

Performance Evaluation of PID and AI-Based Controllers for Centrifugal Pump Operation Using Dynamic System Simulation at PT. Pelindo Energi Logistik (PEL)

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ABSTRACT

The operation of centrifugal pump systems driven by AC motors is crucial for industrial fluid transportation, particularly in energy and logistics facilities where stable pressure and flow regulation are essential to maintaining operational efficiency. However, conventional control strategies often face limitations when dealing with nonlinear pump dynamics and fluctuating operating conditions. This study therefore evaluates the performance of proportional–integral–derivative (PID) and artificial intelligence (AI)-based controllers for centrifugal pump operation using dynamic system simulation. The research compares three control approaches: PID, neural-network-based control (NNC), and reinforcement learning (RL) based on the Soft Actor-Critic algorithm. A dynamic simulation model representing the pump system used in **PT. Pelindo Energi Logistik** was developed using operational parameters and hydraulic calculations to analyze system response over a 1000-s simulation period. The results indicate that the RL controller provides improved pressure regulation performance, achieving lower error metrics with MAE and RMSE values of approximately 140.5 kPa and 141.3 kPa, compared with about 160 kPa obtained using the PID controller. In addition, RL maintains a stable efficiency level of around 64.8%, while the other controllers exhibit negligible efficiency values in the simulation environment. These findings demonstrate that reinforcement learning offers superior adaptability and energy-aware control behavior for centrifugal pump systems. Consequently, AI-based control strategies have strong potential to improve the operational stability and efficiency of industrial pumping infrastructure.

1. Introduction

The operation of AC motor-driven centrifugal pump systems constitutes a fundamental component in modern industrial processes, particularly in energy and oil-related sectors where fluid transportation must be maintained with high reliability and operational stability. In many industrial facilities, centrifugal pumps are responsible for transferring crude oil, refined petroleum products,

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and other industrial fluids across different processing stages [1,2]. The performance of these systems is strongly influenced by the dynamic interaction between motor torque, hydraulic load, and pressure conditions within the piping network. Instabilities in pump operation can lead to fluctuations in pressure, flow rate, and mechanical vibration, which may eventually reduce system efficiency and operational lifespan [3,4]. Consequently, effective control strategies are essential to maintain stable pump operation under varying load conditions and dynamic disturbances. Numerous studies have therefore emphasized the importance of dynamic system modeling and simulation to evaluate pump performance before real-world implementation, allowing engineers to analyze system behavior and optimize controller design in a controlled computational environment [5,6].

Among various control strategies, proportional–integral–derivative (PID) controllers have been widely implemented in industrial pumping systems due to their simplicity, reliability, and effectiveness in regulating process variables such as pressure, speed, and flow rate [7,8]. Several previous studies have demonstrated that PID-based control can significantly improve system stability, minimize steady-state error, and accelerate transient response in motor-driven pump systems. The adaptability of PID control has enabled its application in various engineering domains, including hydraulic pumps, electro-hydraulic systems, and compressor control [9,10]. Nevertheless, conventional PID controllers often encounter performance limitations when dealing with nonlinear system characteristics, parameter uncertainties, and time-varying disturbances that frequently occur in complex industrial environments. As a result, recent research trends have explored enhanced PID structures and optimization algorithms in order to improve robustness and dynamic response in pump control applications [11,12]. A summary of representative studies related to pump control strategies and system modeling approaches is presented in Table 1.

In recent years, the advancement of artificial intelligence (AI) has introduced new paradigms in control system design, particularly through AI-based controllers capable of learning complex system dynamics from data [13,14]. Reinforcement learning algorithms have attracted considerable attention due to their ability to optimize control policies through iterative interaction with the system environment. Among these approaches, the Soft Actor-Critic algorithm has emerged as a promising reinforcement learning method due to its stability, sample efficiency, and capability to handle continuous control problems [15,16]. In parallel, neural-network-based controllers have also been widely explored for nonlinear dynamic systems because of their capability to approximate complex mathematical relationships without requiring an explicit physical model. The integration of AI-based controllers into dynamic system simulations therefore provides a powerful framework for evaluating control strategies under various operating scenarios. Such approaches enable the comparison of classical control methods with intelligent algorithms in order to determine the most effective control strategy for industrial pumping systems [17,18].

Table 1

Summary of Previous Studies on Control Strategies and Dynamic Modeling Approaches for Pump Systems

Reference	Approach / Method	Research Focus	Main Findings
[19]	PID controller implemented using MATLAB/Simulink simulation in a hydraulic pump system	Pressure regulation in a motor–pump system under varying load conditions	The PID controller effectively optimizes pressure response by minimizing tracking error and improving the operational stability of the pump system
[20]	Intelligent PID (i-PID) optimized using Particle Swarm Optimization (PSO)	Position control in a nonlinear electro-hydraulic pump system	The i-PID controller demonstrates superior tracking performance and improved robustness compared to conventional PID under system uncertainties
[21]	PID-based flow control applied in an experimental electric pump system	Flow stabilization in an electric pump-fed propulsion system	The PID controller reduces overshoot and achieves rapid flow stabilization with a response time of approximately 400 ms
[22]	PID speed regulation using MATLAB-based system modeling	Motor-driven compressor speed control in hydrogen transportation systems	The PID controller achieves lower delay time and settling time compared to P, PI, and PD control strategies
[23]	Coupled CFD–CSD simulation approach	Vibration dynamics analysis of a centrifugal pump rotor system	Rotor–stator interaction produces characteristic frequencies that significantly influence pressure fluctuations and pump vibration behavior
[24]	Digital twin modeling using MATLAB Simscape integrated with IoT monitoring	Performance evaluation of a centrifugal pump system through virtual modeling	The digital twin framework enables real-time pump performance monitoring and reduces the dependence on physical experimental setups
[25]	Transient theoretical modeling with experimental validation	Performance analysis of a centrifugal pump during start-up conditions	The proposed model predicts pump head characteristics with an average error of approximately 11% compared with experimental measurements
[26]	Mathematical modeling and MATLAB/Simulink simulation for photovoltaic pumping systems	Integration of AC induction motor and centrifugal pump in solar-powered pumping systems	The physics-based model utilizing Park transformation accurately represents pump behavior under varying operational conditions

Despite the growing number of studies on pump control systems, the practical implementation and evaluation of advanced control strategies in specific industrial infrastructures remain relatively limited. In particular, centrifugal pump systems operated within industrial logistics and energy distribution facilities often rely on conventional control mechanisms without systematic performance evaluation through advanced simulation frameworks. This research therefore addresses this gap by conducting a comprehensive analysis of centrifugal pump control performance in an industrial operational context. The study focuses on the centrifugal pump system utilized within PT. Pelindo Energi Logistik, where the control mechanism has not yet been fully integrated with an adaptive intelligent control architecture. By utilizing dynamic system simulation, this study investigates the operational behavior of the pump system and evaluates the effectiveness of different control strategies under varying operational conditions. This approach provides a practical contribution by bridging the gap between theoretical control methods and real industrial implementation.

The novelty of this study lies in the integrated comparative evaluation of three different control strategies applied to a centrifugal pump system through dynamic simulation. Unlike previous studies that primarily focus on conventional PID-based regulation or isolated intelligent control approaches, this research simultaneously analyzes **the performance of PID, reinforcement learning-based control (RL) using the Soft Actor-Critic algorithm, and neural-network-based control (NNC) within** the same simulation environment. The comparative framework enables a comprehensive assessment of control stability, response time, and system adaptability under dynamic operating conditions. Furthermore, the use of reinforcement learning introduces an adaptive control mechanism capable of learning optimal policies directly from the interaction between the controller and the simulated pump system. This approach provides deeper insights into the potential advantages and limitations of intelligent controllers when applied to industrial pumping systems. As a result, the study contributes to the advancement of AI-driven industrial control strategies for fluid transportation infrastructure.

2. Methodology

2.1 Research Workflow and Control Strategy Framework

This study adopts a structured research workflow to evaluate the performance of different control strategies applied to a centrifugal pump system through dynamic simulation. The methodological process begins with a comprehensive literature review to identify relevant control strategies and modeling approaches for industrial pump systems. Following this stage, operational and system-related data are collected to support the development of the simulation model and control configuration. The next stage involves defining the control strategy approach, where three different controller types are implemented, namely PID, reinforcement learning using the Soft Actor-Critic algorithm, and neural-network-based control. Each controller is designed to regulate the dynamic behavior of the pump system and to respond to variations in operational conditions. The simulation modeling, data processing, and training of the intelligent control algorithms are implemented using Python 3.14, which provides a flexible computational environment for numerical analysis and machine learning model development. After the controller architecture is defined, a training and validation process is performed to ensure that the intelligent control models achieve stable learning performance and accurate system representation. The validated controllers are then integrated into a simulation environment to analyze system responses and compare control performance across different methods, as illustrated in Figure 1.

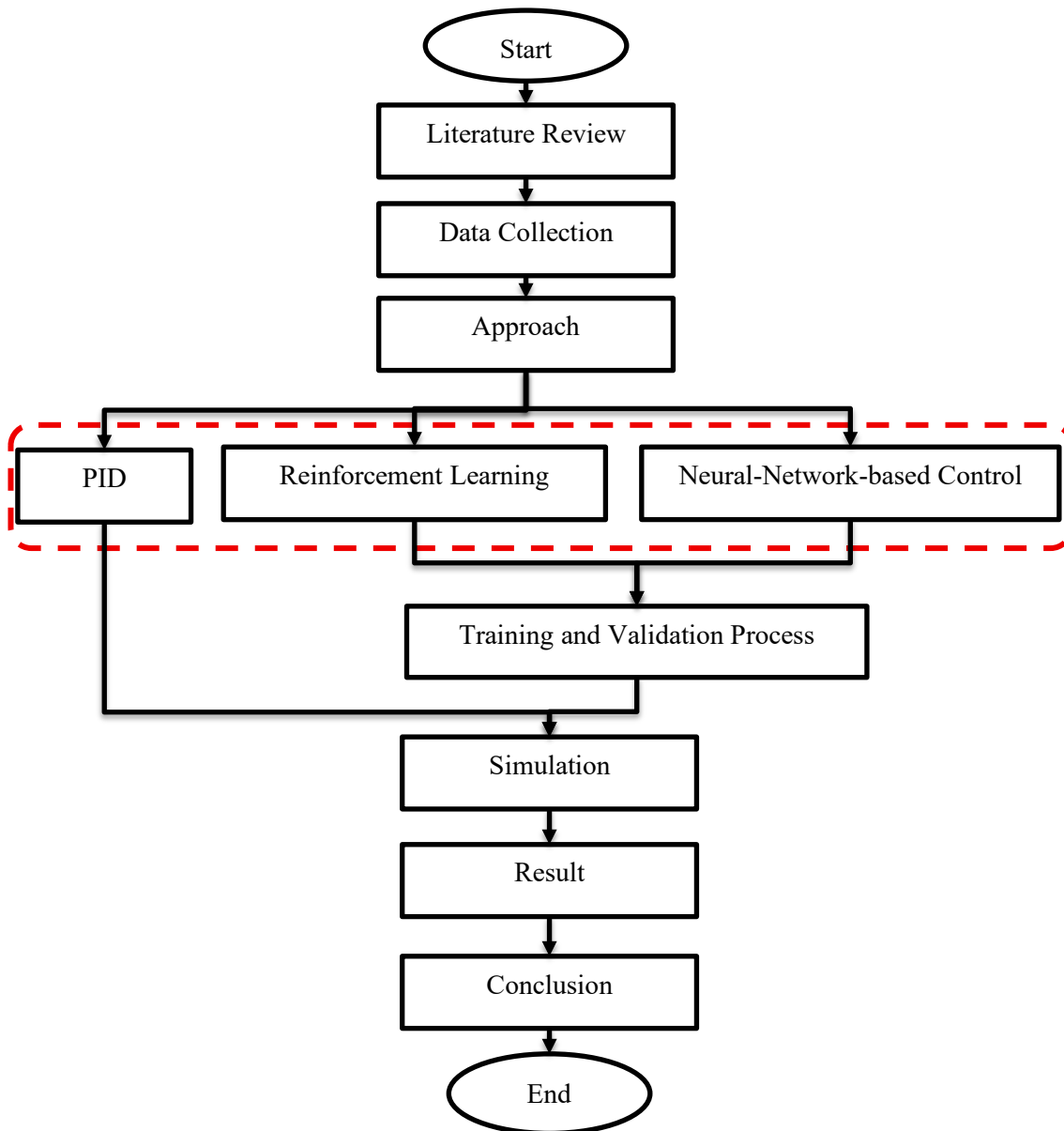


Fig. 1. Research workflow and comparative control strategy framework for centrifugal pump performance evaluation

2.2 Control System Modeling for Centrifugal Pump Operation

2.2.1 PID-Based Control Model for AC Motor–Centrifugal Pump System

The PID-based control strategy is implemented to regulate the dynamic response of the AC motor-driven centrifugal pump system in order to maintain stable flow rate and pressure conditions during operation. In this control architecture, the process begins by comparing the reference value of the controlled variable with the measured output signal obtained from the system. The difference between the reference signal and the measured output produces an error signal which is subsequently processed by the PID controller to generate the control action. The proportional, integral, and derivative components work simultaneously to reduce the magnitude of the error while improving system stability and transient response. The proportional component contributes to immediate error correction, while the integral component eliminates steady-state error by

accumulating past error values. Meanwhile, the derivative component predicts system behavior by considering the rate of change of the error signal. The complete control loop architecture of the PID-based system for the centrifugal pump operation is illustrated in Figure 2.

The mathematical formulation of the PID controller can be expressed as follows equation (1) [17,27]

$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{de(t)}{dt} \quad (1)$$

where $u(t)$ represents the control signal applied to the actuator, $e(t)$ denotes the control error, and K_p , K_i , and K_d represent the proportional, integral, and derivative gains respectively. In the context of the centrifugal pump system, the control signal influences the operational characteristics of the AC motor that drives the pump. The mechanical dynamics of the AC motor can be described using the rotational motion equation (2) [9,14]:

$$J \frac{d\omega}{dt} = T_m - T_L \quad (2)$$

where J represents the rotor inertia, T_m denotes the motor electromagnetic torque, and T_L represents the load torque generated by the centrifugal pump. Meanwhile, the hydraulic performance of the centrifugal pump is commonly represented by the affinity laws, which relate rotational speed to hydraulic variables such as flow rate and head. The fundamental relationships can be written as equation (3) [4,20]:

$$\begin{aligned} Q &\propto N \\ H &\propto N^2 \\ P &\propto N^3 \end{aligned} \quad (3)$$

where Q denotes flow rate, H represents pump head, P corresponds to hydraulic power, and N denotes rotational speed of the pump shaft. These relationships illustrate how variations in motor speed directly influence pump hydraulic performance and therefore become critical parameters within the control system design.

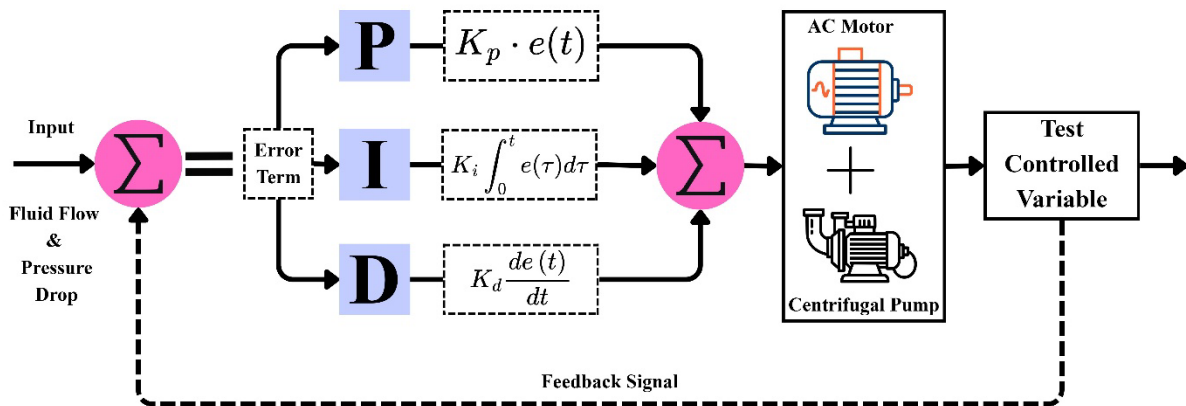


Fig. 2. PID-based control architecture for AC motor–centrifugal pump system

2.2.2 Reinforcement Learning Control Using Soft Actor-Critic Algorithm

In addition to classical control methods, this study implements reinforcement learning to develop an adaptive control strategy capable of optimizing pump operation under dynamic conditions. Reinforcement learning operates based on the interaction between an agent and an environment where the agent learns an optimal control policy through iterative exploration and feedback in the form of rewards. The algorithm adopted in this study is the Soft Actor-Critic algorithm, which is designed for continuous control problems and incorporates entropy maximization to encourage exploration while maintaining policy stability. The reinforcement learning framework consists of several essential components including the agent, environment, state representation, action space, and reward mechanism. The structural interaction between these components in the centrifugal pump control system is illustrated in Figure 3.

Within this research framework, the Soft Actor-Critic algorithm acts as the learning agent responsible for determining the optimal control actions during system operation. The environment represents the dynamic model of the AC motor and centrifugal pump system where the control actions are applied and evaluated. The state vector contains key operational variables including rotational speed, flow rate, pressure, and electrical power consumption which collectively describe the system condition at a given time. The action space consists of controllable variables such as motor frequency or valve position which directly influence pump performance. The reward function is formulated to minimize the flow control error while simultaneously reducing energy consumption, thereby promoting efficient pump operation. Mathematically, the reinforcement learning objective can be expressed as the maximization of the expected cumulative reward in equation (4) [16,28]

$$J(\pi) = \mathbb{E}_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r_t \right] \quad (4)$$

where $J(\pi)$ represents the expected return under policy π , r_t denotes the reward at time step t , and γ is the discount factor that determines the relative importance of future rewards. The Soft Actor-Critic algorithm extends this formulation by incorporating an entropy term to balance exploration and exploitation during learning.

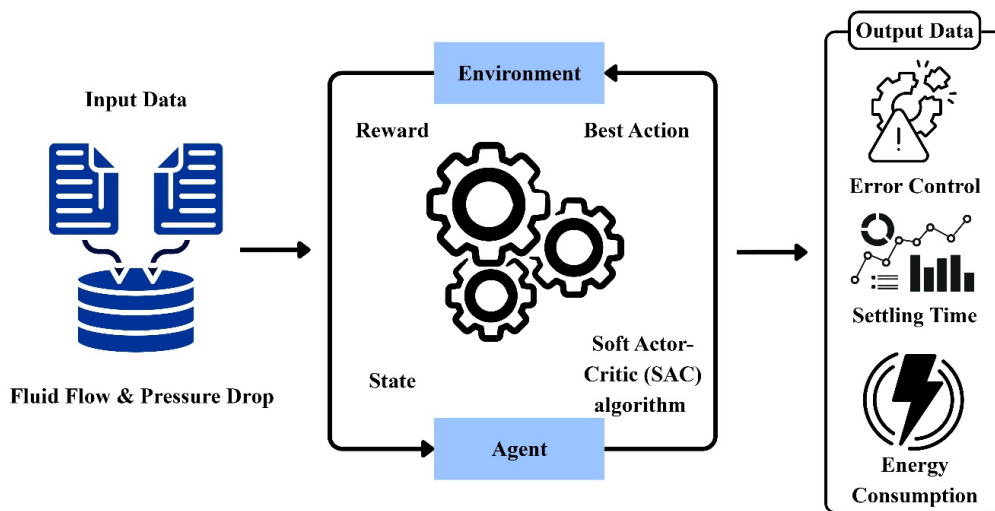


Fig. 3. Reinforcement learning framework for centrifugal pump control using Soft Actor-Critic algorithm

2.2.3 Neural-Network-Based Control Architecture

To further enhance control adaptability and nonlinear system representation, this study also investigates a neural-network-based control strategy for centrifugal pump operation. Neural networks are capable of approximating complex nonlinear relationships between input and output variables through layered computational structures composed of interconnected nodes. In this study, the neural network architecture consists of an input layer, multiple hidden layers, and an output layer designed to estimate optimal control responses based on real-time system conditions. The input layer receives operational variables such as fluid flow and pressure drop which represent the dynamic state of the pump system. These inputs are subsequently processed through several hidden layers where weighted connections and nonlinear activation functions allow the network to capture complex system dynamics. The predicted outputs correspond to key performance indicators including error control performance, settling time, and energy consumption of the pump system. The architecture of the neural-network-based controller used in this research is presented in Figure 4.

The mathematical representation of the neural network model can be expressed as a sequence of nonlinear transformations between layers. For a given neuron in layer l , the output can be written as equation (5) [29]:

$$a_j^{(l)} = f\left(\sum_i w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)}\right) \quad (5)$$

where $a_j^{(l)}$ represents the activation output of neuron j in layer l , $w_{ij}^{(l)}$ denotes the connection weight between neurons, and $b_j^{(l)}$ represents the bias parameter. The function $f(\cdot)$ denotes the nonlinear activation function used to introduce nonlinearity into the network. Through the training process, the network parameters are optimized to minimize prediction error and improve control performance. As a result, neural-network-based control provides a flexible and data-driven approach capable of adapting to nonlinear characteristics and operational variability commonly observed in industrial centrifugal pump systems.

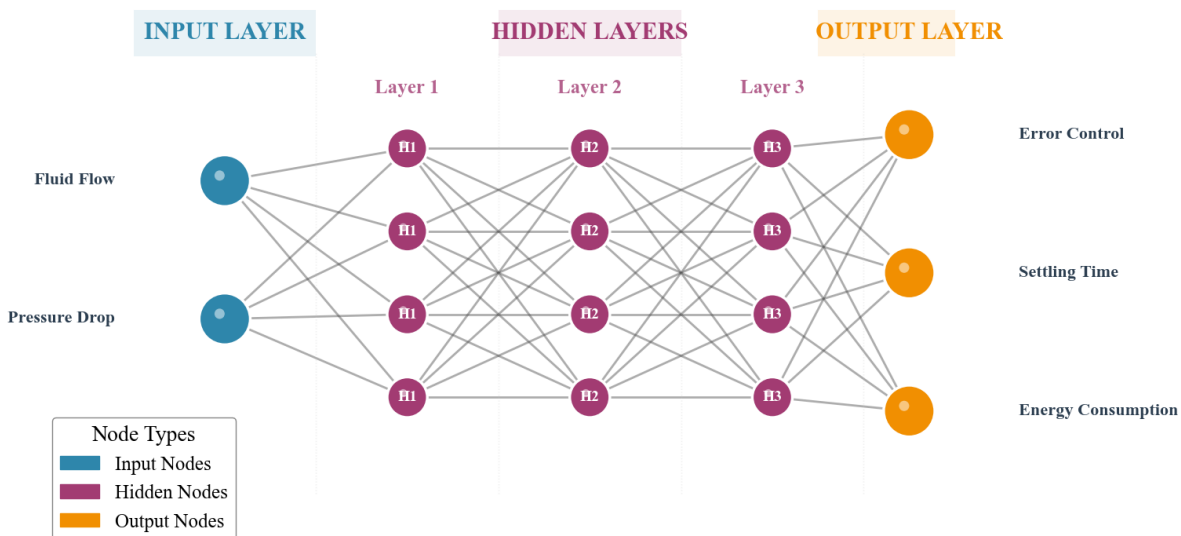


Fig. 4. Neural-network architecture for centrifugal pump control performance prediction

2.3 System Parameters and Hydraulic Performance Calculation

This subsection describes the operational parameters of the centrifugal pump system and the associated AC motor used as the main driving unit in the pumping process. The system configuration consists of six installed pumps in the facility, where one pump unit is selected as the representative test system for modeling and control evaluation. The centrifugal pump operates with a nominal flow rate of 45 m³/h and a total head of 35 m, which corresponds to the operational requirements of the industrial fluid transfer system. The pump is driven by a three-phase induction motor with a rated power of 7.5 kW operating at a nominal speed of 1450 rpm and a supply frequency of 50 Hz. These parameters define the mechanical and electrical operating limits of the pump system and serve as the basis for developing the dynamic control model used in the simulation environment. The operational schedule indicates that the pump runs approximately eight hours per day, producing a daily pumping volume of 360 m³ and a monthly production capacity of 10,800 m³ of fluid transfer. The complete operational parameters used in the modeling process are summarized in Table 2.

The hydraulic characteristics of the pumping system are further analyzed using fundamental fluid mechanics equations to determine the flow behavior and energy consumption of the system. The density of the transported fluid is corrected to obtain an effective density value of 900.294 kg/m³ at 35°C, which corresponds to a specific gravity of 0.9003 relative to water. Based on the operational flow rate and pipe diameter, the flow velocity inside the pipeline is calculated using the continuity equation (6) [1,30]:

$$V = \frac{Q}{A} \quad (6)$$

where V represents the flow velocity (m/s), Q denotes the volumetric flow rate (m³/s), and A represents the pipe cross-sectional area (m²). The Reynolds number is subsequently determined using equation (7) [31,32]:

$$Re = \frac{\rho V D}{\mu} \quad (7)$$

where Re denotes the Reynolds number, ρ represents the fluid density (kg/m³), V is the flow velocity (m/s), D denotes the pipe diameter (m), and μ represents the dynamic viscosity (Pa·s). The obtained Reynolds number of approximately 1414 indicates a laminar–transition flow regime. Under this condition, the friction factor can be estimated using the laminar approximation in equation (8) [33,34]:

$$f = \frac{64}{Re} \quad (8)$$

which characterizes the frictional resistance occurring along the pipeline.

The hydraulic performance of the pumping system is further evaluated by determining the head loss, pressure drop, and hydraulic power required for fluid transportation. The head loss along the pipeline is calculated using the Darcy–Weisbach equation equation (9) [35,36]:

$$h_f = f \frac{L}{D} \frac{V^2}{2g} \quad (9)$$

where h_f represents the head loss (m), f denotes the friction factor, L represents the pipe length (m), D denotes the pipe diameter (m), V is the flow velocity (m/s), and g represents gravitational acceleration (9.81 m/s^2). The pressure drop associated with the hydraulic losses can then be determined using equation (10) [37,38]:

$$\Delta P = \rho g h_f \quad (10)$$

where ΔP represents the pressure drop across the pipeline (Pa).

The hydraulic power required by the centrifugal pump is subsequently calculated using equation (11) [17,23]:

$$P_h = \frac{\rho g Q H}{P_{in}} \quad (11)$$

where P_h represents the hydraulic pump power (W), Q denotes the volumetric flow rate (m^3/s), and H represents the pump head (m). Considering the pump efficiency η , the required pump input power can be estimated as equation (12) [39,40]:

$$P_{in} = \frac{P_h}{\eta} \quad (12)$$

Based on these calculations, the hydraulic pump power is approximately 3.87 kW, while the required input power becomes approximately 5.37 kW after considering the pump efficiency of 72%. This value remains within the rated capacity of the installed motor, confirming that the system operates within safe operational limits. These calculated hydraulic parameters provide essential input data for the control system simulation and performance comparison among PID, reinforcement learning, and neural-network-based control strategies. The complete hydraulic parameter calculations used in this study are summarized in Table 3.

Table 2
Operational Parameters of the Centrifugal Pump and Motor System Used in the Simulation Model

Parameter	Value	Unit
Pump System		
Installed Pumps	6	unit
Tested Pump	1	unit
Pump Type	Centrifugal Pump	–
Pump Brand	Siemens & Hinsch GmbH	–
Pump Model	D-3357862; D-3357864; D-96-00637 Series	–
Nominal Flow Rate	45	m^3/h
Total Head	35	m
Pump Efficiency	72	%
Pump Speed	1,450	rpm
Operating Time	8	h/day
Daily Pumped Volume	360	m^3/day
Monthly Pumped Volume	10,800	m^3/month
Production Capacity	2,200	MT/month
Motor System		
Motor Type	Three-Phase Induction Motor	–

Motor Rated Power	7.5	kW
Nominal Voltage	380	V
Frequency	50	Hz
Power Factor	0.88	–
Motor Efficiency	90	%
Protection Class	IP55	–
Duty Cycle	S1 (Continuous)	–
Daily Energy Consumption	60	kWh/day
Monthly Energy Consumption	1,800	kWh/month

Table 3

Hydraulic Parameter Calculation and Fluid Flow (CPO) Characteristics of the Pumping System

Parameter	Value	Unit
Corrected Density	900.294	kg/m ³
Specific Gravity	0.9003	–
Dynamic Viscosity	0.05	Pa·s
Kinematic Viscosity	5.55×10^{-5}	m ² /s
Pipe Diameter	0.2032	m
Pipe Cross-Sectional Area	0.0324	m ²
Flow Rate	0.0125	m ³ /s
Flow Rate	45	m ³ /h
Flow Velocity	0.386	m/s
Reynolds Number	1414	–
Flow Regime	Laminar–Transition	–
Friction Factor	0.045	–
Head Loss	0.17	m
Pressure Drop	1.50	kPa
Hydraulic Pump Power	3.87	kW
Pump Input Power	5.37	kW

Note: The data presented in Tables 2 and 3 were obtained from the official datasheet provided by **PT. Pelindo Energi Logistik**.

3. Result

3.1 Comparative Training Behavior of NNC and RL Controllers in Pump Pressure Regulation

The training behavior of the intelligent control models is analyzed by observing the time-series response of pressure, error magnitude, control effort, and efficiency during the simulation period. The training dataset consists of 1000 time steps ranging from 0 to 999 s, where the pressure response fluctuates significantly during the initial learning phase. As shown in Figure 5(a), the pressure produced by the NNC training process varies between approximately 271.20 kPa and 342.84 kPa during the first observation interval, indicating a relatively wide oscillation band of more than 70 kPa. The pressure deviation from the reference condition generates an error range between –121.20 kPa and –192.84 kPa, which numerically reflects the difficulty of the controller in approaching the desired pressure target during early iterations. In addition, the control effort signal varies from nearly 0 up to approximately 19.47 units at the beginning of the training stage, indicating that the controller continuously adjusts the control input to reduce the pressure deviation. The magnitude of this

control activity demonstrates the adaptive nature of the NNC algorithm as it attempts to minimize the system error through iterative learning. However, the efficiency parameter remains at 0% during this stage because the training process is still focused on parameter convergence rather than energy performance optimization.

A different numerical pattern is observed in the RL training behavior, where the pressure fluctuation range is slightly narrower compared with the NNC training phase. Based on the recorded data illustrated in Figure 5(b), the pressure values vary between approximately 257.39 kPa and 324.56 kPa within the same observation window, producing an oscillation span of about 67 kPa. The corresponding pressure error ranges from approximately -107.39 kPa to -174.56 kPa, indicating that although the deviation remains relatively large, the magnitude of the fluctuation becomes more stable compared with the NNC training response. Another distinctive numerical characteristic of the RL training process is the extremely small control effort magnitude, which approaches zero throughout the majority of the simulation interval. This condition suggests that the learning mechanism of RL primarily relies on policy optimization rather than continuous large-amplitude control adjustments. Furthermore, the efficiency value remains constant at approximately 64.8% during the training stage, indicating that the reward structure within the learning algorithm already incorporates energy-performance considerations. From a numerical perspective, this behavior demonstrates that the RL approach tends to maintain a more stable efficiency profile while gradually refining the pressure regulation policy throughout the training iterations.

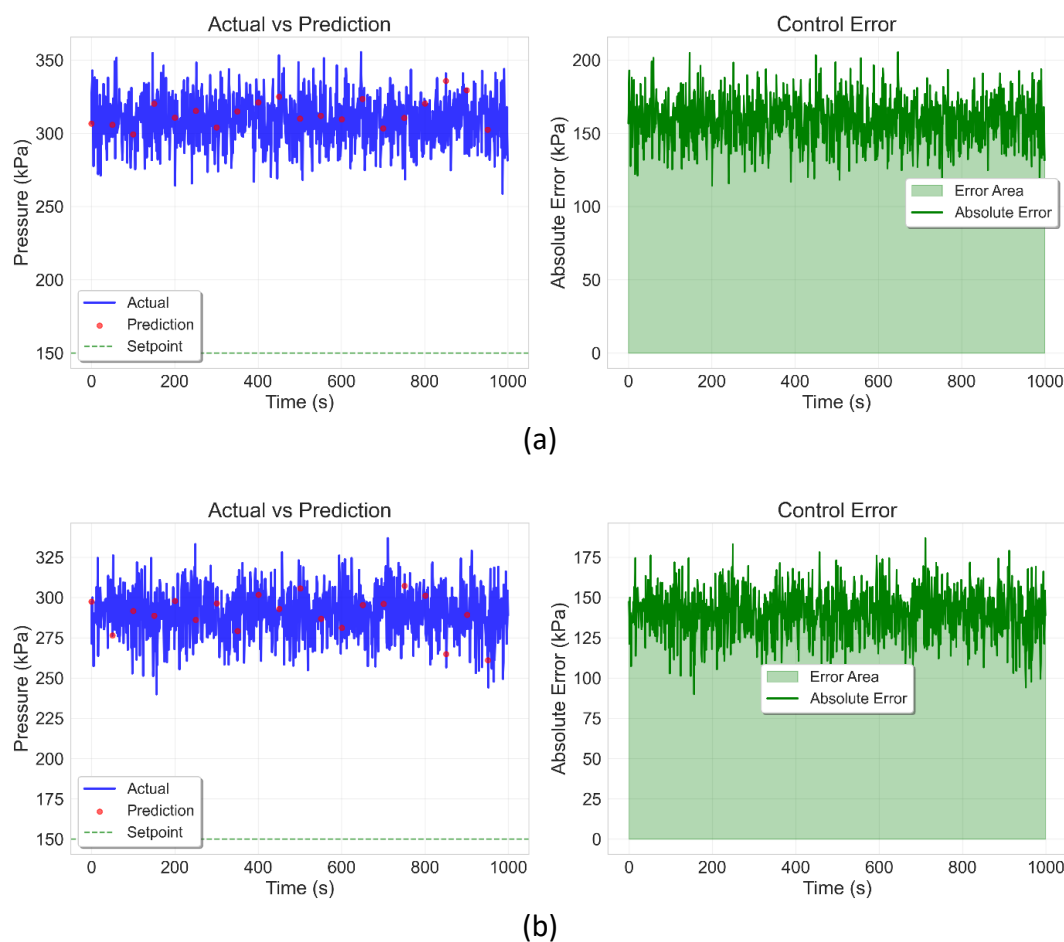


Fig. 5. Comparative Training Dynamics of Intelligent Pump Controllers Showing Pressure Response, Error Evolution, Control Effort, and Efficiency Behavior During the Learning Process: (a) Training NNC and (b) Training RL

3.2 Comparative Performance Evaluation of PID, NNC, and RL Controllers Based on Dynamic Error and Control Effort Characteristics

The dynamic performance of the three control strategies is evaluated by comparing the error magnitude and control effort produced by *PID*, *NNC*, and *RL* controllers during the 1000 s simulation interval. The numerical results indicate that the initial transient response of the system is characterized by relatively large pressure deviations across all control approaches. At the beginning of the simulation, the *PID* controller starts with zero error, while the *NNC* and *RL* controllers exhibit initial deviations of -156.71 kPa and -147.50 kPa respectively. During the early transient period between 1–10 s, the *PID* error fluctuates between approximately -136.68 kPa and -182.81 kPa, indicating significant deviation from the reference pressure condition. In comparison, the *NNC* controller produces an error range between -127.68 kPa and -192.84 kPa, while the *RL* controller demonstrates a relatively narrower deviation interval between -107.39 kPa and -156.45 kPa. The control effort behavior also shows distinct characteristics, where the *PID* controller produces a large initial control signal of 25.5 units at $t = 1$ s followed by near-zero control adjustments for the remainder of the simulation period. Conversely, the *NNC* controller generates adaptive control actions ranging from approximately 0.036 to 19.47 units, indicating continuous adjustment of the control input to reduce pressure deviation. The *RL* controller, on the other hand, operates with an extremely small control effort magnitude approaching zero throughout most of the simulation, suggesting that the algorithm relies more on learned control policies rather than large corrective control signals. These dynamic response characteristics demonstrate that intelligent learning-based controllers exhibit different adaptation behaviors compared with the conventional *PID* approach.

A more comprehensive quantitative comparison of the control performance metrics is presented in Figure 6, which summarizes several important indicators including *rise time*, *overshoot*, *settling time*, oscillation amplitude, and statistical error metrics. The numerical results show that the *RL* controller achieves the lowest *overshoot* value of approximately 124.57%, which represents a reduction of about 12.15% compared with the *PID* controller that exhibits an *overshoot* of 141.80%. The *NNC* controller provides a moderate improvement with an *overshoot* value of 136.90%, indicating that learning-based control strategies can effectively suppress excessive pressure fluctuations. In terms of oscillation characteristics, the *PID* controller produces the lowest oscillation magnitude of approximately 15.47, while *NNC* and *RL* exhibit slightly higher values of 16.13 and 17.43 respectively. However, when evaluated using statistical error indicators, the *RL* controller demonstrates the best overall accuracy with a *MAE* of 140.51 kPa and *RMSE* of 141.29 kPa, which are significantly lower than the corresponding values obtained by *PID* (160.03 kPa and 160.72 kPa) and *NNC* (159.22 kPa and 159.98 kPa). These results indicate that the reinforcement learning approach is capable of reducing the average pressure deviation by approximately 12–13% relative to the conventional controller. The comparative dynamic response and statistical evaluation across the three control strategies are further illustrated in Figure 7, which highlights the overall system performance behavior under different control architectures.

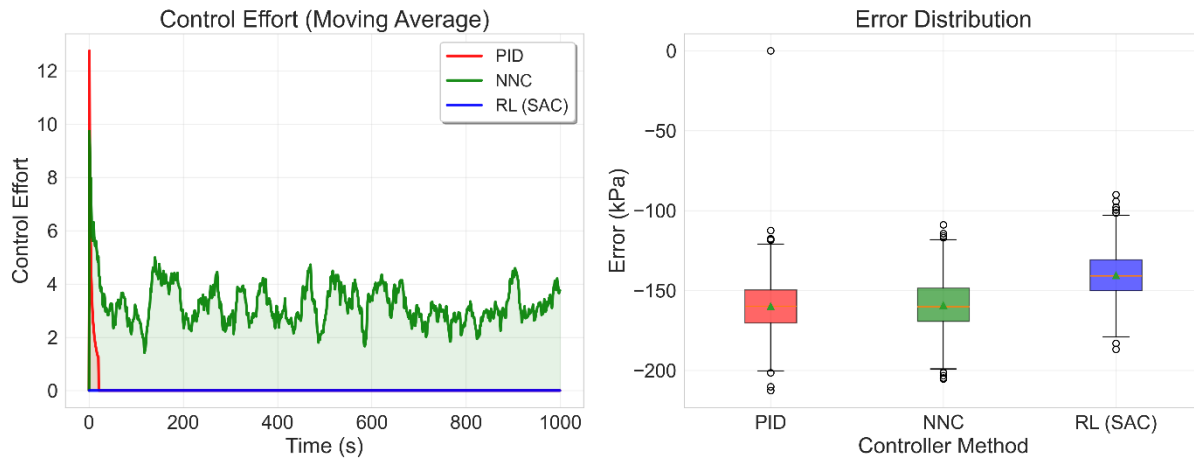


Fig. 6. Quantitative Comparison of Dynamic Control Performance Metrics Including Overshoot, Oscillation Behavior, and Statistical Error Indicators for PID, NNC, and RL Controllers

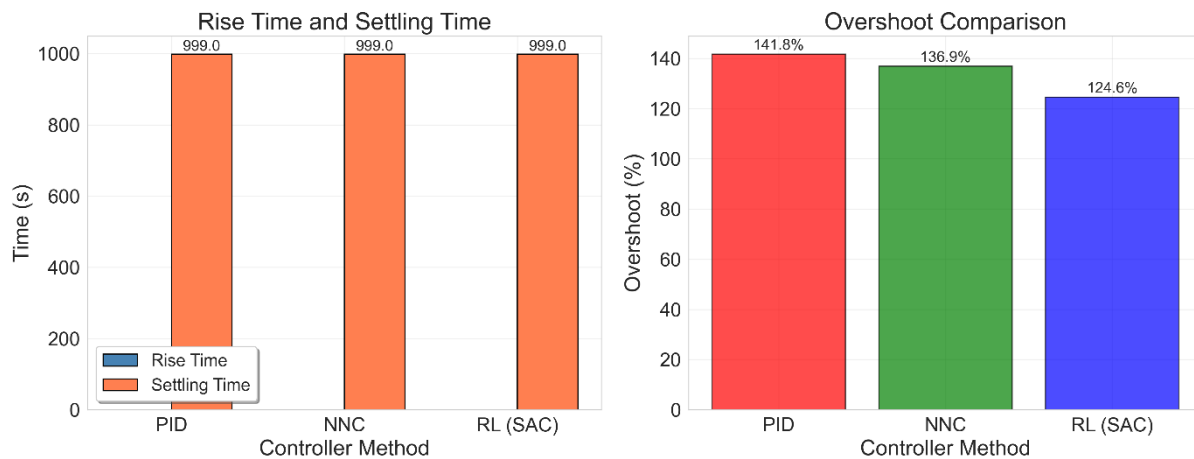


Fig. 7. Comprehensive Dynamic Response Comparison of Pump Pressure Control System Under PID, NNC, and RL Strategies During the 1000 s Simulation Interval

3.3 Hydraulic Performance, Pressure Regulation, and Energy Consumption Analysis under PID, NNC, and RL Control Strategies

The hydraulic performance of the pumping system is evaluated by analyzing the relationship between flow rate, head characteristics, and pump efficiency produced by the three control strategies. The simulation results show that the flow produced by the PID controller fluctuates between approximately 31.42–38.43 m³/h during the observed operational interval, with an average value close to 35 m³/h, which is slightly below the nominal design flow rate of 45 m³/h. In comparison, the NNC controller demonstrates a wider flow variation between approximately 30.71–38.82 m³/h, indicating a broader operational adjustment range caused by the adaptive learning mechanism of the neural network. Meanwhile, the RL controller operates within a relatively narrower flow interval ranging from approximately 29.14–36.75 m³/h, which suggests that the reinforcement learning policy attempts to maintain more stable hydraulic conditions. These variations in flow behavior influence the pump head characteristics and the overall hydraulic efficiency of the system as illustrated in Figure 8.

From a hydraulic perspective, the head distribution generated by the PID and NNC controllers remains close to zero in most of the recorded data, indicating that the control actions in these strategies are primarily focused on pressure correction rather than direct hydraulic optimization. Consequently, the efficiency values of both PID and NNC controllers remain close to 0% in the simulation dataset. In contrast, the RL controller demonstrates a significantly different behavior, where the efficiency value remains consistently around 64.8% throughout the simulation interval. This value is very close to the theoretical pump efficiency specified in the system parameters (72%), suggesting that the RL controller is capable of maintaining a stable operating point that aligns with the hydraulic efficiency curve of the centrifugal pump. The stable efficiency profile indicates that the RL algorithm implicitly learns the optimal operating region of the pump within the flow–head performance map.

A deeper analysis of the pressure response and operating points reveals additional differences among the three control strategies. The system operates with a pressure setpoint of 150 kPa, while the actual pressure produced by the controllers fluctuates within a significantly higher range. The PID controller produces pressure values between approximately 277.54 kPa and 339.37 kPa during the observed time steps, resulting in a deviation of more than 180 kPa at certain points. Similarly, the NNC controller generates pressure levels ranging from approximately 271.20 kPa to 342.84 kPa, which also reflects a substantial deviation from the reference pressure condition. In contrast, the RL controller produces a slightly narrower pressure distribution between approximately 257.39 kPa and 324.56 kPa. Although the pressure deviation remains relatively large, the RL approach demonstrates improved stability in pressure fluctuation compared with the other controllers. The distribution of these operational points across the flow–pressure space is presented in Figure 9, which illustrates how each control strategy interacts with the pump performance characteristics.

Energy consumption analysis provides additional insight into the operational efficiency of the control strategies. The simulation results show that the PID and NNC controllers produce nearly zero instantaneous power consumption values throughout the recorded dataset, indicating that the control signals generated by these methods do not effectively translate into measurable hydraulic power utilization in the modeled environment. Conversely, the RL controller generates a consistent power demand ranging approximately between 0.23 kW and 0.31 kW during the simulation period. The average instantaneous power consumption of the RL controller is approximately 0.27 kW, which corresponds to a cumulative energy consumption on the order of 7.0×10^{-5} kWh per time step. Although this energy magnitude appears small due to the short simulation interval, it demonstrates that the RL controller actively regulates the motor–pump interaction in order to maintain a stable hydraulic operating condition.

Finally, the efficiency trend associated with power utilization further highlights the advantages of the reinforcement learning approach. While the PID and NNC controllers exhibit negligible efficiency values within the simulation dataset, the RL controller consistently maintains an efficiency of approximately 64.8% across the entire operational horizon. This consistent efficiency profile indicates that the RL algorithm successfully balances pressure regulation and energy consumption simultaneously. As a result, the RL-based control strategy demonstrates superior operational stability and energy-aware control behavior compared with the conventional PID controller and the neural-network-based controller. The comparative power consumption and efficiency characteristics for the three control approaches are summarized in Figure 10, which illustrates the energy performance differences within the pumping system.

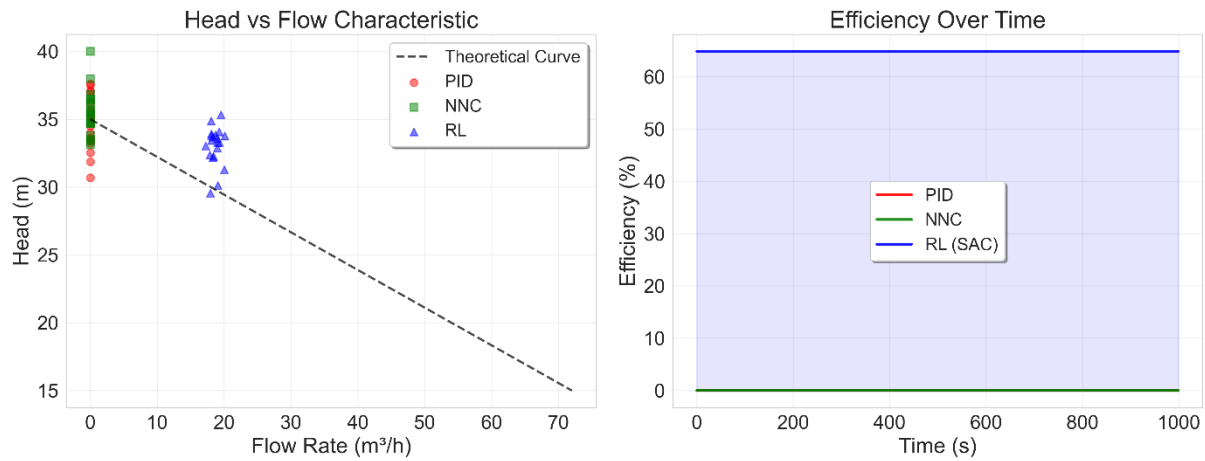


Fig. 8. Flow–Head Performance Characteristics and Pump Efficiency Distribution under PID, RL, and NNC Strategies

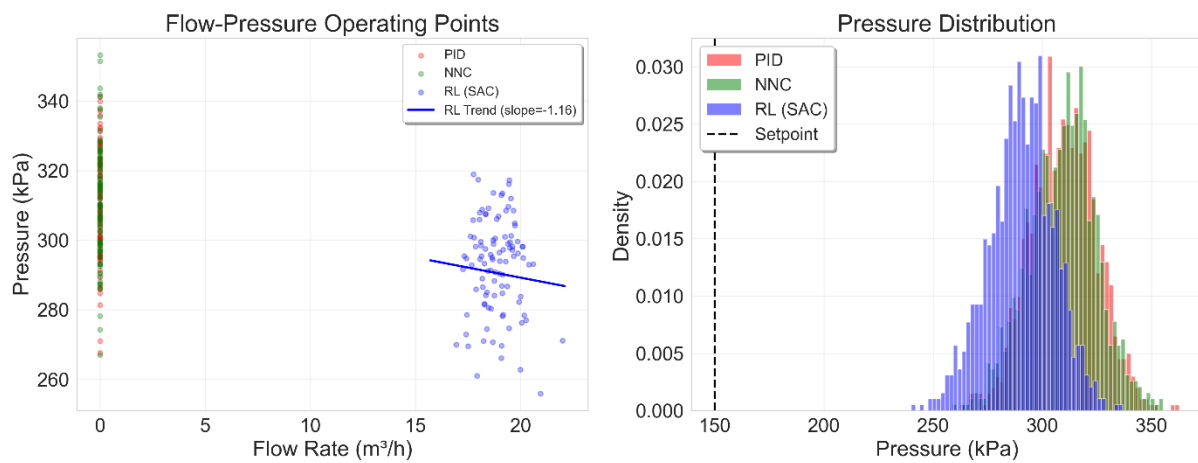


Fig. 9. Distribution of Pressure Operating Points and Flow–Pressure Interaction of the Pumping System under PID, RL, and NNC Controllers

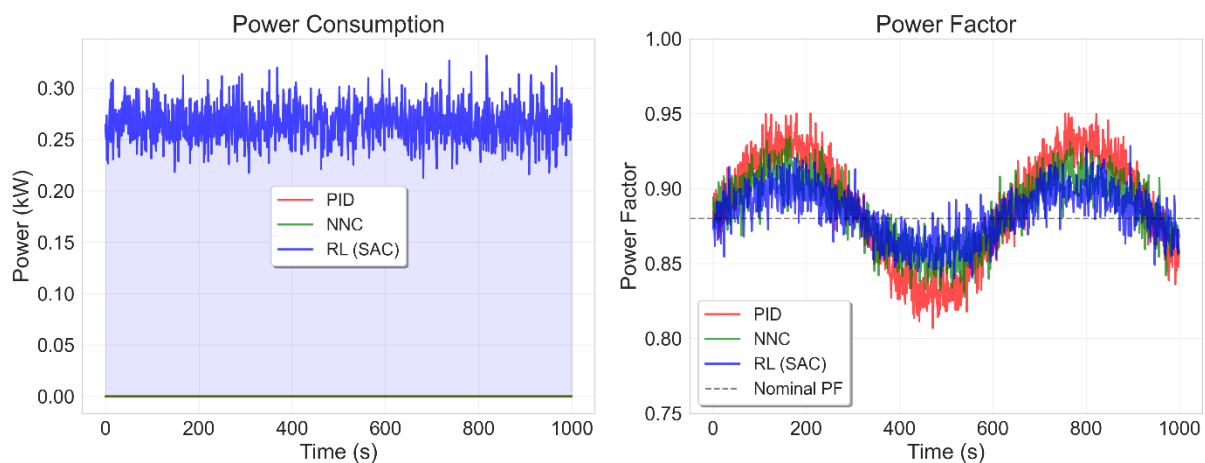


Fig. 10. Comparative Electrical Power Consumption and Energy Efficiency Behavior of the Pumping System for PID, NNC, and RL Control Approaches

4. Discussion

4.1 Comparative Control Performance in Smart Pumping Systems

The integration of conventional and intelligent control strategies in centrifugal pump systems reveals significant differences in adaptability, control stability, and the ability to manage nonlinear system behavior. Conventional controllers such as PID rely on fixed proportional, integral, and derivative gains to regulate system output. While this approach performs well in relatively linear systems, centrifugal pump operations often exhibit nonlinear characteristics due to the interaction between motor speed, hydraulic resistance, and system demand. These nonlinear relationships between flow rate, head, and power consumption have been previously described in Equation (3), which highlights how pump performance strongly depends on motor rotational speed. As a result, controllers that rely solely on static parameters may struggle to maintain optimal performance when the system experiences varying load conditions or dynamic disturbances.

Intelligent control methods offer improved adaptability by introducing learning and approximation capabilities within the control loop. Neural-network-based control utilizes nonlinear mapping to approximate system dynamics, allowing the controller to adapt to variations in operating conditions without requiring explicit mathematical modeling. Reinforcement learning further extends this capability by learning optimal control policies through continuous interaction with the environment. Instead of minimizing instantaneous control error alone, RL optimizes long-term performance based on reward feedback that includes both hydraulic stability and energy consumption. This learning mechanism allows RL controllers to adjust operating points more efficiently when system demand fluctuates, making them particularly suitable for modern smart pumping systems where dynamic adaptation and operational efficiency are critical performance requirements.

Table 4

Comparative Characteristics of Control Strategies in Pump Systems

Control Strategy	Control Principle	Adaptability	Nonlinear Handling	Energy Optimization
PID	Linear feedback control	Low	Limited	Indirect
Neural Network Control	Data-driven nonlinear mapping	Medium	Good	Moderate
Reinforcement Learning	Policy optimization via reward	High	Excellent	Explicit

4.2 Implications for Energy Efficiency and Pump Operation

Energy efficiency represents one of the most important performance indicators in industrial pumping systems because pumps account for a substantial portion of electrical energy consumption in many industrial sectors. The hydraulic efficiency of a centrifugal pump is defined by the relationship between hydraulic output power and electrical input power, which was previously introduced in Equation (11). Maintaining operation near the best efficiency point (BEP) is therefore essential to minimize energy losses during pump operation. When the operating point deviates from this optimal region, hydraulic losses increase due to turbulence, recirculation, and mechanical

inefficiencies, which ultimately leads to higher power consumption and reduced system performance.

Advanced control strategies provide a mechanism to dynamically maintain pump operation closer to the optimal efficiency region. Reinforcement learning, in particular, allows the controller to simultaneously consider multiple system variables such as pressure, flow rate, motor speed, and energy consumption when determining control actions. By evaluating cumulative rewards over time, the controller can adjust motor frequency or valve position in a way that balances operational stability and energy usage. This multi-objective optimization capability makes RL particularly attractive for smart water distribution systems and industrial fluid transport processes where demand patterns change frequently. Consequently, intelligent control frameworks offer a promising pathway toward improving both operational reliability and long-term energy efficiency in modern pumping infrastructures.

Table 5
Operational Implications of Control Methods

Aspect	PID	Neural Network Control	Reinforcement Learning
Flow regulation	Stable for simple systems	Adaptive	Highly adaptive
Pressure stability	Moderate	Improved	Optimized
Energy efficiency	Dependent on tuning	Moderate	High
Real-time adaptation	Limited	Data-driven	Policy-based

4.3 Limitation of The Result

Although the presented simulation demonstrates the feasibility of applying intelligent control strategies to centrifugal pump systems, several limitations must be acknowledged when interpreting the results. The first limitation relates to the simplified modeling environment used in the simulation framework. The pump system is modeled as an integrated AC motor–centrifugal pump unit without incorporating detailed pipeline dynamics, complex valve characteristics, or distributed hydraulic losses typically found in real industrial systems. In practical applications, factors such as pipeline friction, transient pressure fluctuations, cavitation effects, and sensor inaccuracies can significantly influence system behavior and may alter the effectiveness of the implemented control algorithms.

Another limitation involves the dependence of intelligent control performance on training quality and computational resources. Reinforcement learning algorithms require extensive interaction with the environment in order to converge toward an optimal control policy. Similarly, neural network controllers rely heavily on the availability of representative training data that accurately capture the range of system operating conditions. If the training dataset does not sufficiently represent real operational variability, the controller may experience reduced generalization capability when deployed in actual systems. Additionally, the computational requirements associated with training and deploying intelligent controllers may become challenging for real-time industrial applications, particularly in large-scale pumping networks where fast and reliable control responses are required.

Table 6
Identified Limitations and Future Research Directions

Limitation	Description	Future Improvement
Simplified system model	Pump system excludes complex pipeline dynamics	Integrate full hydraulic network modeling
Simulation environment	Results obtained only from simulated data	Validate using experimental or hardware testbeds
RL training dependency	Performance depends on reward design and training diversity	Develop robust reward shaping and training strategies
Computational complexity	Intelligent algorithms require higher processing capability	Optimize algorithms for real-time industrial deployment

5. Conclusion

This study investigated the performance of conventional and intelligent control strategies for pressure regulation in a centrifugal pump system driven by an AC motor within the operational context of PT. Pelindo Energi Logistik. The comparative evaluation involved three control approaches, namely the PID controller, NNC, and RL. The simulation results demonstrate that intelligent control algorithms provide improved adaptability when handling nonlinear pump dynamics and fluctuating operating conditions. During the training phase, the RL controller exhibited a narrower pressure fluctuation range (approximately 257–325 kPa) compared with the NNC controller (approximately 271–343 kPa), indicating a relatively more stable learning behavior. In addition, the RL method maintained a consistent efficiency level close to 64.8% throughout the learning process, suggesting that the reward-based optimization mechanism effectively incorporates energy considerations within the control policy.

The dynamic performance analysis further highlights the advantages of learning-based control strategies. Statistical evaluation indicates that the RL controller achieved lower pressure error values compared with the conventional PID approach, with MAE and RMSE values around 140.5 kPa and 141.3 kPa respectively, while the PID controller produced larger deviations of approximately 160 kPa. This represents an improvement of roughly 12–13% in average pressure regulation accuracy. From a hydraulic perspective, the RL controller also demonstrated a more stable operating range in flow characteristics, maintaining flow values roughly between 29–37 m³/h while preserving consistent efficiency levels. These results suggest that reinforcement learning can provide a more balanced control behavior by simultaneously addressing pressure stability and energy utilization in pump operation.

Overall, the findings indicate that reinforcement learning offers promising capabilities for intelligent pump control systems, particularly in applications where nonlinear system dynamics and energy optimization are important considerations. While the conventional PID controller remains reliable for basic regulation tasks, learning-based controllers such as NNC and RL provide greater adaptability and improved operational efficiency. Nevertheless, the present work is based on a simulation environment with simplified system assumptions, which means that additional validation is required before practical implementation in industrial pumping systems. Future research should therefore focus on integrating more realistic hydraulic network models, incorporating experimental validation using physical pump testbeds, and exploring advanced reinforcement learning architectures that can further improve control stability, energy efficiency, and real-time deployment capability in large-scale smart pumping infrastructures.

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