Applied Chemical Engineering (2025) Volume 8 Issue 3 ISSN: 2578-2010 (O)
doi: 10.59429/ace.v8i3.5736

ORIGINAL RESEARCH ARTICLE

Optimization of the design of anoxic/oxic process in wastewater treatment plant using genetic algorithms

Ahmed Makki AL-Sulaiman[1*], Ali Turki Alzeyadi[1], Hasan Mahdi M. Al-Khateeb[2]

[1] *Civil Eng. Dep, College of Engineering, University of Al-Qadisiyah, 58002, Qadisiyah, Iraq,*

[2] *Civil Engineering Dep, Faculty of Engineering, University of Kufa, 540011,Najaf Province, Iraq*

***Corresponding author:** Ahmed Makki AL-Sulaiman, ahmed.jabbar@qu.edu.iq

ABSTRACT

Optimizing the biodegradation process in wastewater treatment plants (WWTPs) is a crucial factor in enhancing the performance and cost-effectiveness of biological treatment. This study investigates the optimization of anoxic/oxic processes using genetic algorithms (GA) to minimize capital, maintenance, and operational costs while improving nitrogen removal efficiency. A WWTP in Karbala, Iraq, was selected as a case study, and GA was applied to identify the optimum design parameters for different influent conditions. The results indicate that the optimal detention time for anoxic units ranges from 3 to 4 hours, while oxic units perform best with detention times between 8 and 12 hours. The return activated sludge (RAS) cycle was optimized at 0.8–1.5 hours, with an ideal solids retention time (SRT) of 13 days. For the secondary clarifier, optimum diameters were found to be 90 m, 50 m, and 15 m at maximum, average, and minimum flowrates, respectively. The GA-based approach demonstrates robust performance in handling multi-variable optimization, ensuring stable treatment efficiency under varying influent loads. Findings highlight that efficiency increases from 85% to 98% with decreasing influent flow, while stability is maintained despite fluctuations in suspended solids. This work confirms that GA provides an effective decision-support tool for WWTP design, offering reliable parameter predictions that enhance system sustainability and adaptability. The proposed framework can guide future developments in wastewater process optimization and serve as a transferable methodology for other environmental engineering applications.

Keywords: Anoxic; oxic; optimization; wwtp; genetic algorithm

ARTICLE INFO

Received: 25 August 2025
Accepted: 12 September 2025
Available online: 18 September 2025

1. Introduction

Nitrogen is a necessary nutrient for the synthesis of proteins, amino acids, nucleic acids, and other compounds. It is mainly absorbed as ammonium or nitrate through fine roots [1,2]. Excess of nitrogen can harm aquatic habitats by decreasing dissolved oxygen levels and eutrophicating water systems, which can kill fish and other marine life [3,4]. Numerous nitrogen-containing pollutants, including ammoniac nitrogen, nitrite nitrogen, nitrate nitrogen, etc., are frequently found in wastewater [5]. In order to stop the careless discharge of sewage below the legal limit, wastewater must be denitrified [6]. hysical, chemical, and biological processes can be used to categorize the primary methods of removing nitrogen from wastewater [7,8]. Numerous physical treatment techniques, such as ion exchange, adsorption, and ammonia stripping, are costly and result in secondary pollution that needs to be addressed further [9,12]. Chemical treatment techniques such as precipitation, magnesium ammonium phosphate hexahydrate, and breakpoint chlorination are costly, labor-intensive, and necessitate secondary processing [13,16]. The biological option is well-developed. But the procedure is time-consuming, energy-intensive, and frequently necessitates additional carbon sources. With no secondary pollution and a high pollutant degradation efficiency [17]. Numerous researchers have been written about the removal of nitrogen from wastewater [18,20]. One of the significant issues in terms of sewage treatment is to dispose of it into the aquatic systems as a harmless influent within a specific period at a low treatment cost. This is achieved through suitable scientific and practical methods to reach the maximum possible efficiency of sewage treatment. Different optimization methods have been used to describe the optimal design for biological treatment in wastewater treatment plants, and the genetic algorithm (GA) is one of them. The (GA) approach is considered a robust tool for the optimization of biological processes. It can provide an estimation for the optimal processing design according to the constraints of the required quality of the effluent. [21]. Busacca, et al., (2001) Stated that the GA includes many analytical features in dealing with data, such as dealing with a large number of variables and different types of them, such as continuous or discrete variables. GA provides a list of optimum variables instead of a single solution. Moreover, it works with numerical, experimental, or analytical functions. Additionally, GA can obtain the most effective cost of the selected process [22]. The goal of the genetic-based control algorithm for biological wastewater treatment facilities is to lower operating costs while simultaneously improving effluent quality. Rather of keeping the dissolved oxygen level in the final basin constant, the suggested controller enables it to be changed based on operational circumstances. (GA) is employed in the higher-level control design to confirm the intended value of the lower level according to the concentration values of ammonium and ammonia nitrogen in the tertiary treatment. An adjustment zone is identified in order to change the higher level's tuning parameters. As a result, the effluent quality is enhanced, which contributes to a reduction in overall operating expenses. The benefits of the suggested approach are illustrated by simulation results [23]. Explains how to use a stochastic optimization approach (GA) to solve the aeration optimization problem of a wastewater treatment facility that is intermittently aerated. By gradually turning the aeration on and off, this method creates the alternating oxic and anoxic conditions required for nitrogen removal in a single basin. Additionally, these studies had to simplify the problems in order to employ optimization techniques, which typically need a large amount of computing power to provide merely a local optimum for the problem. Using a full model of the treatment process, the demonstration demonstrates an optimization technique to minimize the pollutant load in the receiving water body rather than the operational cost. The findings were assessed using strict evaluation criteria and demonstrated that, in comparison to conventional control systems, an optimal solution may be identified quickly utilizing a GA-based optimization strategy, which can save up to 10% on energy usage and pollutant load [24].The optimization of complete wastewater systems receives more attention since it has become clear that the current approach of optimizing the subsystems of sewerage often results in sub-optimal solutions. However, because of its intricacy, it has proven to be quite problematic in practice. The optimization target, which is determined by an objective function, and the numerous variables involved (multi-dimensional search) are connected to the wastewater system optimization problem. GA is one of the search or optimization methods that can handle such complicated environments. GA has the potential to be used to optimize wastewater systems. Key components for a successful GA application for this kind of challenge were the goal function specification and the GA's properties, particularly the mutation probability. It is determined that GAs can solve extremely difficult optimization issues pertaining to the enhancement of entire wastewater systems. A comparative analysis of neural networks and genetic algorithms for wastewater characterization from spectrophotometry was performed. Also, optimal control of wastewater treatment plants through these artificial networks and genetic algorithms [25,26].

2. Materials and methods

2.1. Study area

In this work, the properties of the influent of the anoxic/oxic treatment were determined to correspond to those of the effluent from Karbala Unified Wastewater Treatment Plant (WWTP), located on the Karbala–Najaf highway, south of Karbala city, west of central Baghdad. The Karbala government wastewater treatment plant is located at 32°32'21"N, and 44°04'55"E, as shown in Figure 1, which shows a satellite image taken from Google Earth of the WWTP. It is located in the town of Hor Mansour, near Lake Razzaza.

Figure 1. Karbala Sewage Treatment Plant station's location

The sewage is treated biologically by using a conventional activated sludge unit as a secondary treatment in the Wastewater Treatment Plant (WWTP). The Total nitrogen was obtained from the laboratory of the sewage treatment plant for 12 months along the year 2024 as depicted in Figure 2.

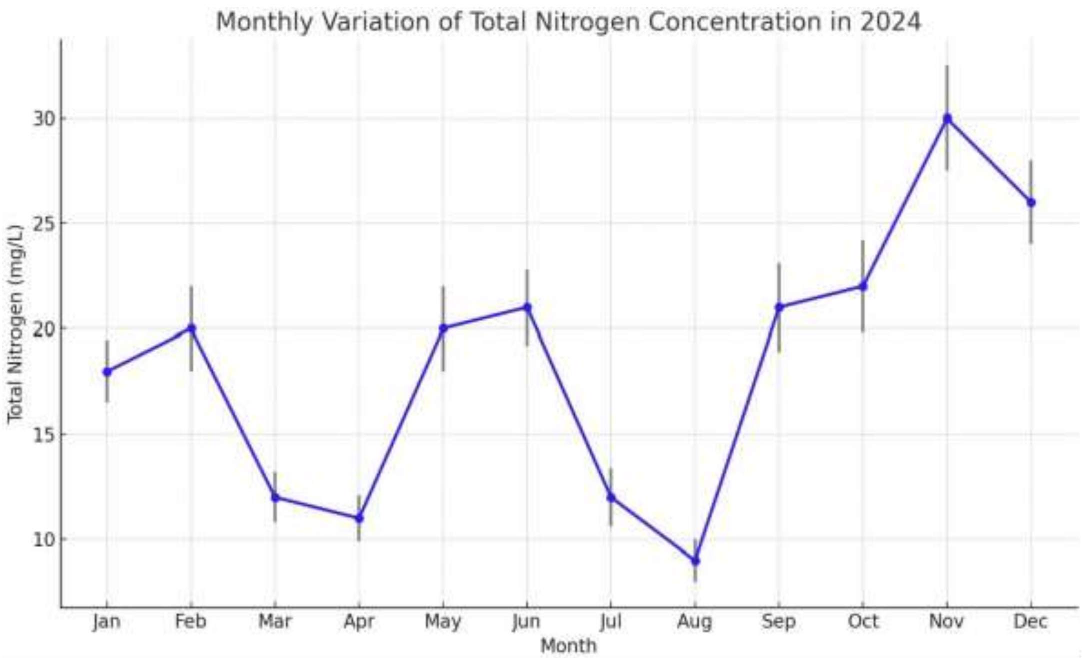

Figure 2. Total Nitrogen Effluent from Sewage Treatment Plant

Accurately determining the flow rate values in a wastewater treatment plant (WWTP) is crucial for optimizing the sewage treatment process at every stage. Thus, the flowrates at the Karbala sewage treatment facility were estimated as (170000, 60000, and 40000) m^3/day for the maximum, average, and minimum flowrates, respectively.

2.2. Characteristics of wastewater

Monthly analysis is conducted to determine the wastewater properties at the WWTP. The characteristics examined include pH, Electrical Conductivity (EC), Temperature, Total Dissolved Solids (TDS), Total Suspended Solids (TSS), Chemical Oxygen Demand (COD), Biological Oxygen Demands (BOD_5), Total Phosphorous (TP) and Total Kjeldahl Nitrogen (TKN). Table 1 displays the levels of important water quality metrics that are associated with the quality of wastewater influent. The primary sources of wastewater influent are predominantly derived from municipal sewage, along with a potential combination of stormwater and surface water.

Table 1. Characteristics of wastewater samples during the study period

Parameter	Unit	Min. value	Max. value	Average
pH	---	7.3	8.04	7.66
Electrical Conductivity (EC)	ms/cm	4687	6180	5501
Temperature	ºC	20.1	33.7	29.63
Total Dissolved Solids (TDS)	mg/L	3144	4374	3710.57
Total Suspended Solids (TSS)	mg/L	40	140	80.06
Chemical Oxygen Demand (COD)	mg O_2/L	140	250	162.28
Biological Oxygen Demands (BOD_5)	mg O_2/L	50	115	67.86
Total Phosphorous (T. P.)	mg/L	4.7	9.6	7.625
Total Kjeldahl Nitrogen (TKN)	mg/L	19.26	32.9	25.415

2.3. WWTP operation and design criterion

The treatment plant consists of anoxic, oxic, and secondary clarifier units. The incorporation of these units is essential to the biological nutrient removal process in contemporary wastewater treatment facilities. Comprehending the functions and design concerns of each unit is crucial for the effective operation and enhancement of WWTPs, finally guaranteeing the generation of top-notch effluent that complies with regulatory criteria and safeguards the environment. Table 2 presents the design criterion that this research will use to get the optimal design for producing high-quality effluent from the WWTP.

Table 2. Adopted design of anoxic/oxic units

Treatment Unit	Design Criteria	Unit	Value
Anoxic	Detention Time (t_{an})	hr	3~4
	Detention Time (t_a)	hr	8~14
Oxic	Solids retaining time (SRT)	day	8~15
	Return sludge (R)	hr	0.8~1.5
Secondary Clarifier	Diameter (Ds)	m	15~92

The research work is concentrated on optimizing the design criteria at the maximum, average, and minimum values of TNin, which are 10, 20, and 30 mg/L, respectively. This is done by evaluating the TN_{ef} values of 4, 5, and 6 mg/L. The selected TN_{in} levels were those of the secondary effluent from Sewage in Karbala City. The chosen TN_{ef} values were carefully selected to fall within the acceptable range for water reuse in agricultural and domestic uses. The results obtained from applying genetic algorithms (GA) for the optimal design were graphed to compare each design criterion against TN_{ef} for various TN_{in} values at the highest influent flowrate. The treatment plant consists of anoxic, oxic, and secondary clarifier units. In the anoxic zone, denitrification is achieved by facultative bacteria that reduce nitrate and nitrite into nitrogen gas in the absence of oxygen. This is followed by the oxic zone, where nitrifying bacteria oxidize ammonium into nitrite and nitrate under aerobic conditions. The secondary clarifier then facilitates sludge settling and effluent polishing. Together, these units enable effective biological nutrient removal (BNR).

2.4. GA creation

The objective of the GA is to ensure that the design requirements are met the maximizing nitrogen removal efficiency. Therefore, the GA will optimize parameters related to both the anoxic and oxic process of the nitrification unit as illustrated in Table 2 based on the input data (Concentration of Total Nitrogen TN and Flowrates). The flow chart in Figure 3 presents the steps of creating the GA. The GA objective function can be represented as:

Objective Function= f ($T_{an,a}$, R, SRT, Ds)

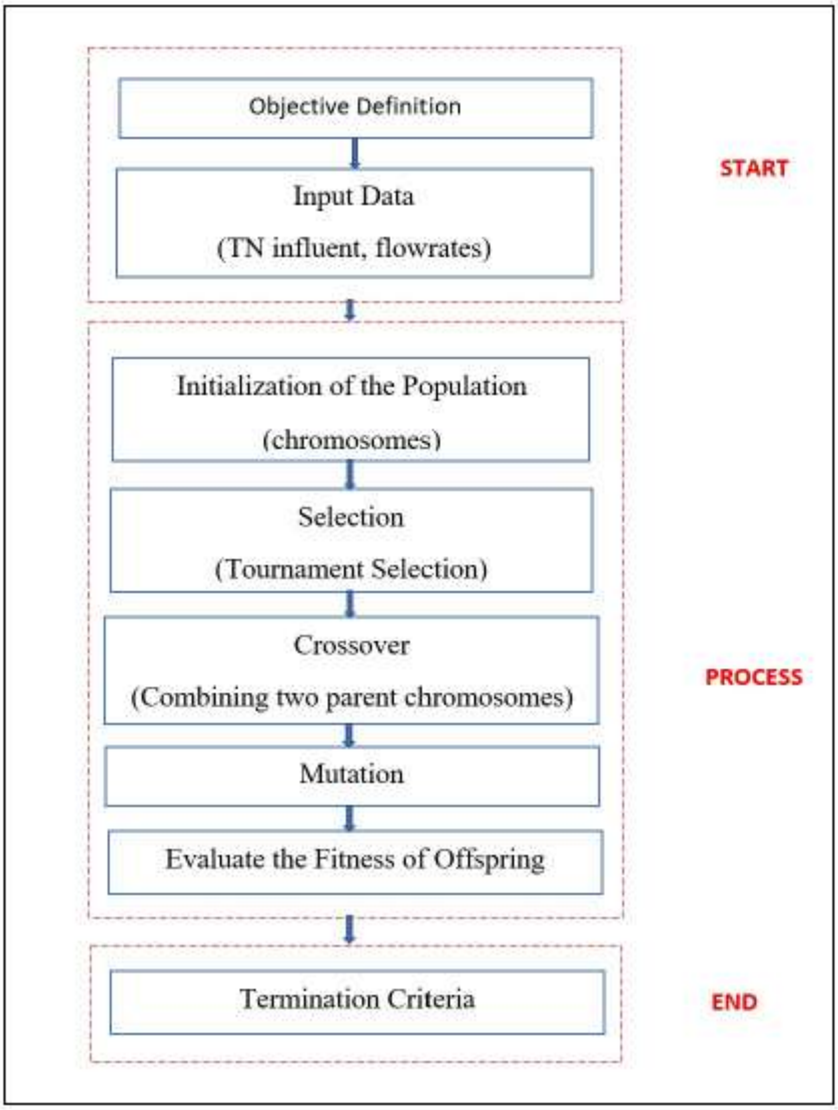

Figure 3. Flow chart of the GA technique

The GA starts with a randomly initialized population by determine the algorithm chromosomes. The design variables for the anoxic and oxic unit will be represent the chromosomes in the GA as equations below:

Chromosome_1= [Tanoxic, Ranoxic, SRTanoxic, Dsanoxic]

Chromosome_2 = [Toxic,Roxic, SRToxic, Dsoxic]

Tournament selection is the method of selection that be chosen to create the solutions. Each quality of solution is evaluated according to perform the fitness function. In our study, the evaluation of fitness function will perform to find the better solution that meets the required nitrogen removal, detention time, and clarifier size. Tournament selection was considered as a selection process in our study because it is broadly utilized in practical applications of the genetic algorithm due to its efficiency and flexibility. The next stage in our GA creation is the crossover to produce solutions (offspring) by combining the created chromosomes. This step will help to generate new population that lead to achieve the best solutions. The mutation takes in consideration in our algorithm to maintain the diversity of the population and avoids the stuck of the algorithm at the optimal solution. After applying crossover and mutation, evaluate the fitness of each offspring using the same objective function. The offspring with the best fitness will be selected for the next generation. Finally, the GA will stop when a specified termination criterion is achieved. The termination criterion that set up in this GA is that the objective function has achieved an adequate value and/or the best solution has converged over several generations.

3. Results and discussion

3.1. Optimum design of anoxic/-oxic units

Figure 4 demonstrates that the fluctuation in concentrations of TN_{in} and TN_{ef} has affected the detention time at the maximum flowrate in WWTP, particularly in the anoxic unit. The results exhibited a decrease in detention duration from 0.53 to 0.5 at TN_{in} = 10 mg/L and TN_{in} = 20 mg/L, respectively. Although the TN_{in} concentration remains constant at 30 mg/L, the detention time was 0.5 day. This variation occurred when the concentration of TN_{ef} was 4 mg/l. Conversely, there was a little rise in the duration of detention at TN_{ef} 5 mg/l. The value ranged from 0.5 to 0.505 day when TN_{in} was 10 mg/L and 20 mg/L, respectively. At a TN_{in} concentration of 30 mg/L, the detention time decreases to 0.479 day. Finally, the detention time with TN_{ef} 6 mg/l remained unchanged. Nevertheless, it has exhibited minor fluctuations around the value of 0.5 day.

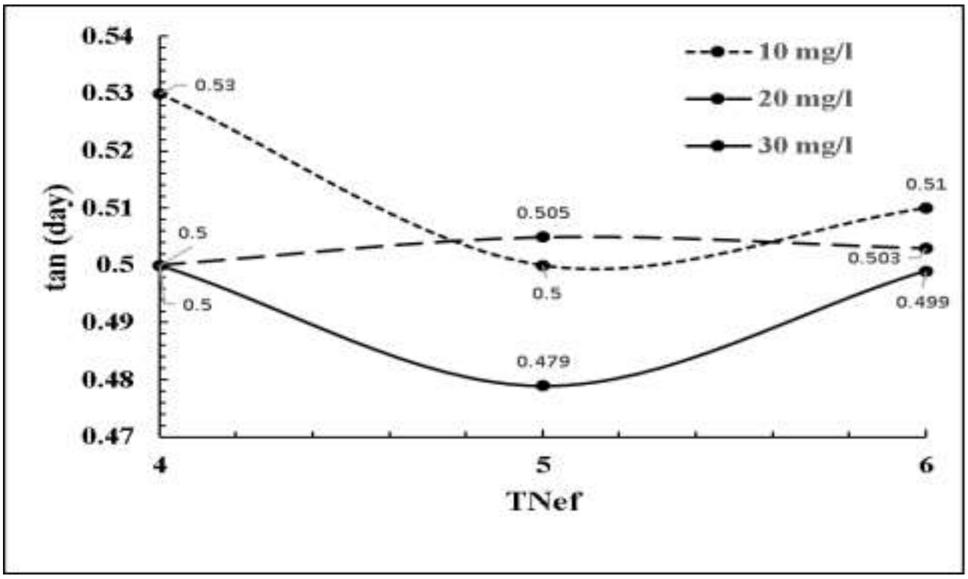

Figure 4. Detention time analysis for the anoxic unit at max flowrate

Typically, the detention periods remain very constant across different nitrogen concentrations, about around 0.5 day. Slight fluctuations in detention times were observed, as depicted in Figure 4. Based on these findings, it can be concluded that the system's performance is not significantly affected by variations in TN_{in} and TN_{ef} within the specified limits. The detention duration was marginally reduced while the TNef increased for TN_{in} = 30 mg/L. This suggests that there is a minor impact when there is a slightly higher efficiency in removing nitrogen at higher influent concentrations.

The data received from the oxic unit showed a clear trend of decreasing detention times, as depicted in Figure 5. The detention time decreases from Tn_{ef} = 4 to 5 at the TN_{in} = 10 mg/L, indicating that an increase in effluent nitrogen requires a decrease in detention time. The detention period for TN_{in} values of 20 and 30 mg/L, remained constant at (0.24~0.25) day, indicating a consistent pattern at increasing influent concentrations in the oxic unit.

During the experiment, it was noticed that increasing the TN_{in} value while keeping Tn_{ef} fixed at 4 hr., led to a decrease in detention time. This suggests that the operational efficiency of the oxic unit is higher while handling higher quantities of nitrogen influent to achieve a lower effluent concentration. The detention periods for Tn_{ef} = 5 and 6 hr exhibit negligible variation as TN_{in} increases, indicating that the performance of the oxic unit is consistent regardless of the influent concentrations.

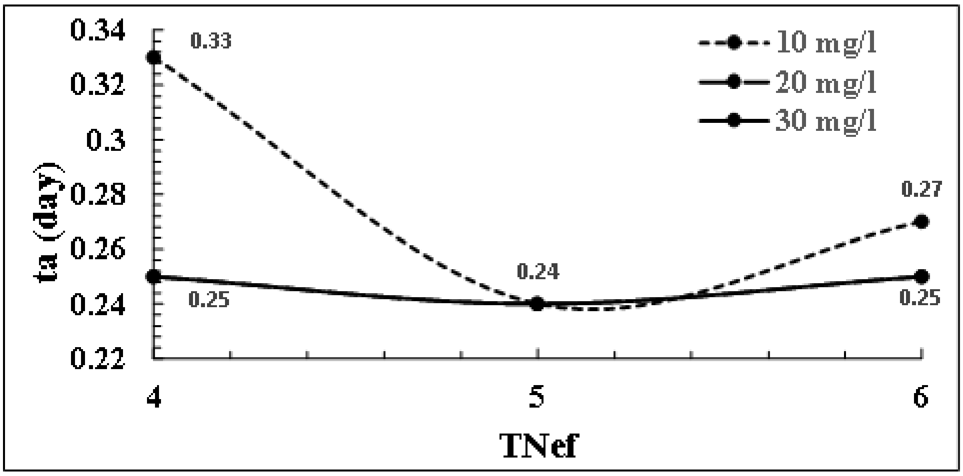

Figure 5. Detention time analysis for the oxic unit at max. flowrate

The detention times of the oxic unit exhibit a pattern that suggests its operating efficiency. A concentration of TN_{in} = 10 mg/L necessitates a somewhat extended detention period for the oxic unit to achieve a lower TN_{ef} = 4 mg/L. This suggests that in order to comply with stricter effluent requirements, the biological treatment in this unit must work harder while handling lower nitrogen amounts. However, the required detention time stays constant as the TN_{in} reaches between (20 and 30) mg/L, indicating that the system can manage higher loads without a substantial increase in treatment time duration.

The anoxic unit consistently performs continously and steadily for retention periods of (12 to 12.7) hours, despite variations in nitrogen concentrations. On the other hand, it is important to note that the differences in TN_{in} and TN_{ef} affect how long the oxic unit is detained. The optimal detention times in the oxic unit vary more, from (6 to 7.3) hours. As seen in Figure 5, this fluctuation indicates that the oxic unit is more responsive to changes in nitrogen levels.

In general, the anoxic unit maintains a constant detention time regardless of the nitrogen circumstances, but the detention time of the oxic unit is more sensitive to changes in TN_{in} and TN_{ef}, which demonstrates its adaptable processing properties.

The results indicate that there is a modest drop in the removal rate R as the effluent concentration TN_{ef} increases. The trend shown in Figure 6 is consistent with the discovery that the optimal value of the recycle sewage rate R only slightly decreases as the influent concentration TN_{in} increases, falling within the range of (0.15 to 0.18) hr.

The treatment system demonstrates a steady level of efficiency, indicated by the reasonably stable range of R (0.15-0.18), despite variations in the TN load. Ensuring stability is essential to ensure that the system can effectively handle changes in influent concentrations without experiencing major declines in performance. The marginal reduction in R at elevated TN concentrations suggests that although the system's efficiency is somewhat influenced by larger nitrogen loading, it still falls within an acceptable range, hence reducing potential effects on total treatment efficacy.

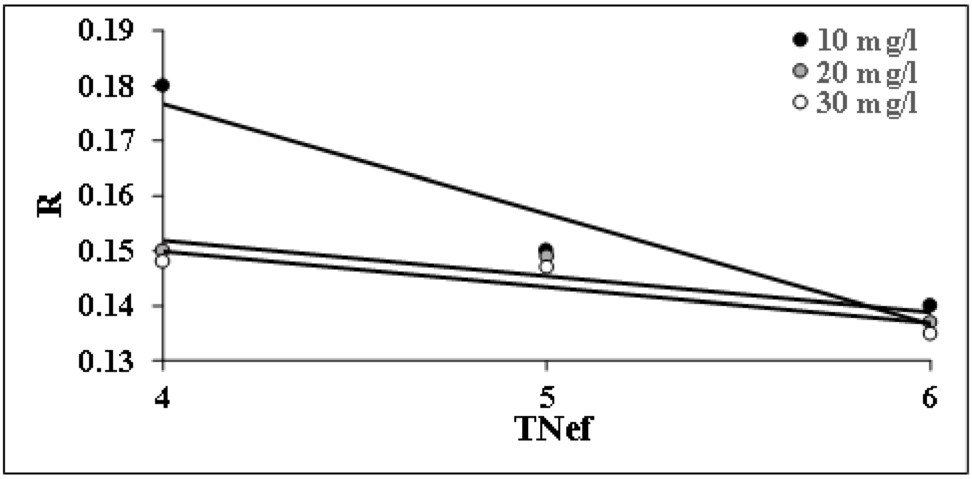

Figure 6. Effect of TNin and TNef on R for max influent flowrate

However, the results suggest that the SRT remains mostly unchanged despite fluctuations in both the influent and effluent concentrations. The SRT value of 24 days, as depicted in Figure 7, indicates the ideal retention time for maximal effectiveness of the system.

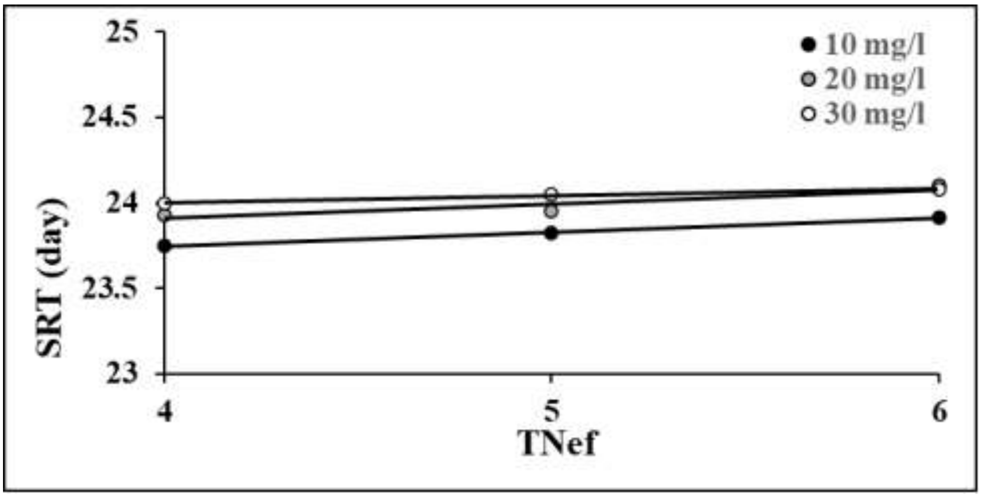

Figure 7. Effect of TNin and TNef on SRT for max influent flowrate

The findings as indicated in Table 3, that the optimum diameter of the secondary clarifier (Ds) is influenced by the variations in TN concentrations. As TNef increases, the required diameter of the secondary clarifier decreases. The obtained values for Ds range between (15 -18) m, with the maximum diameter corresponding to the lowest TNef concentration (4 mg/L) and the minimum diameter corresponding to the highest effluent TN concentration (6 mg/L).

This pattern is important because it indicates that the secondary clarifier's design and operation need to be modified based on the nitrogen loads in the influent and effluent. For effective settling and separation processes, greater diameters are needed at lower TN concentrations; at greater TN concentrations, smaller diameters might be adequate. This connection shows that variations in TN have an impact on the clarifier's hydraulic loading and surface overflow rates, necessitating careful design considerations to maximize treatment efficiency under various operational conditions.

Table 3. Effect of TNin and TNef on Ds for max influent flowrate

TN_{ef}		Secondary Clarifier Ds (m)	
4 mg/L	18	15	15
5 mg/L	15	15	15
6 mg/L	14.98	14.9	14.9

Practically, these results highlight how important it is to modify the secondary clarifier's capacity to satisfy the particular needs for removing Total Nitrogen (TN) in order to preserve the system's effectiveness and efficiency when dealing with different nitrogen loads. Maintaining the highest performance in wastewater treatment processes requires the ability to adjust the clarifier's size in response to variations in TN concentration.

3.2. Effect of influent flowrate

The ideal design criteria for a wastewater treatment plant are influenced by the fluctuation in the rate of incoming flow. This component is essential for the maintenance and performance of treatment processes. This study examines the implementation of a Genetic Algorithm to determine how the design criteria can be changed based on varying flowrate conditions. The ideal design criteria for oxic and anoxic treatment are reported in Table 4, for three different influent flowrates: 170000 m^3/day (maximum), 60000 m^3/day (average), and 40000 m^3/day (minimum).

Table 4. Optimum design criteria of plant for different values of influent flowrate

Influent flowrate (m^3/day)	Design Criteria				
	Tan (d)	Ta (d)	R	SRT(d)	Ds (m)
170000	0.5-0.53	0.25-0.31	0.15-0.18	24	15-18
60000	0.5-0.57	0.25-0.36	0.15-0.21	24	15-25
40000	0.5-0.58	0.25-0.34	0.15-0.163	24	15-15.5

The reported data indicate the correlation between the parameters of the best design and the influent flow rate. The design criteria for parameters such as Tan, Ta, and Ds revealed a tighter range at a flowrate of 170000 m^3/day. The ammonia (NH_3) removal efficiency was approximately 85%, beginning of treatment weakness due to hydraulic load. This implies that the system functions within stricter limitations when the flowrates are higher, most likely to effectively manage the larger amount of water.

On the other hand, the design parameters will increase as the flowrate declines to 60000 m^3/day. For instance, when the Tan reaches a value between (0.5 and 0.57) days, and Ds expands to a range of (15 to 25) m. The ammonia (NH_3) removal efficiency was approximately 92%, indicating consistent nitrification. This extension will result in increased design flexibility, allowing the treatment process to successfully handle changes in both the quantity and quality of the influent at lower flowrates.

A continual modification in the design requirements has been made at a flowrate of 40000 m^3/day, with a subsequent increase in Tan to a value ranging from (0.5 to 0.58) days, while the Ds have decreased to a value between (15 and 15.5) m. The ammonia (NH_3) removal efficiency was approximately 98%, indicating very strong nitrification. This suggests that the therapy procedure necessitates meticulous regulation of specific parameters. Specifically, the depth of sludge required to ensure optimal performance. The design criteria were seen to change in response to variations in flow rates, highlighting the importance of customizing the design of a treatment plant to specific operational conditions. Higher flowrates necessitate more stringent control over the design parameters to accommodate any increase in load, whereas lower flowrates offer greater flexibility. However, in some locations, unique adjustments can be required. These findings emphasize how crucial it is to have a dynamic approach in plant design, wherein influent flowrate-based parameter modifications are taken into account to ensure effective and reliable treatment results. To ensure the reliability of the GA predictions, the optimization procedure was executed in multiple independent runs with different initial populations. The algorithm consistently converged to similar optimal values for detention times, SRT, and clarifier diameters, indicating stability of the solution. Furthermore, a sensitivity check revealed that small variations in influent TN concentration and flowrate did not significantly affect the optimized results, thereby confirming the robustness and reliability of the proposed GA-based design framework.

4. Future perspectives and cross-disciplinary relevance

The optimization of wastewater treatment systems using genetic algorithms can be further enhanced by integrating insights from cross-disciplinary domains. Hybrid simulation and machine learning frameworks have been shown to improve predictive accuracy and robustness in sustainable process optimization [27]. Reviews on genetically engineered biopolymers and tribological performance in additive processes also emphasize the role of optimization in achieving superior functional outcomes [28,29]. Similarly, studies focusing on process parameter control and microstructural tailoring of advanced alloys and polymers highlight the applicability of optimization tools across diverse engineering domains [30-32].Optimization-driven strategies have also been employed in the development of sustainable polymers and composites, demonstrating parallels with environmental process optimization [33-35]. The incorporation of machine learning models for process efficiency and sustainability assessment aligns closely with the objectives of wastewater treatment design, ensuring energy efficiency and resilience under dynamic operating conditions [36]. Research on bio-based foams and nanofiller-enhanced composites further reinforces the broader role of optimization in tailoring system properties for targeted applications [37-39]. In the domain of civil and construction materials, sustainable concrete and geopolymer systems have been optimized using advanced computational methods, providing valuable analogies to wastewater treatment design under complex operating environments [40-42]. The use of multi-criteria decision-making and fuzzy optimization in additive manufacturing [43] highlights how decision-support frameworks can be adapted to WWTP operations, ensuring robustness in the face of variable influent conditions. Collectively, these studies [27–46] provide evidence that optimization principles are widely transferable across chemical, environmental, and manufacturing domains. Building on these insights, future work could integrate genetic algorithms with machine learning and multi-criteria frameworks to further advance the efficiency, adaptability, and sustainability of wastewater treatment plant design.

5. Conclusions

The use of genetic algorithms (GA) for optimizing design parameter and for designing a wastewater treatment system is an effective and robustness technique. This potential to predict the optimal design variable values, stands out its ability to be a trustworthy source for system optimization problems. The ability to determine the best values for design variables highlights its promise as a reliable tool for optimizing systems. Moreover, the incorporation of a penalty function alongside GA has proven to be beneficial in identifying the optimal design that satisfies constraints in complex issues, such as those found in advanced wastewater treatment design. According to the research results, the efficiency of oxic/anoxic treatments increased in proportion to the reduction in flow from 85% to 98% corresponding to the decrease in retention time (HRT). It is worth noting that these values remained stable and were not affected by fluctuations in suspended solids

(SS). The steady stability found suggests that distinct variations in influent characteristics have no effect on the accurate determination of important design parameters. The findings highlight the potential for developing advanced wastewater treatment systems through the use of genetic algorithms (GA), offering a means of enhancing the efficiency and effectiveness of wastewater management solutions.

Scientific Ethics Declaration

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

There is no funding for this task.

Acknowledgment

The authors would like to thank the Karbala Sewerage Directorate for providing this wonderful opportunity to obtain information and statistics of the treatment plant, and also thank Al-Qadisiyah University/College of Engineering for valuable support and assistance in completing this task.

Conflict of interest

The authors declare no conflict of interest

References

1. Parsons C., Stüeken E.E., Rosen C.J., Mateos K., Anderson R.E., (2020), "Radiation of Nitrogen-Metabolizing Enzymes across the Tree of Life Tracks Environmental Transitions in Earth History", Geobiology; 19:18–34. doi: 10.1111/gbi.12419.
2. Mohamed D., Fergany M., Elhabbasha E.F., El-temsah M. (2022), "Productivity Improvement of Canola Genotypes Under Salinity Stress Conditions by Integration between Mineral and Nano-Scale Forms of Nitrogen Fertilizer", Arab. Univ. J. Agric. Sci. ;30:1–16. doi: 10.21608/ajs.2022.140893.1481.
3. Ahmed S.F., Kumar P.S., Kabir M., Zuhara F.T., Mehjabin A., Tasannum N., Hoang A.T., Kabir Z., Mofijur M. Threats, (2022), "Challenges and Sustainable Conservation Strategies for Freshwater Biodiversity", Environ. Res;214:113808. doi: 10.1016/j.envres.2022.113808.
4. Abdel-Shafy, H.I., Mansour, M.S.M., and Al-Sulaiman, Ahmed M., (2019), "Anaerobic/aerobic integration via UASB/enhanced aeration for greywater treatment and unrestricted reuse", Water Practice & Technology, 14(4), pp. 837–850. doi: 10.2166/wpt.2019.065
5. Rajta A., Bhatia R., Setia H., Pathania P., (2020), "Role of Heterotrophic Aerobic Denitrifying Bacteria in Nitrate Removal from Wastewater", J.Appl.Microbiol. ;128:1261–1278. doi: 10.1111/jam.14476.
6. Abdel-Shafy, Hussein I. & Al-Sulaiman, Ahmed M., (2014) "Efficiency of degreasing / settling tank followed by constructed wetland for greywater treatment". Egyptian. J. Chemistry, 57(5-6), pp. 435–446 doi: 10.21608/EJCHEM.2014.1062
7. Winkler M.K., Straka L. (2019), "New Directions in Biological Nitrogen Removal and Recovery from Wastewater", Curr. Opin. Biotechnol. ;57:50–55. doi: 10.1016/j.copbio.2018.12.007.
8. Abdel-Shafy, H.I.; and Al-Sulaiman, Ahmed M., (2015), "Assessment of physico-chemical processes for treatment and reuse of greywater", Egyptian Journal of Chemistry, 57(3), pp. 215–231. doi: 10.21608/EJCHEM.2014.1042
9. H. I. Abdel-Shafy, A. M. Ibrahim, A. M. Al-Sulaiman, and R. A. Okasha, (2024), "Landfill leachate: Sources, nature, organic composition, and treatment: An environmental overview", Ain Shams Eng. J., vol. 15, no. 1, p. 102293, doi: 10.1016/j.asej.2023.102293
10. Scandelai A.P.J., Zotesso J.P., Jegatheesan V., Cardozo-Filho L., Tavares C.R.G. (2020), "Intensification of Supercritical Water Oxidation (ScWO) Process for Landfill Leachate Treatment through Ion Exchange with Zeolite", Waste Manag. ; 101:259–267. doi: 10.1016/j.wasman.2019.10.005.
11. Priya E., Kumar S., Verma C., Sarkar S., Maji P.K., (2022). "A Comprehensive Review on Technological Advances of Adsorption for Removing Nitrate and Phosphate from Waste Water", J. Water Process Eng. ;49:103159. doi: 10.1016/j.jwpe.2022.103159.
12. Cai Y., Zhu M., Meng X., Zhou J.L., Zhang H., Shen X., (2022), "The Role of Biochar on Alleviating Ammonia Toxicity in Anaerobic Digestion of Nitrogen-Rich Wastes: A Review". Bioresour. Technol. ;351:126924. doi: 10.1016/j.biortech.2022.126924.

13. Huang H., Liu J., Zhang P., Zhang D., Gao F. (2017), "Investigation on the Simultaneous Removal of Fluoride, Ammonia Nitrogen and Phosphate from Semiconductor Wastewater Using Chemical Precipitation" Chem. Eng. J. ;307:696–706. doi: 10.1016/j.cej.2016.08.134.
14. Aghdam E., Xiang Y., Ling L., Shang C. (2021) "New Insights into Micropollutant Abatement in Ammonia-Containing Water by the UV/Breakpoint Chlorination Process" . ACS EST Water. ;1:1025–1034. doi: 10.1021/acsestwater.0c00286.
15. Capodaglio A.G., Hlavínek P., Raboni M., (2015). "Physico-Chemical Technologies for Nitrogen Removal from Wastewaters: A Review", Rev. Ambient. 10:481–498.
16. Cruz H., Law Y.Y., Guest J.S., Rabaey K., Batstone D., Laycock B., Verstraete W., Pikaar I. (2019), "Mainstream Ammonium Recovery to Advance Sustainable Urban Wastewater Management", Environ. Sci. Technol. ;53:11066–11079. doi: 10.1021/acs.est.9b00603.
17. McCarty P.L. (2018), "What Is the Best Biological Process for Nitrogen Removal: When and Why?", Environ. Sci. Technol. ;52:3835–3841. doi: 10.1021/acs.est.7b05832.
18. Mishra S., Singh V., Cheng L., Hussain A., Ormeci B. (2022), "Nitrogen Removal from Wastewater: A Comprehensive Review of Biological Nitrogen Removal Processes, Critical Operation Parameters and Bioreactor Design", J. Environ. Chem. Eng. ;10:107387. doi: 10.1016/j.jece.2022.107387.
19. Yellezuome D., Zhu X., Wang Z., Liu R., (2022). "Mitigation of Ammonia Inhibition in Anaerobic Digestion of Nitrogen-Rich Substrates for Biogas Production by Ammonia Stripping: A Review", Renew. Sustain. Energy Rev. ;157:112043. doi: 10.1016/j.rser.2021.112043.
20. Karri R.R., Sahu J.N., Chimmiri V., (2018), "Critical Review of Abatement of Ammonia from Wastewater". J. Mol. Liq. ;261:21–31. doi: 10.1016/j.molliq.2018.03.120.
21. Metcalf & Eddy, I., (2003), "Wastewater Engineering: Treatment and Reuse",4th edition., McGraw Hill Companies, Inc, New York,. 1.
22. Busacca, P. G., Marseguerra, M., Zio, E., (2001), "Multiobjective optimization by genetic algorithms: application to safety systems". Reliability Engineering and System Safety, 72; 59-74. doi: 10.1016/S0951-8320(00)00109-5
23. Hai Trung Do, Nam Van Bach, Lanh Van Nguyen , Hoang Thuan Tran, Minh Tuan Nguyen, (2021), " A design of higher-level control based genetic algorithms for wastewater treatment plants", Engineering Science and Technology, an International Journal, DOI:10.1016/j.jestch.2021.01.004
24. B. Holenda, Endre Domokos, Á. Rédey, J. Fazakas, (2007), "Aeration optimization of a wastewater treatment plant using genetic algorithm", DOI: 10.1002/oca.796
25. Ahmed Majeed Al-Kadmi and Zuhal Hamza, (2014), "Optimal Wastewater Treatment Design by Using Genetic Algorithm", Thiqar University Journal of Engineering Sciences, 5(2),pp.28-45. doi: 10.31663/utjes.v6i1.66
26. Hamza, Zuhal A.H. & Al-Sulaiman, Ahmed M., (2023), "Rainwater Quality Assessment Based on Artificial Neural Network Using Mathematical Models", Environment and Ecology Research, Vol. 11, No. 6, pp. 963 - 972, https://doi.org/10.13189/eer.2023.110607.
27. Subramani Raja, Ahamed Jalaludeen Mohammad Iliyas, Paneer Selvam Vishnu, Amaladas John Rajan, Maher Ali Rusho, Mohamad Reda Refaa, Oluseye Adewale Adebimpe. Sustainable manufacturing of FDM-manufactured composite impellers using hybrid machine learning and simulation-based optimization. Materials Science in Additive Manufacturing, 2025, 4(3), 025200033. https://doi.org/10.36922/MSAM025200033
28. Aarthi, S., Subramani, R., Rusho, M. A., Sharma, S., Ramachandran, T., Mahapatro, A., & Ismail, A. I. Genetically engineered 3D printed functionally graded-lignin, starch, and cellulose-derived sustainable biopolymers and composites: A critical review. International Journal of Biological Macromolecules, 2025, 145843.
29. Subramani, R., Leon, R. R., Nageswaren, R., Rusho, M. A., & Shankar, K. V. Tribological Performance Enhancement in FDM and SLA Additive Manufacturing: Materials, Mechanisms, Surface Engineering, and Hybrid Strategies—A Holistic Review. Lubricants, 2025, 13(7), 298.
30. Lazarus, B., Raja, S., Shanmugam, K., & Yishak, S. Analysis and Optimization of Thermoplastic Polyurethane Infill Patterns for Additive Manufacturing in Pipeline Applications, 2024.
31. Raja, S., Murali, A. P., & Praveenkumar, V. Tailored microstructure control in Additive Manufacturing: Constant and varying energy density approach for nickel 625 superalloy. Materials Letters, 2024, 375, 137249.
32. Subramani, R. Optimizing process parameters for enhanced mechanical performance in 3D printed impellers using graphene-reinforced polylactic acid (G-PLA) filament. Journal of Mechanical Science and Technology, 2025, 1–11.
33. Subramani, R., Rusho, M. A., Thimothy, P., Mustafa, W. W., Ali, S. T., Hashim, R. D., ... & Kumar, A. P. Synthesis and characterization of high-performance sustainable polymers for FDM applications. Applied Chemical Engineering, 2024, 7(4).
34. Raja, S., Jayalakshmi, M., Rusho, M. A., Selvaraj, V. K., Subramanian, J., Yishak, S., & Kumar, T. A. Fused deposition modeling process parameter optimization on the development of graphene enhanced polyethylene terephthalate glycol. Scientific Reports, 2024, 14(1), 30744.
35. Subramani, R., & Yishak, S. Utilizing Additive Manufacturing for Fabricating Energy Storage Components From Graphene-Reinforced Thermoplastic Composites. Advances in Polymer Technology, 2024, 2024(1), 6464049.

36. Subramani, R., Ali Rusho, M., & Jia, X. Machine learning-driven sustainable optimization of rapid prototyping via FDM: Enhancing mechanical strength, energy efficiency, and SDG contributions of thermoplastic composites. Applied Chemical Engineering, 2025, 8(2), ACE-5621. https://doi.org/10.59429/ace.v8i2.5621
37. Raja, S., Ali, R. M., Sekhar, K. C., Jummaah, H. M., Hussain, R., Al-shammari, B. S. K., ... & Kumar, A. P. Optimization of sustainable polymer composites for surface metamorphosis in FDM processes. Applied Chemical Engineering, 2024, 7(4).
38. Selvaraj, V. K., Subramanian, J., Lazar, P., Raja, S., Jafferson, J. M., Jeevan, S., ... & Zachariah, A. A. An Experimental and Optimization of Bio-Based Polyurethane Foam for Low-Velocity Impact: Towards Futuristic Applications. In International Conference on Advanced Materials Manufacturing and Structures, 2024, pp. 244-261. Springer Nature Switzerland.
39. Subramani, R., Mustafa, M. A., Ghadir, G. K., Al-Tmimi, H. M., Alani, Z. K., Rusho, M. A., ... & Kumar, A. P. Advancements in 3D printing materials: A comparative analysis of performance and applications. Applied Chemical Engineering, 2024, 3867-3867.
40. Selvaraj, V. K., Subramanian, J., Krishna Rajeev, P., Rajendran, V., & Raja, S. Optimization of conductive nanofillers in bio-based polyurethane foams for ammonia-sensing application. Polymer Engineering & Science, 2024.
41. Sujitha, V. S., Raja, S., Rusho, M. A., & Yishak, S. Advances and Developments in High Strength Geopolymer Concrete for Sustainable Construction–A Review. Case Studies in Construction Materials, 2025, e04669.
42. Sujitha, V. S. N., & Raja, S. Synergistic enhancement of geopolymer concrete using graphene oxide and nano nickel oxide: RSM-optimized multifunctional composites for sustainable infrastructure. Structural Concrete, 2025. https://doi.org/10.1002/suco.70205
43. Selvaraj, V. K., Subramanian, J., Rajendran, V., Raja, S., Yuvaraj, L., Jeevan, S., ... & Zachariah, A. A. Sustainable development, optimization, and simulation of bio-based polyurethane foam composites for enhanced building acoustics. Journal of Building Engineering, 2024, 111576.
44. Raja, S., Praveenkumar, V., Rusho, M. A., & Yishak, S. Optimizing additive manufacturing parameters for graphene-reinforced PETG impeller production: A fuzzy AHP-TOPSIS approach. Results in Engineering, 2024, 24, 103018.
45. Selvaraj, V. K., Subramanian, J., Rajendran, V., Raja, S., Yuvaraj, L., Jeevan, S., ... & Zachariah, A. A. Sustainable development, optimization, and simulation of bio-based polyurethane foam composites for enhanced building acoustics. Journal of Building Engineering, 2024, 111576.
46. Raja, S., Ali, R. M., Karthikeyan, S., Surakasi, R., Anand, R., Devarasu, N., & Sathish, T. Energy-efficient FDM printing of sustainable polymers: Optimization strategies for material and process performance. Applied Chemical Engineering, 2024, 7(3).