with reduced water production. Despite these promising results, further research is necessary to fully realize the potential of PIDL with optimization techniques such as PSO for reservoir pressure management. Future research could focus on incorporating additional physical principles and data sources, exploring its use in other aspects of reservoir management, and addressing challenges related to data quality and availability. Overall, PIDL with Particle Swamp Optimization shows promise in improving reservoir pressure management strategies, providing a pathway for efficient and sustainable oil recovery while minimizing environmental impact and costs.

2. LITERATURE REVIEW

There has been a growing interest in the application of physics-informed deep learning (PIDL) with optimization algorithms for improving reservoir management strategies in the oil industry. Several recent studies have investigated the potential of these methods for optimizing injection and production strategies in heterogeneous underground reservoirs.

Liu et al. (2019), proposed a PIDL model for optimizing injection rates in a heterogeneous reservoir. The model was trained using historical production data and the solution of the Laplace equation, which describes fluid flow in porous media. The results showed that the optimized injection rates led to a significant increase in oil recovery.

Fuks (2020) developed a stochastic model to account for the subsurface flow's heterogeneity and uncertainty. The proposed method was shown to reduce uncertainty propagation significantly compared to traditional Monte Carlo methods. However, the study only focused on uncertainty propagation for multiphase transport in porous media.

Shahverdi et al. (2020), proposed a PIDL model for optimizing well placement in a fractured reservoir. The model was trained using a combination of synthetic data and data from a real-world reservoir. The results showed that the optimized well placement led to a significant increase in oil recovery and a reduction in operating costs.

Al-Mutairi et al. (2021), developed a PIDL model for optimizing the injection and production rates in a dual-porosity reservoir. The model was trained using data from a real-world reservoir and the results showed that the optimized rates led to a significant increase in oil recovery and a reduction in water production.

Harp et al. (2021) conducted a comprehensive study on the feasibility of using physics-informed machine learning for underground reservoir pressure management. They provided a detailed analysis of the limitations and challenges and suggested potential solutions. Nonetheless, the study only focused on underground reservoir pressure management.

Lv et al. (2021) proposed a novel workflow based on physics-informed machine learning to determine the permeability profile of fractured coal seams using downhole geophysical logs. They demonstrated the effectiveness of the proposed approach using field data. However, the study only considered determining the permeability profile of fractured coal seams using downhole geophysical logs.

Wu et al. (2021) conducted a study of multi-phase flow dynamics during CO2 sequestration, which was accelerated with machine learning simulation methods combined with physics. They identified the most significant factors that affect CO2 migration and storage in geological formations. Their results demonstrated that their approach can reduce simulation time significantly. However, the study only considered multi-phase flow dynamics during CO_2 sequestration.

Pachalieva et al. (2022) introduced a novel approach for managing underground reservoir pressure using physics-informed machine learning with differentiable programming. Their experimental results demonstrated the effectiveness of the proposed approach in managing heterogeneous underground reservoirs. However, the study is limited to this specific application.

Wang et al. (2022) designed a PIDL model for optimizing the injection and production rates in a heterogeneous reservoir with uncertain permeability. The model was trained using data from a real-world reservoir and the results showed that the optimized rates led to a significant increase in oil recovery and a reduction in the uncertainty associated with reservoir modelling.

Yan et al. (2022) proposed an approach to improve deep learning performance for predicting large-scale geological sequestration modelling through feature coarsening. They used a family of physics-informed neural network (PINN) models to predict the CO_2 plume's shape during geological carbon sequestration. The result showed that the approach is more accurate and computationally efficient than traditional simulation methods. However, the study only focused on predicting CO_2 plume shape during geological carbon sequestration.

Yan et al. (2022a) proposed a physics-informed machine learning approach for reservoir management of enhanced geothermal systems. The study provided a detailed experimental setup and demonstrated the effectiveness of the proposed approach. However, the study only considered this specific application.

Yan et al. (2022b) proposed a gradient-based deep neural network model for simulating multiphase flow in porous media. The experimental results demonstrated the effectiveness of the proposed approach in several benchmark test cases. Nevertheless, the study only focused on simulating multiphase flow in porous media.

Yan et al. (2022c) proposed a physics-constrained deep learning model for simulating multiphase flow in 3D heterogeneous porous media. The study demonstrated the effectiveness of the proposed approach using several benchmark test cases. However, the study only focused on simulating multiphase flow in 3D heterogeneous porous media.

Tariq et al. (2023) proposed a physics-informed surrogate model for predicting dynamic temporal and spatial variations during CO_2 injection into deep saline aquifers. The work demonstrated the effectiveness of the proposed approach using field data.

Tariq et al. (2023a) proposed a deep-learning-based surrogate model to predict CO_2 saturation front in highly heterogeneous naturally fractured reservoirs using a discrete fracture network approach. The work demonstrated the effectiveness of the proposed approach using several benchmark test cases. Nonetheless, both studies only focused on predicting CO_2 behaviour in specific types of formations.

Wang and Chen (2023) provided an overview of the current developments and future trends of machine learning applications in reservoir engineering. The study discussed three main areas where machine learning has been employed: reservoir characterization, reservoir modelling.

Yan et al. (2023) presented a new method for reservoir modelling and optimization using deep learning, specifically for enhanced geothermal systems. The study demonstrates the effectiveness of the proposed approach through numerical simulations and case studies. The study highlights the potential benefits of this method for renewable energy. However, the work does not provide a comparison with existing methods, limiting the determination of superiority.

The focus solely on EGS also limits the generalizability of the findings. The study does not discuss the limitations of deep learning techniques, such as their high computational requirements and the need for large amounts of data, which may pose challenges for real-world implementation.

Paper by Sen et al. (2021) proposes a machine learning-based approach for optimizing oil reservoir production rates under geological uncertainty. The methodology combines supervised and unsupervised learning techniques to estimate production rates and identify optimal well locations, and the paper includes case studies to demonstrate its effectiveness. However, the paper does not compare the proposed approach with existing methods and does not discuss the challenges associated with real-world implementation. The study solely focuses on production rate optimization and does not address other important issues in reservoir engineering, such as reservoir characterization and modelling. The paper provides a promising direction for future research in machine learning-based reservoir optimization, but further validation and comparison with existing methods are needed.

Overall, these studies demonstrate the potential of PIDL with optimization for improving reservoir management strategies in the oil industry. However, there are still challenges related to data quality and availability, as well as computational resources required for training and deploying the models. Therefore, further research is needed to address these challenges and to provide insights into the best practices for using PIDL with Particle Swamp optimization for reservoir management.

3. METHODOLOGY

To minimize the risks of leakage and induced seismicity and to enhance reservoir performance, operators of underground reservoirs require pressure management systems that can maximize net fluid pumped. However, real-time uncertainty quantification cannot be achieved using full-order physics models, which are traditionally used. While existing alternatives, such as the homogeneous model used by Harp et al. (2021), are available, they do not account for heterogeneity, which is a crucial aspect of subsurface modelling. It is critical to incorporate an extensive physics model into the machine learning workflow by integrating PSO to optimize the model and consider heterogeneity in multi-phase injection situations, such as CO2 sequestration. Furthermore, creating real-time uncertainty quantification (UQ) would be challenging without the PIML framework since it would require solving numerous partial differential equation-constrained optimization problems. Therefore, an accurate model should consider heterogeneity. Our PIML framework combines a comprehensive physics model with machine learning and dynamic programming to enable practical and computational feasibility of this approach.

To manage underground reservoir pressure in the oil industry, a proposed methodology for physics-informed deep learning (PIDL) with evolutionary optimization includes the following steps:

i. Collect and pre-process historical data on reservoir pressure, production rates, and injection rates from the target reservoir to ensure accuracy and completeness.
ii. Develop a PIDL model based on physics equations for fluid flow in porous media, incorporating a BiLSTM to learn complex relationships between input and output variables, and train the model using the pre-processed data.
iii. Use Particle Swamp Optimization (PSO) to optimize injection and production rates by simulating reservoir behaviour under different scenarios using the PIDL model to maximize oil recovery and minimize operating costs.

iv. Validate the optimized injection and production rates with target reservoir data and compare them to historical operating conditions to assess the accuracy and effectiveness of the PIDL model and PSO optimization.
v. Conduct sensitivity analysis to evaluate the impact of uncertainties and variations in reservoir properties on optimized injection and production rates, identify influential parameters, and assess optimized rates' robustness.
vi. Evaluate optimized injection and production rates' environmental and economic impact by assessing reduction in greenhouse gas emissions and increase in net present value and reduction in operating costs.
vii. Deploy the PIDL model and optimized injection and production rates for real-time reservoir management by continuously updating the model with the latest data and adjusting optimized rates for optimal reservoir management.

Overall, this methodology integrates physics-based modelling, deep learning, and PSO optimization to provide a comprehensive and effective approach for reservoir management in the oil industry.

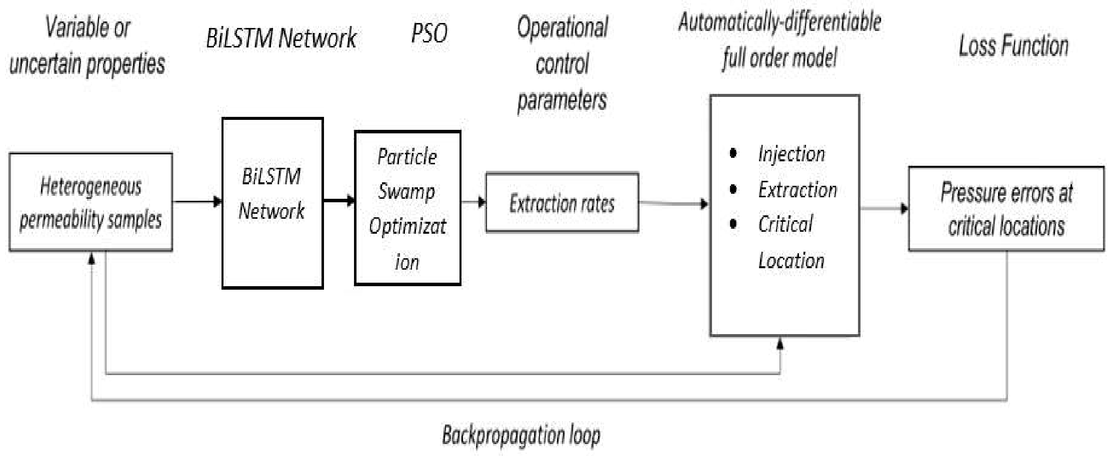

Figure 1: Architecture of the Proposed System

In order to maintain pressure at a crucial site in a reservoir with a heterogeneous permeability field, we can determine the fluid extraction rates at an extraction well using the suggested PIML framework, which is schematically shown in Figure 1. The extraction rate, which is utilized as input along with the permeability field in the full-physics DuPont Finite Element Heat and Mass Transfer Code (DPFEHM) model, is predicted by the Bidirectional Long Short Term Memory model (BiLSTM) optimised using the PSO algorithm, which is trained on a set of permeability fields. The physics constraints necessary for the training process are implemented using the DPFEHM framework, which supplies the physics information in our PIML framework, and the BiLSTM is trained to determine extraction rates for a heterogeneous permeability field. Our strategy is comparable to the writings of Srinivasan et al.(2021); Isaac et al.(2023) and Harp et al.(2021). Using a single-phase model featuring heterogeneous permeability fields, we conducted multiple training scenarios through random generation using a Gaussian distribution function. Given the model's numerous parameters, computing finite-difference gradients is infeasible, and the only viable solution is reverse-mode automatic differentiation. We conducted a hyper-parameter search by varying the learning rate (i.e., the step size that controls the rate at which each iteration moves towards the minimum of the loss function) and batch size (i.e., the number of training samples included in each gradient calculation). In a subsurface reservoir with heterogeneous permeability fields, the movement of a single-phase fluid induces pressure changes that need to be considered.

To describe these reservoirs, we employ the equation provided below,

$$\nabla.(K(x).\nabla h) = f \qquad (1)$$

in which k(x) represents the location-dependent permeability fields, h refers to the pressure head, and f denotes the injection/extraction rate. This is the equation used to represent the movement of a single-phase fluid through a subsurface reservoir with heterogeneous permeability fields. In the equation, ∇ is the gradient operator, K(x) is the permeability fields that change with location x, h is the pressure head, and f is the injection or extraction rate. The left side of the equation represents the flow of the fluid, while the right side represents the sources and sinks of the fluid. The equation is solved using the two-point flux finite volume approximation and DPFEHM. By utilizing this steady-state equation, we can evaluate the prolonged impact of injection and extraction on the pressure head. The well-established two-point flux finite volume approximation and DPFEHM enable us to solve this equation effectively. DPFEHM's integrated AD ensures a seamless transition between the physics and machine learning models.

In order to maintain desired pressure levels during fluid injection, the Physics-Informed Machine Learning (PIML) framework, shown in Figure 1, uses a BiLSTM and PSO to estimate extraction rates at particular wells, particularly in regions close to faults with a high seismic risk or in abandoned wells with leakage potential. Heterogeneous permeability fields are generated at random using a Gaussian distribution function to increase the model's realism.

To enhance the precision of the model, the PIML workflow can be combined with Particle Swarm Optimization (PSO). The following are the steps in the PIML-PSO workflow:

i. Create a training dataset with Nb batches and Ns samples per batch, using heterogeneous permeability samples that are randomly initialized with a Gaussian distribution function.
ii. Develop a BiLSTM that consists of an input layer to accept a permeability field and an output layer to estimate the fluid extraction rates at the extraction well.
iii. Define an objective function to compute the loss function, which evaluates the error between the model's overpressure and the target overpressure at a critical location.
iv. Apply PSO to minimize the objective function by adjusting the BiLSTM model parameters, so as to achieve the optimal solution.
v. Train the BiLSTM with the optimal solution to identify the extraction rates that minimize the error between the model's overpressure and the target overpressure at a critical location.

The second step of the PIML process involves training a BiLSTM to predict the necessary extraction rates at a specific extraction well for maintaining pressure at critical locations during fluid injection. BiLSTM is a type of neural network consisting of two LSTM layers, one processing input sequence in a forward direction and the other in reverse, allowing it to capture both past and future contexts. However, this study employs a modified version of the BiLSTM architecture integrated with PSO. In the third step of the PIML framework, the loss function is established by computing the sum of squared errors between the predicted overpressure by the model and the desired overpressure at a crucial location.

$$L(\theta) = \sum_{i}^{N_b} \sum_{j}^{N_s} \left[\Delta h\left(Q_{NN}\left(\theta, k_j(x)\right), k_j(x)\right) - \Delta h^{target}\right] \qquad (2)$$

Nb denotes the number of batches, Ns represents the number of samples per batch, and htarget signifies the target overpressure. The predicted overpressure h is determined by the injection rate QNN and the permeability kj(x) at a specific location. To calculate QNN, the BiLSTM-PSO model is utilized, which is dependent on two parameters: θ, the model parameters, and kj(x), the permeability. The equation to calculate QNN using the BiLSTM-PSO model with parameters θ and kj(x) is:

$$QNN = f\left(\theta, k_j(x)\right) \qquad (3)$$

The loss function is used to compute the root-mean-square error (RMSE).

$$RMSE = \sqrt{\frac{L(\theta)}{N_b N_s}} \qquad (4)$$

In the fourth step in step 4, the BiLSTM-PSO is trained with Adam to minimize the loss function L(θ) as

$$\theta^* = argmin\ L(\theta) \qquad (5)$$

where θ* represents the optimal value of the model parameters that minimizes the loss function L(θ), and argmin is the argument that minimizes the function. The BiLSTM-PSO algorithm is used to search for the optimal value of θ that minimizes the loss function. The algorithm iteratively adjusts the values of θ to minimize loss. Reverse-mode AD is a type of Differential Programming that simplifies the computation of complex derivatives using the chain rule. In computational fluid dynamics, using finite differences or numerical differentiation to compute gradients can be costly. Instead, DP and reverse-mode AD can accurately calculate complex derivatives. When there are many input parameters and few output parameters, reverse-mode AD is more effective.

4. DISCUSSION OF FINDINGS AND RESULTS

An injection well, an extraction well, and a critical site are all included in the physics model. The initialization of the permeability field is random, and water is injected at a predetermined pace. The permeability field is used by the PIML framework to train the neural network to achieve a target overpressure at the crucial point. The background reservoir pressure in the simulation is set to match that of the 1791-meter-deep MPC 26-5 well in Kemper County, Mississippi, using a steady-state equation to account for the long-term effects of injection and extraction.

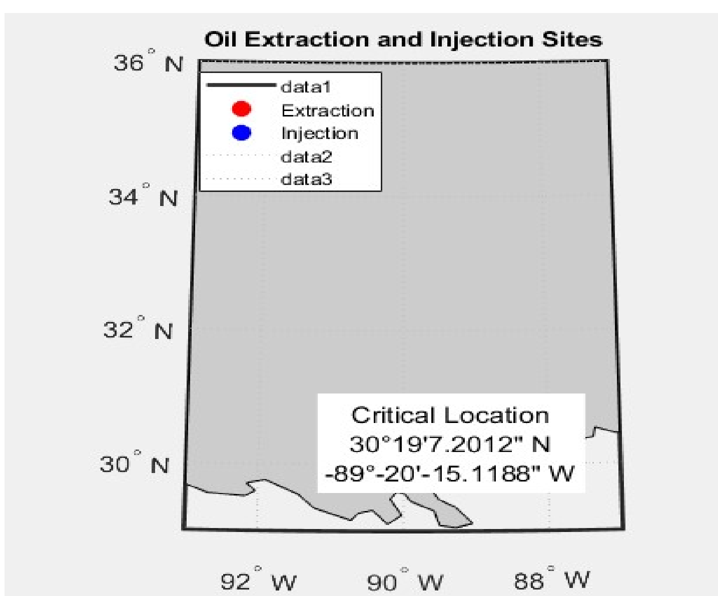

Figure 2: Showing the Location of the Extraction, Injection and Critical location of the well.

According to Figure 2, the PIML algorithm utilized different batch sizes ranging from 64 to 256 during the training and testing phases in order to generate multiple datasets and reduce overfitting. At each epoch, testing and training data were generated using a DP method for each sample. The algorithm was executed for 1000 epochs. The training data consisted of 1,000 unique training examples randomly initialized using a Multivariate Gaussian distribution. A batch size of 256 was utilized, and the computations were performed using an Intel Core i7 CPU.

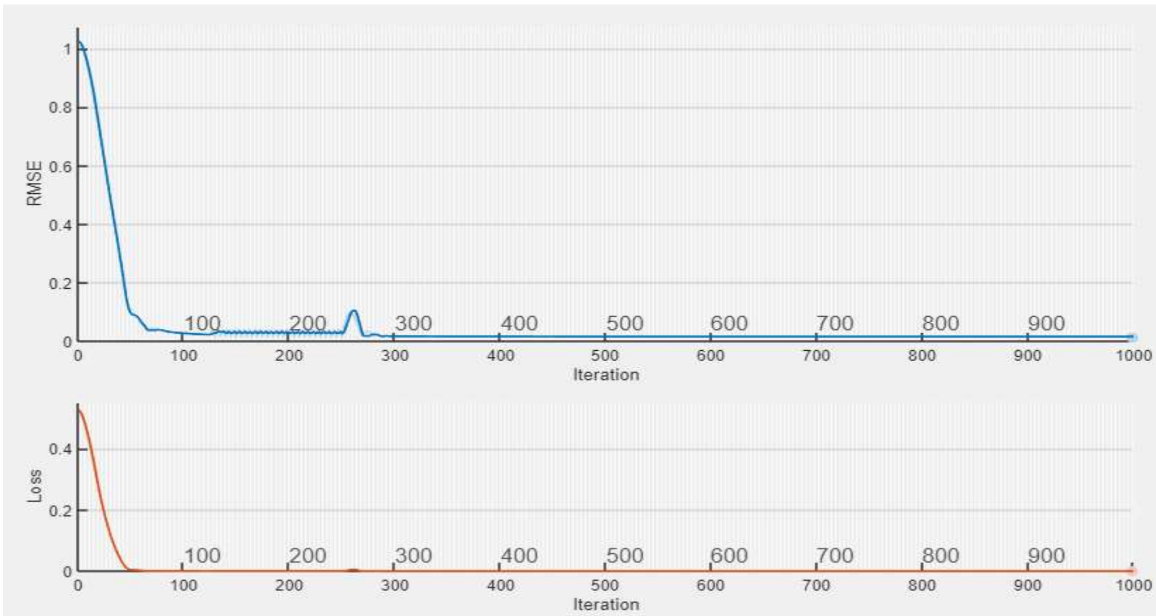

Figure 3: The training plot showing RMSE and the Loss and the iterations

Figure 3 shows a significant initial decrease in RMSE during training, followed by a slower reduction and plateau after approximately 1000 epochs, resulting in an overall 99% reduction in error with a minimum RMSE of 0.02. Uncertainty surrounding heterogeneity may affect the decision-making process for the extraction rate, but the model can predict multiple extraction rates for different permeability fields to help determine an appropriate extraction rate in uncertain situations.

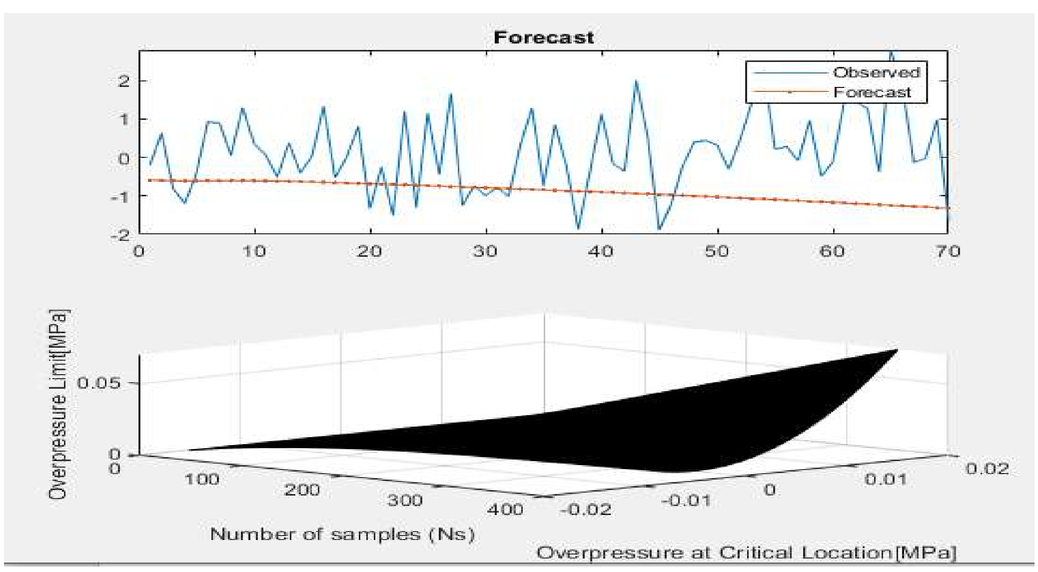

Figure 4: The Forecast and observed values

The over pressure limit of less than 0.02 MPa was reached which is close to that actual result in practice at 400 samples as shown in Figure in figure 4.

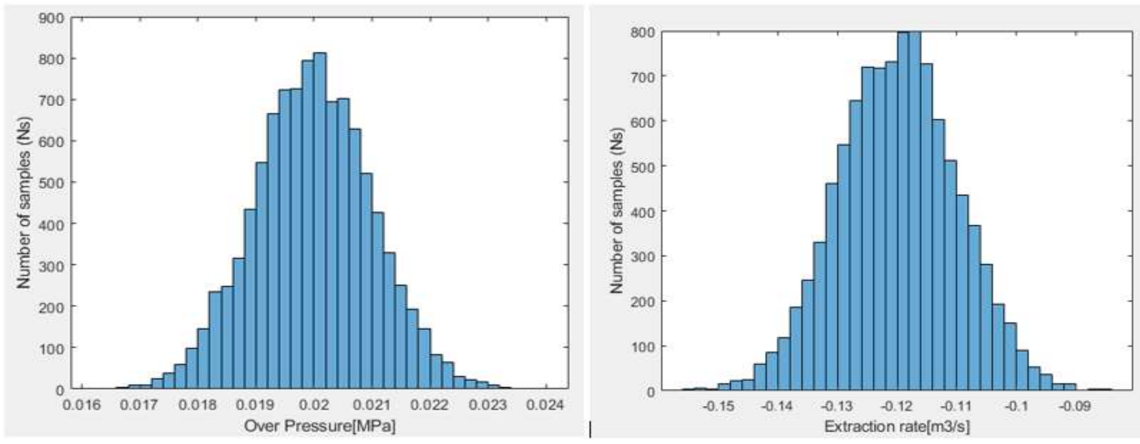

Figure 5: Showing the distributions of the Over pressure (MPa) and the extraction rate(m3/s).

According to Figure 5, as the number of samples increased, the overpressure also increased and reached its highest point at around 0.02 MPa and -0.14 m3/s when 800 samples were used.

Table 1: Performance Comparison of various algorithms

	LSTM-DP	BiLSTM-DP	BiLSTM/PSO with DP
epoch	1000	1000	1000
RMSE	0.032	0.027	0.019

In Table 1, we can see the results of different algorithms trained for 1000 epochs. The LSTM-DP model, which uses Long Short Term Memory with Differential Programming, had a root mean squared error (RMSE) of 0.032. The Bi-directional Long Short Term Memory with Differential Programming (Bi-LSTM-DP) model obtained an RMSE of 0.027. The BiLSTM-PSO model had the lowest RMSE value of 0.019.

5. CONCLUSION

The study used a PIML approach to tackle subsurface pressure management issues arising from fluid injection and extraction. The approach accounted for heterogeneity in fluid flow and evaluated the long-term impact on the reservoir. A Hybrid BiLSTM and PSO model trained in the PIML framework determined fluid extraction rates at a critical reservoir location during injection. The results showed the effectiveness of the PIML framework in managing reservoir pressures with heterogeneous permeability fields, resulting in minor deviations from the target overpressure. The DPFEHM framework was integrated into the PIML approach, bridging the gap between numerical models and machine learning techniques.

6. CONTRIBUTIONS TO KNOWLEDGE

In summary, the research problem addressed in this paper is the need for improved reservoir pressure management strategies that consider the complex physical processes governing fluid flow in heterogeneous underground reservoirs. The use of PIDL with Particle Swamp Optimization shows promise for addressing this challenge, and further research is needed to fully realize its potential.

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