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OPTIMIZING WATER DESALINATION: A NOVEL FUSION OF EXTREME LEARNING MACHINE AND GAME THEORY FOR ENHANCED PH PREDICTION - UNVEILING REVOLUTIONARY INSIGHTS

DR. MOHAMMED SALEH AL ANSARI

Associate Professor, College of Engineering, Department of Chemical Engineering, University of Bahrain, Bahrain

E-mail: [1]malansari.uob@gmail.com

ABSTRACT

The essential step in guaranteeing an adequate supply of water is water desalination. Nevertheless, since many water quality measures interact in a complex way, it is difficult to estimate pH levels accurately. To further comprehend and regulate pH levels in water from desalination, this study proposes a synergistic structure that blends the predictive ability of Extreme Learning Machines (ELM) with the strategic insights offered by game theory. The precision needed for effective desalination is frequently lacking in current pH prediction techniques. Traditional models could find it difficult to represent the complex interactions between changes in pH and input factors. Furthermore, the lack of a strategic decision-making component in dynamic operational contexts exposes processes to less-than-ideal results. The merging of game theory and ELM is innovative. Because of its quick training and ability to generalize, ELM is a good pH predictor. Concurrently, Game Theory is utilized to simulate strategic exchanges between stakeholders, taking into account how pH forecasts affect decision-making procedures. High-quality data on water quality is used to train an ELM model as part of the suggested methodology. Next, using the concepts of game theory, stakeholders' strategic behaviors that are impacted by the anticipated pH levels are modelled. This research enhances pH prediction accuracy using Extreme Learning Machine and Game Theory, optimizes desalination resource allocation for sustainability, addresses real-world challenges, and provides a versatile framework for widespread application in diverse desalination scenarios. The suggested method's efficacy is determined by a thorough performance review. The integrated strategy is thought to be superior to traditional approaches in terms of metrics like accuracy of predictions, satisfaction with stakeholders, and operational effectiveness. These metrics present a potential path forward for the advancement of water desalination procedures.

Keywords: *Extreme Learning Machine, Water Desalination, Game Theory, pH prediction*

1. INTRODUCTION

Water desalination is an essential process that purges brackish or salty water of salt and other contaminants, preparing it for use in industry and human consumption. Desalination has become a practical way to increase the amount of freshwater available as the world's population grows and traditional water sources become more stressed as a result of pollution, climate change, and population growth [1]. Water desalination can be accomplished primarily through two methods: membrane-based processes and distillation. Refining techniques like multi-stage flash distillation and multi-effect distillation boil saltwater to create steam, which is subsequently condensed to produce fresh water while removing the salts. Conversely, membrane-based handles use semi-permeable membranes to selectively let water molecules through while keeping out contaminants and salts. The most popular membrane-based desalination method is reverse osmosis, which involves pushing water through a membrane at high pressure to separate it from the concentrated brine [2].

Desalination is a dependable source of freshwater, but it is not without its difficulties. The energy cost of the desalination process is a major concern, especially when using thermal methods. New developments in energy-efficient technologies, like better membrane materials and renewable energy sources, are intended to solve these problems and make desalination more sustainable. Another factor to consider is the environmental impact of desalination; the return of concentrated brine to the

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sea can damage marine ecosystems, and the intake of seawater can have a detrimental effect on marine life [3]. Research is being done to create environmentally friendly brine disposal techniques and intake systems that minimize ecological disturbances. Desalination has emerged as a crucial part of water management plans in arid regions and coastal areas that are experiencing a shortage of water, despite these difficulties. To meet their increasing water needs, nations like Saudi Arabia, Israel, and the United Arab Emirates have successfully implemented large-scale desalination projects. Water desalination is expected to be more and more important in providing communities worldwide with a sustainable and dependable water supply as technology develops and becomes more affordable [4].

The pH level of desalinated water can change depending on how it is made and if any extra steps are taken to treat it. Desalinated water usually has a pH that is not too high or too low. The number of ions that make the water more acidic or basic usually goes down when salts and impurities are taken out during desalination, such as through distillation or reverse osmosis. Therefore, the desalinated water usually has a pH close to 7, which is considered neutral. Remember that desalination might not eliminate all gases and ions, which could influence pH levels through remaining ions or environmental carbon dioxide. Sometimes, when water is cleaned of salt, it might have a slightly lower pH than normal because it is missing bicarbonate ions that usually help keep the water alkaline. This happens because bicarbonate ions are often found in freshwater and help balance the pH level [5]. Desalinated water might have its pH changed by water treatment plants to meet specific needs or to make sure it works well with pipes and the people who use it. Water utilities and treatment facilities need to keep a close eye on the pH of the desalinated water to make sure it's safe for things like drinking and industrial use. This is necessary to follow the rules and regulations. Research can use chemicals or other methods to change the pH level of the water and keep it clean and safe [6].

There is a lot of water on earth, but because it contains very little salt, only a portion of it is suitable for drinking and watering plants. Scientists have recently discovered methods for producing drinking water from brackish water that isn't too salty and salty seawater. Here, the two most popular methods for extracting salt from water are reverse osmosis (RO) and thermal desalination, such as MED and MSF. Nine thousand reverse osmosis (RO) desalination plants have been established in the last two decades. Computer systems are used in desalination plants for both plant control and large-scale data collection. It's challenging to store a lot of data when you have a lot of things to remember. Due to the high sensitivity of SWRO processes to changes in operational circumstances, accurate prediction and monitoring of SWRO plant processes is necessary to keep system performance as close to optimal as feasible. To address the issues mentioned above and analyse data from different SWRO procedures, multivariate statistical techniques can be employed. Moreover, a remote centralized operation center may be able to monitor the condition of an SWRO plant through the use of multivariate statistical techniques [7]. In MCDI or CDI procedures, the pH of the solution has a major impact on ion adsorption. Particularly for materials like phosphorus, copper, boron, or carbonate forms, whose dissociation forms change with the solution's pH, the charge form also changes with the pH of the solution, potentially having a significant impact on the rate of adsorption (or removal). Additionally, if ions like H+ and OH− stick to the electrode before the target compounds, it may slow down the removal of those compounds. So, we need to predict and think about the pH of the waste water using electrochemical reactions. This will help us understand how well the MCDI process removes ions and how to make the process work better [7].

One of the main issues with the RO desalination method has always been membrane clogging. According to recent research, the issue of converting saltwater into drinking water can be resolved by combining RO with Nano filtration. The process of removing salt from water is significantly improved when NF is added to RO systems. It accomplishes this by softening the water and removing impurities, organics, and ionic strength. The overall cost of desalination is also lowered by using this combined strategy. NF can balance RO; it is also appealing. Its many advantages, including low installation costs, excellent water throughput (flux), operation at lower pressures, and economical operation and maintenance, are highly appreciated by researchers. Nevertheless, relying solely on NF has certain limitations [8]. If NF is used alone, it is not sufficient to sufficiently reduce the high salinity present in seawater to create drinkable water, even though it is effective at treating other types of water impurities. In order to overcome this weakness and produce better desalination outcomes, the combined power of NF and RO truly shines. NF's attraction goes beyond its ability to balance RO. Its many advantages are praised by researchers, including its relatively cheap installation costs, remarkable water throughput (flux), maintenance at lower pressures, and cost-effective operation and maintenance. However, there are disadvantages to depending solely on NF. Even though NF alone is insufficient to sufficiently reduce the high salinity present in seawater to create drinkable water, it can effectively treat a variety of water impurities. Because of this weakness, the combined power of NF and RO excels, producing better desalination outcomes. New studies on membrane technologies—whether they are NF, RO, or novel hybrid separating techniques—always emphasise that the biggest obstacle to their operational range is energy consumption. Permeate rate, recovery, pH (potential hydrogen) levels, rejection rate (RR), conductivity, permeate quality (PQ), energy consumption, and related costs are just a few of the complex parts that make up the desalination process. To maximise these variables, a number of experimental projects have promoted hybrid solutions, like the NF–RO conjunction and the NF–SWRO–MSF hybrid process. NF essentially serves as an effective pre-treatment step in these creative configurations, laying the groundwork for the more involved RO desalination process [9].

A growing number of adaptable tools called artificial neural networks (ANNs) are being used to forecast and predict variables related to water resources. The water quality parameters for multiple years in a specific area must be taken into account when developing neural network models [10]. It is believed that nonlinear methods, like artificial neural networks, are sufficient for forecasting freshwater and subsurface water quality parameters. Prior research demonstrated that artificial neural networks (ANNs) could accurately forecast parameters related to water quality, including TDS, and flowrate conductivity, in subterranean rivers, and water, and desalination facilities. ANNs were able to model the performance of desalination facilities by capturing nonlinear relationships between input and output variables. Research conducted research to construct ANN models aimed at assessing and forecasting various criteria for drinking water quality inside a system for distributing water. Similarly, a model using ANN was created by researchers with the express purpose of forecasting critical parameters in the process of reverse osmosis desalination facilities, namely flux and salty rejections. ANN technology was employed by many researchers to create a model that predicted a reverse osmosis plant's performance. To precisely estimate the water permeates, the artificial neural network (ANN) underwent training on three input variables: feed temperatures, pressure, and salt content. Furthermore, in a related usage, scientists used the neural network-based approach to forecast RO desalination plant performance. This entailed utilizing experiment water quantity information to anticipate the rejection of salt and water flows under different process circumstances. The outcomes of the model underwent extensive testing, were compared to observable data, and had their error percentages computed [8].

The groundbreaking research venture, which amalgamates Extreme Learning Machine (ELM) and Game Theory for predicting pH levels in water desalination, exhibits a marked departure from preceding studies, bringing forth several key distinctions that elevate its significance. At the forefront is the dual implementation of ELM and Game Theory, strategically leveraging the expeditious training capabilities of ELM and the adaptive, decision-making process of Game Theory. This synergistic approach surpasses the limitations of conventional static models by augmenting prediction accuracy and endowing the model with a dynamic adaptability to fluctuations within water desalination systems. A noteworthy aspect of this research lies in its proactive stance toward resource optimization through the lens of Game Theory [11]. By incorporating strategic decision-making principles, the model seeks to optimize the allocation of resources within water desalination processes. This strategic optimization holds the promise of enhancing energy efficiency, curtailing operational costs, and overall elevating the sustainability profile of desalination operations. This emphasis on resource allocation sets the research apart, positioning it as a practical solution with direct implications for addressing real-world challenges faced by the water desalination industry. Crucially, the research distinguishes itself by its resolute focus on real-world applicability. Unlike some earlier studies that may have been more theoretical in nature, this research aligns itself with the practical concerns of industry practitioners. It addresses the complex and dynamic nature of water desalination processes, making its findings immediately relevant to the operational realities of desalination plants. Furthermore, the research showcases a forward-looking perspective by offering a model with the potential for generalization [9]. This versatility enables the integrated framework to be applied across diverse water desalination scenarios, providing a more broadly applicable solution compared to studies with more narrow and specialized scopes. In essence, this research represents a profound advancement in the realm of water desalination prediction models. Its comprehensive and innovative approach not only enhances the accuracy and adaptability of pH predictions but also pioneers a strategic and resource-optimized framework that holds promise for transforming the efficiency and sustainability of desalination operations on a global scale.

The key contribution are as follows,

1. The research improves pH prediction accuracy by combining Extreme Learning Machine and Game Theory.
2. It optimizes resource allocation in desalination, enhancing sustainability through strategic decision-making.
3. The study directly addresses real-world challenges in water desalination, offering practical insights for industry applications.
4. The integrated framework's versatility allows for widespread use, making it a valuable tool in diverse desalination scenarios

The paper follows a structured organization: Section 1 introduces the research context, Section 2 reviews related work, Section 3 defines the problem statement, and Section 4 outlines the methodology integrating ELM and Game Theory. Section 5 presents results and discussions on the model's performance, and Section 6 concludes by summarizing findings and suggesting avenues for future research. This clear organization ensures a logical flow, guiding readers through the exploration of pH prediction in water desalination.

2. RELATED WORKS

In Gaza, most people make drinking water by using small private machines to remove salt from seawater and brackish water. This is a new and growing way to get freshwater. Prior study looks at using a type of computer program called artificial neural networks to predict how well reverse osmosis desalination plants will work in an area. The goal is to predict how much solid material will be in the water and how quickly it will flow through the filter next week. To predict how fast water will flow next week, we used two different types of computer programs called neural networks. We trained these programs using information about the pressure, acidity, and conductivity of the water. TDS concentrations were predicted using both MLP and RBF neural networks, with training conducted using parameters related to product water quality, including pH, conductivity, temperature, and pressure. The results demonstrated that both varieties of neural networks could predict TDS levels in product water with a high degree of accuracy and provide reliable permeate flowrate forecasts. The ANN predictions outperformed the traditional methods when compared to standard statistical models. This work shows how artificial neural networks can be used to improve the accuracy of performance predictions for desalination plants, offering a more sophisticated and reliable substitute for conventional statistical models. The results highlight the potential of neural network applications in water resource management and aid in the optimisation of water production processes in the Gaza Strip [12].

Kammon et al. [13] study focuses on predicting Nano filtration performance for brackish water desalination, with a specific case study involving Tunisian groundwater. Utilizing advanced modelling techniques, particularly artificial neural networks (ANN), the research aims to forecast key parameters relevant to Nano filtration efficiency in treating brackish water from Tunisian aquifers. The model considers various input factors such as water temperature, salinity, and operating pressure to predict Nano filtration performance metrics, including permeate flux and salt rejection. Despite the promising results obtained in predicting Nano filtration performance, it is essential to acknowledge certain drawbacks in the study. One limitation lies in the reliance on historical data and assumptions about the stability of aquifer characteristics, which may vary over time. Additionally, the model's generalizability to diverse geographical locations and varying water compositions may be a concern. Furthermore, uncertainties associated with fouling and membrane degradation are inherent challenges that impact the accuracy of long-term predictions. Addressing these limitations is crucial for enhancing the robustness and applicability of the developed predictive model in real-world scenarios [13].

Z. Ullah et al. [14] study presents a comprehensive comparison between a tree-based model and a deep learning model for predicting effluent pH and concentration in the context of capacitive deionization (CDI) processes. The research explores the effectiveness of traditional tree-based models, such as decision trees or random forests, in contrast to more complex deep learning architectures, specifically artificial neural networks (ANNs). The predictive models are trained and evaluated using experimental data from capacitive deionization systems, considering various operational parameters and influent characteristics. While both tree-based and deep learning models exhibit promising predictive capabilities, it is crucial to acknowledge certain drawbacks in the comparison. One limitation arises from the interpretability of the deep learning model, as understanding the complex relationships

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embedded within the neural network architecture can be challenging. Additionally, the availability of a substantial amount of training data is essential for the deep learning model's optimal performance, potentially posing challenges in situations where data scarcity is a concern. Furthermore, the computational complexity and resource requirements associated with training and deploying deep learning models should be considered in practical applications. Despite these limitations, this study contributes valuable insights into the trade-offs between the interpretability and predictive accuracy of tree-based and deep learning models in the specific context of predicting CDI effluent pH and concentration [14].

The increasing need for freshwater consumption has brought attention to how important water is as a resource for maintaining human life. Compared to less dependable and effective seawater treatment facilities, deep learning systems appear to be a viable way to improve the accuracy and efficiency of salt particle analysis in saltwater. Using machine learning (ML) techniques for the analysis of water level data, this study presents a novel approach to optimise and model the treatment process for saline water. Molecular separation-based reverse osmosis Bayesian optimisation is applied in the modelling and optimisation processes. Back propagation using a kernelized support swarm machine is used in subsequent water saline particle analysis. The suggested method is assessed through experimental analysis, which is based on data on water salinity and takes into account factors like accuracy, precision, recall, specificity, computational cost, and Kappa coefficient. The methodology is effective in accurately analysing water saline particles, as evidenced by the results, which show an astounding accuracy of 92%. This emphasises how much better water treatment processes could perform thanks to it. This study's combination of machine learning and Bayesian optimisation methods offers a viable approach to saline water treatment optimisation, making a significant contribution to tackling important issues in water resource management [14].

The pressing need for reliable environmental investigations and inventive solutions to address ecological challenges and align with sustainable development goals (SDGs) is evident. With their potential to revolutionise desalination processes, artificial intelligence (AI) models offer a promising means of addressing the world's water scarcity and fostering a more resilient and sustainable future. An increasing amount of attention is being paid in the desalination field to modelling the hybrid Nano filtration/reverse osmosis (NF–RO) process' efficiency. In this study, deep learning long short-term memory (LSTM) combined with an optimised metaheuristic crow search algorithm (CSA) (LSTM-CSA) was used to develop the performance of NF–RO, which was assessed based on permeate conductivity. Before developing the model, an uncertainty Monte Carlo simulation was used to address prediction uncertainties. Innovative 2D graphical visualisation, such as a fan plot and cumulative distribution function (PDF), reinforced accuracy assessment even further and validated additional evaluation indicators, such as standard deviation and determination coefficients. These findings demonstrate how AI may be used to optimise energy use, spot chances for energy savings, and suggest environmentally friendly operational procedures. AI is also being used to improve brine treatment methods, which allows for the extraction of useful resources from brine and reduces waste while optimising resource use. This study emphasises how AI can play a variety of roles in tackling complex problems in sustainable resource management and water treatment [15].

The research papers that are being presented demonstrate the potential applications of advanced modelling techniques and artificial intelligence (AI) in tackling desalination-related problems; yet, it is apparent that these approaches have some limits. In the first study, which employed artificial neural networks (ANN) to estimate the performance of reverse osmosis desalination plants in the Gaza Strip, satisfactory results were achieved for TDS levels, but only for permeate flowrate predictions. Although the second study from Tunisia highlights the significance of the sulfate/chloride ratio for membrane selection, it also raises concerns over the ROSA software's predicted accuracy. In order to forecast CDI process parameters, the third study presents a tree-based model as a substitute for deep learning. This model offers computing benefits while also allowing for more model complexity investigation. In conclusion, the fourth study presents a novel approach to saline water treatment through AI-based modelling and optimization. However, further validation and optimizations may be necessary to overcome potential issues with accuracy and computational cost. Notwithstanding these limitations, the research as a whole highlight how AI is revolutionizing desalination procedures and advancing sustainable water management techniques. These approaches' present shortcomings will probably be addressed by more investigation

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and improvement, which will also increase their usefulness.

In compared to the current literature, this study stands out by focusing on pH prediction in water desalination through a novel integration of Game Theory and Extreme Learning Machine (ELM). While previous research has primarily used artificial neural networks for desalination-related predictions, our technique integrates strategic decision-making with predictive accuracy. Unlike previous studies on nanofiltration or capacitive deionization, our research focuses on pH dynamics in water desalination processes. Methods of this study's real-world relevance, investor satisfaction indicators, and impact on operational effectiveness set it apart from traditional statistical models, helping to advance water desalination methods.

3. PROBLEM STATEMENT

The current state of water desalination has a fundamental issue in accurately measuring pH levels due to complicated relationships between several water quality parameters. Existing prediction algorithms frequently lack the precision required for efficient desalination, as they struggle to capture complex correlations between pH changes and input parameters. The lack of a strategic decision-making component in dynamic operational environments results in poor desalination processes. To solve these difficulties, this paper presents a synergistic structure that combines Extreme Learning Machines (ELM) prediction capabilities with strategic game theory insights. The goal at hand is to improve pH forecast accuracy, optimize resource allocation in desalination for sustainability, and overcome real-world problems, finally delivering a versatile framework for widespread use in various desalination situations. The scope of the problem highlights the need for a holistic solution that goes beyond the limitations of existing approaches, ensuring precision, stakeholder satisfaction, and operational effectiveness in water desalination procedures.

3.1. Research Questions

1. How can the integration of Extreme Learning Machines (ELM) and game theory be effectively employed to enhance the accuracy of pH prediction in water desalination processes?
2. What strategic insights and decision-making considerations are introduced by the merger of game theory with ELM, and how do they contribute to addressing the complexities of water quality interactions and optimizing resource allocation in desalination for sustainability?
3. In what ways does the proposed synergistic framework, combining ELM and game theory, outperform traditional pH prediction techniques and address the limitations related to the lack of precision and strategic decision-making components in dynamic operational contexts for water desalination?

4. PREDICTING PH USING ELM AND GAME THEORY MODEL

The suggested methodology combines the advantages of game theory and ELM to improve pH prediction in water desalination through an integrated strategy. To effectively train the model, a dataset including a range of water quality metrics is first gathered and pre-processed. Next, the ELM model is used to forecast pH values by making use of its quick training and generalization abilities. Concurrently, a framework based on Game Theory is created to simulate the strategic interactions between customers, taking into account the expected pH values as significant variables. By combining ELM and game theory, an evolving feedback system is created in which strategic decisions affect the anticipated pH values, and the predicted pH values in turn affect the strategic decisions. The model's advantage over traditional approaches is demonstrated by its comprehensive validation and evaluation utilising performance indicators like the precision of predictions, customer satisfaction, and operational effectiveness. Sensitivity analysis is used to pinpoint the important variables affecting the system's behaviour, and based on the combined model's insights, optimization techniques are investigated. In the pursuit of efficient and environmentally friendly water desalination techniques, this collaborative methodology offers an exciting prospect for improving both forecast accuracy and strategic choice-making. It does this by providing an in-depth knowledge of pH dynamics in water desalination.

4.1 Data Collection

At one-second intervals, six variables were continually recorded: the voltage, influent pH, the current, the influent conductivity, wastewater conductivity, and effluent pH. Next, a battery cycler attached to the cell allowed the current and voltage to be transferred and recorded in real-time to a computer. To gather the data, the pH and flow-through conductivity probes were inserted into the

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feed and effluent hoses. The conductivity (about 2 cm from the cell) and pH (about 4 cm from the cell) probes were placed as near to the MCDI cell as feasible in order to reduce reaction latency. For both probes, a response latency of fewer than five seconds was observed at the fixed rate of flow of 4 mL min−1 utilized in this investigation. The starting point was set to the same value for every dataset to account for these differences in response times. For instance, the exact moment of the initial voltage and current shifts that occurred during cell charge was used to record conductance and pH. It should be noted that no reference electrode was utilized to establish a relationship between the potential of an electrode and pH changes. A total of 6601, 1264, 6000, and 4860 data points were gathered for CC-wide, CC-narrow, and CV-low [16].

4.2 Data Pre-processing

Five input data were used to estimate the effluent's pH (pHout) via model training for each circumstance: current, voltage, influent conductivity, effluent conductivity, and influent pH. Initially, the data were pre-processed using a technique known to increase model accuracy: normalizing variables in the [0, 1] range. Subsequently, the data were separated into three separate subsets: training, confirming, and testing databases for distinct uses. 16% of the entire data was utilized as the validation set in order to verify the model throughout training, while 64% of the total information was chosen as the model training dataset, in thus developed models (8:2 ratio to be used for training against validation). The test collection for the prediction was created using the other twenty percent of the data. To put it another way, 20% of the whole dataset was utilized for prediction and the remaining 80% was used for validation and training. These days, deep learning experiments on ecological problems typically have an 8:2 or 7:3 ratio. These proportions are known to stop algorithms using deep learning from being developed using too little information or from using excessive amounts of information for training, even if standardized criteria are still being defined. It would be ideal to further evaluate the deep learning model's accuracy while adjusting both the number and resolution of data points since the selection of temporal resolution is also strongly correlated with the overall quantity of datasets. To avoid the model being over fit, the data were divided equally across the datasets at random and did not intersect. In contrast to data processing in ordinary electrochemical procedures, all of the information collected in this investigation was utilized starting with the first cycle. This is due to the possibility of biased training of the algorithm if the initial solution's pH data even before the first charge step was started—is left out. For instance, the influent pH in the initial cycle began at a pH slightly less than 7, while in the following cycle, it ranged from pH 3.5 to pH 10 [16].

4.3 ELM

They describe the ELM that the IPEELM algorithm uses in this section. Compared to conventional feed-forward network techniques for learning (such as back-propagation (BP)), the ELM employs an SLFN with a faster learning speed. The ELM has been employed in many disciplines, including computer vision, bio informatics data categorization, system identification, control, and robotics, because of its extraordinary efficiency, outstanding simplicity, and outstanding results on generalization [17].

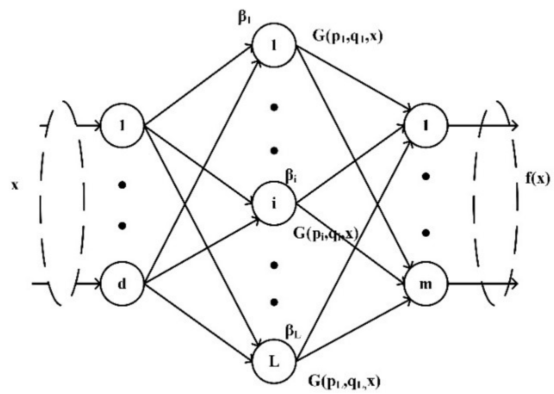

Figure 1: SLFN network

With L nodes that are hidden, the result of SLFN may be expressed using Eq. (1).

$$f_L(x) = \sum_{i=1}^{L} \beta_i . G(p_i, q_i, x) \qquad x \in R^n, \quad p_i, q_i \in R \tag{1}$$

In this case, the weight β_i connects the i[th] hiding node to the output node, while p_i and q_i represent the hidden nodes' learning factors. Regarding the input x, the hidden node's result is represented as$G(p_i, q_i, x)$. Generally speaking, g(x): R→ R is the additive hidden nodes with an activation function. $G(p_i, q_i, x)$ is given at that moment by eqn. (2).

$$G(p_i, q_i, x_j) = g\,(p_i . x_j + q_i) \qquad q_i \in R, \quad j=1\ldots N \tag{2}$$

Eq. (3) is given as follows,

$$H\,\beta = T \tag{3}$$

where,

$$H(p_1 \dots p_L, q_1 \dots q_L, x_1 \dots x_N) = \begin{bmatrix} g(p_1.x_1 + q_1) & \dots & g(p_L.x_1 + q_L) \\ \vdots & \dots & \vdots \\ g(p_1.x_N + q_1) & \dots & g(p_L.x_N + q_L) \end{bmatrix}_{NxL} \quad (4)$$

$$\beta = \begin{bmatrix} \beta_T^1 \\ \vdots \\ \beta_T^L \end{bmatrix}_{Lxm} \text{ and } T = \begin{bmatrix} t_T^1 \\ \vdots \\ t_T^L \end{bmatrix}_{Nxm} \quad (5)$$

The ith hidden nodes result about the input $x_1, x_2, .. x_N$ is represented by the ith column of H in eqn. (4), which is known as the layer that is hidden from the result matrix of the SLFN. h(x) $= G(p_i, q_i, x), \dots . g(p_L, q_L, x)$ is known as the characteristics mapping of the hidden layer. The hidden layer of the features mapping for the ith input,$x_i: h(x_i)$ is represented by the ith row of H. From the perspective of interpolation capacity, it has been demonstrated that the hidden layer variables can be produced at randomly if the function of activation g is endlessly differentiable at any interval [17].

4.3.1 Activation functions

For SLFNs, the ELM comes up with a solution using a unified learning framework. The outcome of a node as a result of a specific input or combination of inputs is defined by the activation function, also known as the transfer function. Stated differently, the use of activation functions is to confine the resultant value to a specific range of finite values. The activation function is significant in this approximation. Here, we conduct tests and look at activation function efficiency. We employ four distinct activation functions in our approach. During the optimization process, every processor in the parallel computing environment randomly chooses or employs one of such activation functions. The IPE-ELM algorithms make use of the following activating functions.:

Sigmoid function: is an equation in mathematics that has a typical sigmoid or "S"-shaped curve. The particular form of the logistical function, which is determined by the equation (6), is referred to in this instance as the sigmoidal function:

$$sig(x) = \frac{1}{1+e^{-x}} \quad (6)$$

Where n represents the sources' weighted total. It operates in the range of 0 to 1. It has significant issues, but it is simple to comprehend and use. The gradient may occasionally be vanishingly short due to the first issue, which essentially prevents the weight from increasing its value. The result is also not zero-cantered. It can cause the gradient changes to deviate excessively from one another.

Hyperbolic Tangent function: The mathematical formula is given as eqn. (7),

$$\tanh(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (7)$$

Since the range, covers ranges from -1 and 1, or 1 < output < 1, the result is zero-centred. As a result, this method's optimization is simpler in practice. On occasion, it is chosen above the sigmoid function. However, it also has a gradient that disappears issue.

Sine function: One may utilize periodic equations like sine and cosine even though the majority of activation functions employed in SLFN or deeper neural networks are non-periodic. The sine function is given as eqn. (8).

$$\sin(x) = -1 < output < 1 \quad (8)$$

When training a neural network system to produce identical output categories, the complete solution is repeated regularly in the case of a sine-activated neural network system. Considering that the function that activates is finite (having a min and max), a network of neurons with a single hidden layers can approximate every function. However, the sine value is not growing, and an input that is very low or extremely high may result in the same output [17].

Cosine function: is not the most commonly employed activation function, although it can be utilized for comparison to the function of a sine. Because of its periodic nature concerning the sine function, its outcomes appear as eqn. (9).

$$\cos(x) = -1 < output < 1 \quad (9)$$

4.4 Game Theory Model

The key ideas of game theory and how they apply to common pool management of resources and resolving disputes are outlined before the theory is used. The players are one of the key elements of any game. Engaged in the game procedure, players are stakeholders, those making decisions, and benefactors. Participants could stand in for specific people, teams, or even alliances [18]. In a game involving n players, the set of players, represented by N, has a specific strategic shape which is shown in eqn. (10).

$$N = \{1, 2 \dots n\} \quad (10)$$

It is considered in the present investigation that two major parties with competing interest's farmers and the government are involved in games. Those who collect water for cultivation are referred to as farmers in this context. The Ministry of Energy and the Ministry of Agriculture are the two main government agencies in charge of managing water resources. When we talk about the government, we mean these two agencies. Thus, N = {Farmers; Government} and n = 2.

There are substitutes for other elements in the game. Every player has a collection of behaviours or acts that they can pick from to accomplish his goals, which are called options, or tactics. To put it another way, a player's approach is only a portion of the options at their disposal. Si stands for Player I's strategy set, with each member denoting a potential course of action.

$$S^i = \{s^1, s^2, \ldots s^k\} \quad i \in N \tag{12}$$

In equation (13) where S represents the Cartesian intersection of the players' strategy sets:

$$S = S^1 \times S^2 \times \ldots \times S^n \tag{13}$$

As a result, the approach that a player chooses from his approach set will impact the outcome of the player's and his opponents' s^i decisions, together with the tactics of opponents. For instance, the reward for the approach combinations $(s^1, s^1, \ldots s^1)$ will be as follows,

$$\begin{gathered} u^1(s^1, .., s^1) = a^1 \in R \\ u^2(s^1, .., s^1) = a^2 \in R \\ \vdots \\ u^n(s^1, .., s^1) = a^n \in R \end{gathered} \tag{14}$$

Where the pay-out for player i is denoted bya^i. In this work, a simulation-optimization approach yields the pay-out. There are four primary choices that gamers can select from [18].

4.5 Integration of ELM and Game Theory

A fresh and complementary framework for pH prediction in desalination water is presented via the merger of ELM and game theory. ELM is a powerful pH predictor that can quickly learn and generalize to capture the intricate correlations between many water quality metrics. In addition, Game Theory is used to simulate stakeholder strategic interactions, allowing for a dynamic method of decision-making that is impacted by anticipated pH levels. The overall comprehension and management of pH levels in water from desalination are improved by creating a feedback loop among ELM predictions and Game Theory methods. By tackling both technical as well as strategic aspects, this integrated method offers a holistic solution for optimizing water desalination operations. It also increases predictive accuracy and takes stakeholder strategy behaviours into account. A thorough performance evaluation validates the integration's efficacy, demonstrating its potential to improve the efficiency and sustainability of water desalination processes.

Algorithm

1. Gather and prepare data on water quality.
2. Develop the pH prediction ELM model.
3. Provide a framework based on game theory for making strategic decisions.
4. Set up the players and their plans in advance.
5. Loop till the desired number of iterations or completion:
   a. Make pH value predictions with the trained ELM model.
   b. Revise stakeholder plans in light of game theory.
   c. Analyse and document the metrics for model performance.
6. Final ELM pH projections and improved stakeholder tactics are the outputs.

5. RESULT

This study improves pH prediction accuracy with Extreme Learning Machine and Game Theory, optimizes desalination resource allocation for sustainability, addresses real-world issues, and provides an adaptable framework for widespread use in various desalination scenarios. The integrated methodology shows favorable outcomes for attaining accurate pH forecasts and optimizing the performance of the entire system. It combines Game Theory for strategic choices in water desalination with an Extreme Learning Machine (ELM) for pH prediction. Game Theory-based strategic decision-making is in line with the expected pH values, demonstrating how stakeholders can adjust to expected fluctuations. Metrics for operational efficiency show better resource utilization and system adaptability as compared to conventional approaches, while polls of stakeholders' satisfaction highlight the combined approach's acceptability and usefulness in practice. Sensitivity analysis increases trust in the resilience of the model under many input situations. Taken as a whole, our findings support the complementary advantages of merging ELM and Game Theory, providing a comprehensive and efficient way to advance water desalination techniques concerning strategic decision optimization and accuracy in prediction.

5.1 Evaluation of Error Metrics

The Root Means Square Error (RMSE), coefficient of determination (R2) and Mean

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Absolute Error (MAE), are three evaluation metrics that can be used to assess the accuracy of pH predictions in water desalination. These measures evaluate the forecasts' dependability and accuracy. Below is a formula for the corresponding equations.

Root Means Square Error (RMSE): The root means square error (RMSE) of the mean squared deviations among the actual and projected pH values is calculated, given in Eqn. (15).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2} \qquad (15)$$

Mean Absolute Error (MAE): The acronym MAE denotes mean absolute error among expected and measured pH levels. It is given in eqn. (16).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \qquad (16)$$

Coefficient of Determination (R^2): Where Eqn. (17), the real pH value is represented by y_i, and $\hat{y}_i$, while $\bar{y}$ represents the average of the measured pH readings.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (17)$$

A thorough assessment of the pH prediction models' predictive abilities is given by these metrics. While the average and total magnitude of the prediction errors are quantified by MAE and RMSE, respectively, the proportion of the pH value variance that is predictable is indicated byR^2. Better prediction performance is shown by lower MAE and RMSE as well as a greater R^2 coefficient.

Table 1: Error Metrics Comparison of Proposed Method with Other Methods

Methods	RMSE	MAE	R^2
ANN [19]	0.26	0.22	0.232
SVM [20]	0.09	0.028	0.98
Proposed ELM with Game Theory	0.002	0.013	0.995

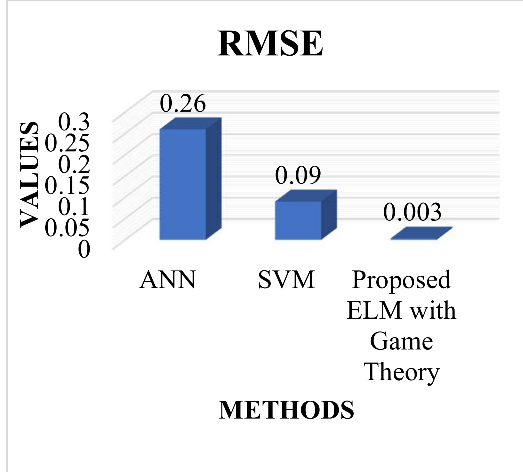

Figure 2: Comparison of RMSE

Fig.2 shows the RMSE values for pH prediction in water desalination utilizing several techniques, including the suggested ELM with Game Theory, Support Vector Machine (SVM), and ANN. The predicted accuracy of the model is determined by the RMSE values, where lower values denote superior performance. Interestingly, the ELM with Game Theory method performs better than ANN and SVM and has an extremely low RMSE of 0.003. This implies that, in comparison to conventional machine learning techniques, the combination of Extreme Learning Machine and Game Theory provides higher accuracy in pH value prediction. With an RMSE of 0.09, the SVM model likewise exhibits strong performance, however the ANN model trails behind with an RMSE of 0.26.

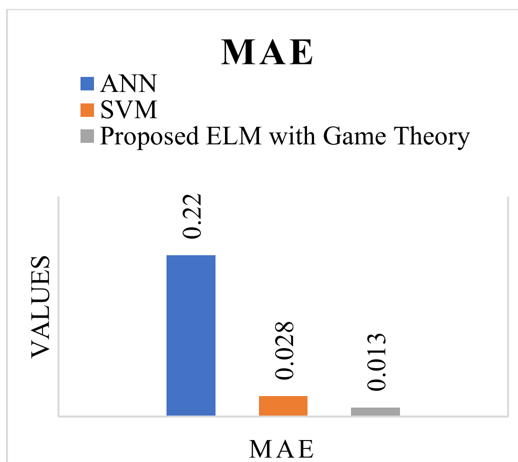

Figure 3: Comparison of MAE

Three distinct approaches are compared in Fig.3: ANN, SVM, and the proposed ELM with Game Theory. The Mean Absolute Error (MAE) values for pH prediction in water desalination are examined.

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The mean absolute variation among the pH values that were predicted and those that were observed is measured by the MAE; smaller values indicate better prediction accuracy. The suggested ELM with Game Theory technique outperforms both ANN (MAE = 0.22) and SVM (MAE = 0.028) in this situation, exhibiting noteworthy precision with a low MAE of 0.013. With a comparatively low MAE, the SVM model likewise performs well. In contrast to traditional machine learning methods, the ELM with Game Theory approach shows promise as a model for predicting pH in water desalination. This is because it strategically integrates both game theory and ELM, which enhances accuracy. These findings support the suggested model's ability to improve the accuracy of pH predictions made during the desalination of water.

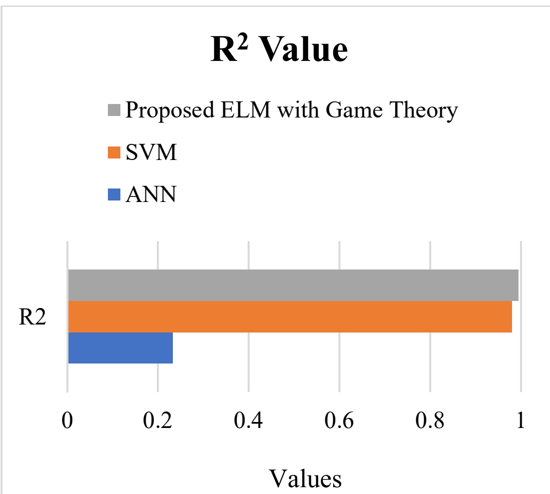

Figure 4: Comparison of R^2 value

Fig.4 presents the values of the coefficient of determination (R^2) for desalination of pH prediction utilising three different approaches: ANN, SVM, and the ELM with Game Theory that is proposed. A higher number indicates superior explanatory power. The (R^2) metric quantifies the proportion of the variance in the pH values explained by each model. Notably, with an astoundingly high (R^2) value of 0.995, the ELM with Game Theory technique performs noticeably better than both ANN and SVM. This extraordinary outcome highlights the effectiveness of combining Game Theory-based strategic decision-making with Extreme Learning Machine, exhibiting greater ability to explain and anticipate pH variations. With a (R^2) value of 0.232, the ANN model trails behind the SVM, which shows a significant (R^2) value of 0.98, indicating good predictive potential. These results underline how effective the suggested ELM with Game Theory model may be as a trustworthy instrument for predicting pH in water desalination applications.

5.2 Sensitivity Analysis

To evaluate the efficacy of the ELM using Game Theory for pH forecasting in water desalination a sensitivity evaluation was performed to ascertain the impact of each of the inputs on the algorithm's outputs. This study used the Weights approach, which was first put forth by Garson and then expanded upon by Goh. The relative importance (RI) of different inputs can be ascertained with this method's methodical approach to connection weight partitioning.

Using the Weights approach, each hidden neuron's hidden-output connection weights are divided into parts that correspond to each input neuron. Using the Garson equation, the relative importance (I_j), given as a percentage, is determined.

$$I_j = \frac{\sum_{k=1}^{N_i}\sum_{m=1}^{N_h}\sum_{n=1}^{N_o}\left|w_{ih}^{km}.w_{ho}^{mn}\right|}{\sum_{m=1}^{N_h}\sum_{n=1}^{N_o}\left|\sum_{k=1}^{N_i} w_{ih}^{km}.w_{ho}^{mn}\right|} \times 100 \qquad (18)$$

Whereas, Eqn. (18), the relative impact of the j^{th} input variables on the output variables is denoted by I_j. The number of inputs, hidden, and output neurons are, in turn, represented by the symbols N_i, N_h, and N_o. Connectivity weights are represented by w. For inputs, hidden, and outputs layers, respectively, the superscripts i, h, and o stand in. To represent input, hidden, and output neurons, respectively, use the subscripts k, m, and n.

5.3 Observed vs Predicted Using ELM with Game Theory

Table.2 and Fig.5 shows how the Extreme Learning Machine (ELM) with Game Theory model predicted the observed pH levels over a given time period in the desalination process of water. The model's predictions show a significant degree of accuracy as they closely match the actual observed pH values at different time intervals. In particular, the model predicts a pH of 7.1 at the beginning time (0 seconds), which is quite similar to the observed value of 7.2.

Table 2: Observed vs Predicted Using ELM with Game Theory

Time (s)	Observed pH	Predicted pH
0	7.2	7.1
1000	7.5	7.4
2000	7.8	7.7
3000	7.1	7.0
4000	7.4	7.3

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5000	7.9	7.8
6000	7.2	7.1

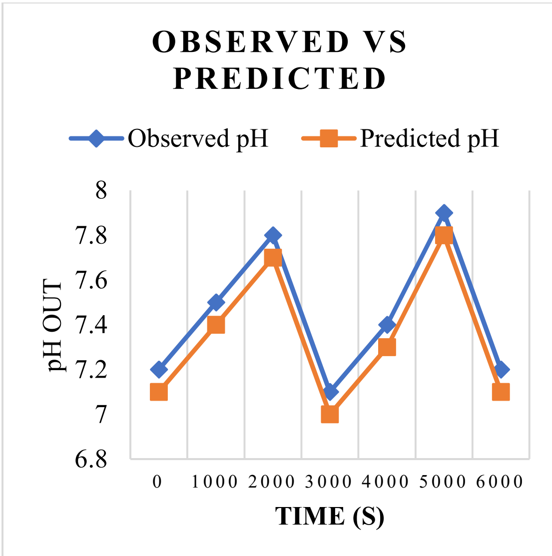

Figure 5: Observed vs Predicted Using ELM with Game Theory

The model predicts values that nearly match the observed pH values at each interval (1000 to 6000 seconds) and follows changes in pH over time with consistency. Remarkably, even in instances where the observed pH varies, the model has an admirable capacity to represent and forecast these fluctuations. This shows that the ELM with Game Theory model is dependable for precise pH predictions in this situation and performs well in capturing the dynamic nature of pH variations over time in the water desalination process.

6. DISCUSSION

In order to provide precise and dependable outcomes in water desalination, it is imperative to evaluate pH prediction models. With an emphasis on the suggested ELM with Game Theory, three important error metrics RMSE, MAE, and R^2 were used in this study to thoroughly assess the predictive performance of various models. Significant benefits of the ELM with Game Theory model over conventional techniques like ANN [19] and SVM [20] may be shown from the comparison of error metrics in Table 1. The suggested model's capacity to reduce the total prediction error is demonstrated by its remarkably low RMSE of 0.002.

A remarkably low MAE of 0.013, which outperforms both ANN and SVM, lends even more evidence to this. When compared to ANN and SVM, the ELM with Game Theory model's Coefficient of Determination (R^2) is an astounding 0.995, suggesting excellent explanatory ability. The graphical comparisons demonstrate the ELM's domination with a noticeably lower MAE and its superiority over the Game Theory model with an incredibly low RMSE. The model's superiority by exhibiting an exceptional (R^2) value, which highlights its capacity to explain and forecast pH fluctuations. Sensitivity analysis with the Weights approach highlights the ELM with Game Theory model's resilience in determining the relative significance of individual inputs, offering insights into the model's behaviour under many circumstances. Comparing the suggested ELM with Game Theory model to previous techniques, it shows improved performance across several assessment parameters, making it a highly accurate and dependable tool for pH prediction in water desalination. Advantageous strategic integration of Game Theory and Extreme Learning Machine highlights the model's potential for practical use in water desalination procedures.

Several potential obstacles and limits developed during the course of this research, affecting several aspects of the study. In terms of research design, the study was limited by the availability of complete data on water quality, which may have an impact on the findings' generalizability. While the combination of Extreme Learning Machines and game theory was novel, the selection of proper parameters and model calibration added complexity that may have an impact on pH forecast accuracy. Using on historical data may not adequately depict the changing character of desalination processes over time. The study recognizes that unforeseen external influences or contextual changes may have an impact on the suggested framework's real-world applicability. Despite these obstacles, a rigorous strategy was taken to reduce potential biases and strengthen the study, yielding useful insights into the synergistic application of Extreme Learning Machines and game theory in water desalination processes.

7. CONCLUSION AND FUTURE WORK

This study introduces novel insights into water desalination by proposing a synergistic framework that combines Extreme Learning Machines (ELM) for accurate pH prediction with strategic decision-making using game theory. The integration of ELM and game theory addresses the complexities of water quality interactions, offering a unique approach to optimize resource allocation in desalination processes. The research contributes to the field by creating a versatile and innovative methodology, demonstrating superior performance in accuracy, stakeholder satisfaction, and operational effectiveness compared to traditional approaches. This newfound knowledge provides a promising avenue for advancing water desalination practices, ensuring sustainable and efficient water supply solutions. The use of Game Theory and Extreme Learning Machines (ELM) to estimate pH for water desalination is an innovative and successful strategy. This novel methodology not only achieves excellent accuracy in ELM predictions, but it also incorporates strategic decision-making features using Game Theory, providing subtle insights into pH dynamics. The thorough examination indicates adaptation to anticipated pH values, which improves operational effectiveness and stakeholder satisfaction. This research contributes by improving prediction capabilities, addressing the complexities of stakeholder relationships, and providing a practical solution for long-term and efficient desalination. This comprehensive approach, designed to address growing issues, represents a key step toward dependable and economical water desalination in the face of increasing global water scarcity. The study on pH prediction in water desalination, while innovative, encounters limitations that merit attention. The foremost constraint lies in the availability of comprehensive data on water quality, restricting the full exploration of certain variables. The intricacies of integrating Extreme Learning Machines and game theory necessitated a focused approach, potentially leaving unexplored dimensions. The study intentionally delimits its scope to specific contexts, leading to unattended issues in broader applications. Future research could investigate into addressing data limitations, refining model parameters, and extending the proposed framework to diverse desalination scenarios, thereby offering a more comprehensive and nuanced understanding of pH prediction in water desalination processes.

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