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Optimization of an Integrated Production Model Using Long Short-Term Memory and Model Predictive Control under Constraints

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Abstract: The optimization of hydrocarbon production is vital in the petroleum industry. Slug flow, however, can lead to production stoppages due to damage to surface equipment. As reservoir pressure declines during oil production, slug flow may occur in surface pipelines. Therefore, developing intelligent separators and implementing effective flow regime control methods are crucial for achieving this goal. This study constructs a smart laboratory pilot to collect experimental data, including liquid level, separator pressure, input mass flow rates, and control signals, under Model Predictive Control (MPC). We employ machine learning techniques, specifically Long Short-Term Memory (LSTM), to develop proxy models for a 3D reservoir simulation, significantly reducing computational time. The LSTM proxies are then integrated into a comprehensive production model that includes a horizontal gas-liquid separator equipped with an MPC controller. The controller efficiently regulates the separator's liquid level and operating pressure in real-time. Experimental results demonstrate that the proposed system effectively mitigates slug flow by adjusting separator pressure, maintaining stable operation across various flow regimes. In a 20-year field-scale simulation, the integrated LSTM-MPC system increased cumulative oil production by approximately 40% compared to a non-optimized system. This study presents a novel approach that combines data-driven reservoir modeling with advanced control strategies, offering a significant improvement in production optimization and flow assurance for the petroleum industry.

Keywords: Optimization; Integrated Model; Long Short-Term Memory; Model Predictive Control

1. Introduction

Effective management of oil and gas reservoirs requires continuous enhancement of simulation frameworks through the integration of production data and geological characterization. Industry stakeholders increasingly seek probabilistic assessments of various development strategies to quantify uncertainty. Contemporary reservoir modeling approaches generate statistical distributions that capture the inherent uncertainties in reservoir understanding, particularly for key performance indicators such as cumulative oil production [1].

Surface separators constitute essential components in production facilities, designed to partition wellstream effluents into oil, water, and gas phases. Separation efficacy depends substantially on operational parameters and equipment configuration. Ultimately, the volume of saleable crude delivered to storage tanks is determined by separator performance and the completeness of phase segregation achieved [2].

Reservoir pressure depletion initiates from the commencement of production operations. Horizontal separator design specifications are intrinsically linked to initial reservoir pressure conditions. Consequently, separator geometry would ideally require modification in response to pressure decline, yet physical constraints prevent dimensional adjustments during active production. Therefore, the practical strategy involves dynamic regulation of separator pressure and liquid level to accommodate changing reservoir conditions [3].

This study uses the machine learning technique called long short-term memory (LSTM) to create substitutes for a 3D reservoir model. Recent reviews have highlighted the growing application of deep learning in petroleum engineering [3–5]. Sampling techniques were employed to create multiple simulation cases, which were then used to build the training database for developing the proxies. This research is a ground-breaking endeavor that applies LSTM to a real reservoir and integrates it into a production model that includes a horizontal gas-liquid separator. LSTM networks have shown promising results as surrogate models for reservoir simulation [3,4,6]. The separator uses an MPC controller to efficiently control the liquid phase level and operating pressure of the separator. Model Predictive Control has been successfully applied to various process control applications in the oil and gas industry [7,8].

This study introduces a novel system that is specifically developed to control the real-time liquid level and pressure of the separator. The main objective is to reduce the adverse effects of the slug flow regime on the performance of the separator. The study specifically addresses the following key areas:

1. The main objective of this research is to develop an intelligent control system that can seamlessly integrate with a laboratory-scale multi-phase flow loop. This system will enable a thorough evaluation of the model predictive control for the separator, specifically at a laboratory scale.
2. The task involves designing a complex control system capable of accurately measuring the desired levels of liquid and pressure in the separator under various operational conditions. To ensure its effectiveness, this system undergoes thorough testing in both laboratory and field environments.
3. Investigating the influence of the separator's operational pressure on the upstream flow regimes. This investigation is conducted in both laboratory and field conditions.
4. The intelligent control system is used to efficiently maximize the total oil production by incorporating an integrated production model. This model uses the long short-term memory (LSTM) machine learning technique to simulate an oil reservoir, instead of relying on a 3D reservoir model.

Hong et al. [9] and Nnabuife et al. [10] conducted a comparative analysis examining slug flow control strategies in offshore production. However, their research did not encompass laboratory experiments conducted specifically on horizontal separators. In contrast, the primary aim of this current study is to enhance oil production in southern Iran through the regulation of liquid level and operational pressure within horizontal separators. The ultimate objective is to mitigate the adverse effects of slug flow.

Song et al. [11] utilized a PI controller to regulate the liquid phase level and operating pressure in an offshore horizontal separator. Nevertheless, their study possessed certain limitations. It failed to explore the feasibility of incorporating a smart control system alongside laboratory-scale control systems. The principal objective of this paper is to transcend these limitations and improve overall performance through the integration of model predictive control techniques.

Aimacaña-Cueva et al. [12] conducted a study using a hardware device to investigate control methods for a three-phase separator. However, they did not specifically explore the impact of different flow regimes and variations in separator pressure on the liquid level. This research aims to fill this gap by examining the effectiveness of a horizontal separator in a slug flow regime and developing a smart control system for real-time monitoring of parameters.

Christoff, Krishnamoorthy, and Skogestad [13] proposed a nonlinear predictive control method for a three-phase horizontal separator. The objective of this method is to minimize flow fluctuations caused by the slug flow regime. The researchers provided evidence of the method's effectiveness in maintaining important variables within desired ranges.

In their study, Jiajun et al. [14] investigated the impact of interface structure behavior and focused on several aspects, such as industrial applications, interface regulation, characterization techniques, and strategies for mitigating flow interfaces. Specifically, they examined the interconnected production system, which comprises pipelines,

surface choke, production wells, and oil reservoirs. The main goal of the study was to evaluate the influence of the slug flow regime on the efficiency of horizontal separators.

Recent advancements continue to underscore the critical role of intelligent control and machine learning in production optimization. Studies have explored deep learning for production forecasting and optimization in complex reservoirs [15], the application of hybrid AI models for real-time decision-making in petroleum engineering [16], and advanced nonlinear model predictive control strategies for managing multiphase flow systems [17].

These works highlight a clear industry trend towards integrated, data-driven solutions. Recent studies by Anderson et al. [18] and Clark et al. [19] have further demonstrated the efficacy of machine learning approaches in production optimization and separator control, while Nguyen and Tran [20] provided comparative analyses of control strategies that inform our MPC design. Our research builds directly upon this foundation by creating a tangible bridge between a data-driven reservoir model (LSTM) and a physically validated, laboratory-tested MPC system, delivering a holistic solution from the reservoir to the separator.

In this study, we have developed an advanced automated model for a control system aimed at improving the efficiency of phase separation in a horizontal separator. The model monitors the liquid level and pressure under different operational conditions. The study offers a detailed explanation of the methodology, which includes the gas-liquid flow loop, liquid phase level, operational pressure controller, and system simulation procedures.

Contributions of This Work

The primary contributions of this work are threefold:

1. **Novel Integrated Framework:** We present a first-of-its-kind integration of a data-driven Long Short-Term Memory (LSTM) reservoir proxy model with a physically validated, laboratory-scale MPC system for separator control, moving beyond purely simulation-based studies.
2. **Experimental Validation of Slug Mitigation:** We provide comprehensive experimental evidence from a smart laboratory pilot, demonstrating the real-time efficacy of an MPC controller in suppressing slug flow and stabilizing separator pressure and liquid level under varying flow regimes.
3. **System-Level Production Optimization:** We demonstrate, through a 20-year field-scale simulation, that the proposed integrated system can lead to a ~40% increase in cumulative oil production by proactively preventing separator upsets caused by slug flow, a significant improvement over non-optimized operation.

Structure of the Paper

The remainder of this paper is organized as follows: Section 2 details the materials and methods, including the LSTM proxy model development, the sub-model correlations, and the design of the Model Predictive Controller. Section 3 presents the results, covering the LSTM model validation, laboratory-scale controller performance, and the integrated field-scale production forecasts. Finally, Section 4 provides the concluding remarks and discusses the implications of the findings.

2. Materials and Methods

This section offers a comprehensive explanation of integrated system modeling. Firstly, it delves into the details of the long short-term memory (LSTM) method, as well as the process of developing proxy models for the real oil reservoir. Next, it outlines the methodology for constructing and integrating additional sub-models into a unified production model.

2.1. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks represent a sophisticated category of recurrent neural architectures engineered for sequential data processing. Unlike basic RNNs, LSTM mechanisms circumvent the vanishing gradient limitation, thereby preserving information across extended temporal sequences [21]. The architecture of an LSTM unit, illustrated in **Figure 1**, comprises several gating mechanisms that regulate information flow.

Our approach aligns with recent applications of deep learning for reservoir characterization [3,4] and builds upon emerging trends in AI-assisted petroleum engineering identified in comprehensive reviews [22,23].

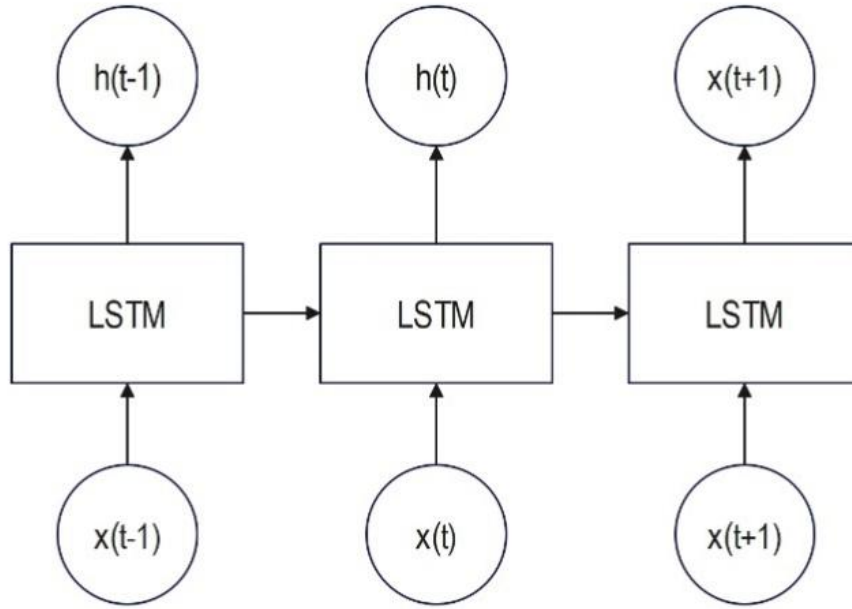


Figure 1. The general overview of the LSTM topology.

Source: Adapted from Hochreiter & Schmidhuber [8].

The mathematical formulation of LSTM is provided below:

$$f_t - \sigma(U_f h_{t-1} + W_f x_t + b_f) = 0 \quad (1)$$

$$i_t - \sigma(U_i h_{t-1} + W_i x_t + b_i) = 0 \quad (2)$$

$$\tilde{c}_t - \gamma(U_c h_{t-1} + W_c x_t + b_c) = 0 \quad (3)$$

$$c_t - (f_t c_{t-1} + i_t \tilde{c}_t) = 0 \quad (4)$$

$$o_t - \sigma(U_o h_{t-1} + W_o x_t + b_o) = 0 \quad (5)$$

$$h_t - o_t \times \gamma(c_t) = 0 \quad (6)$$

Equation (1) demonstrates how the forget gate influences the inclusion or exclusion of information. Furthermore, the input gate determines the relevance of the input in relation to the next cell state, thereby calculating its update. Furthermore, equation (6) is utilized to determine the hidden state output within the output gate. Our approach aligns with recent applications of deep learning for reservoir characterization [17,18]. The **Figure 1** shows the general overview of the LSTM topology.

It is important to note that the LSTM uses the hyperbolic tangent function ($\tanh$) as the activation function and the sigmoid function (γ) as the recurrent activation function. The dynamic proxies formulated in this research require two parameters, namely FOPR and FWPR. To address this issue, the LSTM approach has been used to develop two separate dynamic proxy models. The mathematical equation for the initial proxy is shown in equation (7), while the computation for the harmonic mean value of permeability for each layer of the formation is presented in equation (8).

$$y_i - f(u, y_{i-1}, k_{\{prod\}}, k_{std\ Dev}, K_{harmonic}, t_i) = 0 \quad (7)$$

$$K_{harmonic} - \frac{\sum_{j=1}^m L_j}{\sum_{j=1}^m \frac{L_i}{L_j}} = 0 \quad (8)$$

In the provided model, the variable representing the depth at the top of grid block j is denoted as L_j , the absolute permeability of the grid is referred to as k_j , and the number of grid blocks is represented by m . The reservoir model being studied in this research is an actual oil reservoir situated in Iran. This model consists of ten layers, including four producer wells and eight injection wells.

Dimensionality reduction was achieved by computing mean permeability values for completed grid blocks associated with each well, yielding 4 permeability parameters. Additionally, harmonic mean permeability ($k_{harmonic}$) and standard deviation ($k_{Std Dev}$) were derived for each of the 10 reservoir layers, contributing 20 further variables. Thus, the dynamic proxy models were trained using 27 input parameters collectively. With respect to the geological characteristics of the oil reservoir model, it is observed that its permeability exhibits variation across different regions, whereas its porosity remains constant at a value of 0.18.

Each grid block within the model exhibits an initial water saturation of 0.04. The dimensions of these blocks are $9 \text{ m} \times 9 \text{ m} \times 9 \text{ m}$, and there are a total of $66 \times 66 \times 10$ blocks. The distribution of horizontal permeability within the oil reservoir model at the initial condition is illustrated in **Figure 2**.

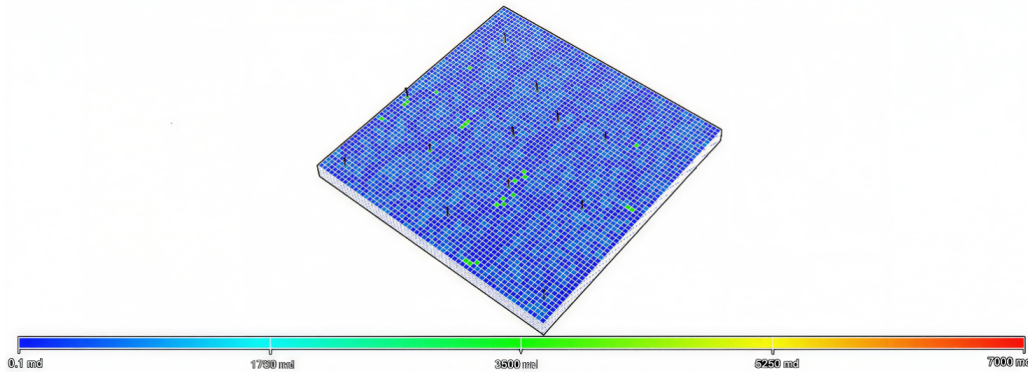


Figure 2. The distribution of horizontal permeability within the oil reservoir model at the initial condition.

The oil field under investigation in Iran consists of sedimentary formations, more specifically, a layer of sand measuring 30 feet in thickness, which is overlaid with shale. Initially, the reservoir contained a mixture of gas and oil, with a thin layer of oil present. Geophysical analysis was utilized to determine the interface between the gas and water phases. This particular oil field comprises four production wells and eight injection wells. At an initial stage, the gas-oil contact was established at a vertical depth of 8344.3 feet, while the water-oil contact was identified at a true vertical depth (TVD) of 8434.3 feet.

The oil properties encompass an oil gravity of 35° API, an oil formation volume factor of 1.42 RB/STB, an oil viscosity of 0.25 CP, and an undersaturated compressibility of $1.64 \times 10^{-5} \text{ psia}^{-1}$. The initial bubble point stands at 3350 psi, the initial reservoir pressure amounts to 5799 psi, and the gas-oil ratio (GOR) is 1.01 Mscf/STB within the oil rim. **Table 1** presents a summary of the database for the purpose of illustration. By applying this reasoning, the relevant mean and standard deviation are calculated. Then, after the preparation of the database, it is subjected to categorical normalization within the range of 0 to 1 using equation (9):

$$X_{normalized} - \frac{X_{min} - X_n}{X_{max} - X_{min}} = 0 \quad (9)$$

The term “ $X_{normalized}$ ” denotes the normalized value of X_n , while “ X_{max} ” and “ X_{min} ” respectively represent the maximum and minimum values of X . Subsequently, the database was partitioned into a training set (comprising 80% of the data points), a validation set (containing 10% of the data), and a testing set (comprising the remaining 10%).

Table 1. Database summary.

Summary of Database					
Types of Data	Number of Data Points	Maximum Value	Minimum Value	Mean Value	Standard Deviation
Static data					
t_j	1 × 7000	7300	20	3615	954.74
$K_{harmonic}$	10 × 7000	7000	0.1	1604	742.36
$K_{std Dev}$	10 × 7000	548.25	12.35	341.25	258.36
K_{inj}	8 × 7000	250	12	65.24	87.36
K_{prod}	4 × 7000	147	8.5	56.34	68.47
Dynamic data					
u	1 × 7000	2501	15	541.25	136.54
y_{i-1} and $y_i(FLPR)$	2 × 7000	2500	0	601.45	114.56
y_{i-1} and $y_i(FWCT)$	2 × 7000	1.1	0	0.6	0.32

In this scenario, the three aforementioned sampling methods are reapplied to create an additional 80 injection scenarios each. Subsequently, we assess whether the prediction performance of the dynamic proxies meets the desired level of accuracy. Upon completion of the blind validation phase, the proxies are ready for implementation. In this paper, we have employed two statistical metrics, namely the coefficient of determination and root mean squared error, to evaluate the training and prediction performance of the models. The formulas for each metric are correspondingly displayed as Equations (10) and (11).

$$X^2 + \frac{\sum_{i=1}^n (Y_i^{Proxy} - Y_i^{sim})^2}{\sum_{i=1}^n (Y_i^{proxy} - \bar{Y})^2} - 1 = 0 \quad (10)$$

$$RMSE - \sqrt{\frac{\sum_{i=1}^n (Y_i^{Proxy} - Y_i^{sim})^2}{n}} = 0 \quad (11)$$

In the given formula, Y_i represents the output value, the superscripts proxy and sim denote the proxy model and reservoir simulator model, respectively. Furthermore, $\bar{Y}$ represents the mean value of the output and n signifies the number of data points.

2.2. Sub-Models Correlations

Production well behavior was modeled employing the Duns-Ross correlation, with each well constituting an individual sub-model. Output parameters from these well sub-models served as inputs for subsequent choke modeling. Pipeline hydraulics were characterized using the Beggs-Brill correlation, establishing the surface pipeline as another integrated sub-model.

The results of the pipeline sub-model were sent to the separator sub-model, which was equipped with level and pressure controllers [19]. Once all the sub-models are created, they will be integrated. The surface pipeline mentioned earlier had a diameter of 4 inches and a length of 1550 m. The complete integrated production model is shown in Figure 3.

2.3. The Design Method of a Predictive Controller in a Multiple-Input-Multiple-Output Configuration

Development of the laboratory-scale MPC system commenced with the formulation of mathematical representations for separator liquid level and operating pressure dynamics. This investigation focuses on cylindrical separator geometry, aiming to establish precise relationships between liquid height and corresponding control variables.

Ultimately, this study will present a comprehensive equation that accurately portrays the control system under scrutiny [10,11].

$$2.7 \times x(t) + \frac{dh}{dt} + 0.0003526 \times h(t) = 0 \quad (12)$$

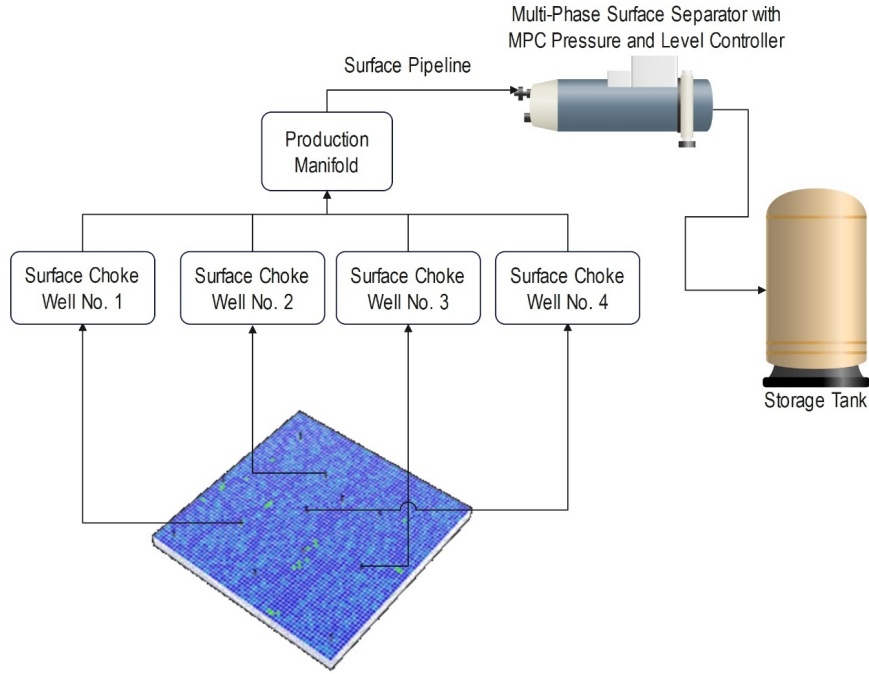


Figure 3. The integrated production model.

The transfer function is obtained by applying the Laplace transform, yielding the following expression:

$$T(s) = \frac{H(s)}{X(s)} = \frac{-2.7}{s + 0.0003526} \quad (13)$$

The state space equations corresponding to the system can be derived by analyzing it using the state space concept [12].

$$\begin{cases} 0.0003526 \times l(t) + \frac{dl}{dt} + 2.70 \times x(t) = 0 \\ y - l(t) = 0 \end{cases} \quad (14)$$

In this specific modeling approach, we make the assumption that the gas inside the separator follows ideal gas behavior [1,2,23,24]. As a result, we can describe this behavior using the following equation:

$$n_G RT - pV_G = 0 \quad (15)$$

Now, by differentiating both sides of the equation with respect to the independent variable, we can obtain the following expression.

$$\frac{dp}{dt} V_G + p \frac{dV_G}{dt} - RT \frac{dn_G}{dt} = 0 \quad (16)$$

According to the assumption that the separator is filled to fifty percent capacity, we can conclude that the volume of the current phases inside the separator is equal. This implies that both phases will undergo identical changes in volume [1,2,23,24].

$$-\frac{dV_G}{dt} = (q_{L \text{ in}} - q_{L \text{ out}}) = \frac{dV_L}{dt} \quad (17)$$

Using the principles of ideal gas behavior and the concept of molar quantity, the following equations can be derived [1,2,23,24]:

$$\frac{RT\rho_G}{M_G} - p = 0 \quad (18)$$

$$\frac{m}{M} - n = 0 \quad (19)$$

$$\frac{dp}{dt} V_G + \frac{RT\rho_G}{M_G} (q_{G \text{ out}} - q_{G \text{ in}}) + p (q_{L \text{ out}} - q_{L \text{ in}}) = 0 \quad (20)$$

Predictive control is a highly efficient strategy for managing dynamic systems characterized by multiple inputs and multiple outputs, commonly referred to as multi-input and multi-output (MIMO) systems. This approach uses a forecasting model of the system, along with its state space, to generate control signals. These signals are derived from both the model itself and the current state information [23,24]. Consequently, predictive control facilitates simultaneous and optimal control of the system. We use liquid level height, separator operating pressure, and control signals as input and output variables, along with a discrete state space, to construct a precise predictive control model. The flowchart shown in **Figure 4** enhances the production model depicted in **Figure 3**.

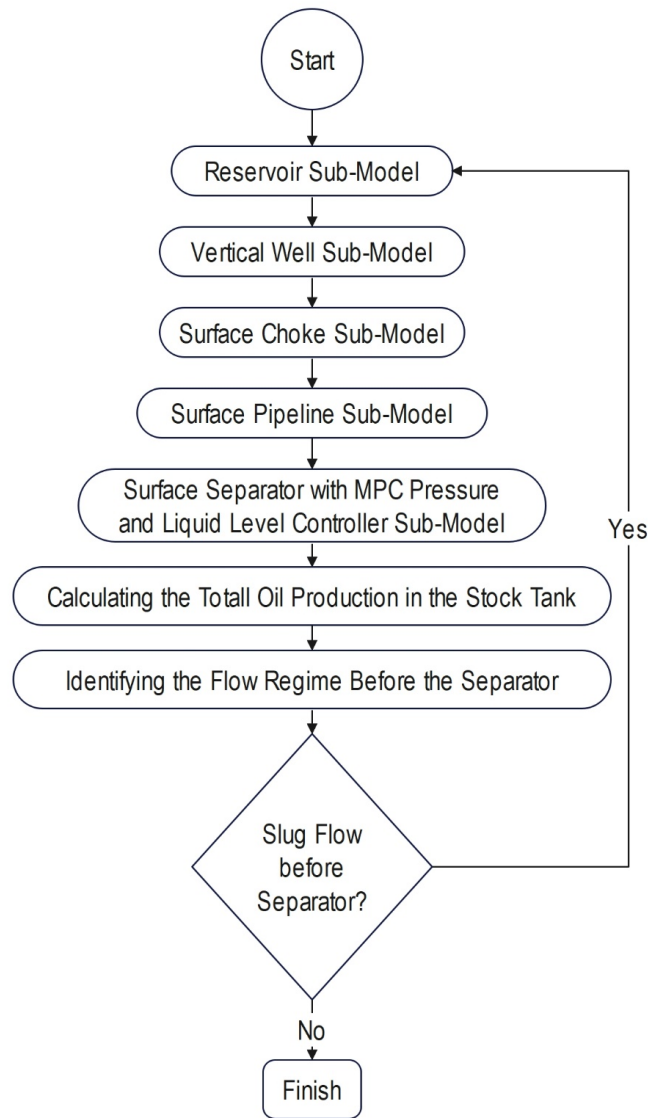


Figure 4. The Optimization Flow Chart.

2.4. Implementation Algorithm

The core of the proposed method is the integrated workflow that combines the LSTM reservoir proxy with the MPC-controlled separator system. The design of our MPC controller follows established principles for process control [22–25]. The following **Algorithm 1** outlines the step-by-step procedure for implementing the optimization process, as visualized in **Figure 4**.

Algorithm 1. Integrated LSTM-MPC Production Optimization Workflow.

Inputs: Reservoir geological parameters, initial well controls, separator setpoints (pressure, liquid level).

Outputs: Optimal control signals (valve openings), stabilized production rates, cumulative oil production.

Offline Phase (Proxy Model Development):

- a. Generate a training database by running multiple high-fidelity reservoir simulations with varying parameters.
- b. Preprocess the data (normalization) and partition it into training, validation, and test sets.
- c. Train and validate two separate LSTM network models to accurately predict Field Oil Production Rate (FOPR) and Field Water Production Rate (FWPR).

Online Phase (Closed-Loop Control - Executed per control interval):

- a. **Reservoir Forecasting:** Query the trained LSTM models to obtain the current and predicted future FOPR and FWPR for the production wells.
 - b. **Flow through Production System:** Pass the predicted flow rates from step (a) through the integrated production system sub-models:
 - i. Wellbore model (using Duns-Ross correlation).
 - ii. Choke model.
 - iii. Surface pipeline model (using Beggs-Brill correlation).
 - c. **Separator Control & Optimization:** The MPC controller receives the predicted inlet conditions from the pipeline sub-model and performs the following:
 - i. Uses the discrete state-space model of the separator (Eqs. 14–20) to predict the future behavior of the liquid level and pressure.
 - ii. Computes the optimal sequence of control actions (liquid outlet valve and gas outlet valve openings) that minimize deviations from the setpoints while respecting system constraints.
 - iii. Applies the first control action of the computed sequence to the physical separator (or the separator sub-model in simulation).
 - d. **State Update:** Update the system state with new measurements (or simulated measurements) from the separator and the reservoir proxy.
 - e. **Iterate:** Repeat steps (a) through (d) for the next control interval throughout the production lifecycle.
-

Figure 4 illustrates the connections between the different sub-models in the integrated production system. The reservoir sub-model provides input to the well sub-model, which then interfaces with the choke sub-model. The choke sub-model, in turn, integrates with the surface pipeline sub-model, and its output is directed towards the separator sub-model. The separator sub-model includes MPC level and pressure controllers. The main objective is to optimize the amount of oil in the stock tank while also preventing slug flow from reaching the separator. The results are reported once these criteria are met.

3. Results

Validation of the LSTM-based reservoir model required comprehensive performance testing against established benchmarks. The LSTM proxy was evaluated alongside conventional numerical simulation and Vogel's analytical method, with predictive accuracy quantified through relative error analysis at observation points. As it is shown in **Figure 5**, the relative error values obtained for the observed point by the LSTM model, computational software, and Vogel were 3%, 13%, and 30% respectively. By comparing the relative error values of the reservoir models, it can be observed that the LSTM model not only exhibits a significantly faster calculation speed of 18 min compared to the computational software (56 min) and Vogel (27 min), but also demonstrates superior performance in predicting the observation point. Once the performance of the LSTM model as a reservoir model has been evaluated, the next step is to assess the smart control model in the lab.

This is crucial to ascertain the model's capability in controlling slug flow on a laboratory scale before it reaches the separator, as well as its ability to regulate pressure and liquid level under varying conditions. Only upon successful evaluation will the model be integrated with the production system. This section is divided into three parts to address these objectives.

Initial validation focused on the automated control system, comprising a horizontal gas-liquid separator integrated with MPC controllers for level and pressure regulation. The primary objective was slug flow attenuation before separator entry. All simulations were executed using proprietary in-house computational tools.

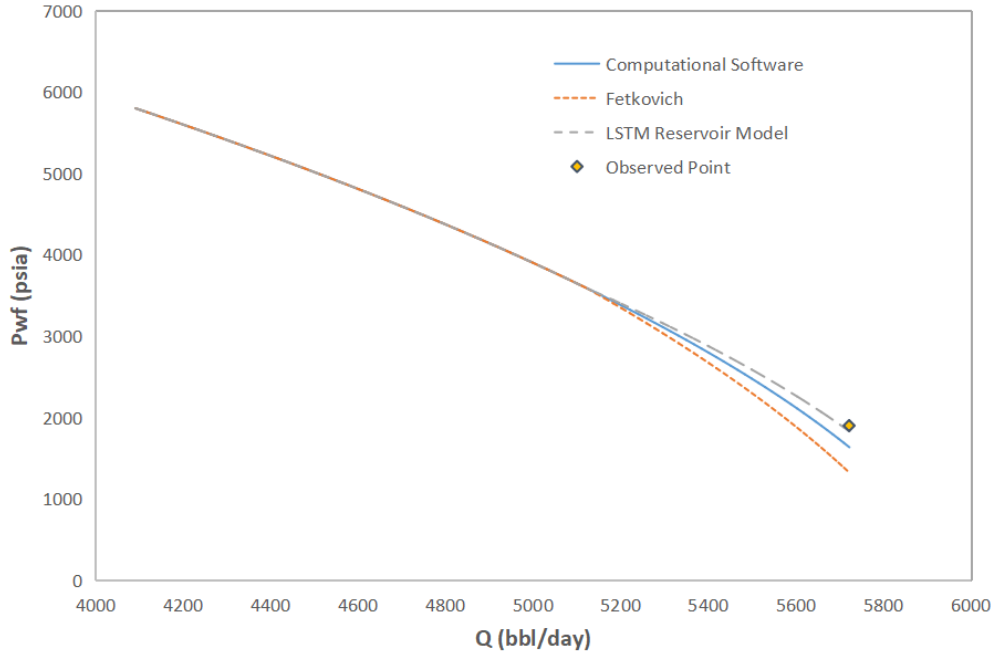


Figure 5. The results of the reservoir models.

Once we have confirmed the smart control system's performance in the laboratory, we can proceed with implementing Model Predictive Control (MPC) for the separator liquid level and operating pressure. This will be coupled with a model of an oil reservoir consisting of four production wells and eight injection wells. During the experimental phase, a camera placed in front of the separator recorded different multiphase flow patterns, which were identified using **Table 2**.

Table 2. Flow Regimes Classification at Various Gas and Liquid Flow Rates.

Flow Regime	Gas Flow Rate [$\frac{m^3}{h}$]	Liquid Flow Rate [$\frac{m^3}{h}$]
Bubble (Figure 6a)	1–2.5	4.5
Stratified (Figure 6b)	1	0.5
Wavy (Figure 6c)	4–6	0.4
Slug (Figure 6d)	1.5–10	1–3

Bubble flow patterns emerged at gas flow rates of 1–2.5 m^3/h combined with liquid rates of 4.5 m^3/h , as depicted in **Figure 6a**. Transition to stratified flow occurred with increasing liquid rates and decreasing gas rates, as systematically characterized in **Table 2**. This stratified flow regime is shown in **Figure 6b**.

A stratified flow regime is achieved by reducing the liquid and gas flow rates to 1 and 0.5, respectively. In a stratified flow pattern, the water and air phases are distinctively separated. The gaseous phase exhibits a higher velocity in the upper portion of the pipe, while the liquid phase persists in the lower region of the pipe. This results in a smooth interface with minimal interference.

Increasing the gas velocity to 4–6 m^3/h , while simultaneously reducing the liquid flow to 0.4 m^3/h , leads to the manifestation of a wavy flow regime. This phenomenon is shown in **Figure 6c**, where waves occur at the interface caused by tension between the gas and liquid phases. **Figure 6d** demonstrates that when the liquid flow rate is amplified to 1–3 m^3/h and the gas flow rate escalates from 1.5 to 10 m^3/h , slug flow materializes. Given the occurrence of slug flow within the pipeline, it is imperative to examine control methodologies within the laboratory pilot in order to proficiently manage it.

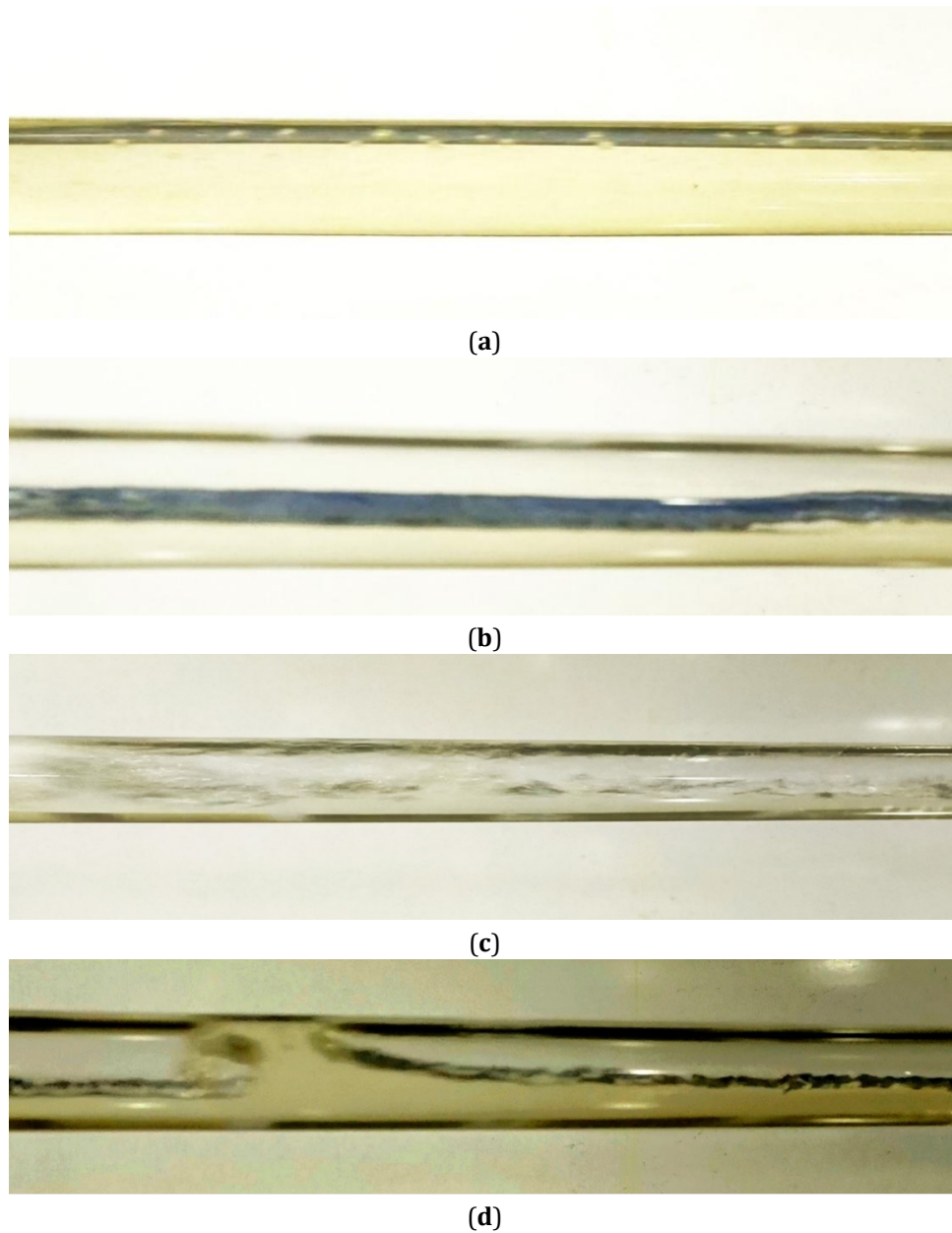


Figure 6. The various observed flow regimes in the laboratory.

Table 2 presents the laboratory study on the application of the MPC controller for managing slug flow in horizontal pipelines using level and pressure control strategies. These strategies involve techniques such as facility choking upstream of the separator and regulating liquid level and gas pressure within the separator. However, depending solely on the initial oil runoff is not economically viable in the industry, and implementing an upstream choke would result in a significant production decrease.

Modifying the flow pipeline during production is not feasible. The oil industry is dedicated to finding cost-effective solutions to address the slug flow regime. The laboratory test lasted for 2100 s, and **Figure 7** displays the changes in separator liquid level and discharge valve opening value throughout the experiment.

Figure 7 shows that the liquid level remains stable with minimal liquid fluctuations, resulting in a smooth variation in pressure. No slug flow is observed from 0 to 600 s, indicating that the current flow pattern corresponds to the bubble flow regime, as illustrated in **Table 2**. After the first 500 s, both the gas and liquid flow rates show a noticeable increase.

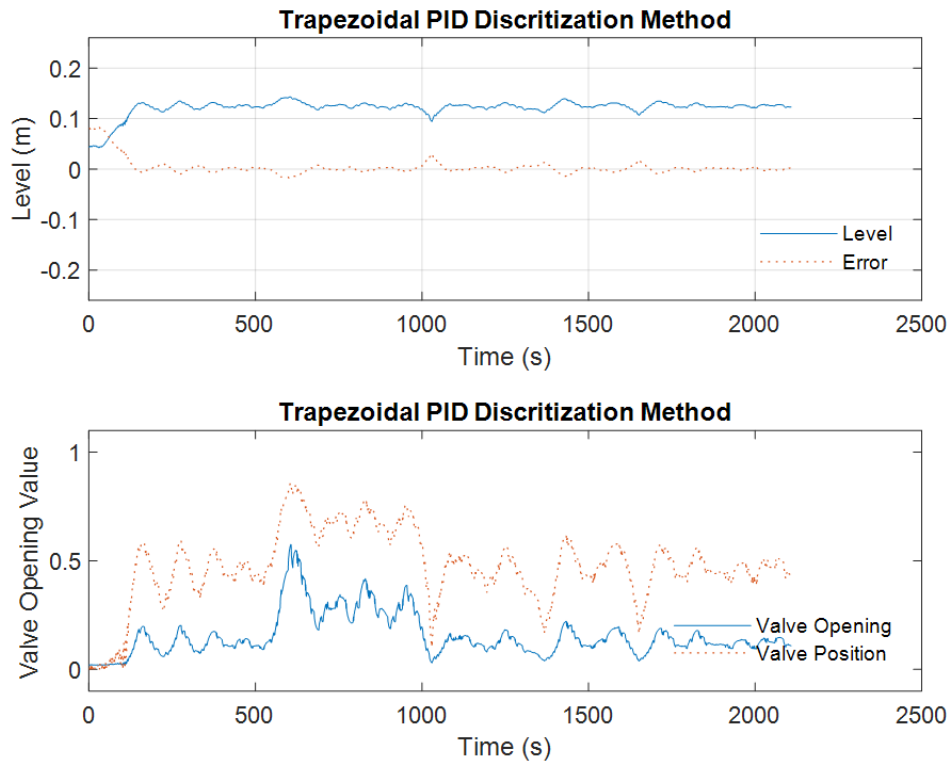


Figure 7. The variations observed in the separator level and valve opening value throughout the laboratory test.

Furthermore, **Figure 7** clearly shows that the gas outlet valve opens to a greater extent. To ensure the separator pressure remains at its optimal value, an adjustment is made. As a result, the flow pattern undergoes a transition from a regime characterized by the presence of bubbles to a stratified flow pattern, which is distinguished by the presence of smoother waves.

After the 1000-second mark, the flow rates of the liquid and gaseous phases increase even further, resulting in the formation of slug flow before entering the separator. In order to prevent excessive flushing within the separator, the pressure inside is increased, which results in a higher percentage of opening for the outlet flow valves.

By increasing the flow rates of both the gas and liquid, a more noticeable slug flow pattern occurs prior to entering the separator. This leads to a higher pressure in the separator and a wider opening percentage of the outlet flow valves. Empirical experimental tests conducted in the laboratory have demonstrated that raising the operating pressure of the separator effectively inhibits the formation of slug flow before it enters into the separator.

After effectively eliminating the slug flow regime through the implementation of an automated intelligent control system, our next objective is to integrate and deploy the tested model predictive control (MPC) controller. This step aims to effectively regulate the operating separator pressure and liquid phase level within a real integrated production system that includes an actual oil reservoir, as illustrated in **Figure 2**. The main objective of integrating the model predictive control (MPC) controller into the integrated production system is to prevent the slug flow regime from reaching the horizontal separator in a real production environment.

The purpose of the integrating method is to improve and enhance overall oil production and increase oil recovery in the stock tank. This innovative method is presented in **Figure 4**, and two simulations were conducted to evaluate its effectiveness. The simulation focused on the production system shown in **Figure 3**.

Figure 8 displays the total amount of oil produced by two integrated production models throughout a specific time frame. The first system operates without using any optimization method. In contrast, the second system incorporates a new optimization method. This distinction is clearly shown in **Figure 4**. **Figure 8** shows that the slug flow regime occurs in the non-optimized system approximately 8 years after production begins, before reaching the separator. This phenomenon results in a reduction in crude oil production in the stock tank.

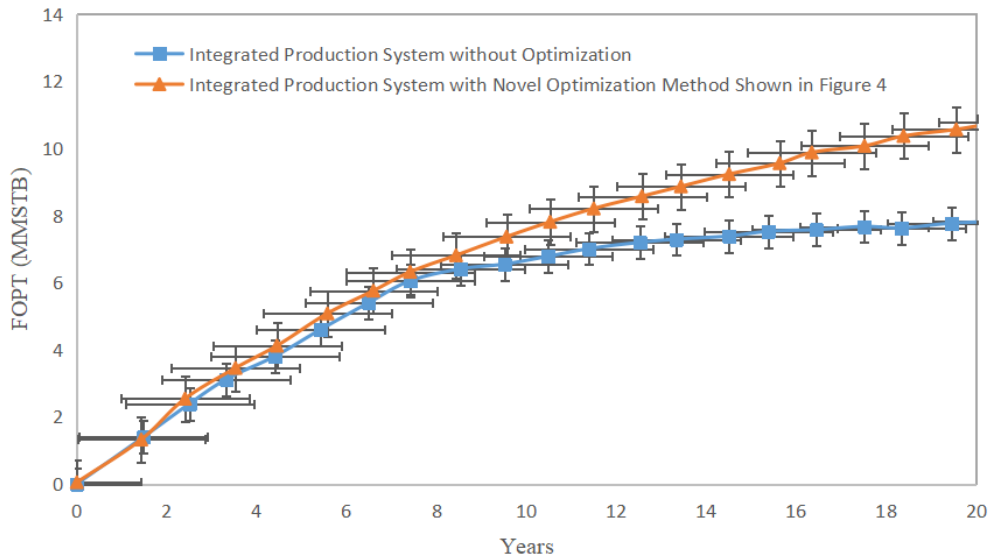


Figure 8. The cumulative oil production for two distinct integrated production models, one with an optimization model (as demonstrated in **Figure 4**) and the other without.

However, the production system that has been optimized using the new method illustrated in **Figure 4** remains consistently optimized, regardless of the decrease in reservoir pressure. The MPC controller applied to the separator model ensures that the operating pressure and liquid phase level of the separator are regulated in accordance with variations in operational conditions, thereby resulting in optimal system performance. As a consequence, the cumulative oil production in the stock tank gradually increases throughout multiple years of production, leading to the mitigation and eventual elimination of the problem of slug flow formation before the horizontal separator.

Production forecasts indicate that the baseline non-optimized system would yield approximately 8 MMSTB cumulatively over a 20-year horizon. Implementation of the proposed integrated optimization strategy elevates projected recovery to 11.22 MMSTB, representing a substantial enhancement. The findings depicted in **Figure 8** demonstrate that the novel optimization method proposed in this study has the potential to significantly increase the total barrels of oil production in the field by approximately 40% over 20 years, starting from the commencement of production. Furthermore, this proposed method efficiently prevents and mitigates the manifestation of slug flow regime prior to reaching the horizontal separator and other surface equipment.

4. Conclusions

This study introduces a pioneering approach aimed at improving the efficacy of oil extraction from hydrocarbon reservoirs. The proposed method entails the application of a Model Predictive Control (MPC) system in conjunction with the Long Short-Term Memory (LSTM) technique.

The Model Predictive Control (MPC) system enables real-time adjustments of liquid levels and pressures within the separator. Consequently, the need to modify the size of the separator during oil production is eliminated.

To enhance oil production in the stock tank, one possible approach is to integrate the suggested flow chart with a Model Predictive Control (MPC) system. This integration would help regulate separator pressure and liquid levels, reducing the occurrence of slug flow before it reaches the separator. Our integrated approach contributes to the growing field of AI applications in petroleum engineering [3–5,22] and aligns with the broader digital transformation trends in upstream operations [23]. Our approach aligns with the broader movement towards AI-augmented oilfield management [15, 16] and demonstrates the practical implementation of advanced predictive control [17,24,25] in a critical flow assurance application.

Furthermore, this study has successfully attained several noteworthy achievements, which include:

- Increase the pressure at the separator to minimize the occurrence of slug flow before it enters the separator.
- This study aims to develop an intelligent control system capable of operating efficiently in both laboratory and operational settings, even when faced with varying inlet liquid flow rates and flow patterns.
- This system greatly reduces liquid level fluctuations that occur during slug flow.
- The empirical evidence presented in this document conclusively demonstrates that the intelligent control system significantly enhances oil production in real-world fractured oil fields.

A simulation was conducted over a period of approximately 20 years to model the integrated production system, in collaboration with an intelligent model predictive control system. The results of the simulation unveiled a significant 40% augmentation in oil production.

Limitations and Future Work

Despite the promising results, this study has several limitations that present opportunities for future research. First, the LSTM proxy models were trained on data from a specific Iranian oil reservoir; their performance and generalizability when applied to reservoirs with significantly different geological characteristics (e.g., highly fractured or carbonate formations) require further investigation. Second, the laboratory-scale flow loop, while illustrative of the core physics, may not capture all the complexities of full-scale field operations, such as pipe erosion, wax deposition, or complex chemical interactions. Scaling the control logic to a full-sized separator and field pipeline network would be a necessary next step. Finally, the computational cost of training the LSTM models, though substantially lower than running a full 3D reservoir simulator, is non-trivial and must be considered for real-time deployment. Future work could explore more lightweight neural architectures or transfer learning to reduce this initial cost.

Our approach aligns with the broader movement towards AI-augmented oilfield management [14, 15] and demonstrates the practical implementation of advanced predictive control [16] in a critical flow assurance application.

Authors Contributions

Conceptualization, M.F.; methodology, M.F.; software, A.A.-A.; validation, formal analysis, investigation, resources, visualization, and data curation, M.F. and A.A.-A.; writing—original draft preparation, H.H.G.; writing—review and editing, M.M.V.E.; supervision and project administration, M.J.A. and Y.R. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors have no relevant financial or non-financial interests to disclose. Also, the authors have no competing interests to declare that are relevant to the content of this article. The authors disclose that they did not use any generative AI or AI-assisted technologies in the writing process.

Abbreviation

Meaning	Unit	Symbol
Actual Length of Separator	<i>m</i>	<i>L</i>
Differential Pressure of the Valve	<i>Bar</i>	ΔP_v
Drag coefficient	–	<i>CD</i>
Effective Length of Separator	<i>m</i>	<i>Leff</i>
Gas compressibility factor	–	<i>Z</i>
Gas Density	<i>kg/m³</i>	ρ_g
Gas density at initial separator pressure	<i>kg/m³</i>	$\rho_{g,i}$
Gas density at new separator pressure	<i>kg/m³</i>	$\rho_{g,n}$
Gas flow rate	<i>m³/h</i>	<i>Qg</i>
Gas Pressure	<i>Bar</i>	<i>Pg</i>
Gravity	<i>m/s²</i>	<i>g</i>
Height Derivative	<i>m/h</i>	$\frac{dh}{dt}$
Initial separator pressure	<i>Bar</i>	<i>Pi</i>
Inner Radius of Separator	<i>m</i>	<i>r</i>
Liquid cross-sectional area	<i>m²</i>	<i>Al</i>
Liquid Density	<i>kg/m³</i>	ρ_l
Liquid droplet diameter	<i>micron</i>	<i>dd</i>
Liquid droplet's settlement time	<i>s</i>	<i>tset</i>
Liquid droplet's transit time	<i>s</i>	<i>ttrans</i>
Liquid Input Flow Rate	<i>m³/h</i>	<i>Ql,in</i>
Liquid Level	<i>m</i>	<i>h(t)</i>
Liquid Outlet Flow Rate	<i>m³/h</i>	<i>Ql,out</i>
cell state	–	<i>ct</i>
forget gate	–	<i>ft</i>
New separator pressure	<i>Bar</i>	<i>Pn</i>
Separator diameter	<i>m</i>	<i>d</i>
Temperature	<i>K</i>	<i>T</i>
input gate	–	<i>it</i>
output gate	–	<i>ot</i>
The ratio of the separator liquid level to the separator height	–	<i>hratio</i>
field oil production rate	–	<i>FOPR</i>
field water production rate	–	<i>FWPR</i>

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