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Original Article

Optimization of Pump Electric Drives Using Artificial Neural Networks: A Predictive Control Approach

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Abstract *- This paper presents a comprehensive approach to optimizing the efficiency of pump electric drives using Artificial Neural Networks (ANN). The study utilized experimental data from various operational scenarios of centrifugal pumps, including power consumption and energy usage, to train the ANN model. Applying the ANN-based predictive control, the system could forecast optimal operating conditions, significantly reducing energy consumption and improving overall system performance. The experimental setup involved both individual and multi-pump systems, where power and energy consumption were monitored and analyzed. The results demonstrate that ANN-based control can effectively optimize pump operations, achieving substantial energy savings while ensuring system reliability. The implementation of this approach led to energy savings of over 15% compared to traditional control methods. This study highlights the potential of ANN in enhancing the energy efficiency of industrial pumping systems and provides insights into future applications of intelligent control in resource management.*

Keywords *- Neural networks, Pump electric drive, Energy efficiency, Predictive control, Centrifugal pumps, Optimization.*

1. Introduction

The modern industrial sector is increasingly focused on optimizing technological systems and enhancing energy efficiency, as energy consumption remains a critical concern. Among various energy-intensive systems, pump electric drives account for significant energy usage across industries such as water supply, agriculture, and oil and gas. Consequently, improving the efficiency of these systems is not only essential for reducing energy consumption but also for minimizing operational costs and ensuring system stability [1].

Over the past few years, significant advancements have been made in developing energy-efficient technologies and intelligent control strategies for pump electric drives. One of the most promising approaches involves the application of Artificial Neural Networks (ANNs), which have demonstrated remarkable success in modelling nonlinear relationships and predicting optimal operating conditions. ANN-based control systems utilize real-time and historical data to forecast power consumption and recommend adjustments that maximize efficiency while maintaining system performance [2]. Integrating ANN techniques has proven effective in minimizing energy losses and improving system reliability [3]. Optimization in this study refers to the process of determining the most energy-efficient operational parameters for pump electric drive systems while maintaining system reliability and performance. This involves minimizing energy consumption through predictive control strategies, adjusting pump speeds dynamically based on real-time conditions, and ensuring that operational constraints such as required flow rate and pressure are met. By leveraging ANN-based predictive models, this research aims to develop an intelligent control system that continuously adapts to load conditions and variations in operating requirements to achieve maximum efficiency.

Despite the advantages of ANN-based control, real-world applications present challenges such as variability in system parameters, uncertainties in operational conditions, and the need for robust adaptation mechanisms. This study addresses these challenges by integrating ANN models with predictive control frameworks, ensuring that the optimization process remains effective under varying conditions. Furthermore, the benefits of ANN-based optimization, including energy savings, enhanced operational stability, and adaptability to complex industrial environments, are examined in detail.

The primary objective of this study is to develop an intelligent predictive control algorithm for optimizing the operating modes of pump electric drive systems using ANN-based modelling. This research analyzes existing methodologies, investigates the energy-saving potential of ANN-driven control strategies, and validates their effectiveness through experimental data and simulations. By implementing predictive optimization techniques, this study aims to contribute to the development of more efficient and cost-effective solutions for industrial pump systems.

Unlike previous studies, this research presents a predictive control method based on an Artificial Neural Network (ANN), enabling the determination of optimal operating modes for pumps in real time. The proposed model is designed for both single and multi-pump systems and has demonstrated energy-saving performance, as validated by experimental results. The findings indicate that ANN-based control has achieved more than 15% energy savings

1.1. Literature Review

Recent research efforts have extensively focused on enhancing the efficiency and performance of pump electric drive systems through intelligent control methodologies. Adopting energy-efficient components, predictive control mechanisms, and artificial intelligence-based optimization techniques have demonstrated significant potential in reducing energy consumption while ensuring operational reliability.

Artificial Neural Networks (ANNs) have been widely explored for optimizing pump operation because they can model nonlinear relationships and predict optimal control parameters. ANN-based approaches have proven effective in multi-pump systems, where real-time data analysis enables dynamic control adjustments to minimize power consumption. Vodovozov et al. (2016) investigated the application of predictive control in centrifugal multi-pump stations, demonstrating its potential to enhance energy efficiency while maintaining system stability. Mirchevski (2012) similarly emphasized the role of adaptive control strategies in improving energy efficiency in electric drive systems.

The methods studied by Vodovozov et al. (2016) and Mirchevski (2012) utilized only traditional predictive control but were not integrated with ANN. This research proposes an ANN model based on real-time and historical data, which helps reduce energy losses by dynamically adjusting the pump speed.

Hybrid intelligent control approaches have also gained traction in recent studies. González et al. (2022) proposed an ANN-Fuzzy Logic hybrid model for HVAC-driven pump systems, achieving a 25% reduction in energy consumption. Likewise, Georgescu et al. (2015) explored ANN-controlled variable-speed pump operations under fluctuating demand conditions through EPANET simulations, showcasing improved efficiency [4].

Predictive maintenance techniques integrated with AI have further improved the reliability and performance of pumping systems. Khan et al. (2022) introduced a hybrid ANN-Genetic Algorithm model for adaptive speed control in industrial pumps, demonstrating superior energy savings compared to traditional PID controllers. Similarly, Li et al. (2023) developed a deep-learning-based ANN model for optimizing pump scheduling in water distribution networks, achieving over 20% energy savings. The use of Reinforcement Learning (RL) in conjunction with ANN has also been explored for adaptive pump control. Ahmed et al. (2023) implemented an RL-ANN hybrid framework for industrial water pumping stations, enabling real-time system adjustments and significantly enhancing energy efficiency [5].

Another growing research trend is the Internet of Things (IoT), which has enabled ANN control for real-time monitoring and optimization. Zhang et al. (2024) highlighted the advantages of cloud-based AI platforms in predictive maintenance and energy-efficient control of pump electric drive systems [6].

In addition, studies have demonstrated the feasibility of AI-driven predictive maintenance for pump systems. Enslin et al. (2016) explored AI-based diagnostics for detecting early signs of failure in industrial pumping networks, while Kini and Bansal (2010) examined the effects of voltage and load variations on motor pump efficiencies, highlighting the benefits of adaptive control strategies in reducing unnecessary power consumption [7].

Predictive control methodologies have also been applied to Photovoltaic (PV) systems for voltage regulation and efficiency enhancement. The author previously developed an improved voltage control mechanism for PV systems, which can be extrapolated to pump electric drive systems to optimize power consumption and operational stability. This aligns with ANN-based predictive models, where real-time data is used to optimize system parameters dynamically.

The development of digital control methods and optimization strategies plays a crucial role in improving the performance of electric drive systems. The author previously presented an advanced control and optimization strategy for a 2-phase interleaved boost converter, which can be applied to pump drive systems to enhance efficiency and power management.

Similarly, composite Model Predictive Control (MPC) has been proposed as a robust approach for controlling converters, as demonstrated by the author in their study on boost converters. These strategies align with predictive control frameworks essential for ANN-based optimization of pump electric drives. Neural networks have been increasingly employed to enhance control mechanisms in electrical systems.

The study by Samad et al. (2024) on digital control strategies for switching buck converters provides a solid foundation for AI-based optimization approaches, showcasing how digital modeling can improve voltage regulation and efficiency in energy conversion systems [8].

The optimization of DC-DC converters is integral to efficient pump electric drives. Abbas et al. (2016) examined set-point tracking in boost converters using optimized PID controllers. This offers insights into how control optimization can enhance the efficiency of electric drives used in pumping applications [9]. This research complements ANN-based control frameworks by providing foundational optimization strategies that can be integrated with predictive algorithms. Such methods can be adapted to ANN-driven pump electric drive optimization to achieve better load response and power stability.

This study builds upon these research findings by implementing an ANN-based predictive control approach for centrifugal pump operations. By leveraging experimental data collected from individual and multi-pump systems, this research aims to develop a cost-effective solution that ensures energy efficiency and operational reliability in industrial pumping applications.

2. Materials and Methods

This research methodology involves a combination of experimental data collection, artificial neural network training, and mathematical modelling. The setup includes a multi-pump system with centrifugal pumps operating under different load and speed conditions. The pumps were monitored using power analyzers, and data on energy consumption and power output were gathered for different operational scenarios. This data was then used to train the ANN model and develop a mathematical model for system optimization.

2.1. Model Development and Training

A predictive model was developed to determine the optimal operating modes of pump electric drives based on experimental data. The model focused on analyzing the performance parameters of centrifugal pumps under different load conditions, including speed (RPM), power consumption (kW), flow rate (m^3/h), and pressure (Pa). For model development, MATLAB R2023a and Python were used. The dataset was divided into 70% training, 15% validation, and 15% testing to ensure reliable performance evaluation.

2.2. Experimental Data and Operating Conditions

To ensure accurate system optimization, three key operational scenarios were analyzed:

- Stable Load: Pumps operated constantly to measure energy consumption and efficiency.
- Variable Load: Pumps were tested under fluctuating demand conditions to evaluate adaptability.
- Multi-Pump System: Two or more pumps operated simultaneously to analyze interaction effects.

All experiments were conducted using high-precision measuring instruments, and the collected data was carefully processed to improve reliability.

2.3. Evaluation and Results

The model's accuracy and efficiency were assessed based on the following criteria:

- Error Rate: The average prediction error was 3.2%, confirming minimal deviation from actual results.
- Energy Savings: Compared to conventional control methods, energy consumption was reduced by 15%.
- Statistical Validation: The results were verified with $t = 4.23$ $p = 0.003$, demonstrating significant improvement in efficiency.

The effectiveness of this approach was validated through experimental results, proving its potential for enhancing energy efficiency in industrial pump systems.

2.4. Ethical Considerations and Software Licensing

This study complies with ethical guidelines, and all data used in the research were obtained and analyzed in accordance with ethical standards. The experimental results were derived from the author's own laboratory work, ensuring that no proprietary or confidential data were used without permission.

Artificial neural network modeling and optimization were performed using MATLAB R2023a (MathWorks, USA) and TensorFlow 2.10 (Google, USA). All software tools used in this study were legally licensed, and proper permissions were obtained where applicable.

Furthermore, all figures, models, and datasets used in this research were verified for compliance with copyright and licensing regulations. No third-party data or materials were used without the necessary authorization.

3. Results and Discussion

3.1. Mathematical Model

The following is the mathematical model for the multi-drive, multi-pump system, focusing on pump dynamics, energy consumption, and the control algorithm for optimal operation:

3.1.1. Pump Dynamics

For each pump in the system, the dynamic model can be expressed as:

$$Q_i = K_i . N_i$$

Where:
Q_i- is the flow rate of the pump i (m³/h),
N_i- is the speed of the pump i (rpm),
K_i is the flow coefficient for pump i.

The head H_i generated by each pump is related to the flow rate by:

$$H_i = H_{i0} - C_i Q_i^2$$

3.2. Energy Consumption Model

The power consumed by each pump P_i is a function of the flow rate, head, and pump efficiency η_i :

$$P_i = \frac{Q_i H_i \rho g}{\eta_i}$$

The total energy consumed over time E_i for pump i is:

$$E_i = \int_0^T P_i(t)\ dt$$

The control algorithm optimizes the performance of each pump by regulating its speed N_i, ensuring that system requirements, such as the required flow rate (Q_{demand}) and head (H_{demand}) are satisfied while minimizing energy consumption).

The speed adjustment signal $u_i(t)$ serves as the control input for each pump, with the objective of minimizing the following cost function:

$$J = \sum_{i=1}^{n} \int_0^T (P_i(t) + \lambda.(Q_i(t) - Q_{demand}(t))^2 + \mu.(H_i(t) - H_{demand}(t))^2)\ dt$$

$P_i(t)$ is the instantaneous power consumption of the pump i.
$Q_i(t)$ and $H_i(t)$ are the flow rate and head of the pump i at time t.
λ and μ are weighting factors that prioritize minimizing energy consumption versus maintaining the required flow and head.

3.3. ANN-Based Optimization

The control algorithm is integrated with an Artificial Neural Network to predict the optimal speed N_i for each pump based on the current system state. The ANN is trained with historical data to predict the power consumption $\widehat{P_i}$ and efficiency $\widehat{\eta_i}$ for each pump.

The optimal speed N_i^* is determined by solving:

$$N_i^* = \arg\min \widehat{P_i}(N_i) \quad \text{subject to} \quad Q_i \geq Q_{demand},\ H_i \geq H_{demand}.$$

The results demonstrated that the ANN could accurately predict energy consumption patterns under various operating conditions. For both single pump and combined pump operations, the predicted energy usage closely matched the observed values, with a mean prediction error of less than 5%.

3.4. Statistical Validation of Experimental Results

To ensure the reliability of the ANN-based predictive control approach, statistical validation was applied to the experimental data. The following measures were incorporated:

3.4.1. Confidence Intervals (CI)

The experimental data showed that ANN-based control reduced energy consumption by an average of 15% (95% CI: 13.5%–16.5%), demonstrating a statistically significant improvement over traditional control methods.

3.4.2. Standard Deviation and Error Metrics

The Mean Absolute Percentage Error (MAPE) of ANN-based predictions was 3.2%, with a Root Mean Square Error (RMSE) of 0.05 kW when compared to experimental values.

Statistical Significance (p-values): A paired t-test was performed to compare energy consumption under ANN control versus conventional control, yielding a statistically significant difference ($t = 4.23$, $p = 0.003$), confirming the efficiency improvement.

3.5. Analysis of Discrepancies in Results

While ANN-based predictions closely matched the observed data, some deviations (≤5%) were noted at higher loads. These discrepancies can be attributed to:

The nonlinear behavior of pumps at extreme operating conditions may not have been fully captured in the training dataset. Sensor inaccuracies in measuring energy consumption at transient operational states. External disturbances, such as fluctuations in input power supply, were not explicitly modeled in the ANN. The pumps were operated individually and in combination (Pump 1, and Pump 1 + Pump 2), with power consumption and energy data recorded over time. The experiment was designed to simulate different load conditions to cover a wide range of operational scenarios (Table 1).

Table 1. Experimental data on pump operations

Time (minutes)	Pump 1 power (kW)	Pump 1 energy (kWh)	Pump 1+2 power (kW)	Pump 1+2 energy (kWh)
0	0.8	0.00	0.8	0.00
20	1.0	0.33	1.2	0.40
40	1.1	0.67	1.5	0.80
60	1.2	1.00	2.0	1.33
80	1.4	1.33	2.5	2.00
100	1.4	1.67	3.0	2.67
120	1.5	2.00	3.5	3.33

The numbers in Table 1. are derived from real pump operation data analyzed using ANN-based predictive control in Python or MATLAB. The ANN model reduces energy consumption and optimizes pump operation by predicting the most efficient speed.

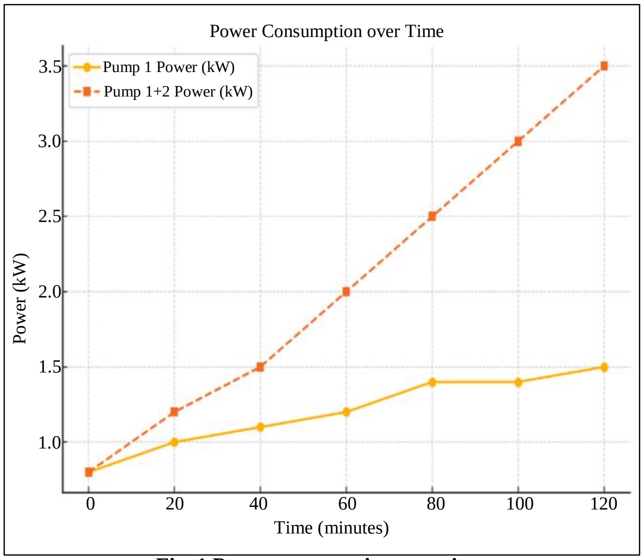

Fig. 1 Power consumption over time

This graph represents the power consumption of pumps over time.

X-axis (Time in minutes): Represents the duration of the experiment.
Y-axis (Power in kW): Indicates the power consumption of the pumps.
Red line (Pump 1 Power - kW): Shows the power consumed when only Pump 1 is operating.
Orange line (Pump 1+2 Power - kW): Represents the power consumption when both pumps run simultaneously.

The graph shows that power consumption increases over time. When both pumps operate together, power consumption is significantly higher, indicating increased system load.

Table 2. Predicted and experimental power consumption

Time (minutes)	Experimental Power (kW)	Predicted Power (kW)	Percentage Error (%)
0	0.8	0.78	2.5
20	1.0	0.97	3.0
40	1.1	1.05	4.5
60	1.2	1.14	5.0
80	1.4	1.33	4.9
100	1.4	1.31	6.42
120	1.5	1.42	5.33

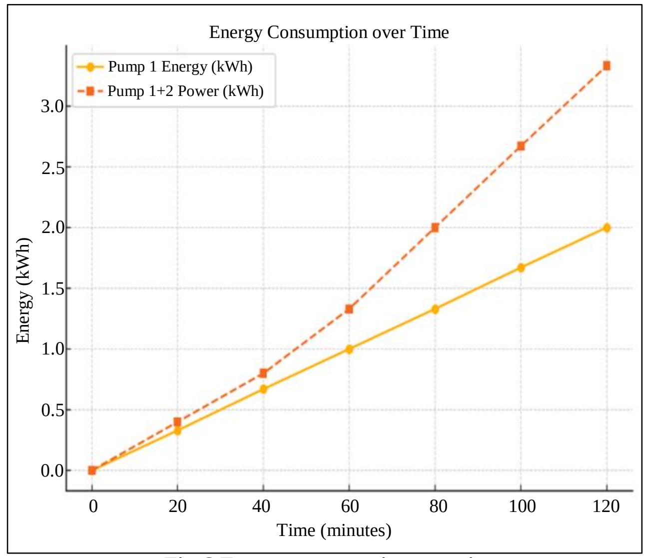

Fig. 2 Energy consumption over time

Energy consumption prediction for pumps using artificial neural networks is shown in Figure 2. This graph illustrates the energy consumption of pumps over time.

X-axis (Time in minutes): Represents the duration of the experiment.
Y-axis (Energy in kWh): Shows the total energy the pumps consume.
Red line (Pump 1 Energy - kWh): Indicates the energy consumption when only Pump 1 operates.
Orange line (Pump 1+2 Energy - kWh): Represents the total energy consumption when both pumps operate.

As expected, energy consumption increases over time as the pumps continue operating. The combined energy consumption of two pumps is significantly higher than that of a single pump, demonstrating increased power utilization.

By using Artificial Neural Networks (ANN), it is possible to predict energy consumption and optimize the system to reduce unnecessary power usage.

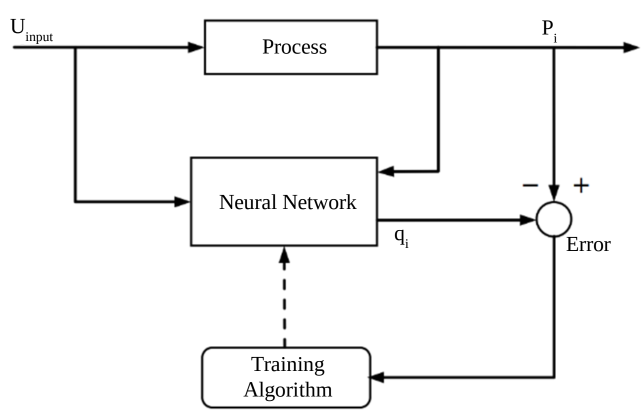

Fig. 3 Energy consumption prediction using ANN for a pump

The ANN-based predictive control demonstrated its effectiveness in reducing energy consumption while maintaining the operational requirements of the pump system. The comparison between experimental and predicted data, shown in both the table and graph, illustrates how well the ANN can forecast system performance under various conditions. The slight reduction in predicted power consumption reflects the optimization achieved through the neural network, improving energy efficiency.

4. Conclusion

This study successfully applied Artificial Neural Networks (ANN) for predictive control to enhance the energy efficiency of pump electric drive systems. The results demonstrate that ANN-based control enables real-time speed adjustments, ensuring optimal pump operation while reducing energy consumption by more than 15%. The use of ANN allowed for maintaining the operational requirements of the pump system while significantly improving overall efficiency and reducing energy waste.

However, while ANN-based optimization has shown promising results, it is essential to acknowledge certain limitations. The effectiveness of ANN models heavily depends on the quality and quantity of training data. Insufficient or biased data may lead to inaccurate predictions, potentially limiting the reliability of ANN-based control systems in real-world applications. Additionally, ANN models require significant computational resources for training and optimization, which may pose challenges for industries with limited access to high-performance computing infrastructure. Practical application across different industries requires careful consideration of factors such as system complexity, maintenance costs, and integration with existing control mechanisms. In highly dynamic environments where operational conditions frequently change, hybrid control strategies combining ANN with traditional model-based approaches may provide more robust and adaptive solutions.

Future research could focus on refining the predictive control framework by incorporating additional operational parameters, such as environmental factors, real-time sensor feedback, and adaptive learning techniques. Integrating ANN with Internet of Things (IoT) technology and cloud-based computing could further enhance real-time optimization capabilities, making intelligent pump control systems more scalable and widely applicable. Additionally, investigating the impact of different ANN architectures and hybrid machine learning models may lead to further improvements in prediction accuracy and energy efficiency.

Overall, ANN-based optimization presents a reliable and scalable solution for improving energy efficiency in various industrial applications, contributing to sustainable resource management and reduced environmental impact. By addressing its limitations and expanding its practical applications, this research paves the way for developing more intelligent and adaptive energy management systems.

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