

Development and Optimization of a Neuro-Predictive Control Algorithm for Electric Drives in Pumping Stations

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ABSTRACT: The present article delineates a control method that has been developed for the purpose of enhancing the operational efficiency of electric drive systems in pumping stations. During the research process, the dynamic characteristics and nonlinear interdependencies of the controlled object—namely, the main pipeline system—were thoroughly considered. In order to surmount the constraints imposed by traditional control methodologies, a predictive control principle founded upon a neural network model was implemented. A flexible algorithm was developed in the MATLAB environment, incorporating system identification and the tuning of controller parameters. The proposed approach ensures stable operation of the system under variable working conditions, reduces pressure fluctuations, and optimizes energy consumption. The experimental tests conducted in this study corroborated the practical effectiveness of the method.

I. INTRODUCTION

In recent years, the reduction of energy consumption and the enhancement of the operational efficiency of pumping stations in water supply and irrigation systems have become critical challenges. The continuous operation of pump units necessitates precise and dependable real-time control. However, the majority of existing pumping stations are based on static and classical control methods, which significantly limit their energy efficiency [1,2].

The variable nature of water flow in trunk pipeline systems, the instability of hydraulic resistance, and pressure surges in pipelines result in uncertain and dynamic systems that are difficult to manage using conventional PID controllers [3]. Consequently, in recent years, advanced control methodologies—particularly predictive control and model-based approaches—have witnessed a marked increase in adoption [4,5].

The employment of neural network models facilitates the precise characterization of the intricate dynamics inherent in controlled systems. These systems are capable of evaluating the current state of the object in real time and predicting its future behavior, thereby generating optimal control signals [6]. Specifically, the employment of neural network predictive controllers (NN Predictive Controllers) facilitates the efficient and adaptive control of electric drive-based pump units [7].

The present paper expounds upon the findings of research endeavours aimed at enhancing the operational stability of electric drives within pumping stations. This objective is pursued by two primary means: first, the implementation of a controller derived from a neural network model, and second, the mitigation of energy expenditure. The efficacy of these approaches is substantiated by empirical evidence, which demonstrates their capacity to curtail hydraulic oscillations. The model, developed in the MATLAB Simulink environment, was subjected to experimental conditions, and the practical effectiveness of the applied algorithm was analyzed.

II. SIGNIFICANCE OF THE SYSTEM

The proposed neural network-based control system plays a significant role in enhancing energy efficiency and reducing pressure fluctuations in pumping stations. The system evaluates the state of the process in real time and generates an optimal control signal through predictive assessment. This approach helps reduce excessive energy consumption and equipment wear. The algorithm, modeled in the MATLAB environment, is distinguished by its ease of integration into practical systems.

III. LITERATURE SURVEY

In recent years, researchers have paid significant attention to the effective control and energy efficiency of pumping stations. Automated control methods and artificial intelligence approaches, in particular, are widely used to reduce energy consumption and enhance system stability.

Model predictive control (MPC) theory, developed by Maciejowski [1] and Bemporad and Morari [2], offers an optimal control strategy for dynamic systems. This method predicts system states and computes control signals within defined constraints. However, MPC relies on conventional modeling and may not provide sufficient accuracy for complex nonlinear systems.

Conversely, models based on neural networks, specifically artificial neural networks, offer high precision in learning and modeling the complex behavior of nonlinear systems. Tanelli and Piroddi demonstrated the practical advantages of neural predictive controllers for nonlinear processes [3]. Their approach predicts a system's future state based on learned data, enabling the realization of optimal control strategies.

Zhang and Wang proposed control algorithms that consider the nonlinear characteristics of hydraulic systems and demonstrated their effectiveness in water supply networks. Similarly, Sharma and Jha emphasized that implementing automatic control in irrigation systems significantly contributes to water and energy conservation.

Demuth and Hagan [6] extensively studied object identification and controller parameter tuning using neural networks. Their development of the Neural Network Toolbox for the MATLAB environment has become a crucial tool for translating theoretical models into practical applications.

In general, the existing literature indicates that predictive control methods based on neural networks represent one of the most suitable solutions for the dynamic and nonlinear nature of pumping systems. This approach helps reduce pressure fluctuations, optimize energy consumption, and improve operational reliability.

IV. METHODOLOGY

The methodology of this research 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 NN model and develop a mathematical model for system optimization.

V. EXPERIMENTAL DATA AND OPERATING CONDITIONS

Considering the elasticity of the main pipeline system, the control of pump units (PUs) is characterized by nonlinear interdependencies, complexities in modeling dynamic behavior, and unstable processes associated with changes in the hydraulic regime of water delivery. These factors hinder the application of traditional control methods. In existing electric drive-based pump systems, classical tuning techniques are typically used for control.

In some cases, water demand in the network changes abruptly (e.g., due to sudden variations in hydraulic resistance within the main line or rapid opening/closing of valves), which leads to significant pressure fluctuations and hydraulic shocks within the pipeline system. Classical pressure control systems are unable to suppress such full-scale oscillatory processes, especially under high rates of change. Therefore, a more effective solution for managing such systems is the implementation of a neural network-based control system.

The synthesis of the neural network-based control system is carried out using the Neural Network Toolbox available in the MATLAB environment.

Below, a brief description of this toolbox is provided, along with the synthesis procedure of the neural controller and modeling results of the PU control system based on neural networks.

Studies have shown that the most effective method for solving this problem is the NN Predictive Controller (Neural Network-based Predictive Controller). This regulator uses a neural network model of the nonlinear controlled object to predict its future behavior. Moreover, the controller calculates an optimal control signal that ensures optimal performance over a specified time horizon.

Thus, the design of a neural network-based controller consists of two stages:

1. Identification of the controlled object
2. Synthesis of the control law.

At the identification stage, a neural network-based model of the object is developed, which is then used in the controller synthesis stage.

VI. PRINCIPLE OF PREDICTIVE CONTROL

Predictive control applies a moving horizon strategy, where the neural network model predicts the system's response to the control actions over a defined time interval. These predictions are implemented through numerical optimization algorithms, which compute the control signal by minimizing a given performance criterion:

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + \rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2$$

Here, N_1, N_2 va N_u re constants that define the limits for tracking errors and control signal computation. Control variables: u' — trial control signal, y_r — desired (target) response, y_m — model response of the controlled object. The coefficient ρ expresses the weight factor included in the quality criterion of the control signal.

Figure 1 illustrates the block diagram of the predictive control process. The regulator includes a neural network model representing the controlled process and an optimization block. The optimization block determines the optimal values by minimizing the control quality criterion. The resulting control signal influences the process accordingly.

Figure 2 presents the structural diagram of the neural network-based control system for the pump unit (PU) developed in the MATLAB Simulink environment.

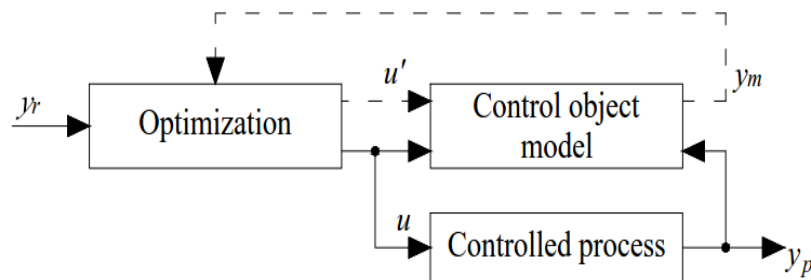


Fig. 9.1 Diagrammatic representation.

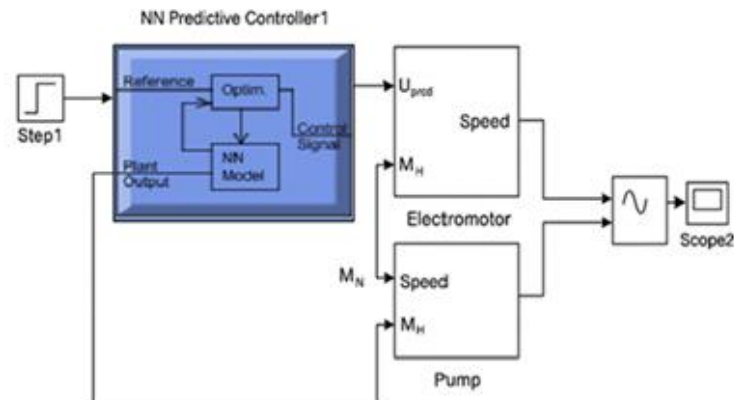


Fig. 2 Model of the pump unit (PU) control system equipped with a neural network regulator

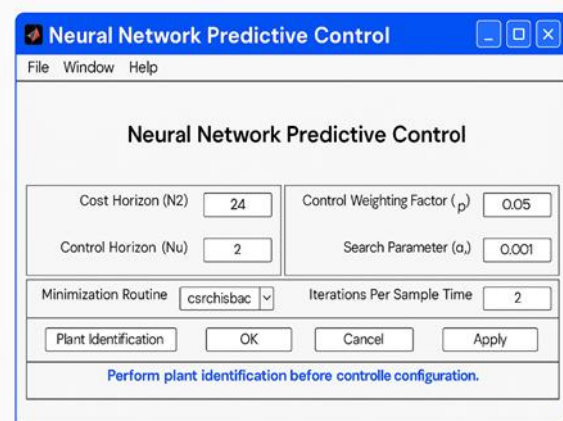


Fig 3. – Regulator parameter tuning interface

The synthesis process of the neuro controller begins by activating the **NN Prediction Controller** block. At this stage, an interface window (shown in Figure 4) appears, serving as the user interface. To determine the optimal parameters of the neural predictive regulator, several synthesis options are considered. Before setting the regulator parameters, it is necessary to construct the neural model of the controlled object. For this purpose, a specialized procedure called **Plant Identification** is used.

The main regulator parameters to be defined are:

- the size of the hidden layer defined by the number of neurons N_n ,
- the sampling rate in seconds (determined by the time interval Δt between two successive data acquisitions), and
- the length of the training dataset N_3 .

Following this, the following optimization parameters are specified:

- upper limit of summation in the quality index N_2 ,
- upper limit of summation for evaluating control effort N_1 ,
- weighting coefficient ρ for forming the performance index and the one-dimensional search parameter α . The **csrchsbac** procedure is chosen for optimization.

As a result of multiple studies, it was proven that values of N_u, ρ and α have little influence on the results of neurocontroller synthesis. However, the values of N_2 (upper summation limit in the quality index) have a significant impact on the performance of the predictive controller. The number of neurons and the discretization step Δt , especially

at small values of, $\gamma = 2$, have a non-negligible influence on the quality of control. For most practical tasks, the optimal values are found in the range $N_2 = 4 \dots 12$

VII. EXPERIMENTAL RESULTS

As studies have shown, the identification of the control object depends on the number of neurons in the hidden layer and the architecture of the neural network. The selection of the number of neurons depends on the complexity of the dynamics of the control object—that is, if the number of neurons exceeds what is necessary, overfitting may occur, and the training process may take a long time. Conversely, if the number of neurons is too small, the neural network may not accurately represent the object's behavior.

It was determined that the optimal number of neurons for this task lies within the range . The training of the network also significantly depends on the length of the training dataset , and experimental studies have shown that the time interval between two successive data acquisition points also affects training.

Results indicate that when , calculation accuracy decreases, and training time shortens. If , the opposite effect occurs. Thus, it can be concluded that the discretization step significantly influences the predictive controller's performance as well as the architecture of the neural network. The optimal values for this task were found to be: .The trainlm training function was used.

The appearance of the Plant Identification window is shown in Figure 4.

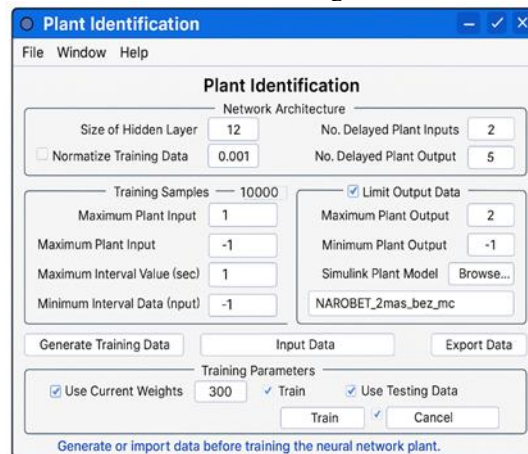


Fig 4 – Plant identification window of the controlled system

As a result of the conducted research, the optimal parameters of the neuro-regulator were determined, corresponding to variants *a–c* as presented in Table 3.

Table 1. Parameters of the Neural network controller (NN prediction controller)

№	NN Controller Parameters	Notation	Variant		
			a	b	c
1	Size of Hidden Layer	N	2	3	5
2	Sampling Interval	Δt	0.1	0.1	0.1
3	No. of Delayed Plant Inputs	N_i	2	2	2
4	No. of Delayed Plant Outputs	N_j	2	2	2
5	Training Epochs	—	200	200	200
6	Training Samples	N_B	800	1200	1000

7	Maximum Plant Input	φ_{max}	10	10	10
8	Minimum Plant Input	φ_{min}	0	0	0
9	Maximum Interval Value	t_{max}	20	5	10
10	Minimum Interval Value	t_{min}	5	0.5	1
11	Cost Horizon	N_2	8	20	10
12	Control Horizon	N_u	6	5	3
13	Control Weighting Factor	ρ	0.05	0.05	0.05
14	Search Parameter	α	0.001	0.001	0.001
15	Iterations Per Sample Time	t	2	2	2

The transient response graphs of the pump unit control system under rapid changes in the disturbance, without considering the pipeline dynamics, are presented in Figures 5 a, b, and c, which correspond to options a–c in Table 1.

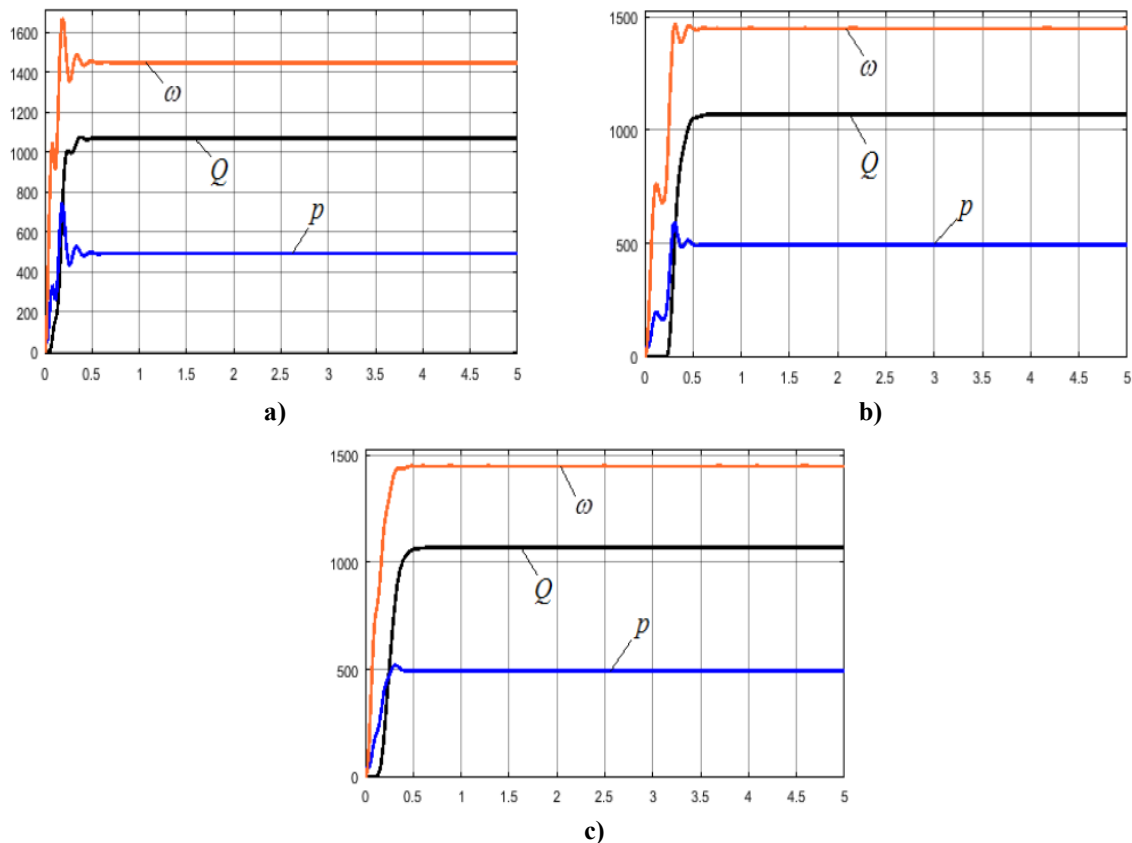


Fig 5. Graphs of flow rate, pressure, and rotational speed of the pump unit under rapid changes in the disturbance, without considering the pipeline dynamics.

VIII. CONCLUSION

In this study, a control algorithm was developed for the electric drive system of a pumping station, based on the principles of neural network-based predictive control. The approach enabled adaptive response to changes in operating conditions, minimized pressure fluctuations, and improved the overall energy efficiency of the system. The model, implemented in the MATLAB environment, demonstrated stable and efficient performance during simulation experiments. The results confirm the practicality of the proposed method in managing complex nonlinear systems such as water pipeline networks.

As part of future work, the algorithm is planned to be tested in industrial settings, integrated into PLC-based control platforms, and enhanced through self-adaptive control mechanisms to increase system autonomy and reliability.

IX. SCOPE

This research focuses on the development and optimization of an intelligent control system for electric drives used in pumping stations. The scope includes the identification and modeling of the nonlinear behavior of water pipeline systems, the application of neural network-based predictive control techniques, and the evaluation of system performance under various operating conditions. The study also involves the implementation of the control algorithm in the MATLAB environment, along with simulation-based testing to assess its effectiveness in reducing pressure fluctuations and improving energy efficiency. Future directions include adaptation of the developed control system for real-time industrial applications and integration into programmable logic controller (PLC) platforms.

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