Optimization of Control Structures in Wastewater Treatment Plants for Enhanced Efficiency

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***Abstract*:** Wastewater Treatment Plants are crucial because they are ensuring environmental sustainability through effective wastewater treatment before discharge or reuse. Nevertheless, the power of these plants is compromised by aspects such as high energy usage, operational costs, and environmental problems like greenhouse gas production and sludge toxicity. This study will address optimization in the WWTP control structure by strengthening efficiency while observing minimum effluent quality compliant with regulatory necessities. By employing advanced control strategies such as real-time monitoring, artificial intelligence, and MPC, the work determines how the process automation might decrease energy use and increase removal efficiency of pollutant. Simulation-based model MATLAB with the utilization of GA, is used by the study, optimizing the operation of WWTP control systems against influent varied conditions such as dry and wet weather. The results show that the proposed AI-driven optimization method significantly improves pH stability, BOD, COD, and ammonia removal while reducing aeration energy consumption. The study concludes that the implementation of advanced control strategies in WWTP operations can lead to cost-effective and environmentally friendly wastewater treatment. Future research should focus on validating these optimization models in real-world settings to support large-scale implementation.

Keywords: Wastewater Treatment Plants, Control Structures, Optimization, Artificial Intelligence, Model Predictive Control, Energy Efficiency.

I. INTRODUCTION

WWTP are essentially public service systems that are meant to serve environmental purposes rather than generate revenue. There is no commercially viable product to recover the considerable energy, chemical, and sludge treatment costs involved in the process of removing pollution from waste water. The environmental impacts of WWTP operations further complicate the sustainability of these processes, including direct GHG emissions from biological processes, indirect GHG emissions from energy usage, and the toxicity of sludge disposal. Effective resource management and emission reduction are essential to ensure both economic viability and sustainability in WWTP operations [1]. Because of the complexity of WWTPs and the many different biological processes occurring, online instrumentation that is dependable, real-time measurements, and advanced control strategies can be more effective. Most of the alternative control methods proposed have been investigated, but not many have been tested in realistic environments with only a few attempts at real validation. Ultimately, the main objective of WWTPs is to reduce pollution levels in wastewater at the lowest possible cost while maintaining effluent quality within legal standards [2].

Wastewater treatment is divided into several stages to ensure the effective removal of pollutants and the safe disposal or reuse of treated water. The process starts with screening, where waste materials are filtered out using coarse screens for initial treatment, and fine screens may sometimes replace sedimentation. Solid waste is then shredded through commination before moving on to primary treatment. All of the suspended matters and floating materials are removed; in addition, large amounts of settled organic and inorganic matters along with grease, oil, BOD_5, and suspended solids are removed during this phase. In this stage, it also minimizes organic nitrogen, phosphorus, and heavy metals (HMs) with primary effluent. Secondary treatment then ensues, in which residual solids and biodegradable materials are deposited and broken down within an aeration tank using microorganisms that de-compose these wastes to inorganic end-products. High-rate processes such as trickling filters, activated sludge, and rotary biological contactors are mainly preferred as they have high efficiency regarding maintaining microbial populations under controlled conditions [3].

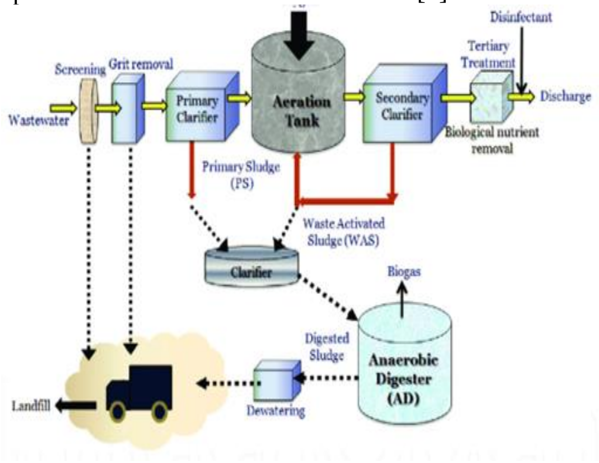

Figure 1 Types of wastewater treatment structure [4].

This figure 1 indicates the process of wastewater treatment, which involves preliminary, primary, secondary, and tertiary treatments in relation to sludge management through anaerobic digestion and biogas recovery towards final discharge or landfill disposal [4]. Furthermore, tertiary treatment improves the quality of water further from wastewater by removing additional organics, nutrients, turbidity, nitrogen, phosphorus, HMs, bacteria, and viruses to be reused for irrigation and other purposes. Disinfection is the last step, using chemicals or physical treatment, depending on the type of wastewater. It includes chlorination, ozone, or ultraviolet (UV), among others, because of the type and meant usage of the water. Chlorine and its compounds are commonly used; however, where pH and organic content differ, a different method might be used to ensure safety standards are met for the reclaimed water to be reused in reservoirs or urban systems of irrigation [3]. The quality and quantity of influent wastewater in treatment plants can vary greatly because of upstream processes, particularly in the paper industry. This leads to rapid fluctuations that can hinder treatment efficiency and affect effluent quality. Traditional COD analyses, whether conducted in a lab or online, tend to be infrequent, time-consuming, and expensive. Additionally, online analysers are at risk of fouling in harsh wastewater conditions, which makes them less ideal for efficient process operation [5].

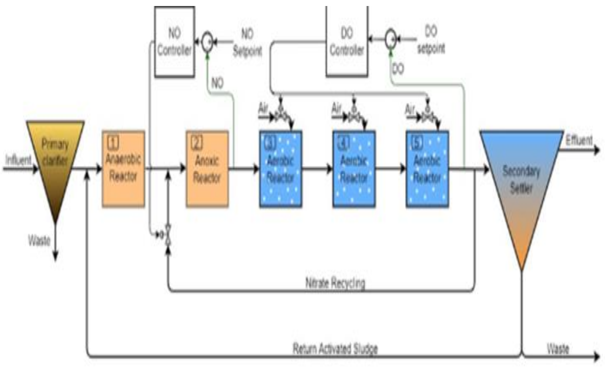

Figure 2 WWTP layout and its control system [6]

The figure 2 depicts a biological wastewater treatment process that focuses on nitrogen removal and the recycling of activated sludge. Initially, wastewater is separated in the primary clarifier before moving into an anaerobic reactor, where organic matter and nutrients are decomposed without oxygen [6]. This is followed by an anoxic reactor that facilitates denitrification, transforming nitrates into nitrogen gas. Subsequently, the wastewater flows through a series of aerobic reactors, where oxygen supports the microbial breakdown of organic matter and ammonia into nitrates. After treatment, the water enters a secondary settler to remove solids, and the clarified effluent is then discharged. The process also involves recycling nitrates back to the anoxic reactor to improve denitrification and returning activated sludge (RAS) from the secondary settler to sustain microbial populations. Controllers are available for DO and NO levels in order to keep the system operating effectively. Wastewater treatment plants (WWTPs) are subject to various influences from influent and thus require effective control systems for treatment. It covers the following important parts: control of the pumps and valves, enhancing energy efficiency as well as dynamic performance with electrohydraulic controllers [7], SCADA systems that help monitor and control remotely by centralizing data gathering and analysis [8], PLCs assisting in automated processes such as controlling dissolved oxygen levels in aeration tanks with real-time adjustment [9], and sensors, like the WaterTechw2 pH8000, that provide accurate pH and temperature measurement along with self-cleaning technology [10]. These technologies are important for ensuring the efficient and reliable operation of WWTPs.

A. Design Considerations for Control Structures of WWTP

Wastewater treatment is generally intended to remove or reduce contaminants that could pose a risk to human health and the environment if discharged untreated into surface or groundwater. While developed nations are making strides in treatment technologies to address increasing water demands, many developing countries struggle with inadequate infrastructure, often due to low public awareness and political obstacles [11]. A solid understanding of wastewater characteristics is essential for designing treatment facilities, as it affects layout, design, sizing, and location. Biological methods, including aerobic treatments like oxidation ponds and activated sludge, as well as anaerobic processes, are key components of effective treatment.

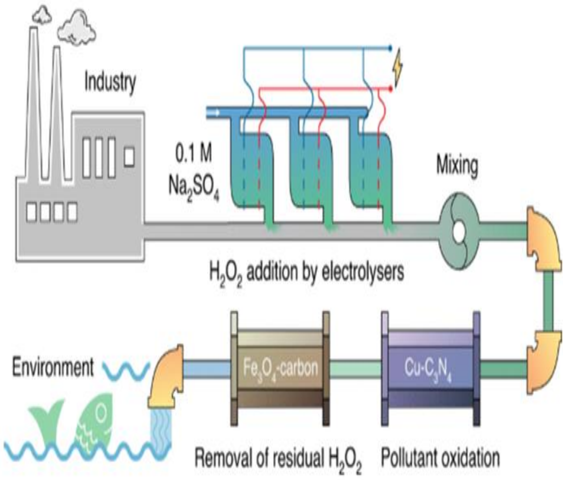

Figure 3. Drawing of wastewater control structure [12]

Figure 3 a process for treating industrial wastewater through advanced oxidation methods. Wastewater that contains 0.1 M sodium sulphate (Na_2SO_4) as an electrolyte is treated with hydrogen peroxide (H_2O_2) added through electrolysis, followed by thorough mixing to promote chemical reactions. The process consists of two main stages: first, the removal of any leftover H_2O_2 using a Fe_3O_4-carbon filter to avoid environmental damage, and second, the oxidation of pollutants with a Cu-C_3N_4 catalyst, which breaks down harmful substances into safer compounds [12]. Finally, the treated water is discharged into the environment in compliance with environmental regulations. In the Al-Hay station, initial designs emphasize an extended aeration activated sludge system, which is commonly used in Iraq due to its cost-effectiveness and ability to meet effluent standards [13]. Automation is vital for enhancing treatment processes by allowing precise control of variables, minimizing labor needs, and improving efficiency through data analysis and advanced control algorithms, ensuring optimal performance at larger scales.

B. Control Strategies in WWTP Operations

Real-time monitoring and control (RTC) systems for urban wastewater treatment require highly accurate and reliable sensors that can resist physical and chemical challenges, with the ability to continuously record and transmit data remotely. RTC concepts aim to optimize control procedures; for example, an implementation in Quebec addresses practical issues and considers future trends [14]. In addition to these, systems for adaptive DPC and based on data may also enhance performance of WWTPs by online optimal control via incorporation of the identifiers of the SOFNNs for predictions in real-time for the condition under dynamic, hence better performance control actions together with improved process operational efficiency [15].

C. Challenges in WWTP Control Structure Design

The increasing demand for water in agriculture, industry, and municipalities calls for the advanced wastewater treatment technologies to overcome the problem of water scarcity and removal of harmful substances that conventional processes cannot [16]. WWTPs are the biggest consumers of energy. The energy costs comprise 25%–40% of the WWTP's operation costs and are responsible for the emission of greenhouse gases. Sustainable practices and energy-efficient technologies, such as anaerobic digestion (AD) for the treatment of sludge, contribute to reducing the energy consumption as well as generation of renewable energy. Sludge treatment, a cost component taking up to 30% of WWTP's expenses, presents opportunities for further use of bio solids in agriculture and carbon sequestration [17, 18].

Having flexible and adaptive wastewater infrastructure is essential for the changing demands for water because of urbanization, technological innovation, and climatic change [19]. Engaging the community and training will enhance the performance of WWTPs, which in most rural areas, still lacks resources and awareness [20]. Accurate data on water demand and innovations for resource recovery need to be integrated into the design of efficient and resilient WWTPs. For example, statistics for average water consumption in municipalities like 350 liters per person per day in some regions can help design the infrastructure while increasing energy and water security [21, 22]. These developments highlight the role of planning and innovation in building wastewater systems.

II. LITERATURE REVIEW

According to an analysis by **Santi Bardeeniz et al. (2025) [23],** carbon dioxide treatment of alkaline wastewater can reduce chemical costs and provide a safer alternative to traditional methods. Narrow operational pH ranges and complex gas-liquid interactions, however, are challenges. Their work developed an artificial intelligence-powered control system that employs carbon dioxide in a tubular reactor at the bench scale for the treatment of alkaline wastewater. To adjust for the natural delays and model mismatches as well as pH disturbances, the proposed control system employs a linear controller, a Smith predictor, and an inverse neural network to control carbon dioxide gas flow in accordance with the desired setpoint. Validation of the proposed inverse neural controller was carried out using actual influence from an electroplating wastewater treatment facility; training was also performed on experimental data from bench-scale reactor pH treatment of synthetic alkaline wastewater. As shown in the results, the proposed strategy successfully keeps the target reactor output pH setpoint while improving the pH-adjusting efficiency by 72.24% and settling time up to 51.36% compared with a proportional-integral controller.

Photocatalytic-coupled microbial electrochemical systems (MESs) is a new technology in wastewater treatment invented by **Qianhao Zeng et al. (2025) [24],** which aims at overcoming some of the deficiencies found in conventional techniques, notably the inability to remove refractory pollutants and high energy consumption. With the simultaneous breakdown of refractory contaminants in wastewater, along with the recovery of bioenergy, technology has shown great promise for advancement. However, problems such as insufficient electrical power generation, photoelectric electrodes with unstable performance, and the conceptualization of high-amplification application systems already hindered practical application of the technology. Fundamentals and widespread coupling techniques of photocatalytic-coupled microbial electrochemical systems were elaborately. The previous work gave a comprehensive discussion of the ideal configurations for the effective treatment of wastewater containing numerous elements, which included nitrates, heavy metals, and refractory organic compounds. In addition, it summarized the synergistic effects of photodegradation and MES which advance the efficacy of pollutant degradation by several mechanisms such as a greater cytochrome potential difference, promotion of conductive nanowires formation, increased electron transfer rates, and inhibition of electron-hole recombination. Finally, their review highlighted the limitations in real-world applications and proposed some ways towards further developing this technology.

According to a study by **Zahra Parsa et al. (2024) [25],** the study focused on the need for the development of control techniques for wastewater treatment systems, which should be based on biological and advanced oxidation processes (AOPs).They ensured that although operational costs are kept to a minimum, quality efficiency consistently complies with environmental laws. It stressed the significance of understanding how dynamic the process is to produce effective control strategies. An explanation and list of the most widely used process control techniques applied in WWTPs are provided below. It underlined that the process of dynamic behaviour and the control purpose should be taken into consideration while choosing the appropriate control scheme. Their study went on to address the difficulties in controlling wastewater treatment processes, such as the shortcomings of developed models, the fact that most control strategies are only effective at the simulation stage, the necessity of real-time data, and the technical and financial complexities of putting advanced controller hardware into practice. It was addressed how building and deploying soft sensors or installing appropriate, precise hardware sensors in the right places throughout the process can meet the requirement for real-time data availability to achieve dependable control. In order to obtain strong and dependable control in WWTPs, the study suggested more research into the available actuators and the selection criteria, particularly for biological and AOP-based treatment techniques.

A novel modular model known as TURN-Sewers was introduced by **Natalia Duque et al. (2024) [26]** to investigate various modifications of centralized wastewater infrastructure toward more decentralized wastewater systems under various urban development scenarios. Comparing various policies and management approaches for sanitary wastewater infrastructure was made possible by the modular model's flexibility and computational efficiency when investigating transitions at the city size. Independent modules in TURN-Sewers replicate the creation, sizing, degradation, control, and computation of performance metrics for various wastewater systems. In order to assist infrastructure planners and other stakeholders in investigating various routes for the shift from centralized to decentralized wastewater infrastructure, the model made use of easily accessible spatial data. The ability of TURN-Sewers to establish various infrastructure management strategies for system extension, rehabilitation, and transition, as well as to evaluate the structural, hydraulic, and economic effects, is demonstrated by an example.

Maira Alvi et al. (2023) [27] looked into how modelling wastewater processes helps with tasks including data analysis, soft sensing, process prediction, and computer-aided wastewater system design. Large and intricate, wastewater treatment operations included several internal recycling loops, a high degree of disturbance variability, multiple regulatory mechanisms, and non-linear (usually stable) behaviour. Data-driven deep learning models are becoming a viable and supplemental method to the semi-mechanistic biochemical models that currently dominate research and application. However, because these modelling approaches have developed in distinct research and practice communities, there has been little recognition of the methods' advantages, disadvantages, parallels, and differences. By offering a thorough manual on deep learning techniques and how to apply them to wastewater process modelling, their work filled that knowledge vacuum. Experts in wastewater modelling who were acquainted with the well-established mechanistic modelling methodology and interested in the potential and difficulties presented by deep learning techniques were the target audience. They wrapped up by talking about and analysing the benefits of various approaches to modelling open-search problems and wastewater processes.

According to **Nitin Kumar Singh et al. (2023) [28],** machine learning (ML) and artificial intelligence (AI) are applied in a variety of fields. Applications of models based on AI and ML have also been documented for biological wastewater treatment system (WWTS) design and monitoring. The available data was examined and presented in terms of bibliometric analysis, the description of the model, particular applications, and key findings for the WWTS under investigation. In the biological wastewater treatment process, the most commonly utilized models were artificial neural networks (ANN), fuzzy logic (FL) algorithms, random forests (RF), and long short-term memory (LSTM). Predictive control of effluent characteristics, including solids, metallic, nutrients, and biological and chemical oxygen demands (BOD and COD), was used to test these models. In the majority of the studies, the accuracy analysis was conducted primarily using the following model performance indicators: determination coefficient (DC), mean square error (MSE), and root mean squared error (RMSE). Additionally, a summary of the results from several models is provided.

Table 1 Comparative Table of Wastewater Treatment Studies

Study	Focus Area	Key Contributions	Challenges Identified
Santi Bardeeniz et al. (2025)	AI-driven CO2-based alkaline wastewater treatment	Developed an AI-powered control system for CO2-based treatment, improving pH-adjusting efficiency by 72.24% and settling time by 51.36% compared to PI controllers.	Narrow operational pH ranges and complex gas-liquid interactions.
Qianhao Zeng et al. (2025)	Photocatalytic-coupled microbial electrochemical systems	Proposed a system for simultaneous pollutant degradation and bioenergy recovery, but noted challenges with power production and system scalability.	Inadequate power production, unstable electrodes, and limited scalability.
Zahra Parsa et al. (2024)	Control techniques for biological and advanced oxidation processes in wastewater treatment	Emphasized the importance of real-time control in wastewater treatment, discussing sensor placement and control challenges.	Model mismatches, real-time data limitations, and hardware complexities.
Natalia Duque et al. (2024)	Modular model for decentralized	Developed TURN-Sewers, a modular model for analyzing centralized-to-decentralized	Urban planning and infrastructure transition complexities.

	wastewater infrastructure	wastewater transitions using spatial data.	
Maira Alvi et al. (2023)	Deep learning for wastewater process modeling	Provided a guide on applying deep learning models to wastewater process modeling, bridging knowledge gaps with mechanistic models.	Limited recognition and integration of deep learning with mechanistic models.
Nitin Kumar Singh et al. (2023)	Machine learning and AI in biological wastewater treatment	Reviewed AI/ML applications in biological wastewater treatment, highlighting ANN, FL, RF, and LSTM models for effluent prediction.	Accuracy and reliability of AI/ML models in biological wastewater treatment.

III. OBJECTIVES

- To optimize the performance of the Wastewater Treatment Plant (WWTP) by implementing various control strategies in attempts to improve the removal of organic substances and nitrogen.
- To further improve strategies such as: regulated concentrations of dissolved oxygen in the aeration tanks, controlled nitrogen through internal recirculation across a range of system configurations with the optimal genetic algorithm-based control approach.
- To validate the proposed algorithm under two different influent conditions, dry and rainy, as a means of testing its applicability and responsiveness in different operational scenarios.

IV. METHODOLOGY

This section comprises with an analytical and numerical description of proposed algorithm for sentiment analysis of a power buffer which is simulated to obtain the performance of the proposed algorithm.

To evaluate the performance of proposed algorithm scheme, the proposed algorithm is simulated in following configuration:

Pentium Core I5-2430M CPU @ 2.40 GHz

4GB RAM

64-bit Operating System

Matlab Platform

A. Replication Environment

MATLAB is the abbreviation for MATrix LABoratory. It is a specific programming package that may carry out fast and efficient logical calculations and input/output operations. It has as many functions as inbuilt for a wide variety of computations. It is accompanied by several toolboxes based on specific analytical disciplines, including statistics, optimization, partial differential equation solutions, and data analysis. This work has been performed by implementing the algorithm proposed through simulation using MATLAB platform. It generates graphical representation using measurement toolboxes and in-built functions to make the representation visible. Also, MATLAB functions have been utilized in performing simulation to analyse outcome by comparing its performance with previously built models.

B. Optimization of Wastewater Treatment Plants

Wastewater produced from household, industrial, commercial, and agricultural sources and storm water and surface runoff, requires appropriate treatment prior to discharge into the environment. Among various available techniques, the widely accepted process is the bio-activated sludge process of wastewater treatment. Wastewater treatment plants are nonlinear, complex systems whose effluent quality cannot be precisely controlled because of the interaction and variability of biochemical and biological processes, in addition to variability of the inflow.

Three benchmark WWTP models, focusing on a nitrogen (N) removal plant, WWTP1 with five serial reactors and a secondary sedimentation tank (SEC). The system consists of anoxic (ANOX1, 2) and aerobic (AER1, 2, 3) tanks, connected through an internal recycling (QINTR), which increases the efficiency of nitrogen removal.

The mathematical modelling of this process results in a system of ordinary differential equations (ODEs) and nonlinear algebraic equations (AEs), which form a differential-algebraic equation (DAE) system. The proposed method separately handles the differential equations using an explicit ODE solver while addressing the nonlinear algebraic equations iteratively through a multi-dimensional Newton-Raphson method, ensuring accurate computation of species concentrations over time.

$$\mathrm{Z}_{i+1} = \mathrm{Z}_i - J_F(\mathrm{Z}_i)^{-1}\, G(\mathrm{Z}_i) \quad (1)$$

In the iterative solution process where Z_i represents the vector of equilibrium states $(z_{1'i}, z_{2'i}, \ldots\ldots, z_{n'i})$ obtained from the previous iteration step$i$. The function $G(\mathrm{Z}_i)$is a vector containing the values of a set of implicit algebraic equations:

$$(\ g_1(z_1, z_2, .., z_n)\ \ g_2(z_1, z_2, .., z_n), \ldots, g_n(z_1, z_2, ., z_n)\ ) \quad (2)$$

It follows that the partial derivatives of must be zero at equilibrium. The full analytic JacobianJ_F, comprised of all row matrices of first-order partial derivatives in all variable, is used for the new state computation, requiring symbolic manipulation of the algebraic equation to find the matrix of all first-order partial derivatives:

$$J¼v(gi, \ldots, gn)/v(zi, \ldots, zn) \quad (3)$$

A numerical Jacobian was found to be less convergent but is included in the given code. The iteration process is repeated if the elements of the error function are larger than the absolute tolerance, which in our case is set to 10^{-12}.

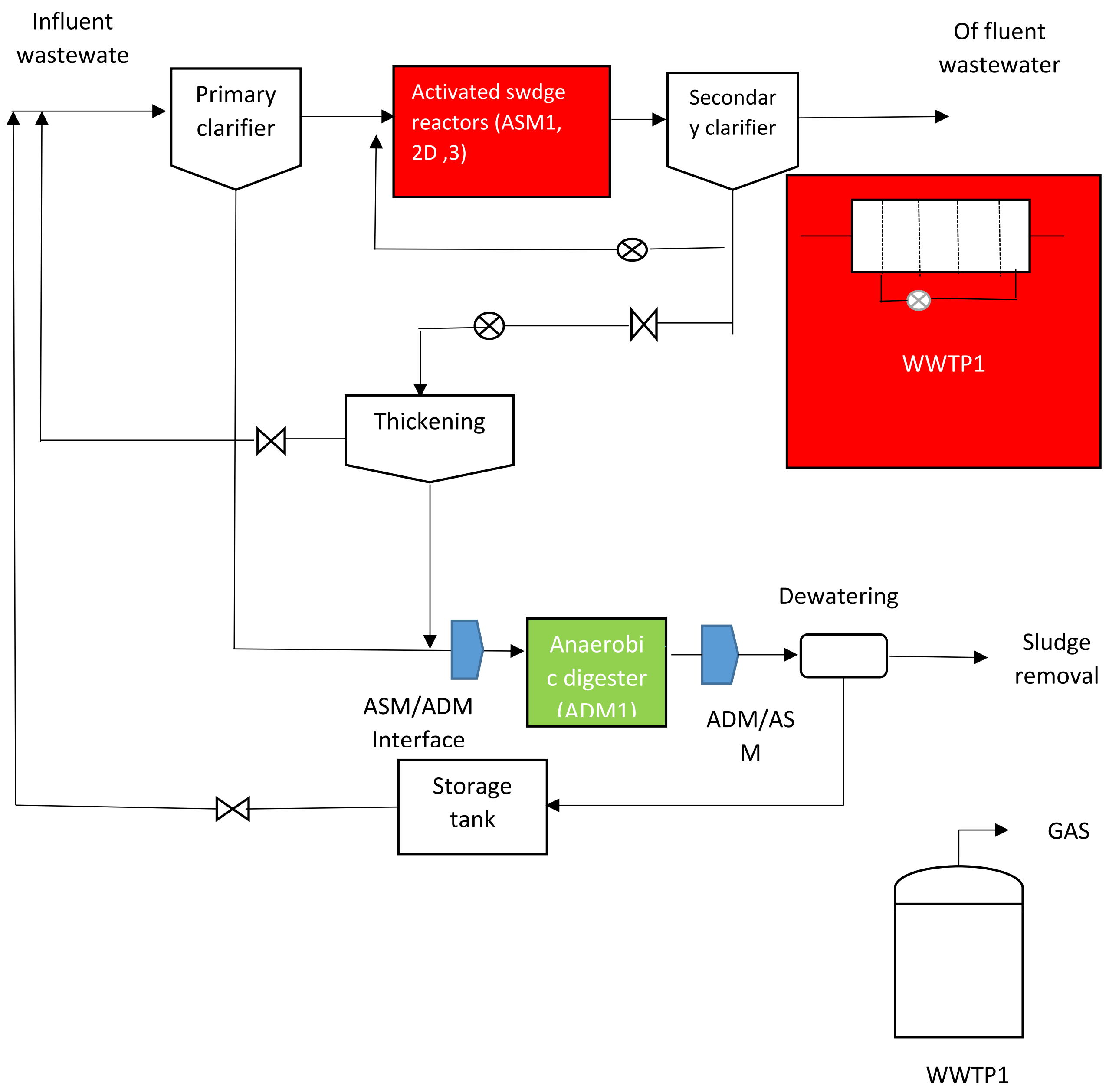

Figure 4 Flow diagram of the wastewater treatment plants under study.

The default implementation of the three ASM models (ASM and ADM) was modified to include the ion speciation/pairing model, resulting in significant changes. The ASM alkalinity state (SALK) was replaced with inorganic carbon (SIC), which ensures mass balance by considering carbon, nitrogen, phosphorus, oxygen, and hydrogen across all state variables per COD mass. Similarly, phosphorus was incorporated using the same method. The model also features CO_2 stripping, where the CO_2 volumetric mass transfer coefficient ($KLaCO_2$) is calculated based on the oxygen transfer coefficient (KLa) and adjusted for the square root of the diffusivity ratio between O_2 and CO_2. To estimate the saturation concentration (${S^*}_{CO_2}$), the Henry coefficient was modified using the van't Hoff equation (KH). Furthermore, pH is vital for microbial growth, as it affects enzymatic activities. While most microbes prefer a pH range of 6.5 to 8.5, there are exceptions, such as fungi that thrive in acidic conditions and certain bacteria and protozoa that do well in neutral environments. Any unusual pH changes in biological treatment processes can disrupt the removal of organic compounds, ultimately affecting biochemical oxygen demand (BOD).

C. Developing a genetic algorithm design for plants

The Genetic Algorithm (GA) is a powerful optimization technique that works through a series of iterations to generate and improve solutions, making it particularly effective in situations where traditional gradient-based methods may not be applicable. The process starts with an initial group of candidate solutions, which are refined over time using genetic operators. In each iteration, the algorithm identifies a set of potential new solutions by applying these operators to the current candidates, then selects a subset for evaluation. The top-performing candidates are carried over to the next iteration, gradually progressing toward an optimal solution based on specific convergence criteria. GA is inspired by the principles of natural selection and evolution, employing genetic mechanisms like selection, crossover, and mutation to enhance solutions. These adaptive strategies help the algorithm avoid getting stuck in local optima and effectively explore the global search space. As a probabilistic method, GA balances exploration and exploitation while systematically investigating neighbouring states, resulting in successful global optimization.

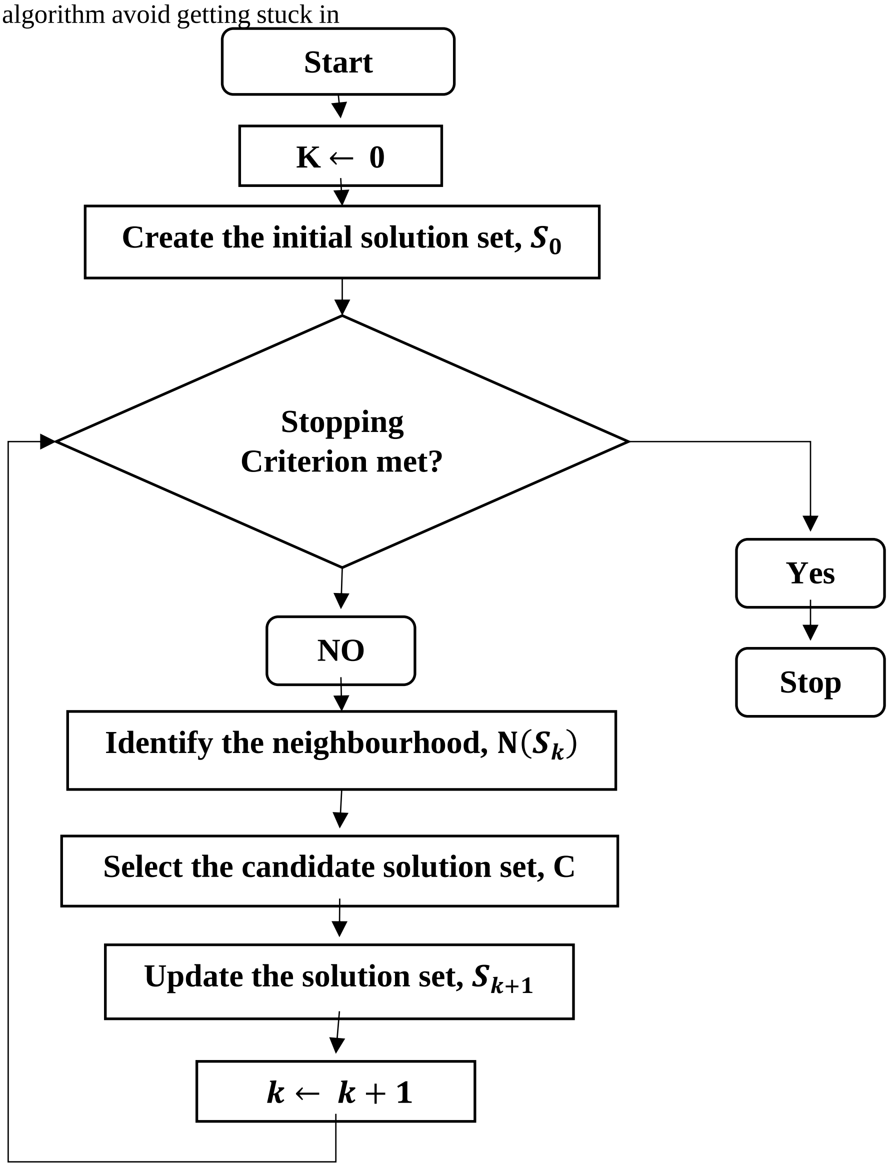

Figure 5 Genetic Algorithm performance flow chart

The optimization of a general parameter, such as membership functions, within a MATLAB-based GA implementation starts with a population of 20 to 100 individuals, which are represented as either binary or real sequences. Each chromosome's performance is assessed using a cost function, with fitness evaluated based on operational and quality metrics like the Operational Cost Index (OCI) and the Effluent Quality Index (EQI). The weight parameters (W_1 and W_2) are adjusted according to the objective: minimizing OCI while ensuring EQI remains stable (W_1=1, W_2=0), minimizing EQI while keeping OCI constant (W_1=0, W_2=1), or optimizing both indices simultaneously. The GA setup typically includes a population size of 150, runs for 300 generations, and has a crossover probability of 0.8 along with a mutation probability of 0.001. The algorithm continues until one of two stopping criteria is met: either a certain fraction of genes has converged, or there is no significant improvement over time.

Table 2 Weighting factors that are optimized for different weather conditions

Weather condition	Weight W_1	Weight W_2	Emphasis
Dry	0.28	0.72	High priority on minimizing EQI while maintaining OCI.
Rainy	0.33	0.67	Slightly increased emphasis on OCI compared to EQI

V. RESULTS AND DISCUSSION

Wastewater treatment processes are nonlinear, multi-variable, unstable, and time-varying in nature. These characteristics make their operation and management challenging. Under stricter water quality standards, energy conservation and emission reduction have become critical concerns. A generalized simplified supervisory control method was used to design an optimal WWTP control strategy aimed at reducing annual energy consumption while enhancing the water treatment process. In addition, control strategy with maximum use of optimum residence time coupled with internal recycle and adaptive genetic algorithm was further used to select the optimal combination of operating variable for bettering water quality, and artificial-intelligence-based technique has been regarded as a rich tool for weighing multiple conflicting design objectives, among which are also pH, BOD, COD, and operative stability in case of WWTPs. A comparison of Outputs of two simulated models developed and implemented in MATLAB/Simulink using commands. The first model uses a reduced supervisory strategy for controlling the system, while the second model uses an optimization strategy of a genetic algorithm for improving the plant's performance. The study analyses the plant performance under two different input conditions, namely:

Case 1: where the plant is fed with influent data on dry weather and

Case 2: where the plant is fed with influent data on rainy weather. The performance of the two control strategies is compared through different wastewater treatment parameters, including pH, COD, BOD, and suspended solids in the effluent, under these distinct input scenarios.

A. Case 1: the plant was fed in dry weather based on influent data

The process of water treatment is evaluated in this case by influent data associated with dry weather conditions. In the complex process of WWTPs, the challenge of balancing multiple performance indicators is addressed through the implementation of an optimization control strategy based on a genetic algorithm. Analysing the influent data using the simplified supervisory control method as well as genetic algorithm-based approach, with specific focus on critical parameters such as pH values at different reactors. Effluent data, including necessary plant performance parameters, is analysed and compared to evaluate the strength of the algorithms in optimizing the treatment process.

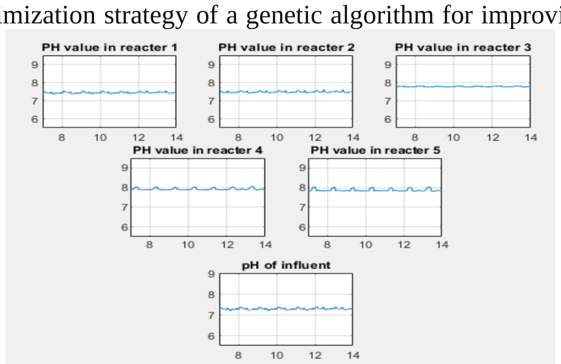

Figure 6 PH values at various stages of WWTP with simplified supervisory controller in case 1

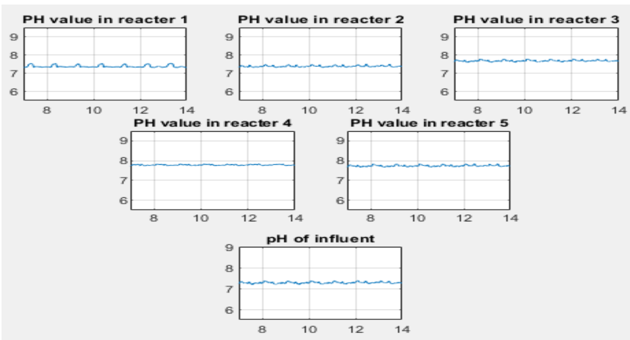

Figure 7 PH values at various stages of WWTP with proposed AI based controller in case1

A multi-tank WWTP has been designed, and pH levels at different stages have been evaluated, as shown in Figure 6 for the regulation and maintenance of desired pH levels at all stages, a standard supervisory control system has been adopted. A WWTP has been designed as a multi-tanked structure with pH evaluation across different stages shown in Figure 7. For improving the pH value in the tanks, an AI-based genetic algorithm control system was proposed to enhance the process effectively and precisely with proper regulation during the entire procedure. Figure 8, Energy utilization in the aeration of WWTP comparing the two control strategies, Standard supervisory controller represented by the blue line with consumption, 6500 kWh/d. The green line represents the proposed controller that can reduce energy consumption to around 6450kWh/d.

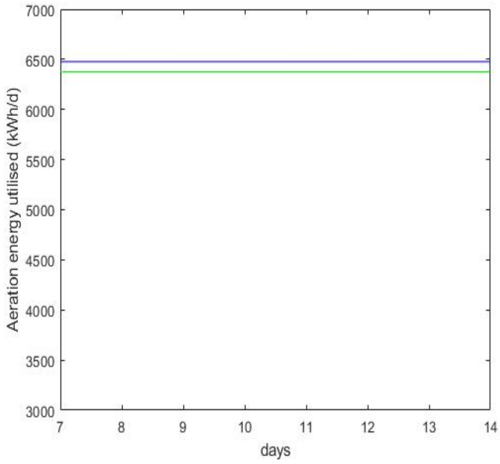

Figure 8 Comparative analysis of aeration energy used to use two controllers in WWTP in case 1

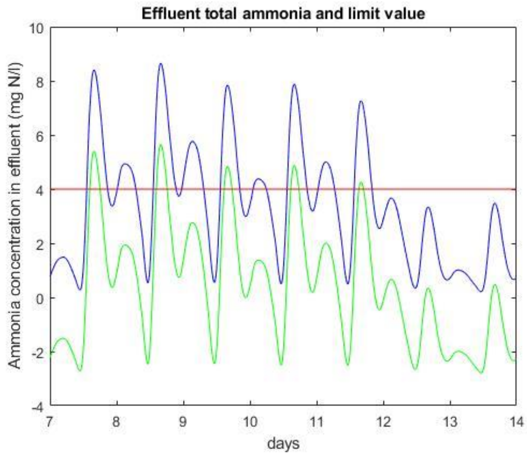

Figure 9 Comparative analysis of Ammonia in effluent using two controllers in WWTP in case 1

The blue graph of figure 9 depicts the ammonia concentration in the effluent using standard supervisory controller and the green graphs depicts the ammonia concentration in the effluent from the proposed controller. The red graphs is the limit value and when compared the green graphs is more under the limit as compared to the blue graph. Figure 10 Comparison of BOD concentration in the effluent of two control approaches. The blue trace is standard supervisory control, whereas the green trace is a new control approach. In this scenario, the proposed controller resulted in a lower BOD concentration that means fewer organic compounds in water. Figure 11 Comparison of COD concentration in the effluent using two control methods. The blue graph is the standard supervisory controller, and the green graph is the proposed controller that achieves a lower COD concentration, meaning a less organic compound concentration in the water.

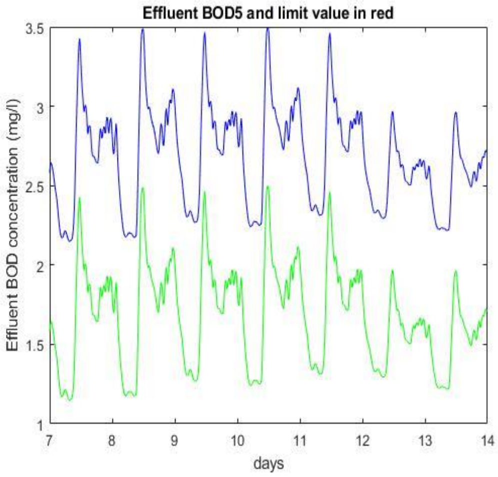

Figure 10 Comparative analysis BOD in effluent using two controllers in WWTP in case 1

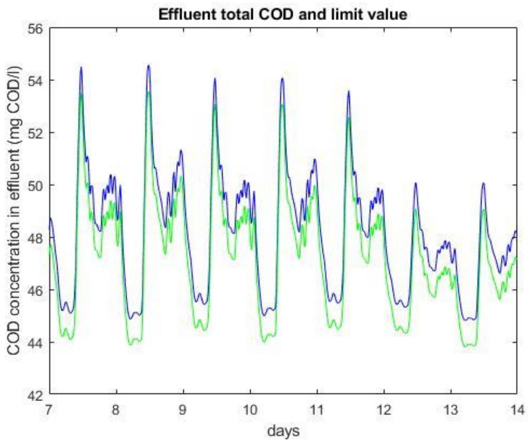

Figure 11 Comparative analysis of COD using two controllers in WWTP in case 1

B. Case 2: Dry Weather Condition-Based Influent Data.

The water treatment process in this case has been fed with data associated with rainy weather conditions. Aiming at the conflict of multiple performance indicators in the complex wastewater treatment process (WWTPs), an effective optimization control based on genetic algorithm is designed and then the analysis of influent data is done by both the algorithms and data is analysed such as PH values in the various reactors. The effluent data are also analysed for various plant parameters and compared with the two algorithms. At 8.5 the rainy water influent data is introduced to bring about changes in the input water PH level. The water treatment process in this scenario is fed with influent data simulating rainy weather conditions. For the case of complex WWTPs with a conflict among several performance indicators, an effective optimization control based on a genetic algorithm is developed. Both algorithms examine the influent data, which include pH values in different reactors. Effluent data for major plant parameters are also evaluated and compared for both control methods. At a pH level of 8.5, rainy water influent data is introduced to observe its impact on the input water pH.

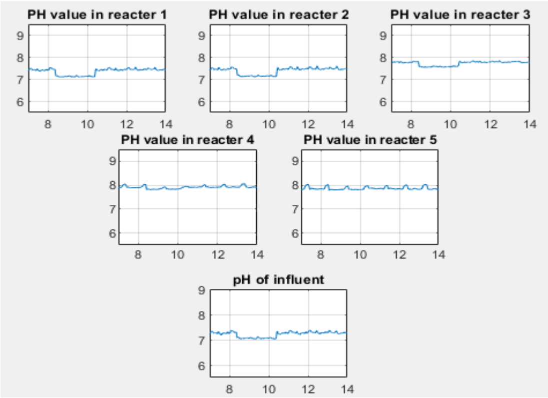

Figure 12 PH values at various stages of WWTP with simplified supervisory controller in case 2

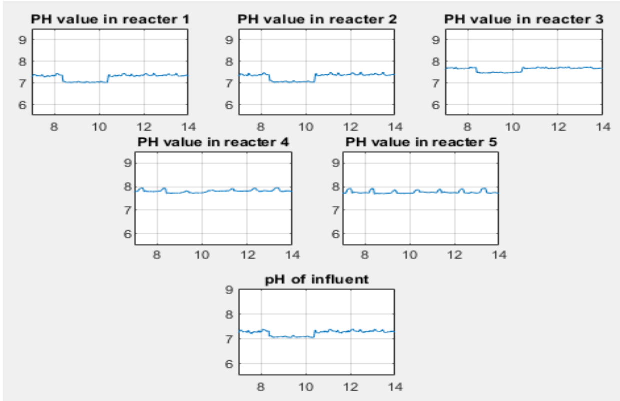

Figure 13 PH values at various stages of WWTP with AI based controller in case 2

A WWTP with multiple tanks has been designed. The pH levels at various stages are evaluated, as shown in Figure 12. This outcome is achieved using rainy water influent data through the standard supervisory control system. A WWTP with multiple tanks is designed and pH levels at various stages are assessed as shown in Figure 13. AI-based genetic algorithm control has been implemented for the same with rainy water influent data.

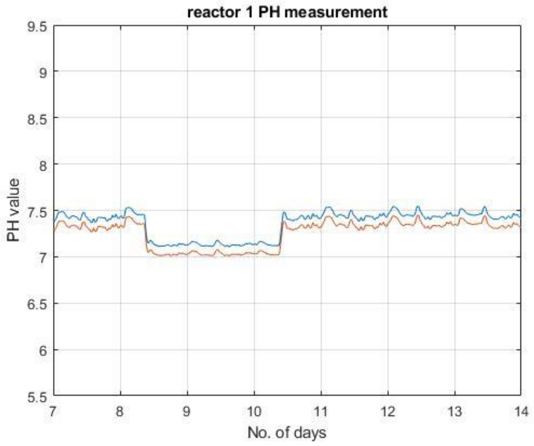

Figure 14 Comparative analysis of PH at reactor 1 of two controllers in WWTP in case 2

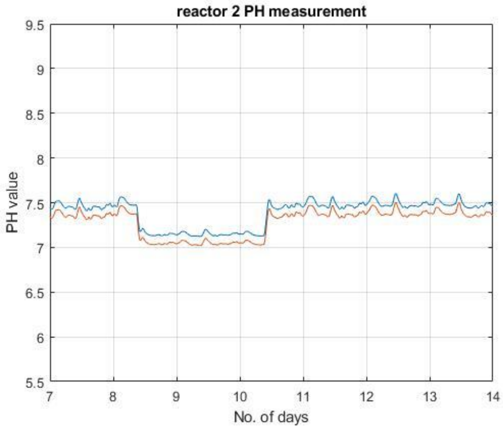

Figure 15 Comparative analysis of PH at reactor 2 of two controllers in WWTP in case 2

Figure 14 pH in Reactor 1 in WWTP is using two control methods. The blue curve is the standard supervisory controller, and the red curve is the proposed controller; the latter keeps near 7, showing higher stability and better control. Figure 15 comparison of pH in Reactor 2 of the WWTP using two control methods. The blue graph is the standard supervisory controller, and the red graph is the proposed controller, which keeps the pH level closer to 7and indicates better stability and regulation.

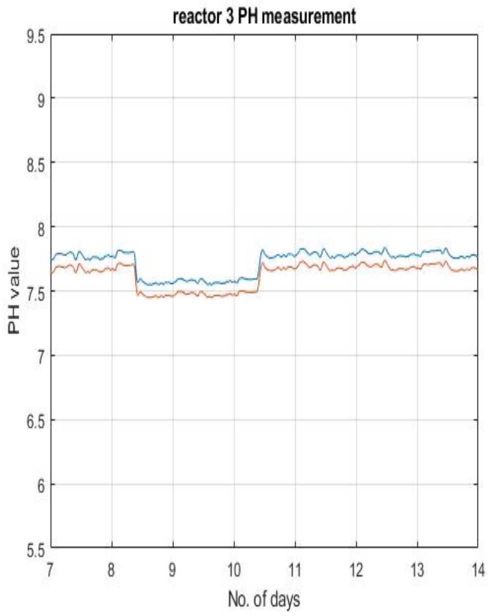

Figure 16 Comparative analysis of PH at reactor 3 of two controllers in WWTP in case 2

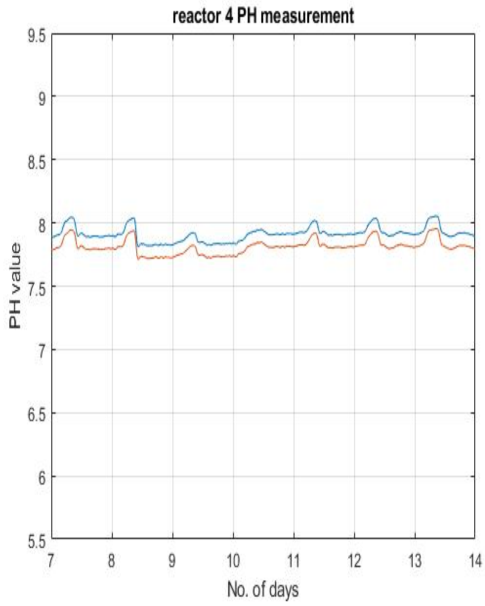

Figure 17 Comparative analysis of PH at reactor 4 of two controllers in WWTP in case 2

Figure 16. pH values using two control approaches in Reactor 3 of WWTP. Blue curve is the traditional supervisory controller, and the red curve is the proposed one, which obtained better stability and control as it approaches a pH value close to 7. Figure 17 pH of Reactor 4 with the two control methods. Blue curve is for the standard supervisory controller while the red curve is for the proposed controller which has a better pH close to 7 as shown in figure 17, it is stable and regulated.

VI. CONCLUSION

Optimization of the control structures of Wastewater Treatment Plants (WWTPs) aims to enhance their efficiency, lower operational costs, and improve the quality of the effluent from the plants, using advanced control strategies. This was achieved using a Genetic Algorithm (GA)-based optimization methodology, simulated by MATLAB, as a means to compare its efficacy with traditional supervisory control techniques. The robustness of the proposed approach was tested under two different influent conditions, namely dry and rainy weather. The WWTP model included several biological processes, such as nitrogen removal, and established a structured optimization framework that integrated controls for dissolved oxygen and nitrogen recirculation. Optimizing the weighting factors W_1 and W_2 of the genetic algorithm, adapting to the conditions of the variable environment, were based on defined optimization objectives. Mathematical modelling along with iterative numerical solutions and heuristic optimization techniques for improvement in performance while maintaining a mass balance over essential elements carbon, nitrogen, and phosphorus was used in the plant design. Results show that the GA-based control strategy outperformed the traditional supervisory control method in several key performance indicators such as pH stability, BOD, COD, ammonia concentration, and aeration energy consumption. Under both dry and rainy conditions, the proposed GA approach kept the pH level closer to neutral, around 7, thereby allowing for more stable microbial activity and better pollutant degradation. Energy consumption for aeration decreased from about 6500 kWh/day to 6450 kWh/day, which reflected improved operational efficiency. In addition, effluent quality improved significantly, with reduced concentrations of ammonia, BOD, and COD, which reflected the effectiveness of the proposed optimization strategy in maintaining high standards.

Conflict of Interest: The corresponding author, on behalf of second author, confirms that there are no conflicts of interest to disclose.

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