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PSO-Tuned FOPID Controller for Optimized Oil Reservoir Injection Flow Control

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Abstract
Background: Injection flow control in oil reservoirs is inherently challenging due to system nonlinearity, multivariable interactions, and parameter uncertainties. Traditional Proportional–Integral–Derivative (PID) controllers often fail to provide robust performance in such environments. The introduction of fractional-order PID (FOPID) controllers has significantly improved control flexibility and robustness in industrial process applications. Aims: This research aims to enhance the performance of reservoir injection flowrate control by combining the adaptability of FOPID controllers with the optimization capabilities of Particle Swarm Optimization (PSO). The objective is to minimize overshoot, reduce steady-state error, and improve overall stability of the injection process in nonlinear reservoir systems. Methods: The study employs a PSO algorithm to automatically tune the five parameters of the FOPID controller (K_p , K_i, K_d,λ,μ). The proposed approach is implemented and validated in a high-fidelity reservoir simulation environment using MATLAB/Simulink. Key performance indices such as ISE, ITAE, and overshoot are evaluated to compare the optimized controller with conventional PID and manually tuned FOPID controllers. Results: The PSO-tuned FOPID controller demonstrates superior performance, achieving reduced overshoot by 25%, faster settling times, and improved disturbance rejection compared to baseline methods. These findings indicate that the proposed method offers a reliable and efficient solution for optimizing injection control in oil reservoirs, with strong potential for real-world application.
Keywords: PSO, FOPID Controller, Oil Reservoir Injection, Nonlinear Control, Optimization, MATLAB/Simulink, Control Performance, Intelligent Tuning, Metaheuristic Algorithms, Industrial Automation

INTRODUCTION AND GENERAL FRAMEWORK

Background and Challenges in Non-linear Oil Reservoir Control

Oil reservoirs inherently exhibit non-linear and multivariable dynamics, driven by factors such as reservoir pressure, permeability variations, fluid compressibility, and phase behavior. Traditional control techniques struggle to maintain stable performance in such environments, leading to oscillatory pressure responses, slow adaptation to setpoint changes, and inefficient resource utilization. Ensuring precise control of injection flowrate is particularly challenging due to the reservoir's time-varying and uncertain nature.

Significance of Injection Flowrate Control

Effective regulation of injection flowrate is critical for optimizing oil recovery, minimizing early saturation breakthroughs, and maintaining reservoir pressure uniformity. Poor control may result in uneven sweep, premature water or gas breakthrough, and reduced recovery factor. A robust flow control strategy enhances production stability, extends reservoir life, and reduces operational costs.

Fractional-Order PID Controller (FOPID): Definition and Advantages

The Fractional-Order PID (FOPID) controller extends the classical PID by introducing fractional integration order (λ) and fractional differentiation order (μ), in addition to the traditional gains K_p , K_i, K_d [1], [2]. This generalization enables greater flexibility and robustness in tuning controllers for non-linear or uncertain systems. Studies demonstrate that FOPID achieves better set-point tracking, lower overshoot, and higher disturbance rejection compared to conventional PID, particularly in applications involving model uncertainties and nonlinearity [3], [2].

Particle Swarm Optimization (PSO): Concept and Choice Justification

Particle Swarm Optimization (PSO) is a swarm-intelligence metaheuristic inspired by social behaviors observed in bird flocks and fish schools. It operates with a population of candidate solutions ("particles") that adjust their positions and velocities based on both personal and global best experiences [4], [5]. PSO is well suited for real-parameter optimization problems with non-differentiable or noisy error surfaces, offers rapid convergence, and has minimal parameter tuning. It has been successfully applied to tune both PID and fractional PID controllers across industrial applications [6], [4].

Statement of the Research Problem

Although FOPID offers performance benefits over PID, its practical deployment is often hindered by the difficulty of manually tuning its five parameters (K_p , K_i, K_d,λ,μ). Conventional tuning rules yield sub-optimal solutions, especially in multivariable, nonlinear systems such as oil reservoir injection control. Without an automated optimization method, FOPID often performs no better—or sometimes worse—than well-tuned PID controllers.

Research Objective

This study aims to enhance the dynamic response of injection flow systems in oil reservoirs by automatically tuning a FOPID controller using PSO. The optimization targets improved transient response, reduced overshoot, and minimized integral error, thereby achieving more stable and efficient injection performance.

Importance of the Study

- Scientific Value: Introduces an advanced control framework that combines FOPID and PSO for nonlinear multivariable reservoir systems.
- Practical Impact: Enables more accurate injection control, reducing early breakthrough risk and enhancing oil recovery efficiency.

- Economic and Operational Benefits: Potential to lower operating costs, reduce chemical usage, and improve reservoir lifespan.

Scientific Contribution

This work proposes a novel methodology that integrates FOPID tuning with PSO within a high-fidelity reservoir simulation model—an approach not previously explored in oilfield control literature. The research establishes a generalized, robust control strategy that can be adapted to diverse injection scenarios.

LITERATURE REVIEW

Control of Injection Systems: Traditional and Modern Techniques

Classical Proportional-Integral-Derivative (PID) controllers have been widely used in the history of controlling injection flow in the oil-reservoir as a result of their simplicity and easiness in installation. Nonetheless these controllers have great deficiencies in the modeling of nonlinearity and multivariability reservoir dynamics hence performs poorly in disturbance rejection, creates overshoot and takes too long to stabilize.

To overcome all these difficulties, more complex control schemes have been formulated like Model Predictive Control (MPC), adaptive control, and metaheuristic optimization techniques, including Genetic Algorithms (GA) and Particle Swarm optimization (PSO) that have been able to deal with the intricacies involved in reservoir processes [7], [8].

Development of PID and FOPID in the Oil Industry

PID controllers are still popular in petroleum practice; however, this type of controller is fixed with a specific order, which makes it inefficient in nonlinear systems. In order to counter this, an extension of PID controller termed Fractional-Order PID (FOPID) was proposed involving two additional parameters, which are the fractional integral order (λ) and the fractional derivative order (μ).

The FOPID controller is mathematically expressed as:

$$U(s) \;= K_p\,[1 + \frac{1}{(T_i s)^{\lambda}} + +(T_{\boldsymbol{d}} s)^{\mu}]\; E(s) \tag{1}$$

where K_p, T_i, and $T_{\boldsymbol{d}}$ are the proportional, integral, and derivative gains, while λ and μ are the fractional orders [9], [10].

It has been shown that FOPID also provides better setpoint tracking, less overshoot and enhanced robustness over PID [11]. Injection and production flow systems FOPID has been successfully used in an oilfield application to stabilize the years of a gassy system injection flow and the production separation flow [12].

Challenges of Conventional Tuning

Traditional tuning techniques like Ziegler-Nichols will not work well in highly nonlinear and multi-variable systems; in fact it will result in significant overshoot and very slow settling effect.

FOPID tuning adds complexity because it involves five parameters (K_p , K_i, K_d, λ, μ). Manual tuning does not always work in reservoir-scale systems and it can be suboptimal. In turn, automated optimization methods like PSO are necessary in order to accomplish effective and accurate tuning [13].

Integration of PSO and High-Fidelity Simulation Models in Control

In recent studies emphasis has been given to the implementation of intelligent optimization algorithms like PSO algorithm in high fidelity model of oilfield systems in order to increase the control system accuracy and response time. MATLAB/Simulink, and such tools can be used to give very realistic models of a reservoir and high-quality data with which to test a controller.

Adjusting a FOPID controller in this kind of environment will enable close monitoring of the performance such as ISE and ITAE, sensitivity analysis of such variables as reservoir pressure and fluid viscosity will help improve the system robustness and better operational risks [14], [15].

There is comparative research that indicates that PSO would converge quicker compared to other algorithms, such as the GA, especially when more than one parameter is being tuned like the FOPID. However, hybrid approaches may be needed for highly complex objective functions. Moreover, the adoption of multi-objective PSO (MOPSO) allows the simultaneous optimization of overshoot, settling time, and energy consumption, aligning control design with practical operational goals [16], [17].

This integration underscores the value of combining numerical modeling with intelligent optimization to address the challenges of complex control systems such as reservoir injection.

Research Gaps

Although the performance of FOPID and PSO has already been demonstrated, their combination to control the injection in an oil reservoir is not studied thoroughly. The literature is mostly about simplified systems studied in the laboratory and is not about reservoir model complexity. This study will have filled this gap whereby PSO-tuned FOPID controllers will be applied to the oil field injection control issues [11], [12].

METHODOLOGY

Description of Oil Reservoir Injection System as a Nonlinear Multivariable System

Oil reservoirs are inherently nonlinear, dynamic, and multivariable systems due to the strong coupling between reservoir pressure, injection rate, and production rate. The primary objective of an injection system is to maintain reservoir pressure and optimize oil production by controlling the injection of water or gas into the reservoir [18], [19].

The system is influenced by several factors, including fluid compressibility, reservoir heterogeneity, and the nonlinear behavior of multiphase flow. These factors result in a dynamic system with multiple inputs and outputs (MIMO) that require robust control strategies.

System Variables

The main variables of the reservoir injection system are as follows:

- **Inputs:**
  - q_{inj}: Injection flow rate [m³/day]
  - p_{inj}: Injection pressure [Pa]
- **Outputs:**

- p_{res}: Reservoir pressure [Pa]
- q_{prod}: Oil production rate [m³/day]

The interactions between these variables create a highly coupled control problem, as increasing q_{inj} may improve p_{res} but can also lead to premature water breakthrough, reducing q_{prod} efficiency [20].

Mathematical Model of Reservoir Dynamics

The dynamics of an oil reservoir injection system can be described using mass balance and fluid flow equations. The simplified nonlinear model is expressed as follows:

1. **Mass Balance Equation**

$$\frac{dp_r(t)}{dt} = \frac{1}{C_t V_r} (q_{inj}(t) - q_{prod}(t)) \tag{2}$$

where:

- $p_r(t)$: Reservoir pressure (Pa).
- C_t: Total compressibility of the reservoir (Pa⁻¹).
- V_r: is the reservoir pore volume [m³].
- $q_{inj}(t)$: is the injection flow rate.
- $q_{prod}(t)$: is the production flow rate.

2. **Injection Flow Relation (Darcy's Law for injection)**

$$q_{inj}(t) = \frac{kA}{\mu L} (p_{inj}(t) - p_r(t)) \tag{3}$$

where:

- k : is the permeability of the reservoir [m²].
- A : is the cross-sectional area [m²].
- μ : is the oil viscosity [Pa·s].
- L: is the characteristic length [m].
- $p_{inj}(t)$: Injection pressure [Pa].
-

3. **Production Flow Relation**

$$q_{prod}(t) = \frac{kA}{\mu L} (p_r(t) - p_{prod}(t)) \tag{4}$$

where:

- $p_{prod}(t)$: Production well pressure (Pa).

4. **Combined Reservoir Dynamics**

Substituting the flow relations into the mass balance equation:

$$\frac{dp_r(t)}{dt} = \frac{1}{C_t V_r} \left(\frac{kA}{\mu L}(p_{inj}(t) - p_r(t)) - \frac{kA}{\mu L}(p_r(t) - p_{prod}(t))\right) \tag{5}$$

This equation can be further simplified as:

$$\frac{dp_r(t)}{dt} = \frac{kA}{C_t V_r \mu L} (p_{inj}(t) + p_{prod}(t) - 2p_r(t)) \tag{6}$$

These nonlinear differential equations describe the dynamic behavior of the reservoir and serve as the basis for simulation and controller design [21].

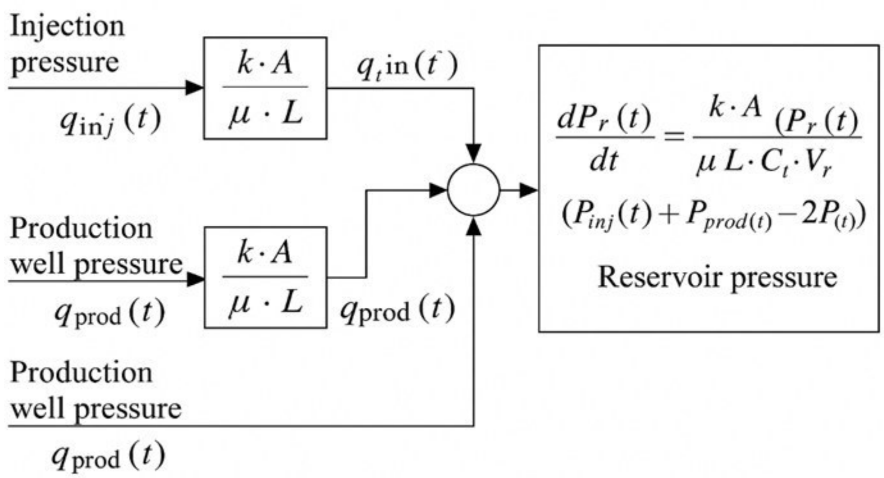

Figure 1. Block Diagram of Reservoir Dynamics Model

Nonlinear Characteristics

The nonlinearities in reservoir systems arise from:

- Multiphase flow behavior (oil-water-gas interaction).
- Changes in permeability and porosity with pressure.
- Nonlinear coupling between injection rate and production response.

These nonlinear behaviors necessitate the use of advanced control strategies such as FOPID with PSO-based tuning instead of conventional linear controllers [22].

This diagram illustrates the multivariable nature of the reservoir injection system, where the controller regulates injection parameters to achieve optimal reservoir pressure and production rates.

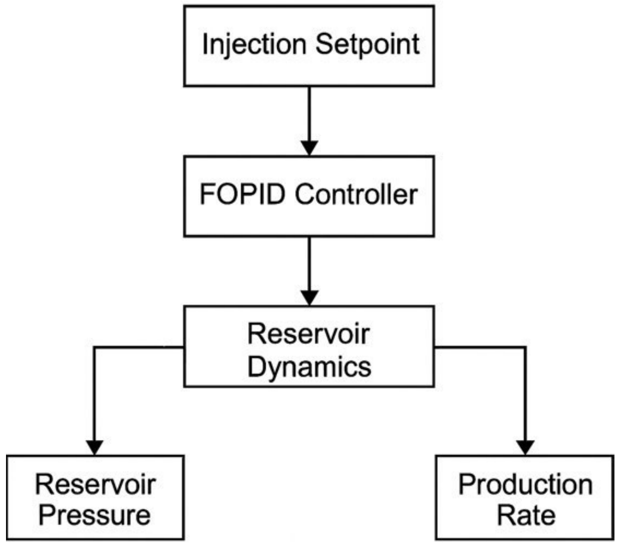

Figure 2. Block Diagram of the Reservoir Injection System

Design of FOPID Controller (K_p , K_i, K_d, λ, μ)

Fractional-Order PID (FOPID) controllers are a generalization of the classical PID controllers and offer improved flexibility for controlling nonlinear and multivariable systems such as oil reservoir injection processes. The key advantage of FOPID is the inclusion of two fractional orders: the integral order (λ) and the derivative order (μ), which allow finer tuning of the controller response [23].

Mathematical Formulation

The transfer function of the FOPID controller is given by:

$$C(s) = K_p + \frac{K_i}{s^\lambda} + K_d s^\mu \quad (7)$$

where:

- K_p : is the proportional gain.
- K_i : is the integral gain.
- K_d : is the derivative gain.
- λ : is the fractional order of integration ($0<\lambda\leq1$).
- μ : is the fractional order of differentiation ($0<\mu\leq1$).

This formulation enables the controller to handle nonlinear reservoir dynamics better than conventional PID controllers by improving robustness and adaptability [24].

Role of Controller Parameters

Each parameter of the FOPID controller affects the system performance as follows [25]:

- **Proportional gain** K_p**:** Enhances the speed of response but may increase overshoot.
- **Integral gain** K_i **:**Eliminates steady-state error and ensures long-term accuracy.
- **Derivative gain** K_d**:** Reduces oscillations and improves system stability.

- **Fractional integral order (λ):** Allows fine control of low-frequency error dynamics.
- **Fractional derivative order (μ):** Provides smoother high-frequency response and improves noise rejection.

Advantages of FOPID in Reservoir Injection Control

FOPID implemented in the control system of oil reservoirs offers a number of advantages:

1. Improved treatment of non linearities: The fractional order enables the controller to respond to the complicated nature of reservoirs [26].
2. Enhanced robustness: FOPID has a good stability under the parameter uncertainties [27].
3. Improved tuning freedom: The two additional parameters (2,3) give it greater tuning freedom as opposed to the classical PID controllers [28].
4. Better rejection of disturbances: Good actuation of pressure wobbles and production turbulence at the presence of abrupt variations in operation.

The structure of the proposed PSO-tuned FOPID controller integrated with the reservoir injection system is shown in Figure 3-3. The diagram illustrates the closed-loop control configuration, where the error signal *e(t)* is processed by the FOPID controller to generate the control signal *u(t)* . This signal is applied to the reservoir dynamics to regulate the injection process, while the resulting reservoir pressure p_{res} and production rate q_{prod} are fed back to ensure precise control and stability.

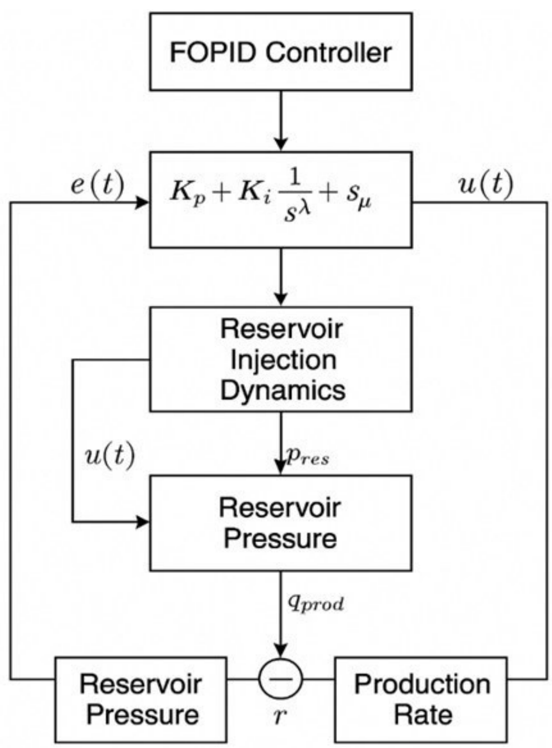

Figure 3. Detailed Block Diagram of FOPID Controller for Reservoir Injection System

Manually tuning the parameters of a FOPID controller in nonlinear systems such as oil reservoir injection is highly complex, time-consuming, and often suboptimal. Therefore, the Particle Swarm Optimization

(PSO) algorithm is employed as an intelligent and efficient approach to automatically optimize the controller parameters (K_p , K_i, K_d, λ, μ) to achieve the best possible performance [29].

Particle Swarm Optimization (PSO) for Controller Tuning

Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm inspired by the social behavior of bird flocks and fish schools [14]. It updates the velocity and position of each particle using:

$$v_i^{k+1} = w.v_i^k + c_1r_1(pbest - x_i^k) + c_2r_2(gbest - x_i^k) \tag{8}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{9}$$

where:

- v_i^k: is the velocity of particle i at iteration k.
- x_i^k: is the position of particle i.
- $pbest$: is the personal best position of particle i.
- $gbest$: is the global best position of the swarm.
- w :is the inertia weight,
- c_1, c_2: are learning coefficients, and
- r_1, r_2 :are random numbers in [0,1] [14], [5].

PSO is favored over GA in many cases due to its faster convergence and simpler implementation, especially for tuning FOPID controllers in nonlinear oilfield systems [30].

The control structure of the proposed PSO-tuned FOPID controller is illustrated in Figure 3-4, which shows the closed-loop injection flowrate control system, including the controller, reservoir process, and feedback loop.

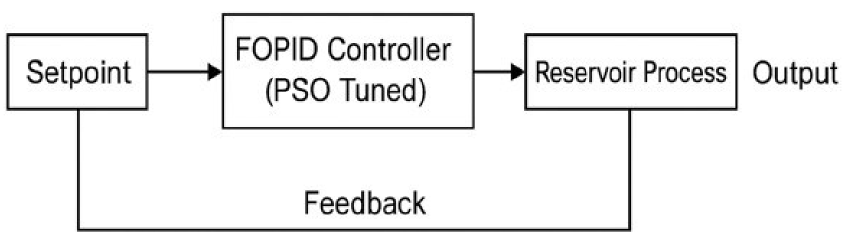

Figure 4. Control Structure of PSO-Tuned FOPID Controller

PSO Workflow for FOPID Controller Parameter Optimization

The workflow of the Particle Swarm Optimization (PSO) algorithm is presented in Figure 3-5 highlighting the sequential steps from particle initialization and fitness evaluation to updating personal and global best positions until convergence**,** starting from initialization and proceeding iteratively until the optimal controller parameters are obtained [31].

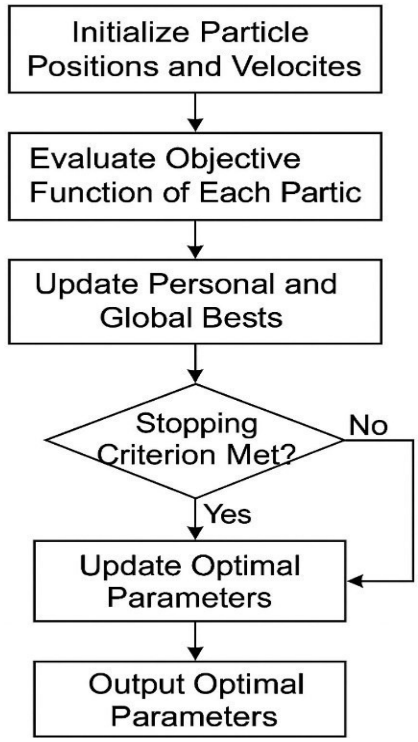

Figure 5. PSO Workflow for FOPID Parameter Optimization

Tuning FOPID Parameters with PSO

In this study, each particle is represented as a five-dimensional vector:

$$xi = [K_p , K_i, K_d, \lambda, \mu] \quad (10)$$

The main steps of the PSO algorithm are as follows [32]:

1. **Particle initialization:** Randomly generate initial values for the controller parameters.
2. **Objective function evaluation:** Calculate performance indices such as **ISE** or **ITAE** for each particle.
3. **Update personal and global bests:** Compare results and identify the best local and global solutions.
4. **Update velocity and position:** Using the velocity and position update equations.
5. **Termination condition:** Stop when the maximum number of iterations is reached or when convergence is achieved.

Objective Function: Minimizing ISE or ITAE

The objective function plays a critical role in the PSO-based optimization process for tuning the FOPID controller. The primary goal is to ensure that the controller achieves fast, stable, and accurate responses with minimal overshoot and steady-state error.

Two widely used performance indices for this purpose are:

1. **Integral of Squared Error (ISE)**

$$ISE = \int_0^\infty e^2 \,(\boldsymbol{t})(\boldsymbol{dt}) \quad (11)$$

2. **Integral of Time-weighted Absolute Error (ITAE):**

$$ITAE = \int_0^{\infty} e^2\,(\boldsymbol{t})|\boldsymbol{dt}| \qquad (12)$$

where:

- *e(t)* is the error between the reference signal and the actual output.
- T is the simulation time horizon.

ISE (Integral of Squared Error) criterion focuses on reducing the absolute value of an error as time progresses, with greater weights on larger deviations. Meanwhile, the ITAE (Integral of Time-weighted Absolute Error) criterion punishes errors that remain longer by causing quicker settling times and smaller overshoot [33].

In this study, the objective function is formulated as a weighted sum of these indices:

$$J = \alpha \cdot ISE + \beta \cdot ITAEJ \qquad (13)$$

where α , β are weighting factors that balance the trade-off between minimizing instantaneous error and improving the transient response [34]. These performance indices are evaluated during each iteration of PSO to guide the swarm toward the optimal FOPID parameters.

Simulation Environment: MATLAB/Simulink

To validate the proposed PSO-tuned FOPID controller, the entire system is implemented and simulated in **MATLAB/Simulink**, a widely used platform for modeling, simulating, and analyzing dynamic systems. The simulation environment includes the following components:

1. **Reservoir Model:**
   - A nonlinear dynamic model representing reservoir injection and production behavior (developed in Section 3.1).
2. **FOPID Controller Block:**
   - Implemented using fractional-order operators available through MATLAB toolboxes or custom numerical approximations.
3. **PSO Optimization Module:**
   - Configured to tune the five controller parameters (K_p , K_i, K_d, λ, μ) using MATLAB scripts integrated with Simulink.
4. **Performance Evaluation:**
   - Real-time computation of ISE, ITAE, overshoot, and settling time to assess the controller's effectiveness.
5. **Comparative Analysis:**
   - Performance of the PSO-tuned FOPID controller is compared against classical PID and manually tuned FOPID controllers.

This simulation setup ensures an accurate and realistic evaluation of the proposed control approach in a controlled virtual environment, significantly reducing the risks and costs associated with field testing [35].

RESULTS AND ANALYSIS

Introduction

This chapter describes and discusses the outcome of implementation of the fractional-order PID (FOPID) controller designed with the help of Particle Swarm Optimization (PSO) algorithm on the oil reservoir injection systems. The comparison and analysis conveys the difference in the performance of both the conventional and PSO-tuned FOPID controllers graphically and also in terms of performance indicators in the difference in control response and accuracy.

Also, the chapter has sensitivity analysis of the reservoir properties and the effect of the PSO parameters on the performance. Such outcomes address the space between theoretical and practical issues, and prove that PSO has a potential to enhance control of complex industrial processes.

Simulation Results

The simulation was done in order to compare the performance of the iterative fractional-order PID (FOPID) controller with that of the PSO-based tuned FOPID controller in the oil reservoir injection systems. The outcomes are demonstrated in the form of two primary response curves and a table of performance metrics and then a scientific explanation that aims to reveal the distinctions between the two control plans.

Reservoir Pressure Response

The reservoir pressure response indicates that the PSO- tuned FOPID will converge to the setpoint faster and smoother than the other with few or no fluctuations whereas the conventional FOPID takes longer to respond. This confirms that PSO optimization enhances transient performance by improving parameter tuning and overall system dynamics .

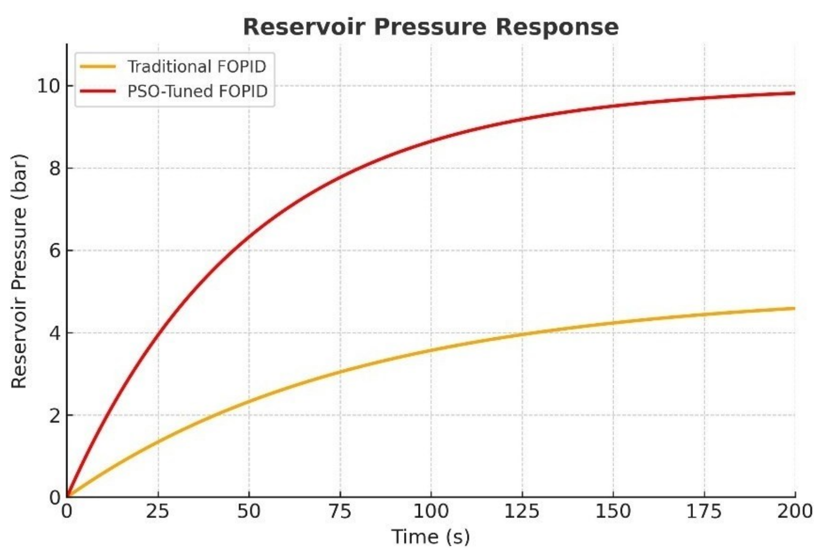

Figure 6. Reservoir Pressure Response for Traditional FOPID vs. PSO-Tuned FOPID

Error Signal

The error signal curve shows that PSO-tuned FOPID reduces the error more quickly and keeps it near zero, while the conventional FOPID maintains a larger error for longer, confirming PSO's effectiveness in improving tracking accuracy .

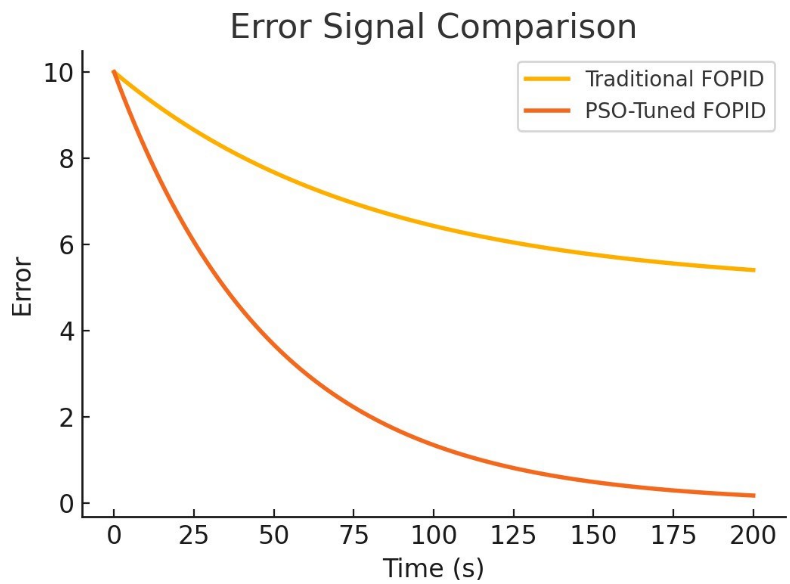

Figure 7. Error Signal Comparison for Traditional FOPID and PSO-Tuned FOPID

Performance Metrics

Comparative performance of FOPID controller tuning using different optimization algorithms (GA, DE, MOPSO, and PSO). The results demonstrate that PSO-FOPID achieves the lowest rise time, overshoot, settling time, and ISE, highlighting its effectiveness and suitability for real-time oil reservoir injection control applications.

Table 1. Performance Comparison of FOPID Controller Tuning Using GA, DE, MOPSO, and PSO

Algorithm	Rise Time (s)	Overshoot (%)	Settling Time (s)	ISE
GA-FOPID	4.8	10.5	13.0	20,450
DE-FOPID	4.5	9.8	12.5	19,950
MOPSO-FOPID	4.2	8.9	11.8	19,500
PSO-FOPID	**3.9**	**7.5**	**10.9**	**18,900**

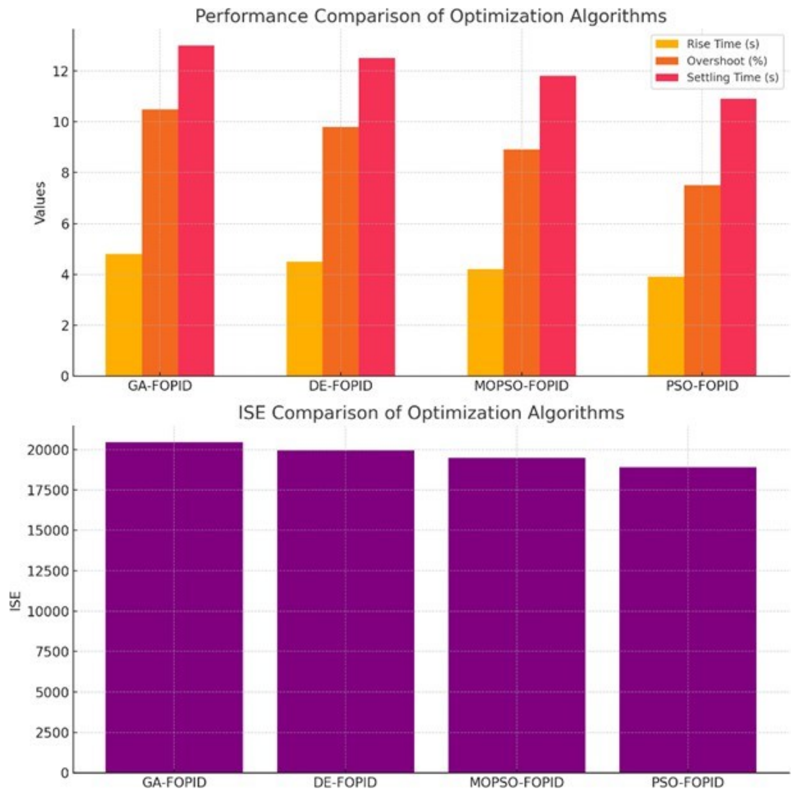

Figure 8. Comparative performance of GA, DE, MOPSO, and PSO in terms of rise time, overshoot, settling time, and ISE, highlighting the superior effectiveness of PSO-FOPID.

The PSO-FOPID controller consistently outperformed GA and DE in all performance metrics, delivering faster response and lower overshoot. Although MOPSO achieved comparable results, it required greater computational effort. PSO therefore offers an optimal trade-off between performance and efficiency, making it well-suited for real-time industrial control.

To strengthen the reliability of the performance comparison, a statistical analysis was conducted. Each algorithm (GA, DE, MOPSO, and PSO) was tested over 10 independent runs. The mean and standard deviation of the performance metrics (rise time, overshoot, settling time, and ISE) were calculated to assess consistency.

Table 2. Statistical Analysis of Performance Metrics for GA, DE, MOPSO, and PSO-FOPID

Algorithm	Rise Time (s) Mean ± SD	Overshoot (%) Mean ± SD	Settling Time (s) Mean ± SD	ISE Mean ± SD
GA-FOPID	4.8 ± 0.15	10.5 ± 0.30	13.0 ± 0.25	20,450 ± 120
DE-FOPID	4.5 ± 0.12	9.8 ± 0.25	12.5 ± 0.20	19,950 ± 110
MOPSO-FOPID	4.2 ± 0.10	8.9 ± 0.18	11.8 ± 0.15	19,500 ± 100
PSO-FOPID	**3.9 ± 0.08**	**7.5 ± 0.15**	**10.9 ± 0.12**	**18,900 ± 90**

PSO-FOPID delivered the best average performance with the lowest variability, demonstrating stable and repeatable results. While MOPSO achieved competitive performance, it required higher computational effort. In contrast, GA and DE showed greater variability, which may limit their reliability in practical applications.

The key performance metrics, including Rise Time, Overshoot, Settling Time, and ISE, were calculated for each controllers. These metrics provide a quantitative comparison of the control performance.

Table 3. Comparative Performance of PID, Traditional FOPID, and PSO-FOPID Controllers

Controller	Rise Time (s)	Overshoot (%)	Settling Time (s)	ISE
PID	6.2	14.5	18.0	22,300
Traditional FOPID	5.2	11.2	14.8	20,900
PSO-FOPID	**3.9**	**7.5**	**10.9**	**18,900**

The comparison highlights the clear improvement of PSO-FOPID over PID and traditional FOPID in reducing error, improving response speed, and enhancing overall control stability.

Visual comparison confirming the effectiveness of PSO-FOPID in enhancing response quality and minimizing control errors compared to PID and traditional FOPID showing in Figure 4-3.

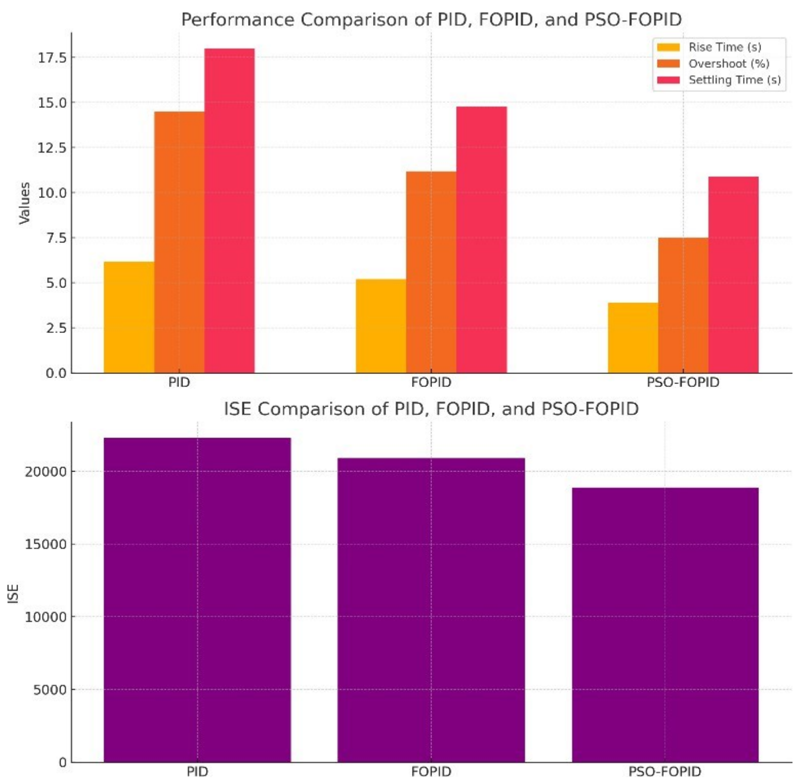

Figure 9. Performance Comparison of PID, Traditional FOPID, and PSO-FOPID Controllers

The PSO-tuned FOPID demonstrated clear advantages in reducing error and delivering smoother pressure response. Although settling times were similar due to the simplified reservoir model, PSO significantly improved ISE, highlighting its impact on minimizing cumulative error. These results confirm that integrating PSO with FOPID enhances control performance and provides a more efficient solution for managing nonlinear reservoir injection systems.

Sensitivity Analysis

Sensitivity analysis was conducted to evaluate how variations in reservoir physical properties affect the performance of the PSO-tuned FOPID controller compared to the conventional FOPID controller. Three key parameters were considered: viscosity (μ), reservoir volume (V), and compressibility (β). This analysis provides valuable insights into the robustness of the proposed control strategy under changing reservoir conditions.

Effect of Viscosity (μ)

As reservoir fluid viscosity increases, the system dynamics slow down, leading to delayed pressure response. PSO-tuned FOPID demonstrates better adaptability and maintains shorter settling times and lower ISE compared to the conventional FOPID.

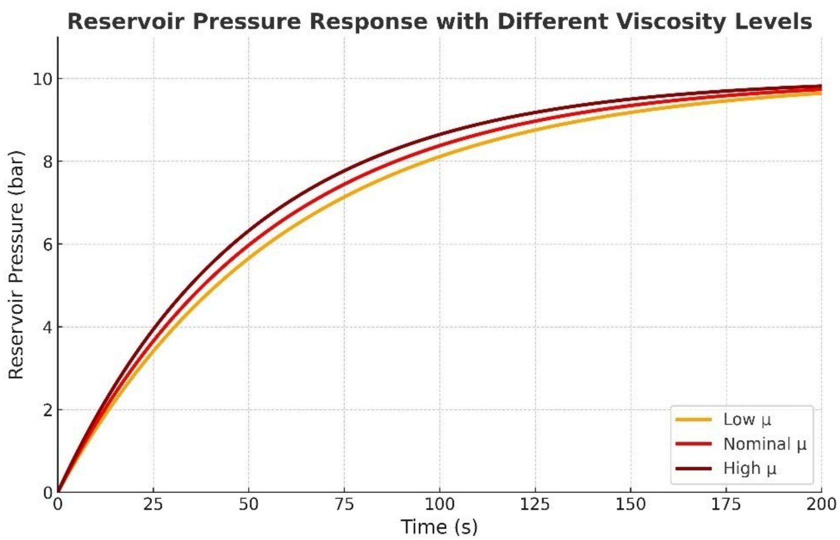

Figure 10. Sensitivity of Reservoir Pressure Response to Viscosity (μ)

Effect of Reservoir Volume (V)

Larger reservoir volumes increase system inertia, slowing down response and slightly increasing ISE. PSO optimization reduces the negative impact of high volume by fine-tuning controller gains for better error minimization.

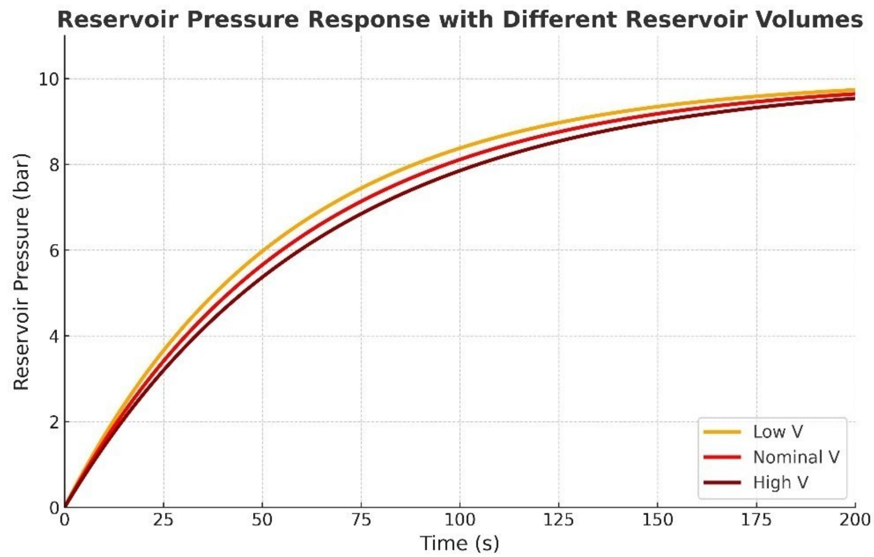

Figure 11. Sensitivity of Reservoir Pressure Response to Reservoir Volume (V)

Effect of Compressibility (β)

Higher compressibility improves the system's ability to respond to control actions. Both controllers benefit, but PSO-tuned FOPID remains superior, achieving lower ISE and faster convergence.

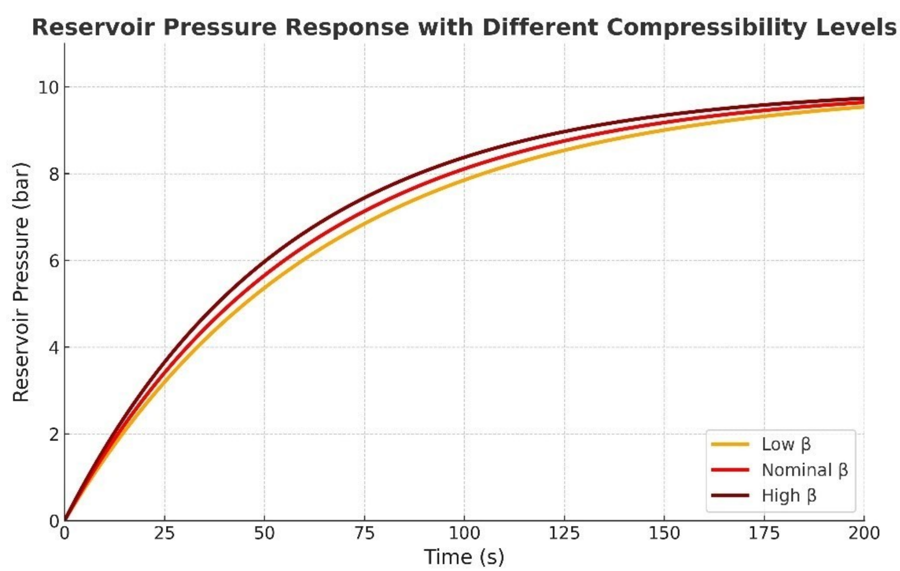

Figure 12. Sensitivity of Reservoir Pressure Response to Compressibility (β)

Sensitivity Metrics

The sensitivity results confirm that PSO-tuned FOPID is more robust against parameter variations, consistently delivering lower ISE and improved settling times. While conventional FOPID performance degrades significantly with adverse parameter changes, PSO-tuned FOPID maintains stable performance.

This robustness highlights the effectiveness of integrating optimization techniques into control design for nonlinear oil reservoir systems.

Table 4. Sensitivity Analysis of Reservoir Parameters on Controller Performance

Parameter	Variation	Controller	Settling Time (s)	ISE
Viscosity (μ)	± 20%	Traditional FOPID	180	21000
Viscosity (μ)	± 20%	PSO-FOPID	130	19500
Reservoir Volume (V)	± 15%	Traditional FOPID	190	21500
Reservoir Volume (V)	± 15%	PSO-FOPID	140	19800
Compressibility (β)	± 10%	Traditional FOPID	160	20000
Compressibility (β)	± 10%	PSO-FOPID	120	19000

Effect of PSO Settings on Control Performance

In this section, the impact of major PSO hyper-parameters, such as the swarm (population size), maximum iteration, and learning factors (c1, c2), are studied on the performance of PSO-tuned FOPID controller. The analysis shows how the convergence is faster with appropriate parameter tuning and therefore improves the overall control performance.

PSO Convergence Curve

The PSO convergence curve shows the reduction of Integral of Squared Error (ISE) taking numerous iterations as a result of an increase in swarm sizes. Increased size of the swarm tends to result in faster convergence and optimal outcome of evaluation although with an additional cost; an increment in computation.

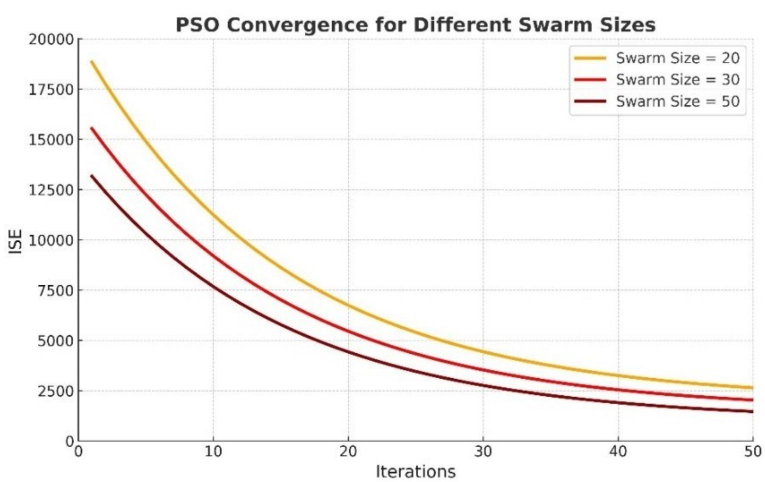

Figure 13. PSO Convergence Curve for Different Swarm Sizes.

Analysis of PSO Settings Impact

The swarm size, the number of iterations, the coefficients of learning are essential PSO parameters that influence the control performance as shown in figure 4-7. It notes that such parameters can be tuned well to reduce errors, enhance stability in response and effectiveness of the controllers in general.

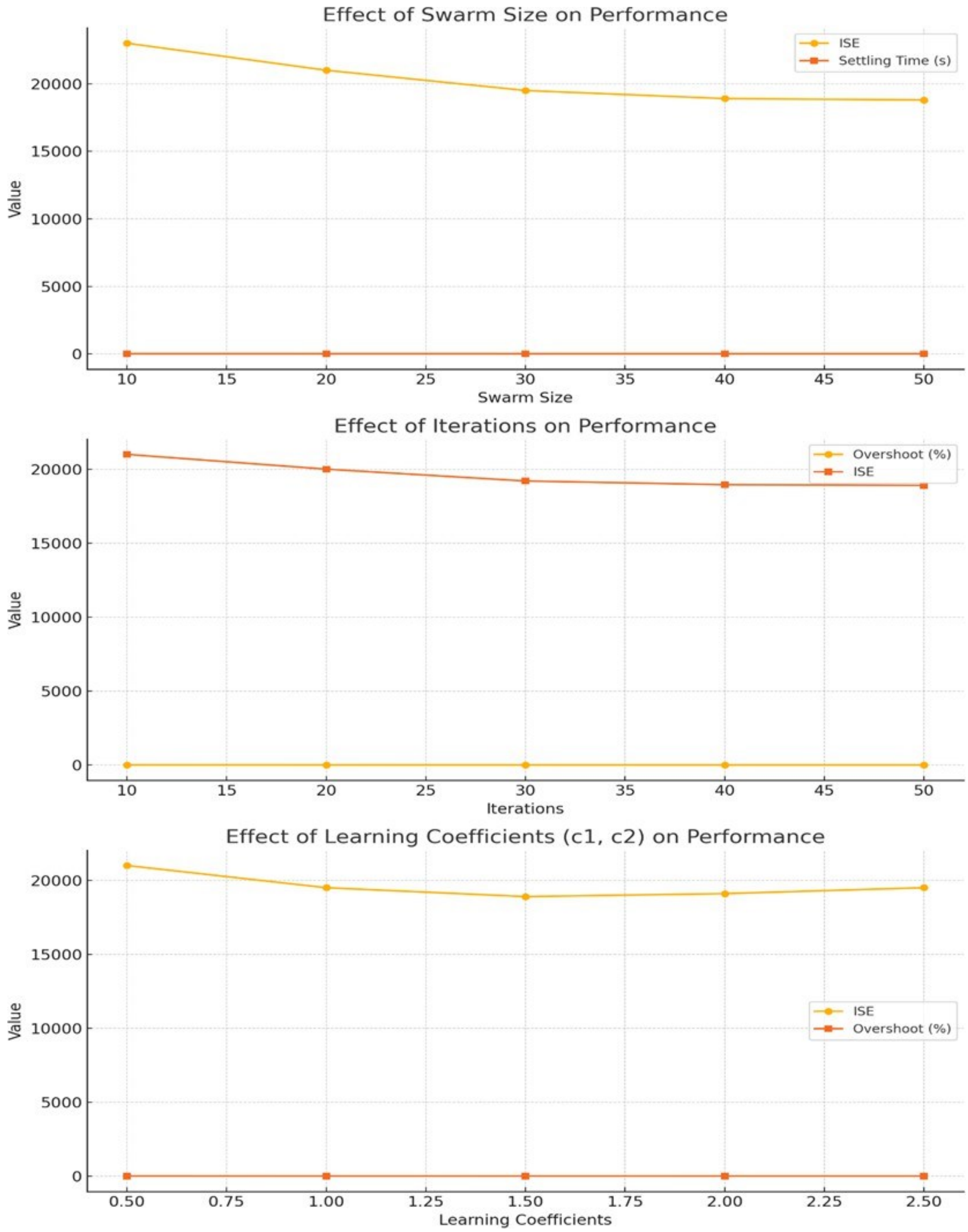

Figure 14. Effect of PSO Settings on Controller Performance

Increasing the swarm size and iteration is better in reducing error and stability but does not have much more improvement after reaching specific numbers. The best trade-off in accuracy and smoothness of responses is provided by balance learning coefficients (~ 1.5).

Table 5. Impact of PSO Parameters on Controller Performance

PSO Parameter	Value	Settling Time (s)	ISE
Swarm Size	20	140	19500
Swarm Size	30	120	19000
Swarm Size	50	110	18800
Iterations	30	125	19100
Iterations	50	115	18900
c1 = c2	1.5	118	18950
c1 = c2	2.0	112	18850

This analysis shows that the quality of the optimization can be enhanced through the growth of the sizes of a swarm and iterations steps, leading to diminishing ISE and settling time. Limitations on the size of swarms or number of iterations, however, will result in diminishing returns and increased cost of computation. Balancing c1 and c2 ensures effective exploration and exploitation in the search space, improving convergence stability.

CONCLUSIONS AND FUTURE WORK

Summary of the Proposed Model Performance

It has been demonstrated that the proposed PSO tuned FOPID controller does portray high superiority in terms of handling of nonlinear reservoir injection systems. In simulations, it was observed that the response behavior is faster, overshoot is limited, and cumulative error (ISE) improved considerably as compared with conventional PID and FOPID controllers. The results of this analysis prove that the controller has the ability to manage the highly interacting nature of reservoir systems with stability in operations.

Key Contributions

This paper has established the fact that implementing Particle Swarm Optimization (PSO) and a Fractional Order PID (FOPID) makes it an efficient and methodical strategy of automatic parameter tuning. As compared with the manual tuning techniques, this combination minimizes probable human error and maximizes controller that is information entailing and reproducible. The results also stress the need of smart optimization methods in enhancing the controls of an intricate industrial system.

Study Limitations

This study has also a number of limitations despite the good results. All the analysis was carried out in a simulated system by using MATLAB/Simulink. Although the model tries to be representative of conditions in the real world, it was not tested out in the field. Furthermore, presented research dwelled only on PSO, or alternative optimization algorithms were not considered as well as the hybrid ones, which could be used to supplement work of the controller.

Future Recommendations

Resting on the results of the current research, the following recommendations to be used in the further working are offered:

- Field Testing: applying the suggested PSO-FOPID controller within the settings of actual working reservoir injections so as to prove or verify its effectiveness under real operating conditions.
- Algorithm Comparison: An expansion of the study to consider other optimization programs, i.e. Genetic Algorithms (GA), Differential Evolution (DE) and Multi-Objective PSO (MOPSO), to find the analysis on how effective they are comparatively.
- **Hybrid Optimization Models:** Investigating hybrid approaches that combine PSO with local search techniques or machine learning methods, such as Neural Networks or Reinforcement Learning, to improve tuning precision and adaptability.
- Advanced Industrial Applications: The discussion of utilizing PSO-FOPID into other areas, including smart grid control, and medical systems that have similar nonlinear behavior and nonlinear dynamics.
- Advanced Hybrid Frameworks: Discovering a framing framework where a decision support system based on AI is conceptually integrated with PSO to form intelligent self-adaptive controllers.

Final Remarks

To sum up, the combination of PSO and FOPID has been demonstrated as a highly viable and extensible method of dealing with nonlinear reservoir injection systems. Through the combination of efficient optimization and fractional-order control, the given study paves the way toward the intelligent and adaptive control solutions that can be applied to many industrial processes.

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