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Research paper

Enhanced PH Neutralization Process Control Using Firefly-Optimized Artificial Neural Network Predictive Controller

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Abstract

The pH neutralization is a challenging process, and it plays a significant role in the chemical process industry. Neutralization is the process of eradicating alkalinity or acidity by combining acids and bases to generate a neutral solution. To have the least amount of environmental impact, acidic or basic wastewater must be neutralized before discharge. Specifically, due to their inherent characteristics, the processes are difficult to control for high nonlinearity and sensitivity near the equilibrium point. To manage the difficult process of pH control, the traditional control techniques are utilized, including Proportional Integral (PI) and Proportional Integral Derivative (PID) controllers. Here, to standardize the pH process Artificial Neural Network (ANN) is employed and is optimized with the utilization of the Fire Fly Optimization (FFO) algorithm for tuning its input parameters. This paper aims to deploy a smoother control signal to achieve efficient load regulation and convenient set-point tracking. The suggested FF-ANN controller outperforms other existing control approaches with improved disturbance rejection, set-point tracking, and excellent sensitivity to changes in model parameters, according to the results of the determined simulation.

***Keywords**: pH process, FF optimized ANN controller, PI controller, PID controller*

1. Introduction

Controlling the pH neutralization process is a complicated issue that has received a lot of consideration due to its importance in the chemical process industry. However, here the nonlinear dynamics and uncertainties of pH processes are difficult to control. As a result, the pH neutralization process is regarded as a standard for analyzing nonlinear controllers. Thus, research into the control and identification of the pH neutralization process is crucial [1-3]. pH neutralization is a common process control task in these industries, and concern about this issue is expanding rapidly due to the environmental effects. Moreover, the consequence of the time delay, complex non-linearity, and time invariance in the process flow, controlling the pH neutralization process has become a more challenging task. A controller must adapt to changes in process parameters in order to achieve the full region of the highly nonlinear pH process [4-6]. Many authors recommend model-based controllers to accomplish this process. However, creating a nonlinear model is a problematic task. It is challenging to establish a model-based controller for a real-time process [7, 8].

Simulation has been carried out to determine the appropriate control strategy for a highly non-linear system, particularly the pH neutralization process [9, 10]. The initial research question is to select appropriate controller tuning parameters. Despite the widespread use of conventional control schemes, achieving the pH set point is challenging and demands an effective controller for tuning. The second issue is the lack of traditional control techniques, which affects and reduces system performance [11-13]. A robust dynamic model for the pH neutralization process requires further computation in an industrial controller to address both issues.

Using an appropriate controller mechanism is crucial for obtaining the pH to the intended value after a deviation, since the pH value is modeled as the logarithmic function of hydrogen ions. Due to its weak disturbance response, excessive oscillation, and large overshoot

troubles, the typical PI controller is ineffective at handling any non-linear processes [14]. A non-linear compensation-based PI controller design is described with good disturbance response and enhanced steady state performance.
Among the most well-known and widely used tuning methods, the Ziegler-Nichols (ZN) tuning method is exploited because of its simplicity and satisfactory performance for a wide range of systems [15]. However, measurement noise might make it difficult to determine the parameters of the step response due to the ZN tuning method. Nevertheless, the researches show that ZN tuning in the pH neutralization process control results in shorter settling times. In contrast, compared to other tuning approaches, this method also offers quicker and simpler tuning procedures. Also, the ZN approach can conduct quick recovery from disruptions and drive the system process into marginal stability, but it can also cause oscillatory response [16]. To overcome all these issues, PID preferred here, the PID controller is selected for the pH neutralization simulation system because it can manage the variable due to its strong nonlinearity characteristic, time-varying nature, sensitivity to small disturbances, and more practical orientation. Due to all of these, the simulation study's PID controller design and setup produced a dependable control system and safely achieved high pH neutralization performance of the operating process [17-18].
The employment of ANN is a feasible solution for constructing reliable pH controllers. In control and monitoring applications, ANN has been successful due to its ability to handle issues, including ANN is a significant solution for complexity, nonlinearity, and the creation of reliable process controllers [19]. The performance of the ANN controller was optimized using several nature-based algorithms to improve its performance. The pH system's complexity is extremely troublesome to modify the controller parameters [20, 21]. Numerous studies have attempted to determine the ideal controller parameter values using a variety of tuning techniques, including the Genetic Algorithm (GA) and including some other Meta-Heuristic Optimization (MAO) algorithms, for a variety of closed-loop system problems. However, it has low convergence speed and high time consumption. Here, the FFO algorithm is used to improve the performance of the system. FFA is utilized in this study because it prefers to explore in both local and global settings and comprises both exploration and exploitation search agents [22-24]. An FFO generally serves as a signal that is multiplied to attract other fireflies and help them locate and identify its mate, as well as transmit details as to its prey to others.
The final contribution of this paper is to propose an ANN controller for efficiently managing the pH process and to estimate the extremely nonlinear neutralization process. The parameters of the controller are attained using the FFO algorithm. This work proposes and evaluates a PID control approach in which the parameters are changed by the ANN. The outputs of the ANN are used to determine the tuning parameters. The ANN is trained using control errors, which are the difference between the set-point and the output.
Even though numerous control approaches like PID, PI, and model-based controllers are widely developed for the pH neutralization process, they often fall short in efficiently regulating the time variance, high nonlinearity, and sensitivity near the neutralization point. Conventional approaches struggle with overshoot, poor disturbance rejection, and long settling time, particularly in real-time industrial applications. While a neural network-based controller is effective in regulating difficulties, their performance is heavily based on the optimal tuning of parameters, which is not effectively addressed by traditional approaches. Furthermore, popular optimization approaches such Genetic algorithm and other metaheuristic approaches suffer from a slow convergence rate and high computational cost. Thereby, this research develops an FFO-tuned ANN controller that assures improved performance, faster convergence, and enhanced regulation of pH in nonlinear systems. The hybrid FF-ANN approach allows improved controller performance characterized by diminished overshoot, faster settling time, better disturbance rejection, and smoother control signals, attaining more precise and effective management of the pH process across changing operational conditions.

2. Modeling of Proposed System

The current paper deals with a neutralization process that, due to the format of the proposed process curve, is an immensely nonlinear scheme. Several chemical techniques, including wastewater treatment, numerous chemical reactions, coagulation, boiler feed and cooling tower water treatment, precipitation, and electro-hydrolysis, all depend heavily on pH regulation. Because the pH process is inherently highly nonlinear, a controller depending on a linear control method of the function is effective around a limited pH performing range. The corresponding pH regulation process is explained as follows.

2.1. Modeling of pH Neutralization Process

By computer experiments and simulations on the pH neutralization process, the learning mechanism of controller gain based on the dynamics of the process is developed and tested.

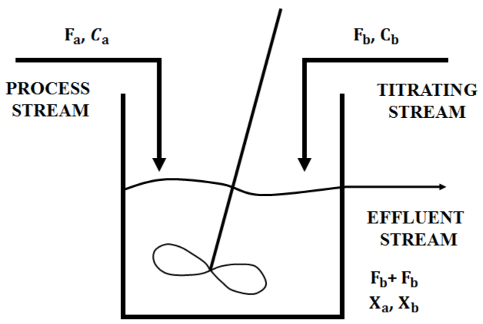

Fig. 1: pH Neutralization Process

This mechanism model is utilized to assume perfect mixing. As depicted in Fig. 1, the Continuous Stirred Tank Reactor (CSTR) contains 2 input streams: influent stream and titration stream ($NaOH$) and one efferent at the output. The following relationships exist between mixing dynamics:

$$V\frac{dX_a}{dt} = F_aC_a - (F_a + F_b)X_a \tag{1}$$

$$V\frac{dX_b}{dt} = F_bC_b - (F_a + F_b)X_b \tag{2}$$

Where $X_a =$ acid solution, C_a = influent stream, , $X_b =$ base Solution, C_b = titration stream F_a = influent stream's flow rate, V = mixture's volume in the CSTR and F_b = influent stream's flow rate.
The equations show that input streams are affected by the dynamic changes in the base and acid component concentrations. The following is a representation of HAC and $NaOH$ interact:

$$H_2O \leftrightarrow H^+ + OH^-$$
$$HAC \leftrightarrow H^+ + AC^-$$
$$NaOH \rightarrow Na^+ + OH^-$$

The electroneutrality condition states that the total exemplary charge in the remedy should be zero. As a result, the equation is,

$$[Na^+] + [H^+] = [AC^-] + [OH^-] \quad (3)$$

The equations for the acetic acid and water equilibrium relations are

$$Ka = \frac{[AC^-][H^+]}{[HAC]}, K_W = [H^+][OH^-] \quad (4)$$

Where Ka represents the acetic acid's constant (1.978× 10^{-5}) and K_W indicates the water's dissociation constant (10^{-14}) on $25\ °C$.
The equation is provided by employing equations 3 and 4, X_a $[HAC]$ + $[AC^-]$ and X_b $[Na^+]$.

$$[H^+]^3 + [H^+]^2\{K_a + X_b\} + [H^+]\{K_a(X_b + X_a) - K_W\} - K_W K_a = 0 \quad (5)$$

The parameters pH = $-log_{10}$ $[H^+]$ and $pK_a = -log_{10}K_a$ a produces the well-known titration curve.

$$X_b + 10^{pH} - 10^{pH-14} - \frac{X_a}{1+10^{pK_a - pH}} = 0 \quad (6)$$

The parameters of the PID controller can be fine-tuned using an ANN. This is presented in the section below.

2.2. Proposed FF Optimized ANN Controller

ANN possesses the potential for better solutions for several issues because of its extensive parallelism and learning capabilities. The control community is aware of neural networks and is curious as to whether these networks are employed to improve control solutions for existing problems or control problems that have resisted the best efforts. The Predictive Controller and ANN System Identification are the 2 main components of the ANN Predictive Controller (ANN-PC), which predicts the characterization of the system over a given time horizon. An ANN represents the plant's forward dynamics, and as shown in Fig. 2, the ANN training signal is the prediction error between the plant output y_p and ANN output y_m.

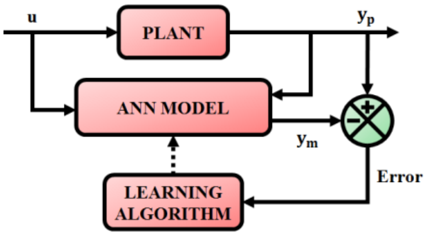

Fig. 2: ANN system identification

The ANN plant model predicts new values of the plant output by utilizing previous inputs and past plant outputs. Using information gathered during plant operation, this network is trained offline in batch mode. In Fig. 3, the structure of the ANN plant model is displayed.

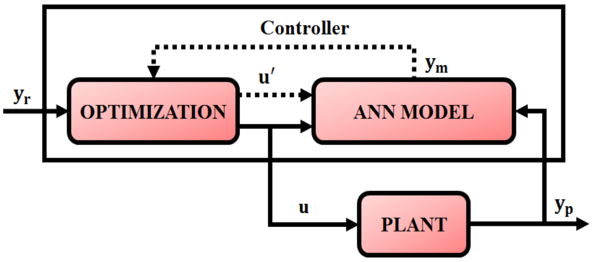

Fig. 3: ANN structure

A defined time horizon is used to conduct the Model Predictive Control (MPC this is also known as receding horizon control, during which the time horizon is being moved ahead. Using the predictions, it is possible to identify the control signal that reduces the requirement specification represented in equation (7).

$$J = \sum_{j=N_1}^{N_2}(y_r(t+j) - y_m(t+j))^2 + \rho\sum_{j=1}^{N_u}(u(t+j-1) - u(t+j) - 2)^2 \quad (7)$$

Where the horizons N_1, N_2 and N_u are used to determine the control increments and tracking error. The desired response is represented by y_r, the tentative control signal is represented by u', and the network model response is indicated by y_m. The value indicates that the contribution of the control raises the sum of squares to the performance index.

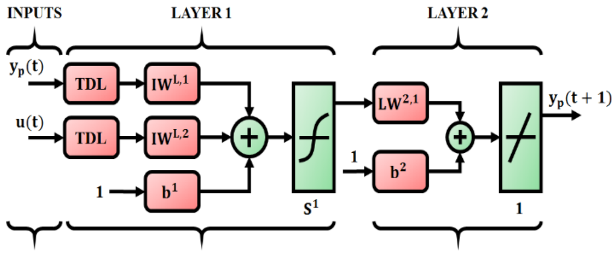

Fig. 4: Predictive controller structure

The MPC procedure is illustrated in Fig. 4. The ANN system architecture and the optimization block constitute the controller. Optimal u is then fed to the plant afterward, when the optimization identifies the values of u' that minimize J. Furthermore, the performance of the ANN controller as a pH process controller is enhanced with the utilization of FF optimization.

2.2.1. Fire-Fly optimization (FFO)

The FFO depends on the firefly's flashing properties. These fireflies' idealized behavior could be categorized as follows: they are unisex and attract people of all genders. The objective functions $f\ (x)$ for $x \in S \subset \mathbb{R}^n$ are then used to represent this brightness when an optimization problem with continuous constraints is being considered. The cost function needs to be minimized:

$$f\ (x*) = \min_{x \in S} f(x) \tag{8}$$

In a swarm of m fireflies (agents), x_i denotes a solution of FF in iteration i $f(x_i)$ is it expensive. At the starting stage, the fireflies are transferred randomly in a space S , by utilizing the determinative strategy. β The attractiveness of FF imitates the attraction level from one to another. The i to another member j is a function of the distance $r_j = \ \mathrm{d}(x_i; x_j)$. this can be an exponential function:

$$\beta = \beta_O\, e^{-\gamma} r_j \tag{9}$$

Absorption coefficient, where β_O and γ are the predetermined maximum and attractiveness value, respectively. The following equation describes how a firefly moves from i to j That is brighter.

$$x_i^{t+1} = x_i^t + \beta_O\, e^{-\gamma} r_{ij}\left(x_j^t - x_i^t\right) + \alpha_t \epsilon_i^t \tag{10}$$

Within the first term, the location $x_i$in the iteration t stands in for a firefly, in the second term, the attraction between fireflies j and i in the third term, ϵ_i^t is a vector of odd numbers with the randomization parameter denoted by α_t. the initial scaling factor is a metric that has the following definition:

$$\alpha_t = \alpha_t \delta^t \tag{11}$$

Where is a number in the range of 0 and 1. The values for and that were employed in this work are displayed subsequently. Using a random array, the firefly algorithm enables relocating the fireflies and eliminating the local minimum problem. The pseudo code of the FFO algorithm is given below, and Fig. 5 indicates the flowchart for the FFO algorithm.

Algorithm 1: FFO Algorithm

```
Objective function f(x), x = (x_i, ...., x_d)^T
Generate initial population of fireflies x_i (i = 1,2, ...., n)
Light intensity I, at x_i is determined by f( x_i)
Define light absorption coefficient γ
while(t < MaximumGeneration)
for i = 1 : n all n fireflies
for j = 1 : i all n fireflies
if( I_i > I_j), Move fire fly i towards j in d_dimension;
end if
Attractiveness varies with the distance r via exp[− γr]
Evaluate new solutions and update light intensity
end for j
end for i
Rank the fireflies and find the current best
end while
```

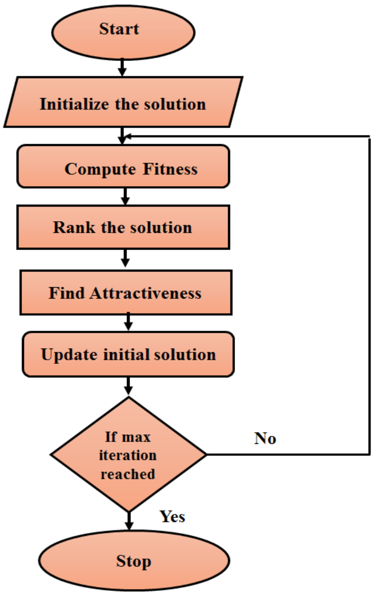

Fig. 5: Flowchart of FFO algorithm

2.2.2 Proposed FF optimized ANN controller for pH process

The datasets are split into training, validation, and testing subsets to train the ANN model. Model parameters are obtained using the training set. To prevent overfitting, the validation subset is utilized to evaluate the precision of the current training. The testing subset is exploited to verify the performance of the ANN model after its parameter set is determined to be optimal. This paper mainly concentrates on training the ANN with the assistance of the FFO algorithm. Fig. 6 depicts the flowchart of the training ANN using the FFO method. During the exploration phase, fireflies are distributed across the solution space to explore diverse candidate solutions, endorsing global search capabilities and diminishing the risk of premature convergence. It allows the ANN to escape local minima by considering varied regions of the error surface. Then, the exploitation phase refines the better solutions by intensively searching around the most impressive fireflies, thereby fine-tuning the ANN parameters for better predictive accuracy. This dynamic balance among broad search and refinement assures that the ANN converges proficiently toward optimal weight configurations. As an outcome, the controller trained via FFO exhibits improved robustness, diminished control error, and better adaptability in managing the time-changing and nonlinear nature of the pH neutralization process.

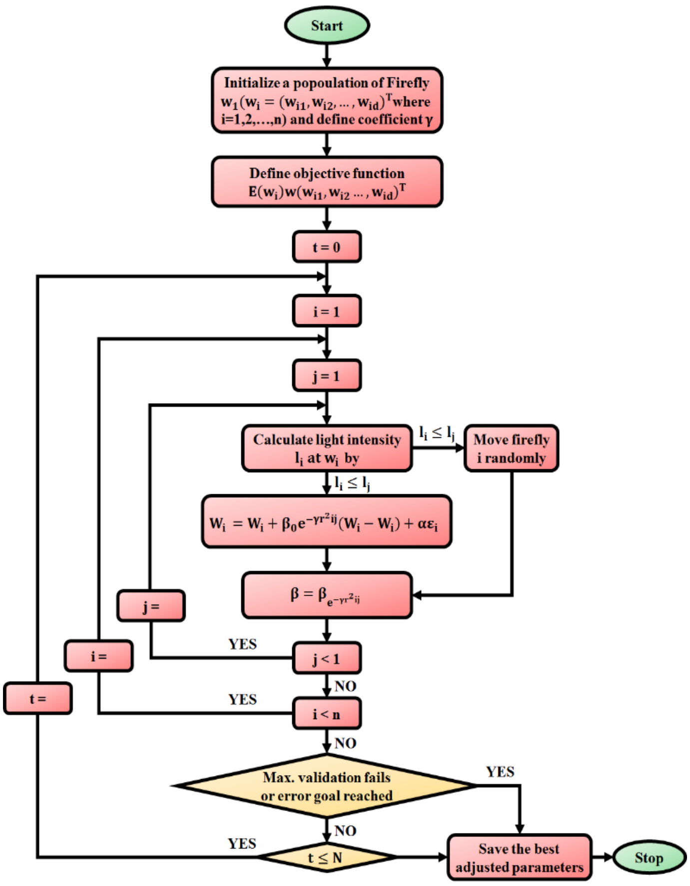

Fig. 6: Flowchart of FF Optimized ANN controller

The selection of FFO parameters like randomization parameter, attractiveness at zero distance, absorption coefficient, population size, and number of iterations has the necessity to attain a balance between global exploration and local exploitation during ANN training. The randomization parameter assures diversity in the population and evades premature convergence, whereas the moderate attractiveness and absorption coefficient facilitate a controlled search radius that avoids excessive attraction over long distances, improving stability. A population size provides a practical trade-off among search efficacy and computational overhead, assuring adequate candidate diversity without overloading system resources. Likewise, the number of iterations offers an adequate opportunity for convergence without incurring avoidable computational costs. These parameter settings are empirically validated to accelerate convergence, improve solution accuracy, and enhance robustness in adapting ANN weights for accurate pH control in highly nonlinear environments. This flowchart shows how to establish the n vector, which includes trainable parameters such as the biases (w) and weights of the ANN network, as well as γ is a defined coefficient. In this circumstance, the error functions are computed for each firefly population (w_i). The thought that a firefly is more enticing if it is brighter serves as the inspiration for the FA algorithm. $I_i = f(w_i)$ is the brightness of the FF i at a position w_i, and other fireflies judge the firefly's attractiveness based on its brightness. The brightness then appears to vary based on the separation between two arbitrary FFs i and j. specifically, the distance affects the judgment. The verified set of errors is tracked in the nature-inspired training procedures FA of the ANN are chosen and preserved if the convergence condition is satisfied. Lastly, the testing subgroup evaluates the performance. It should be noted that the minimal performance target (or maximum tolerated error) and the same stopping conditions (as well as the maximum number of epochs) are established for this section as well. Therefore, utilizing FFO, the ANN controller of parameters was tuned optimally, and it has performed well in pH regulation.

3. Results and Discussion

An FF optimized ANN controller is deployed to establish the performance of the PH regulation process. Table 1 indicates the parameter specification of the proposed controller technique pH for process. The developed model is performed by utilizing an Input-Output (IO) data set gathered from the pH neutralization process. The training process utilizes the first 75% of the data, whereas the validation process utilizes the other 25% of the data.

Table 1: Parameter specification

Parameters	Values
Model Parameters	
K_w	10^{-14}
K_a	1.86×10^{-5}
C_b	$0.5\ mol/L$
C_a	$0.5\ mol/L$
F_a	$10\ m^3/h$
V	$50\ L$
Optimization Parameters (FFO)	
Randomization parameter	0.5
Attractiveness at r=0, β_O	0.2
Absorption coefficient γ	1.0
Population size	20
Number of iterations	100

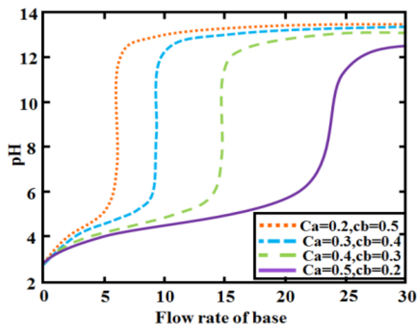

Fig. 7: Variations in the acetic acid titration curve as a function of sodium hydroxide concentration

Fig. 7 demonstrates that the diagram of solution concentration varies while changing the titration curve. After examining the S-shaped curve, it becomes clear that the process exhibits extremely nonlinear behavior. Moreover, the process is highly sensitive near the equilibrium point, which means that even a small input disturbance might result in a significant output fluctuation. Additionally, it is noted that the chemical reactions are dynamic in nature due to the variable concentrations of acidic and basic solutions. To simulate the pH neutralization process and model the nonlinear characteristics, acetic acid and $NaOH$ are exploited as the acidic and basic agents. The titration process is conducted by changing the concentration of sodium hydroxide while keeping the fixed acetic acid concentration, allowing the S-shaped titration curve. This curve presents the highly non-linear nature of the process and the sensitivity of the system near the neutralization point. It encompasses the precise control of pH in systems, while weak acid-strong base interactions exhibit strong non-linear dynamics, demonstrating better efficacy of the controller.

3.1 Standard structure

The Fig. 8 indicates that comparison of disturbance rejection and set-point tracking, from that analysis, leads to the conclusion that the optimized ANN controller has the best set-point tracking capability compared to other control techniques. The FF optimized ANN controller distributes a smoother control signal. Along with the ANN controller, the expanded view of the Region of Interest (ROI) is depicted in Fig. 9.

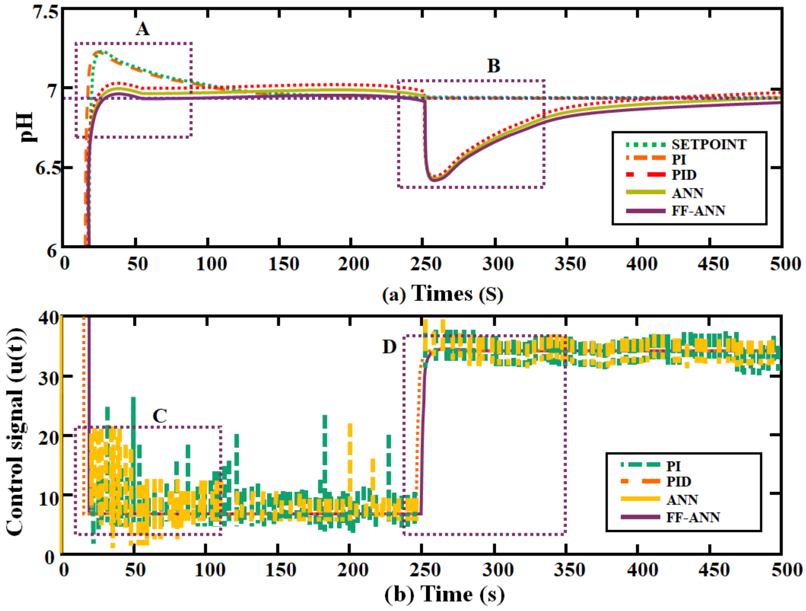

Fig. 8: Comparison of controller performance for set-point tracking and disturbance rejection

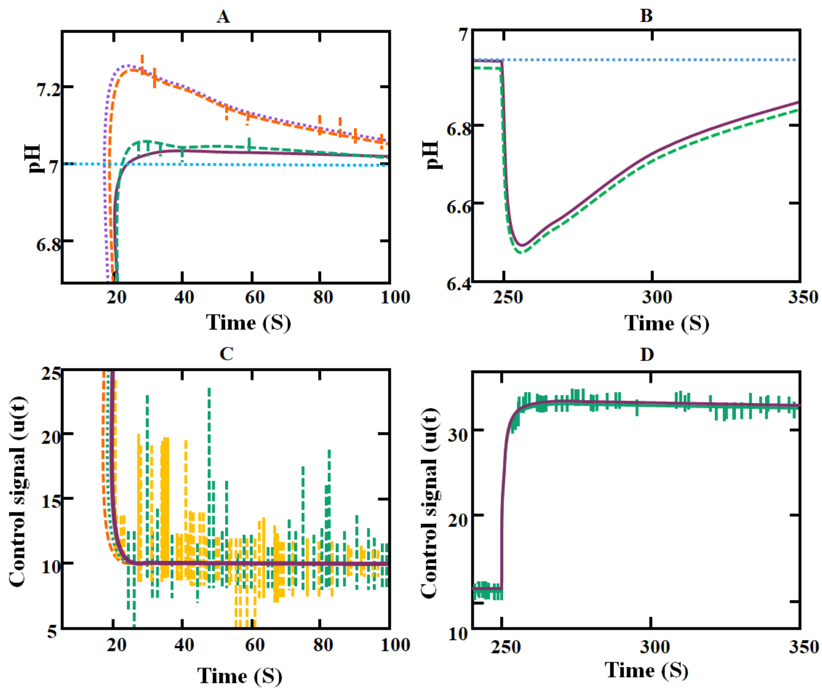

Fig. 9: Expanded view of different ROIs A, B, C, and D

Table 2: Evaluation of the controller's performance

Evaluation Metrics		Controllers			
		PI	PID	ANN	FF-ANN
Percentage Overshoot (% OS)		4.916	4.481	0.9845	0.4913
Set-tling time	Before disturbance (T_{S_1})	110.102	101.449	22.1169	20.7989
	After disturbance (T_{S_2})	370.979	364.557	370.9395	361.5695
Rise time (T_r)		17.17	15.79	19.768	18.789

Table 2 shows the evaluation of controller performance. Here, the FF optimized ANN controller has the lesser overshoot (0.9845%) compared to all other control approaches. Furthermore, from the observation, the FF-ANN controller settles faster in contrast to other control methods.

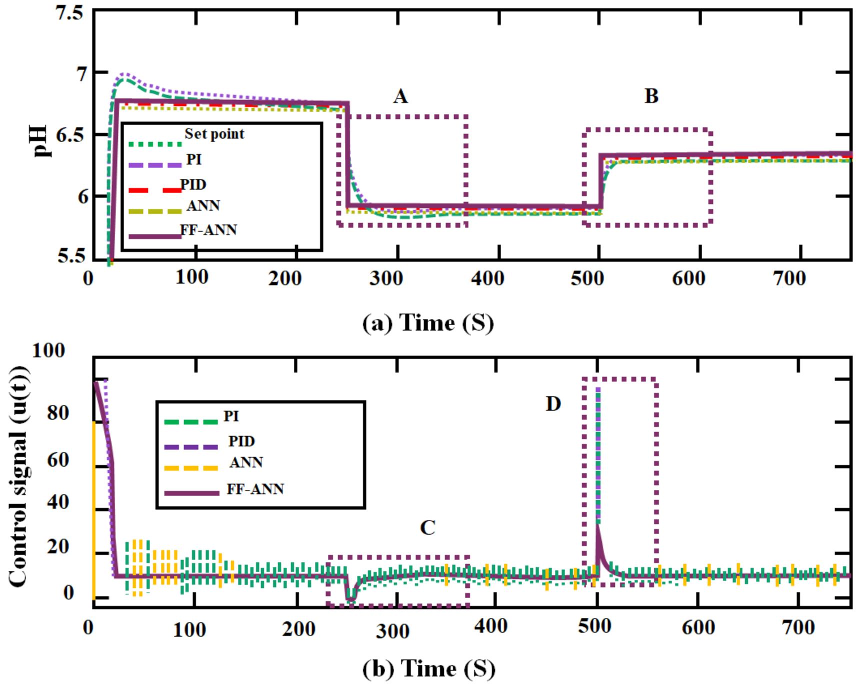

Fig. 10: Variations in set-point performance of controllers

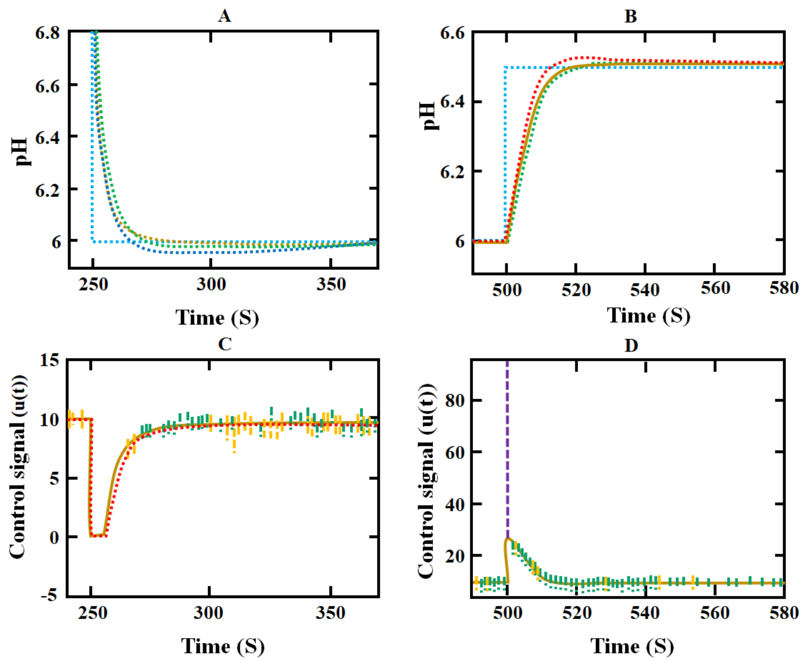

Fig. 11: Expanded view of different ROIs A, B, C, and D

The obtained outcomes are depicted in Fig. 10 as the performance of the FF-ANN controller is also examined in the case of set-point signal variation. This justification regarding the requirement for an improved ANN controller in pH value regulation is further supported by the Expanded ROIs shown in Fig. 11.

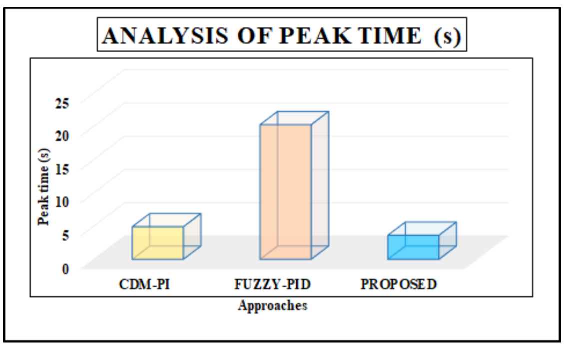

Fig. 12: Analysis of peak time

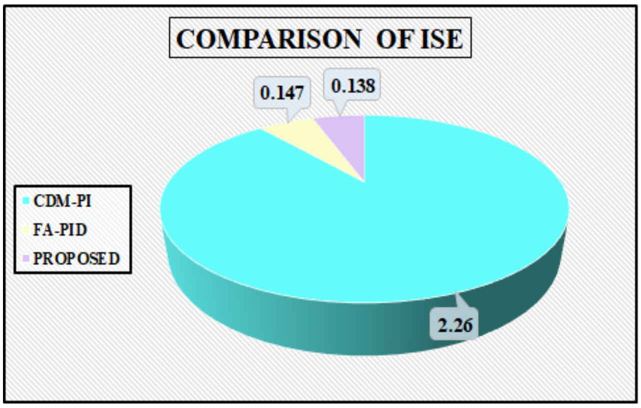

Fig. 13: Analysis of ISE

An analysis of peak time for CDM-PI [25], Fuzzy-PID [26], and the developed approach is shown in Fig. 12. Here, the developed approach has the best peak time of $3.61\ s$ than CDM-PI ($4.89\ s$)and Fuzzy-PID($20.22\ s$) method, thereby attaining improved performance in pH neutralization. Fig. 13 represents the comparison of Integral Square Error (ISE) for the developed approach with CDM-PI [25] and, FA-PID [27] method. The better ISE of 0.138 is attained by the developed approach than CDM-PI(2.26) and FA-PID (0.147)approach.

4. Conclusion

The detection and regulation of pH neutralization is one of the most challenging issues in the relevant fields. Several factors, including significant nonlinearity, strong interference, and time delay, play a role in the pH neutralization process. Every pH neutralization operation requires a unique control system based on its properties and objective. Therefore, this paper focuses on the Fire Fly optimized ANN controller for the purposes of enhancing pH neutralization performance. By utilizing the realistic approach, the PID controllers are tuned to accomplish the regulation of pH neutralization and achieve the high performance of the operating process. Compared to the conventional controllers, the ANN predictive controller achieved faster solving time, lower peak shooting, and smoother manipulated variable behavior. According to the results, the controller performs well over the entire operating range and maintains its robustness despite changes in set points and loads. Real-time deployment in a laboratory-scale pH neutralization setup allows the assessment of controller performance in actual operational uncertainties, sensor noise, and actuator constraints. Incorporating the controller with industrial-grade hardware platforms such as PLCs or embedded systems further establishes its robustness and scalability, is needs to be considered in future research.

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