University of Baghdad
College of Engineering
JOURNAL OF ENGINEERING

Journal of Engineering

journal homepage: www.jcoeng.edu.iq

Volume 31 Number 9 September 2025

Estimating Water Quality along the Tigris River, Iraq: A Novel Approach Using Gravitational Search Algorithm

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ABSTRACT

The quality of drinking water is considered among the most urgent issues worldwide nowadays. Ensuring safe water for human consumption remains the highest priority, while challenges also persist in meeting the water quality needs for industrial and agricultural uses. Most of the relevant studies lack accuracy in assessing water quality. Therefore, this study aims to forecast the quality of drinking water along the Tigris River in Iraq following a new approach. A developed forecasting model that utilizes the gravitational search algorithm (GSA) was deployed. The heuristic optimization tool was utilized for the prediction of the water quality index (WQI) in the research area. Out of twelve water stations, 575 samples were gathered and used for modelling in this study. The water quality was classified according to World Health Organization (WHO) recommendations using the generally applied arithmetic method, the WQI. Based on the concentrations of eleven parameters (BOD, Ca, Cl, EC, HCO_3, K, Mg, Na, NO_3, pH, SO_4, and TDS), the WQI for all samples was computed. The results of this study indicated that the water quality was significantly influenced. The evaluation of the applied model revealed that the GSA-based model exhibited statistically consistent performance (mean = 1.04, Standard deviation (SD) = 0.109, and Coefficient of variation (CoV) = 10.48%), indicating stable predictions compared to other models that demonstrated higher accuracy. The outcomes also showed greater variability in their results, positioning the GSA model as the preferred choice in scenarios that prioritize stability and reliability in water quality predictions.

Keywords: Water quality index, Gravitational search algorithm, Modelling, Tigris River.

1. INTRODUCTION

Driven by a mix of human population growth, quick development, industrial growth, and the consequences of climate change, water quality in the Tigris River, Iraq, has become progressively a reason for concern during the past ten years. Among Iraq's most important water sources, the Tigris River is essential for maintaining industry, providing agriculture, and supplying safe drinkable water. Health is not only crucial to the environment but also to

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Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2025.09.07

Article received: 13/04/2025
Article revised: 15/07/2025
Article accepted: 26/07/2025
Article published: 01/09/2025

the health of the societies that depend on it. Regretfully, recent research has revealed alarming levels of increase in pollutants like heavy metals, organic contaminants, and rising salinity levels. These pollutants affect public health as well as the environment **(Al-Ansari et al., 2014; Khudair, 2023; Al-Mousawey and Abed, 2023).**

To overcome these challenges, scholars have attempted to evaluate the water quality of the Tigris River. Often exceeding national and international safety thresholds, physicochemical analyses have indicated high concentrations of heavy metals, phosphates, and nitrates **(Hassan, 2015; Ahsan et al., 2023; Al-Sulttani et al., 2024; Abdullah et al., 2024)**. Through indicator organism analysis and microbial pollution, biological monitoring has uncovered even more of the river's deteriorating ecological well-being, including poor diversity and pathogenic dominance by microbes **(Mohammed and Khudhair, 2023; Hashim, 2022)**. These developments are complemented by integrating remote sensing with geographic information systems (GIS) so that new methods of remotely sensing water quality across large landscapes have now become feasible. These techniques enable researchers to monitor the variation in pollution and identify the areas of concern by a more cost-effective and efficient means than traditional field-based research **(Abbas et al., 2019; Ahmed et al., 2023; Singh et al., 2009).** Combining these different methods has enabled researchers to better understand the river's water quality problems, thereby informing the identification of pollution hotspots and evaluation of the status over time and space.

The success of protection and rehabilitation strategies for the Tigris River for generations to come depends on these interdisciplinary approaches. Climate change is also influencing water quality concerns in the Tigris River basin, where decreased precipitation and rising temperatures contribute to decreased river flows and enhanced levels of contamination **(Al-Zaidy and AL-Thamiry, 2020; Al-Maliki et al., 2022).** Upstream dam building in adjacent nations has decreased the availability of downstream water, causing increased salt concentrations and changes to the hydrological regime of the river **(Adamo et al., 2020).** These changes not only reduced the water quality but also interfered with the river's natural equilibrium, causing indigenous organisms to go extinct and allowing aliens to penetrate and colonize **(Al-Jawadi et al., 2023)**. Despite their limitations, efforts towards water quality monitoring and regulation have been hampered by inadequate infrastructure, insufficient financing, and inadequate harmonized policies across stakeholders **(Al-Jawadi et al., 2023)**. To ensure long-term control of the Tigris River, integrated approaches integrating sophisticated technologies such as machine learning systems with integrated regulatory systems are essential **(Xu et al., 2021).**

Artificial intelligence (AI) technologies and genetic algorithms (GA) have now effective tools for water quality indicator (WQI) simulation and estimation in recent years. Artificial intelligence-based methods, including support vector machines (SVM) **(Bui et al., 2020)** and synthetic neural networks (ANN), can analyze intricate and non-linear interactions among water quality criteria, thereby enabling them to provide a sure prediction of water quality indicators **(Jaafer and Al-Mukhtar, 2024).** These models process large datasets efficiently, making them appropriate for real-time monitoring. For example, artificial neural network models were used to predict the water quality index (WQI) of the Tigris River, based on precise estimates for parameters such as pH, dissolved oxygen, and turbidity **(Jaafer and Al-Mukhtar, 2024).** Such applications allow trends and risks to be determined and thus improve predictive water management. GA improves the accuracy of precision and optimizes the input parameters, improving AI models **(Jaafer and Al-Mukhtar, 2024; Al-Ansari et al., 2024).** Hybrid models frameworks based on GA and ANN, particularly in data-scarce areas, have outperformed conventional methods. Thus, minimizing computational cost and improving accuracy compared to conventional methods (**Jaafer and Al-Mukhtar, 2024; Kouadri et al., 2022)**. The approaches are very useful in dynamic systems such as the Tigris River, where various water quality issues complicate the matter. The use of artificial intelligence and GA applications in water quality modeling has helped environmental management go a long way. AI models are capable of identifying principal sources of pollution and even predicting the effect of interventions such as land-use change or increased wastewater treatment **(Jaafer and Al-Mukhtar, 2024)**. However, GA does not always guarantee model correctness or computational efficiency, especially under conditions of limited resources. As conventional issues like pollution and climate change remain, the usage of new technologies is crucial to preserve the Tigris River and ensure sustainable water resource management.

In light of the aforementioned, AI and optimization methods for forecasting the WQI offer a transformative approach to address the increasing challenges of water resource management. This is particularly correct in regions such as Iraq, where water quality studies are rare. Conventional approaches to water quality evaluation can depend on labor-intensive and time-consuming laboratory studies that might not fully reflect the dynamic and complicated character of water systems. Leveraging a large dataset gathered over an extended period from 2010 to 2021, this study greatly exceeds the breadth of past studies in terms of both data volume and temporal coverage, thereby addressing an important gap in the current body of research. The study also includes a broad array of water quality parameters (BOD, Ca, Cl, EC, HCO_3, K, Mg, Na, NO_3, pH, SO_4, and TDS), leading to more integrated knowledge about water systems. It is very complicated to analyse all these large datasets; therefore, nonlinear interrelations between water quality indicators are developed by an artificial neural network (ANN), an AI-based model, in this study, thereby enabling more accurate and real-time water quality predictions. These optimization algorithms, like the GSA, greatly boost these models through input parameter optimization and processing efficiency. Together, these novel strategies provide a powerful platform for water quality monitoring, pollution source tracing, and environmental change impacts assessment. For Iraq, where the Tigris River is beset by hyper-pollution and climate-driven stressors that are harmful to ecosystems and human health alike, this is especially crucial. By leveraging artificial intelligence and optimization, stakeholders can design proactive strategies to safeguard water supplies, therefore ensuring their sustainability for the next generations.

2. RESEARCH SIGNIFICANCE

Synthesis of Artificial Intelligence (AI) and optimization techniques integration is a new method to estimate the WQI, to optimize water resource management. Traditional methods are time-consuming and involve high manual labor and are unable to depict the dynamic nature of water systems. ANN and SVM are two of the most data-intensive AI models that can handle large data sets and discover complex, nonlinear relationships between water quality parameters that make real-time, precise prediction possible. Genetic algorithms (GA) are some of the optimization algorithms that augment the usefulness of such models by regulating the inputs and optimizing them. Through the utilization of a single platform, all the above methods provide a solid foundation for water quality monitoring, source contamination tracing, and environmental impact forecasting. This is especially important for regions like Iraq, where the Tigris River is seriously polluted and exposed to climate stresses, which affect ecosystems and human health. Adopting AI and optimization allows stakeholders to create visionary strategies to conserve water resources and sustain their availability in future years.

3. METHODOLOGY

3.1 Study Area

Iraq is a country located in the Middle East, between latitudes 29°02′N and 37°22′N and longitudes 38°45′E and 48°45′E. The total area of the country is approximately 437,367 km^2. It shares borders with Iran to the east, Syria to the northwest, Turkey to the north, Jordan to the west, Saudi Arabia and Kuwait to the south and southwest. Iraq has a 58-kilometer coastline on the Arabian Gulf, which gives it strategic geopolitical importance Central Intelligence**.** On both banks of the Tigris and Euphrates Rivers, the northern, central, and eastern regions of Iraq are home to the majority of the population. In contrast, the western and southern regions are sparsely populated due to harsh climatic conditions and limited infrastructure. The Euphrates River enters Iraq at the village of Fishkhabour, near the Iraq–Turkey–Syria border, and flows approximately 1,430 kilometers through Iraq**.** It eventually joins the Tigris River to form the Shatt al-Arab, which flows about 190 km into the Arabian Gulf **(Issa et al., 2014; Rahi and Halihan, 2018)**. Thirteen monitoring stations were selected to observe 12 water parameters in wet and dry periods between 2010 and 2021. These were based on data from the National Center of Water Resources Management (NCWRM) and the Consulting Engineering Bureau (CEB), data records **(National Center of Water Resources Management (NCWRM), 2017).** Fishkhabour, Al-Mosul Dam, Mosul, Samarra Dam, Tarmiyah, Dijla Arm, Shuhada Bridge, Muthanna Bridge, Kut, Aziziyah, Amarah, Qurna, and Ali Garbi are locations where values encountered were noted; they are listed in **Fig. 1,** which displays sampling stations located on the Tigris River in Iraq.

Figure 1. Sampling stations located on the Tigris River within Iraq.

3.2 Numerical Approach (Gravitational Search Algorithm)

The gravitational search algorithm (GSA), a new heuristic optimization technique first proposed by Rashedi et al. (2009), has recently attracted the interest of researchers. The approach is gravity principle based and operates to improve performance using the population based strategy. From Newton's gravity principle, Eq. (1) and motion principle Eq. (2), GSA is based on its core concept, an isolated system of masses where every mass is a solution to an optimization problem (Rashedi et al., 2009). GSA picks the initial population value from random solutions. However, a quality initial population is very effective in improving GSA's performance and convergence. To implement this, MATLAB tools (such as the Genetic Algorithm Toolbox, Optimization Toolbox, and custom scripting functions) were used in the simulated form to optimize the WQI models. According to the law of gravity, every particle attracts another; the gravitational force between particles is directly proportional to the product of their distance from each other. The mass of an agent hence determines its operation since gravitational force (a) draws others of greater masses and attracts them **(Ojugo et al., 2013)**.

$$F = G\left({}^{M_1\,M_2}/_{R^2}\right) \tag{1}$$

$$a = {}^{F}/_{M} \tag{2}$$

F is the force of gravity; G is the constant of gravity. M_1 and M_2 are the masses of the first and second objects; R is two-object distance. Four parameters are associated with the agent in GSA: inertial mass, active gravitational mass, passive gravitational mass, and location. A fitting function is used to find the gravitational and inertial masses. Although all masses are potential solutions, the GSA method selects one based on inertia and gravitational mass. While any mass is a solution, the GS method is driven by altering the inertia and gravity mass **(Sabri et al., 2013).** Distance and mass are fundamental components of gravitational interactions; however, GSA omits distance in its calculation. Heuristic algorithms are applied in various areas of study, including optimization and machine learning. Of all evolutionary algorithms, GSA possesses great exploration capacity. **(Rashedi et al., 2009)** compared different heuristic approaches with GSA. Solving several nonlinear problems has verified GSA's great capability to handle unconstrained optimization issues. The GSA algorithm was developed to address unconstrained optimization problems using heuristic techniques. Although heuristic algorithms find application in various areas of study nowadays, proof of convergence of these algorithms is still challenging. In the case of the GSA heuristic algorithm, Ghorbani and Nezamabadi-pour **(Ghorbani and Nezamabadi, 2012)** provided formal convergence analysis of the gravitational search algorithm, randomization, and time-varying parameters. They provided noticeable performance of GSA in the region of interaction among the masses. The outcomes produced by the acquisition are authoritative evidence that all the elements meet at an equilibrium point. Further, **(Sharma, 2016)** found that GSA converges quickly under certain conditions. **Fig. 2** illustrates a flowchart for this procedure. The number of agents in the GSA algorithm refers to the size of the population used for optimization, where each agent explores the solution space. The stages of the research, from data collection to prediction, have been illustrated in **Fig. 3**.

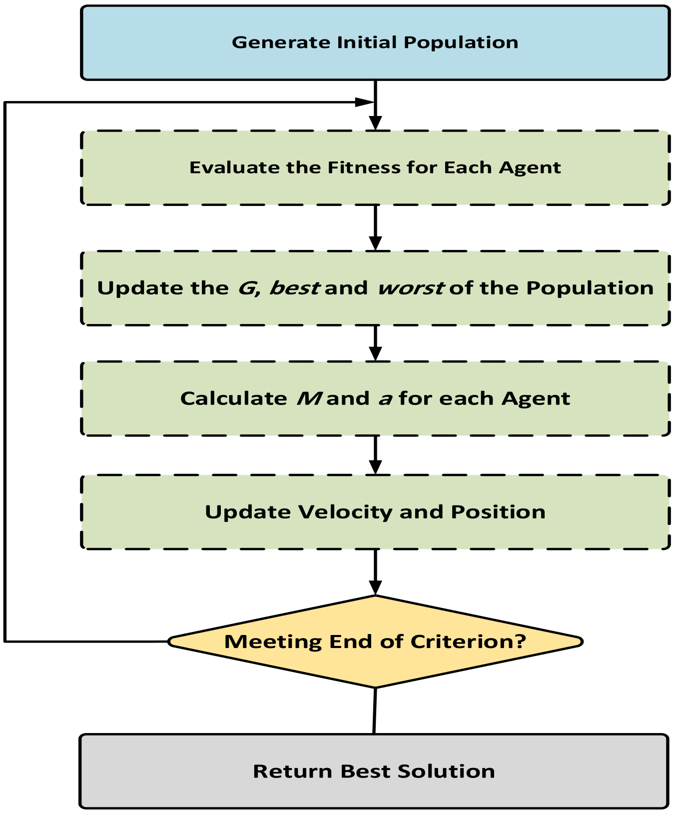

Figure 2. Flowchart of GSA.

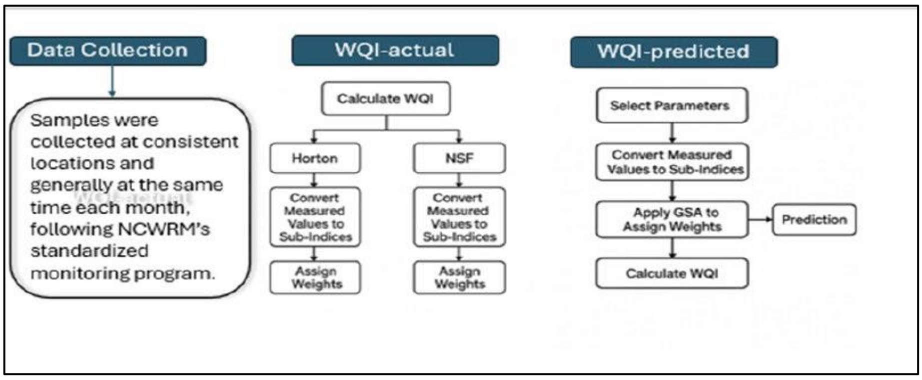

Figure 3. Workflow of the study.

4. RESULTS AND DISCUSSIONS

Numerical modeling has been an important method of resolving difficult engineering and scientific problems that most analytical methods struggle to cope with due to nonlinearity or high dimensionality. In the past several years, the integration of advanced optimization algorithms has altered this image. Among these algorithms is the Gravity Search Algorithm (GSA), which has been an efficient and effective numerical modeling technique.

GSA is based on gravity law and mass interactions and has been determined to be effective in global optimization problems and, therefore, suitable for parameter tuning and diverse types of problems. In the present study, GSA is employed for the optimization of the WQI of potable water, where the data has been divided into two parts: the first part, comprising 80% of the data, was utilized for the development of the suggested model, and the remaining 20% was utilized to verify the effectiveness of the model.

4.1 Building Models Analysis (Horton Modelling Using Gravitational Search Algorithm (GSA))

The gravitational search algorithm, a novel method that is proving to be a powerful optimizer for difficult numerical modeling problems in the environmental sciences in recent years, is employed. This research seeks to present a viable and efficient method to calculate the WQI using GSA and the Horton method. GSA used to optimize the calculations of WQI based on the gravitational metaphor, thus enabling accurate exploration of water quality variations. Through these various parameters, one obtains an overall description of water quality and thus addresses chemical as well as physical issues. This new integrated approach of GSA and Horton's technique provides a potent tool for environmental monitoring as well as water resource management. The WQI index for drinking water was optimized using the Hort-Dr-GSA model, which suggested exploring the effects of agent size through modelling. The primary objective of the function in the GSA method was to minimize the difference between the predicted and actual WQI values. GSA provided models capable of evaluating WQI levels with results closely aligned to real values. Using the Hort-Dr-GSA model, which sought to minimize the discrepancy between expected and actual WQI values, the WQI for drinking water was tuned. The GSA approach produced models rather near to actual WQI levels. **Fig. 4** displays the interactions among the number of agents, the minimal objective function value, and the iterations required for convergence across models with 120, 80, and 40 agents. The minimal objective function value rises as the number of agents drops, therefore suggesting a worse performance of optimization. The values for 120, 80, and 40 agents were 23.11, 27.45, and 32.14, respectively. Furthermore, fewer agents needed more iterations to converge (374, 686, and 822 iterations, respectively), showing that bigger agent populations produce better results with fewer iterations. Emphasizing a trade-off between computing cost, higher with more agents, and optimization performance, this study illustrates distributed optimization concepts. Increasing the agent count improves the model's capacity to investigate the solution space, attain correct results, and converge faster. This emphasizes the need for agent-based interaction in enhancing convergence efficiency and solution quality; therefore, agent population size becomes a major determinant of optimization design.

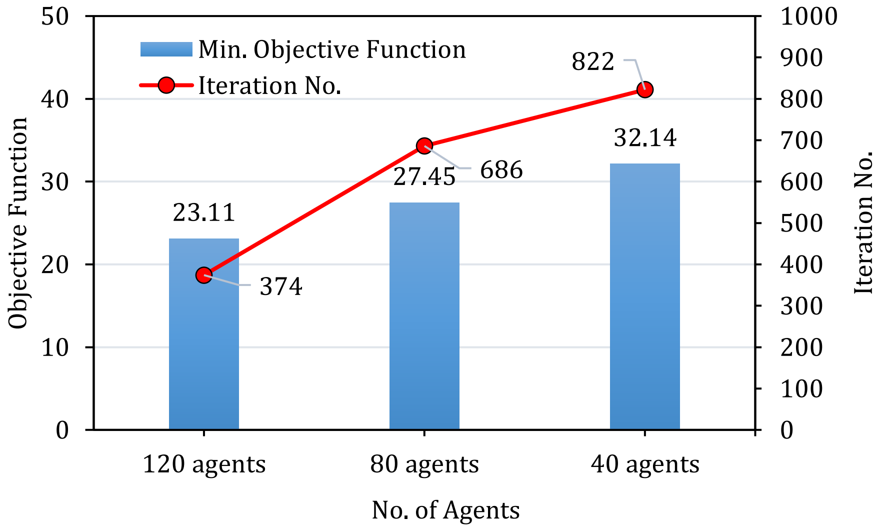

Figure 4. Convergence process for different sizes of agents.

Fig. 5 illustrates the correlation between actual and predicted WQI values using the Hort-GSA model. The data points are tightly clustered along the diagonal line, indicating a strong linear relationship and high predictive accuracy. This visual representation supports the reliability of the model in estimating WQI values. With data points closely along the diagonal, **Fig. 5** indicates a highly beneficial correlation between forecasted WQI values ("WQI-predicted") and actual WQI values ("WQI-actual"). This behavior is verified by a solid line, most likely the line of best fit, thus highlighting the precision of the model. Little variations at larger WQI levels are targeted, nevertheless, point to possible over or under predictions, perhaps caused by model limitations or dataset variation. These variations point to areas needing enhancement to increase correctness for extreme values. With an R-value of about 0.9597, reflecting a remarkable match and hence validating the predictive accuracy of the model, with the correlation coefficient (R) measures the association. With data points closely fitted to the line of greatest precision, the scatter plot supports this strong linear relationship and highlights the dependability of the GSA-based model in WQI forecasting. Minimal variances across the specimens support even more the accuracy of the model in understanding difficult water quality requirements. Though the significant association, small variances at higher WQI values point to possible mistakes from dataset noise, parameter variance, or optimization limitations. Using hyper-parameter adjustment or adding other elements might improve predicted accuracy.

The results confirm the strength of the GSA-Horton method and show its worth for pragmatic water quality control. Adding more agents, 40, 80, and 120, tightens data clustering around the mean, hence lowering variability and raising prediction accuracy. The need to optimize agent count for reliable and consistent WQI predictions is highlighted by this development. **Fig. 4** shows that 120 agents met the minimum objective functions and offered ideal coefficients for the Horton model, therefore attaining the best solution.

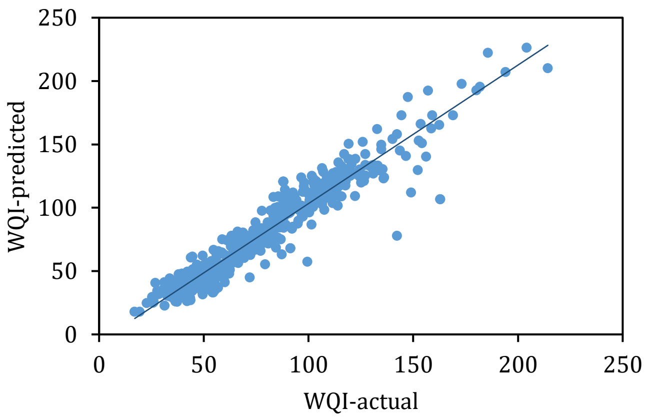

Figure 5. Predicted vs. experimental water quality index using the Hort-GSA model.

4.2 Implications for the Model

The observations suggest that the algorithm benefits significantly from a higher number of agents. This could be attributed to enhanced interactions or a more comprehensive exploration of the solution space, which improves the model's stability and accuracy. The performance analysis reinforces the importance of choosing an optimal agent count for the algorithm to achieve robust and consistent results, as indicated in **Table 1**. **(Smith, 1986)** reported that a Coefficient of Variation (CoV) of less than 10% signifies high accuracy, 20–30% low accuracy, and greater than 30% is reported to depict low precision. Therefore, a

CoV value equal to 11.7989% indicates that the predicted results of the proposed model have high accuracy and consistency. Based on a rational hypothesis proposed by **(Pimentel-Gomes, 2000),** when the correlation coefficient, R, of a model exceeds 0.8, a robust connection is present between the estimated and measured values. The proposed Hort-GSA model for predicting the WQI of drinking water is finalized with these findings, reflecting its capacity to leverage agent diversity for accurate and stable predictions, as shown in Eq. (3).

$$NSF - Dr - GSA = 0.1906 \times Ca + 0.1897 \times Mg - 0.0699 \times Na + 0.1812 \times K + 0.1097 \times Cl + 0.0515 \times SO_4 + 0.0771 \times HCO_3 - 0.3922 \times NO_3 + 0.0148 \times TDS + 0.1447 \times EC + 0.4908 \times pH + 0.0894 \times BOD \quad (3)$$

Where NSF is the National Sanitation Foundation WQI; Dr is the drinking water model indicator.

Table 1. Optimum values of unknown coefficients obtained from the GSA algorithm of Horton model.

Parameter	120 agents	80 agents	40 agents
F1	0.1906	0.3106	0.2928
F2	0.1897	0.4286	-0.1315
F3	-0.0699	0.0122	-0.1919
F4	0.1812	0.1991	0.6554
F5	0.1097	0.077	0.1398
F6	0.0515	0.0527	0.0832
F7	0.0771	0.0077	0.1658
F8	0.3922	0.1011	0.4011
F9	0.0148	0.0067	-0.0026
F10	0.1447	0.3205	-0.0187
F11	0.4908	0.2343	0.4774
F12	0.0894	0.1816	0.834
Mean	1.041	1.032	1.044
SD	0.1228	0.1733	0.2379
CoV %	11.7989	16.7992	22.7852

4.3 Validation Models Analysis

4.3.1 Validation Analysis for Horton Model of Drinking

Table 2 shows that with minimum variations in the WQI-Horton-Drinking model's average values (1.04, 1.03, and 1.05 for 120, 80, and 40 agents, respectively), the WQI-Horton-Drinking model shows stable performance across various agent sizes. This suggests consistency in its prediction power and is independent of the agent's involvement. But as the agent count falls, the standard deviation (SD) increases from 0.109 for 120 agents to 0.219 for 40 agents, thereby stressing a growth in variability. Analogous to this, the coefficient of variation (CoV%) increases from 10.48% to 20.86%, implying that the model's precision decreases somewhat with fewer agents used. WQI-Horton does, however, maintain general dependability, especially in larger agent numbers when variability is under control. Conversely, the WQI-NSF-Drinking model exhibits more notable variations in its measures over various agent sizes. Its average for 120 agents is 1.01, which declines to 0.872 for 80 agents and then rises significantly to 1.35 for 40 agents, therefore demonstrating less stability than the Horton model. Reflecting more variability with lower agent counts, the SD likewise rises significantly from 0.0611 for 120 agents to 0.249 for 40 agents. The CoV%, which starts at a low of 6.05% for 120 agents, increases a little to 6.50% for 80 agents, and then leaps quickly to 18.44% for 40 agents, emphasizing this even more. These results indicate that the Horton model, particularly in smaller datasets, struggles to maintain consistent performance as the number of agents decreases. The model shows a higher standard deviation and coefficient of variation, indicating greater dispersion in performance. However, the average performance of the Horton model remains slightly higher. This suggests that with larger datasets, the model may achieve better accuracy while demonstrating greater stability across agent sizes. In situations requiring less data dispersion, the reduced fluctuations when using a larger number of agents can be a better option. Nonetheless, the flexibility of the Horton model across agent sizes enhances its position as a versatile choice.

Table 2. Horton water quality index models for 20% of the data.

WQI-Horton-Drinking			
Parameter	**120 agents**	**80 agents**	**40 agents**
Average	1.04	1.03	1.05
SD	0.109	0.158	0.219
CoV%	10.48	15.34	20.86

5. CONCLUSIONS

This study suggests a new approach to estimating the WQI in the Tigris River of Iraq by combining advanced optimization techniques and machine learning models. The primary conclusions, supported by statistical data and novel insights, can be drawn from this study as follows:

- The Gravitational Search Algorithm (GSA) proved to be an extremely effective optimization method, significantly enhancing the accuracy of WQI predictions. The study indicated that the 120-agent model had the lowest objective function values (23.11 for Horton-GSA) and required fewer iterations (374 for Horton-GSA) to converge compared to models with fewer agents.
- The study introduced new results on how the population size of an agent affects GSA-based optimization. Doubling the agents from 40 to 120 caused the objective function to decline by 28.6% value for the Horton-GSA model (from 32.14 to 23.11).
- The results demonstrate the effectiveness of advanced optimization methods like GSA in enhancing water quality models. The study also provides a scalable strategy for sustainable water resource management by integrating data from multiple sites along the Tigris River, thereby contributing to global efforts to achieve the United Nations Sustainable Development Goal 6 (clean water and sanitation).
- The developed WQI models, particularly those optimized using larger agent populations, demonstrated high predictive stability and accuracy. In this study, the models demonstrated strong performance, and the study identified areas for further improvement in future studies. For instance, slight underestimations at higher WQI values (e.g., during GSA training, where the regression line slope was 0.8933) suggest the need for enhanced data pre-processing and hyper-parameter tuning. Future research could explore the

integration of additional environmental parameters, advanced data augmentation techniques, and hybrid optimization algorithms to further improve model accuracy.

Acknowledgments

The researchers thank the University of Baghdad for the facilities provided to them and for fulfilling all the prerequisites of scientific research.

Credit Authorship Contribution Statement

Sura Mohammed and Ali Omran Al-Sulttani: Writing–review & editing, Writing –original draft, Validation, Methodology.

Declaration of Competing Interest

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.

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تقدير جودة المياه على طول نهر دجلة، العراق: نهج جديد باستخدام خوارزمية البحث الجاذبي والشبكات العصبية الاصطناعية

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الخلاصة

من بين أكثر القضايا إلحاحًا على مستوى العالم تأتي مسألة جودة مياه الشرب. إذ يُعدّ ضمان مياه آمنة للاستهلاك البشري أولوية قصوى، في حين لا تزال هناك تحديات قائمة في تلبية متطلبات جودة المياه للاستخدامات الصناعية والزراعية. وتفتقر معظم الدراسات السابقة إلى الدقة الكافية في تقييم جودة المياه. تهدف هذه الدراسة إلى التنبؤ بجودة مياه الشرب على طول نهر دجلة في العراق. حيث تم جمع 575 عينة من اثنتي عشرة محطة، واستخدامها في نمذجة البيانات. وقد تم تصنيف جودة المياه وفقًا لتوصيات منظمة الصحة العالمية (WHO) باستخدام الطريقة الحسابية الشائعة، وهي مؤشر جودة المياه (WQI). استُخدمت تراكيز أحد عشر معيارًا (BOD، Ca، Cl، EC، HCO_3، K، Mg، Na، NO_3، pH، SO_4، وTDS) لحساب مؤشر جودة المياه لجميع العينات. وأظهرت نتائج الدراسة أن جودة المياه قد تأثرت بشكل ملحوظ. وقد طورت هذه الدراسة نموذجًا تنبؤيًا جديدًا يعتمد على أداة التحسين التكراري Heuristic Optimization المعروفة بخوارزمية البحث الجاذبي (GSA) للتنبؤ بمؤشر جودة المياه في منطقة الدراسة. وأظهر تقييم النموذج أن النموذج المعتمد على GSA قدّم أداءً ثابتًا من الناحية الإحصائية (المتوسط = 1.04، والانحراف المعياري = 0.109، ومعامل التغاير = 10.48%)، مما يدل على تنبؤات مستقرة مقارنة بالنماذج الأخرى، التي رغم تفوق بعضها من حيث الدقة، إلا أنها أظهرت تباينًا أكبر في النتائج. وبالتالي، يُعدّ نموذج GSA الخيار المفضل في الحالات التي تتطلب ثباتًا وموثوقية في التنبؤات.

الكلمات المفتاحية: مؤشر جودة المياه، خوارزمية البحث الجاذبي، النمذجة، نهر دجلة.