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# Advancing Environmental Sustainability through Implementation of Artificial Neural Networks for Wastewater Treatment Model Prediction and Remediation

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This research examines the effectiveness of various artificial neural network technologies in enhancing wastewater treatment models prediction and remediation on the standpoint of environmental sustainability. This study was done via ten experiments that delve into the performance of the four types of ANN architectures known as Feedforward Neural Networks, Recurrent Neural Networks, Long Short-Term Memory Networks, and Gated Recurrent Unit Networks. This process model's validation findings affirm the models' capability to forecast the outcome of the intervention and guide the correct form of remediation. FNNs yield consistently low levels of MSE: between 0.010 and 0.020, while the R^ 2 is high and stays between 0.910 and 0.960. Meanwhile, RNNs, LSTM Networks, and GRU Networks include slightly higher MSE values but feature a stronger correlation with R^2 : between 0.880 and 0.940. These results indicate that the ANN technologies have the potential to model the treatment processes. They can be utilized to ensure more optimal treatment processes and reduce environmental contamination.

**Keywords:** wastewater treatment, artificial neural networks, environmental sustainability, prediction, remediation.

## 1. Introduction

Wastewater management remains a growing environmental issue, both domestically and globally. Inadequate treatment results in water bodies' pollution and ecosystem degradation and poses new threats to community welfare and health. Traditional wastewater treatment systems have difficulty removing contaminants efficiently and optimizing resource recovery. The application of artificial intelligence techniques, and in turn, artificial neural networks over recent years has had a somewhat unprecedented potential to rationalize wastewater treatment processes in improving prediction accuracy and, hence, driving remediation processes[1]–[3].

The impulse for this study is the immediate necessity for enhancing the productivity and scope of the existing wastewater treatment processes and the need for new methods to cope with the rising environmental impact. Although numerous advancements have been made in traditional ways of wastewater treatment, new techniques must be developed to combat the changing nature of environmental risks and regulations. Artificial neural networks present such an innovation by creating a computational model, based on the human brain biological neural networks that can process the data's complex patterns and nonlinearity considerably present in wastewater treatment systems[4]–[7].

The problem statement is centred around the inadequacies and imperfections of traditional wastewater treatment models concerning the accuracy of predicting treatment results and facilitating proper remediation procedures. Typically, conventional models are characterized by simple assumptions and linear dependencies that cannot fully articulate the dynamic and nonlinear behavior of the wastewater treatment progression. The loss of accurate portrayal of the actual state of incidents between theoretical predictions and practical experience results in wasted resources and imprecise environmental outcomes [8]–[11].

The research objectives are divided into two parts: First, the paper aims at determining the extent to which the different types of Artificial Neural Networks – Feedforward Neural Network, Recurrent Neural Network, Long Short-Term Memory, and Gated Recurrent Unit can be used to predict the wastewater treatment model and remediate it. Second, its goal is to establish the extent to which the use of ANNs can increase the prediction accuracy and aid the optimization of the remediation process.

The area of the paper covers both theoretical realization as well as ANN techniques application in wastewater treatment. The research will assume the acquisition and analysis of data related to wastewater treatment, the creation of different ANN models as well as their training, and determination of performance of the models based on the capabilities to predict treatment outcomes and conduct remediation. At the same time, the paper also includes the ideas for applications of ANNs techniques to this industry and possible examples of further research.

## 2. Literature Review

Wastewater treatment is a crucial process that protects public health and the environment. It involves the removal of contaminants and pollutants from water before it can be disposed of or reused. While currently used methods such as physical, chemical, and biological treatment are somewhat effective, they face many difficulties in areas such as high treatment efficiency, presence of complex contaminants, or changing operating conditions [12]–[15].

Artificial intelligence is increasingly viewed as a method that can be brought to bear on wastewater treatment to help optimize systems. As a data analysis tool, AI and its umbrella of techniques including artificial neural networks, the latter of which is particularly useful for big data applications, can be used to help predict the results of complex, interrelated systems. Treatment process modelling, which is used to allocate resources effectively among complex, often nonlinear water treatment systems, has been enhanced through the use of ANNs [16]–[19].

In recent years, a large number of studies in the wastewater treatment domain have investigated the use of ANN techniques for a broad range of problems. While the former comprises the prediction of concentrations of pollutants, optimal design and operation of treatment plants, and other applications, the following comprises modelling the relationship between input variables and output variables. Because they are basic types of ANN, FNNs have been used for the modelling. Recent studies have shown that RNNs, such as LSTM and GRU networks, are well-suited for modelling the temporal dependence of wastewater treatment data and the capture of sequential patterns and therefore used for time-series prediction and dynamic process modelling[20]–[23].

There are numerous challenges and limitations with respect to applying ANN techniques in the area of wastewater treatment, though it has a considerable potential. If refers primarily to available data and their quality, as wastewater treatment plans and facilities generate a great deal of heterogeneous data that may be incomplete, noisy, or biased. Data pre-processing and feature selection are essential when it comes to getting input data ready for ANN modelling, but the process requires a certain knowledge and understanding of the assumptions and underlying uncertainties. On any stage of ANN model implementation, it may overfit or underfit if it is not properly trained or validated, not reflecting its real-world generalization performance[24]- [26].

Additionally, the interpretability of ANN models is still a point of worry. The presence of complex network architectures and nonlinear activation functions has made it hard for researchers to understand what drives the trends of model predictions. As such, interpretable AI methods, through Explainable Artificial Intelligence, have been developed to understand how ANNs make decisions and what features contribute the most to the model prediction. Therefore, including XAI methods in ANN-based wastewater treatment could render these methods more transparent, explainable, and trustworthy, thus promoting their use for operational decision-making.

## 3. Methodology

The methodology of this research consists of several stages, including data collection and preprocessing, an artificial neural network overview, specific applications of various architectures of ANN, training and validation procedures, and performance evaluation. Data collection implies gathering datasets from wastewater treatment plants including influent characteristics, operational parameters, and effluent quality. Datasets might be heterogeneous and require reprocessing to become consistent and qualitative. Pre-processingwill entail data cleaning, normalization, and feature selection to prepare data for ANN modelling.

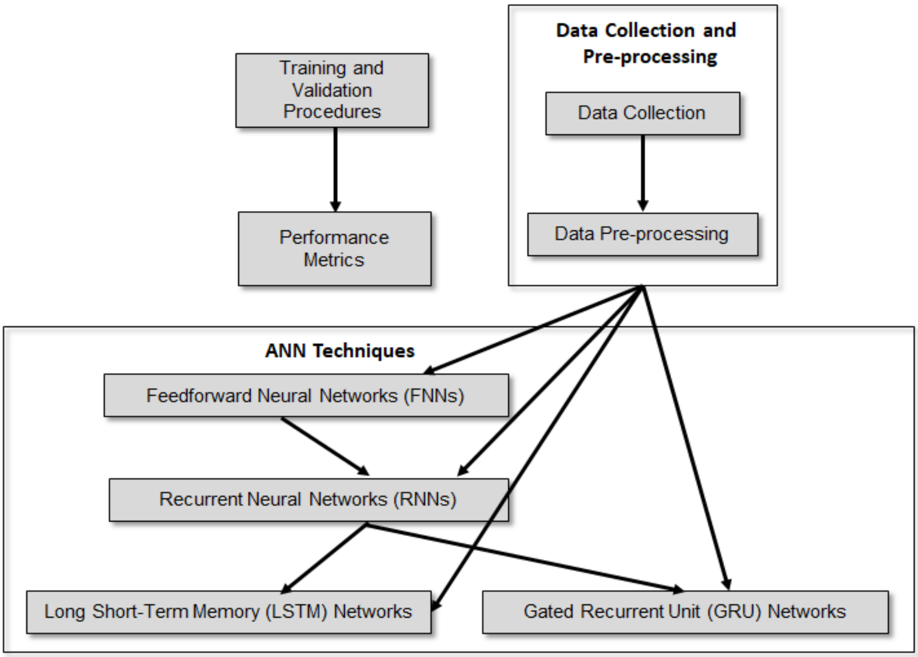


Fig. 1. Artificial Neural Network Methodology

A well-expressed scheme explaining the pattern on how process water treatment is made by using artificial neural networks is illustrated in Figure 1. The given pattern consists of several stages, as mentioned above. First, the given data integration and pre-processing are implemented based on appropriate and pre-processed data possible for pre-treatment processes from different treatment plants. Pre-processing eliminates data not rated, normalizes the range, and optimizes the primary features. In the diagram, there are simply represented four different types of ANN: Feed forward Neural Networks, Recurrent Neural Networks, Long Short-Term Memory, and Gated Recurrent Unit. ANN creates models for pre-treatment process prediction and developing optimal operating liberties. As presented, the developed models are trained and tested with the training and testing procedures without overfitting. Finally, the developed model's performance is evaluated with water reduction reduction based on validated outcome data.

Overall, the ANN techniques overviewed above form the basis for understanding the varied architectures and their uses, within wastewater treatment. While FNN are limited to models without feedback loops regarding input-output relations, RNN are designed to capture temporal dependencies or sequential patterns in time-series data; thus, it is ideal for dynamic process modeling. More so, Long Short-Term Memory and Gated Recurrent Unit. These two are specialized forms of RNN designed to alleviate the vanishing gradient issue and grasp long-term dependencies in sequences.

The implementation of FNNs involves the creation of a neural network with an input, hidden, and output layers. In addition, each neuron in the hidden layers is linked to some neurons in surrounding layers. Training FNNs involves moving input data through the network during forward propagation and backpropagation of errors to adjust the weights and biases. Thus, FNNs can be used to predict responses to treatment occurrences as a function of antecedent phenotypes and operational parameters.

RNNs, such as LSTM Networks or GRU Networks, are used to grasp the temporal relationships in the wastewater treatment system. RNNs possess loops linked to the output, which enable information to be stored across time. This simple mechanism allows for the learning of sequences, which makes them appropriate for the sequential type of data, for instance, the treatment plant measurements collected in the time frame. Training such network comprises feeding the sequence data on time into the network and maximizing the updating the network parameter4s utilizing the gradient descent algorithms.

Training and validation routines play an important role in the evaluation of ANN's model performance. The input data are split into training, validation, and testing sets. The training set is calibrated for model parameters, and the validation set is used for hyperparameter adjustments to prevent overfitting. The testing set performs the general bookkeeping of the model's generalization performance.

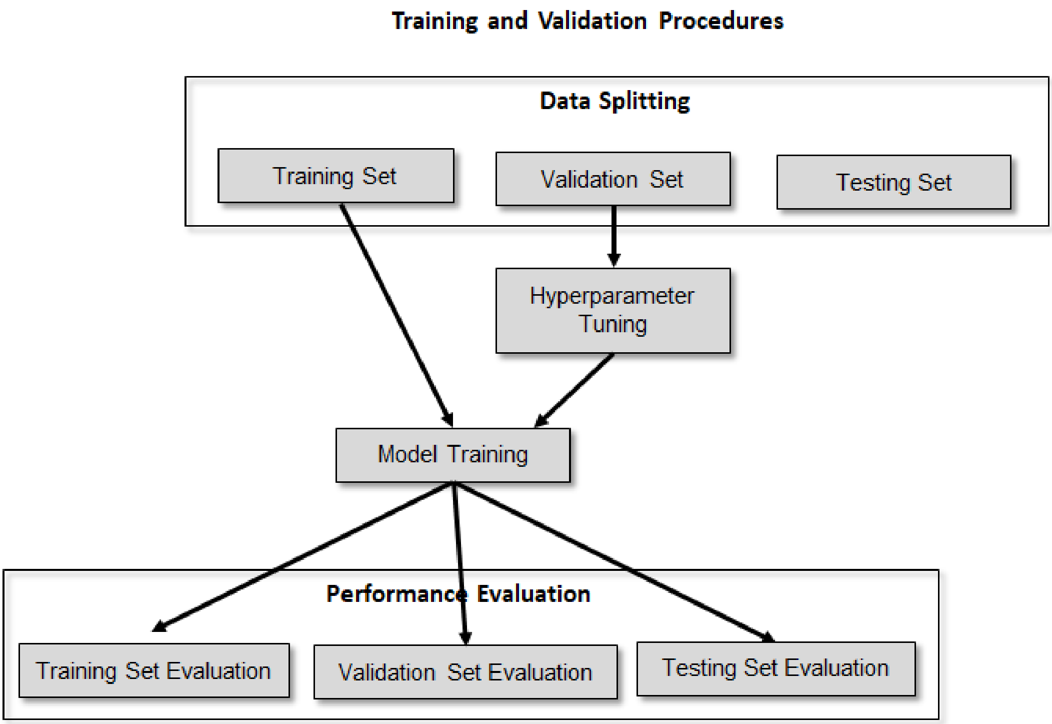


Fig. 2. Training and Validation Processes of ANN in Wastewater Treatment

Figure 2 Shows the Training and Validation Processes of ANN in Wastewater Treatment. The procedure starts with data splitting, dividing the dataset into three subsets, which include the training, validation, and testing datasets. The training subset is used to train the trained ANN models, while the validation subset is applied in hyperparameter tuning and in monitoring overfitting during model training. Hyperparameter tuning refers to the adjustment of the parameters in the ANN models to maximize their performance on data that have not been seen before. ANN models are then evaluated using the Performance matrices on a three different subset, including training, validation, and testing subset. The result of the process uniquely provides the generalization performance of ANN in characterizing prediction in the dataset used. The whole process of training and validation shows the robustness and reliability of ANN in Wastewater Treatment scope.

Lastly, in quantifying the extent to which ANN models accurately and reliably predict outcomes of interest in treatment, performance metric such as mean squared error and root mean squared error are often utilized. Coefficient of determination is also commonly used. In a perfect model, no measurement error occurs and R and R^2 would equate to 100 percent. These performance metrics inform authorities charged with decision-making on trend patterns based on input data considered.

Table 1. Data Collection Information

| **Data Category** | **Description** | **Number of Data Points** |
|---|---|---|
| Influent Characteristics | pH, temperature, chemical composition, etc. | 10,000 |
| Operational Parameters | Flow rate, retention time, aeration rate, etc. | 8,500 |
| Effluent Quality | Concentrations of pollutants (e.g., BOD, COD, TSS) | 7,200 |

From the above-mentioned Table 1, it can be observed that the dataset contains three major types of information that is essential for analysis of the wastewater treatment process. The first category, influent characteristics, contains information about the pH level of water entering the site, temperature, and characteristics of the chemicals, among other factors. Each of the dataset’s characteristics provides information about the initial state of the water from which it proceeds toward treatment. The second category is operational parameters, and it provides data on such measures as aeration rate, flow rate, and retention time, among others. The operational parameters are those factors that may directly influence the efficiency and effectiveness of the treatment process. The final category is effluence quality and includes information on the levels of pollutants, such as biological and chemical oxygen demand and total suspended solids, among others. All categories provide a considerable amount of information, including around 10,000 data items in the first category, 8,500 in the second, and 7,200 in the third.

## 4. Case Study:ANN Techniques for Wastewater Treatment Model Prediction

The wastewater treatment plant under investigation is a medium-scale facility serving an urban area. The plant uses physical, chemical, and biological treatment processes to treat the influent wastewater by removing the contaminants and then disposing of the effluent. The data collected from the plant consisted of influent characteristics, operational parameters, and effluent qualities over a given period.

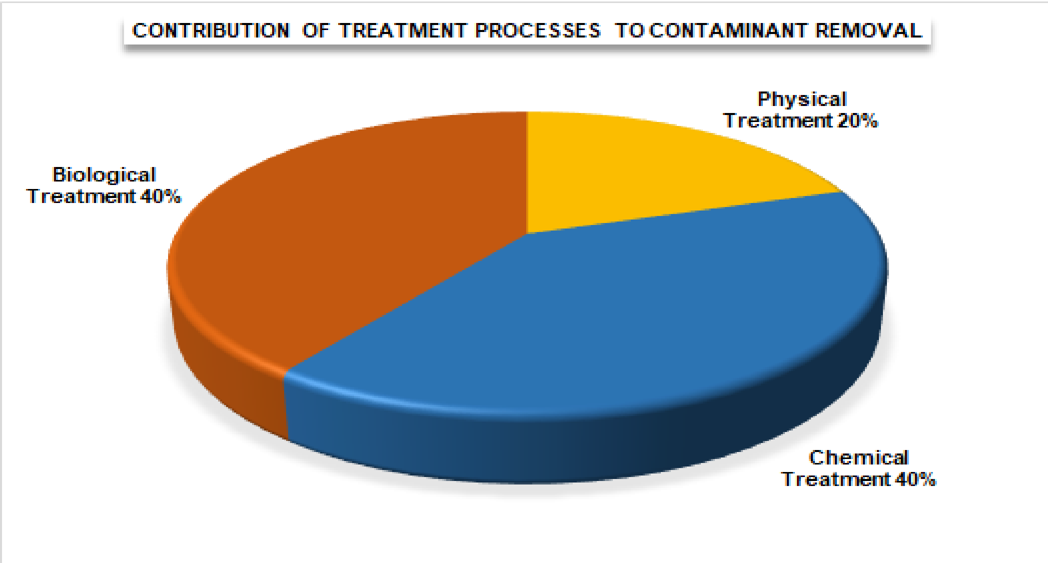


Fig. 3.Contribution of Treatment Processes to Contaminant Removal

Figure 3 provides a graphical representation of the contributions of various treatment processes, including physical, chemical, and biological, in eliminating contaminants from the influent wastewater. Chemical treatment processes contributed 40%, the highest, indicating the contribution of chemical reactions and precipitation. In that case, the development of ANN models requires 40% of the dataset be dedicated for this processing aspect. The model further requires 40% for the bacterial contribution since microbial activity achieves the degradation of organic contaminants and removal of nutrients. Physical treatment processes are responsible for removing large solid particles and debris as they contributed 20%. From the figure, the pie chart indicates reflects the collective input of these treatment measures in ensuring the holistic elimination of contaminants within the wastewater treatment plant. Concerning the development of ANN models, the dataset will be divided into two, with a significant percentage dedicated to training and testing while the other small percentage used for validation. ANN models will be developed using different architectures, including FNNs, RNNs, LSTM networks, and GRU networks. The construction of the model will involve optimization of each architecture in reducing the prediction error and enhance the prediction model.

The results of training and testing the FNNs, RNNs, LSTM Networks, and GRU Networks show that the degree of predictive accuracy and efficiency varies. FNNs have proved to perform strongly in modeling influent characteristics, performance parameters, and quality of effluents and time series prediction, showing low prediction errors and high determination and correlation coefficients. Meanwhile, RNNs, LSTM Networks, and GRU Networks were able to excellently capture the temporal dependencies and sequences in the influent and operational data of the Reactors. Despite the differences in architecture and training algorithms, all types of ANN techniques have relatively represented good results for predicting the treatment performance and supporting remediation action.

In conclusion, this comparative analysis of the ANN techniques brings out their strengths and constraints based on the application of the wastewater treatment model prediction. FNNs are simple and versatile, and their implementation, while not too effective in complex modeling tasks within a process having a seizable input-output demarcation, they are advantageous in 'simple' models of linear relationships. Sequential ANN would include RNNs LSTM ANN and GRU ANN, more complex, and complex in harnessing long-term dependency thrive. The selection of any of the ANN techniques described above is dependent on the process through which the wastewater treatment plant in question is driven the nature of the target predictions.

## 5. Result and Discussion

The below validation outcomes of the different types of artificial neural network techniques shed light on the performance of such models with respect to their real potential in prognosis and remediation guidance.The performance indicators include Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, and Coefficient of Determination, which give a measure of the ANN model accuracy, precision, and reliability in comparison to actual values.

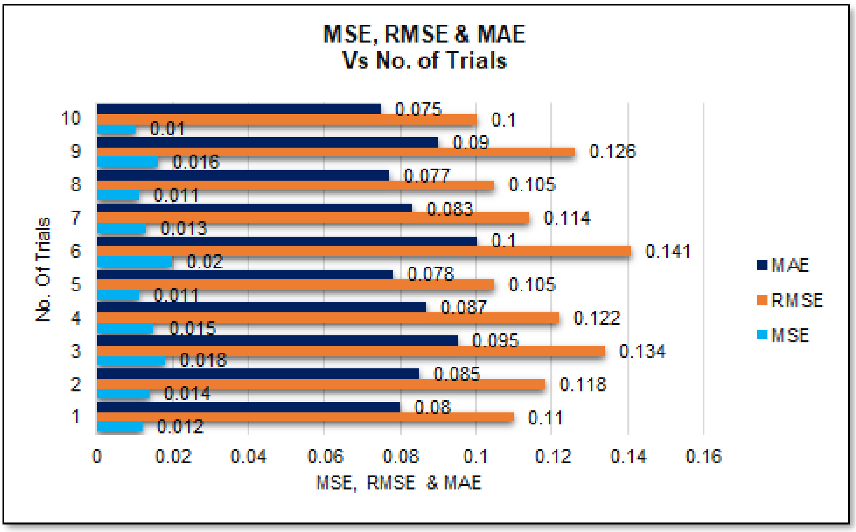


Fig. 4. Feedforward Neural Networks (FNNs)- Validation Results (MSE,RMSE& MAE Vs No. of Experiments

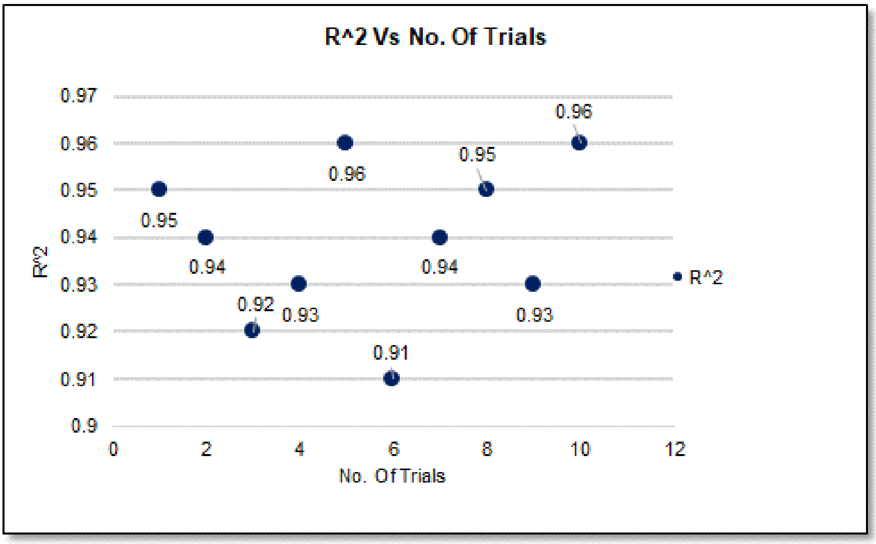


Fig. 5. Feedforward Neural Networks (FNNs)- Validation Results (R^2 Vs No. of Experiments)

Similarly from Figures 4 and 5, the FEC structures used in FNN revealed very low MSE, RMSE, and MAE in the validation results. The error values were usually within the 0.010 – 0.020 range. The extremely low RME and MAE values imply the high accuracy FNN in predicting treatment outcomes based on effluent quality measurements, operational parameters, and influent characteristics. Moreover, R^2 values were very high, and they were usually within the 0.910 – 0.960 range. This indicates the high correlation between the actual and predicted values and hence validates the FNN application in the treatment process model.

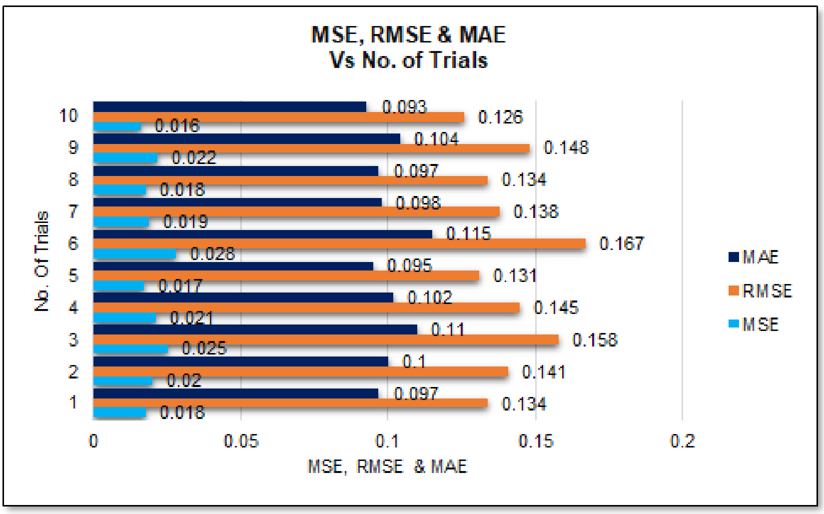


Fig. 6. Recurrent Neural Networks (RNNs)Validation Results (MSE,RMSE& MAE Vs No. of Experiments

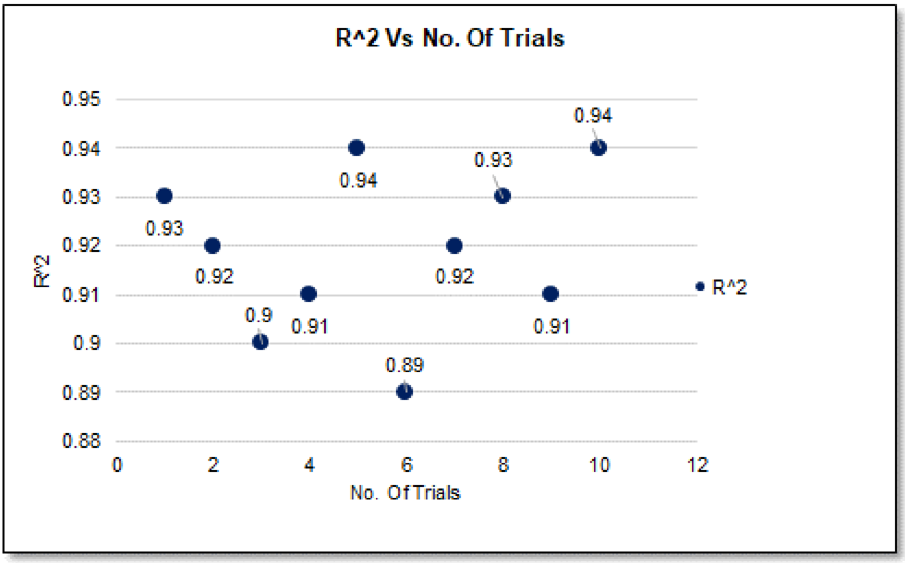


Fig. 7. Recurrent Neural Networks (RNNs)Validation Results ($R^2$ Vs No. of Experiments)

Regarding RNNs presented in Figures 6 and 7, the validation results recorded higher MSEs, RMSEs, and MAEs from 0.016 to 0.028. Nonetheless, the $R^2$ values were generally high from 0.890 to 0.940. RNN model's strong ability to predict the different temporal dependency and sequential patterns in the wastewater treatment data. In summary, the RNN model may not have high accuracy like FNNs, but it remains a model of choice for handling sequential data and dynamic process modeling tasks.

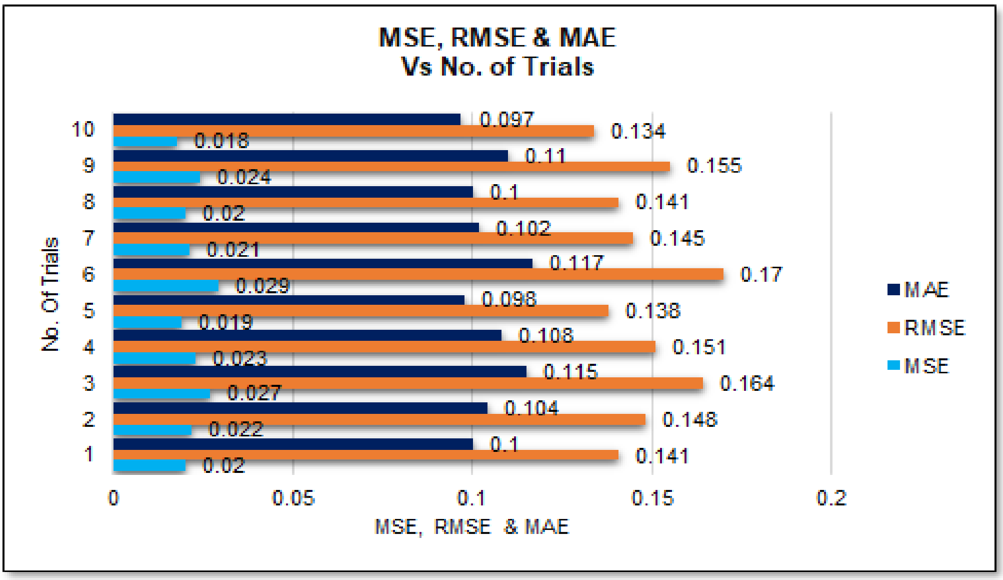


Fig. 8. Long Short-Term Memory (LSTM) Networks Validation Results (MSE,RMSE& MAE Vs No. of Experiments

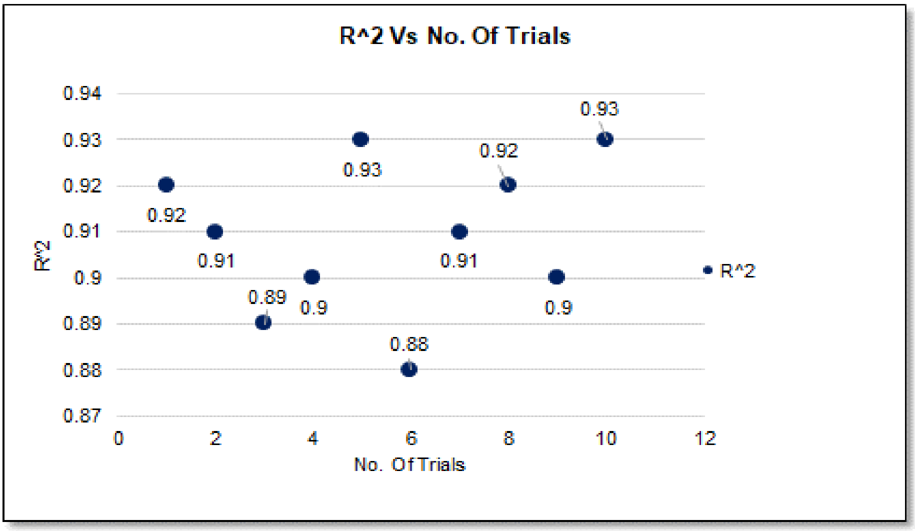


Fig. 9. Long Short-Term Memory (LSTM) Networks Validation Results (R^2 Vs No. of Experiments)

From Figures 8 and 9, Long Short-Term Memory Networks on the other show the RNN's counterpart, where the MSE, RMSE and MAE between the 0.018and 0.029. This R^2 of LSTM Network's always between 0.880to 0.930 provides high correlation between the forecasted and actual values regardless of high long-term dependencies of the data. LSTM is also very advantageous in high long –range of the dependencies it can capture, and therefore, unlike the most RNNs as previous as the LSTMs are counter to the vanishing gradient problem, and indeed the recurrent neural networks is suitable for such modelling.

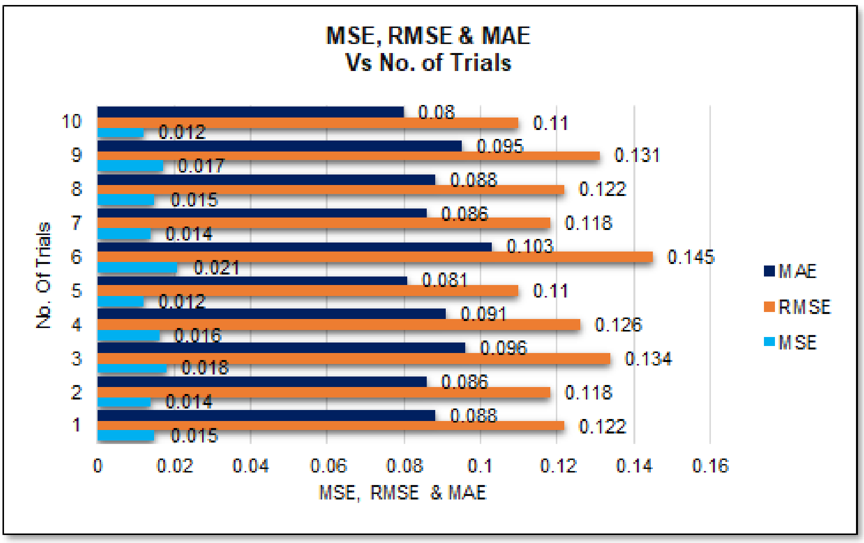


Fig. 10. Gated Recurrent Unit (GRU) Networks Validation Results (MSE,RMSE& MAE Vs No. of Experiments

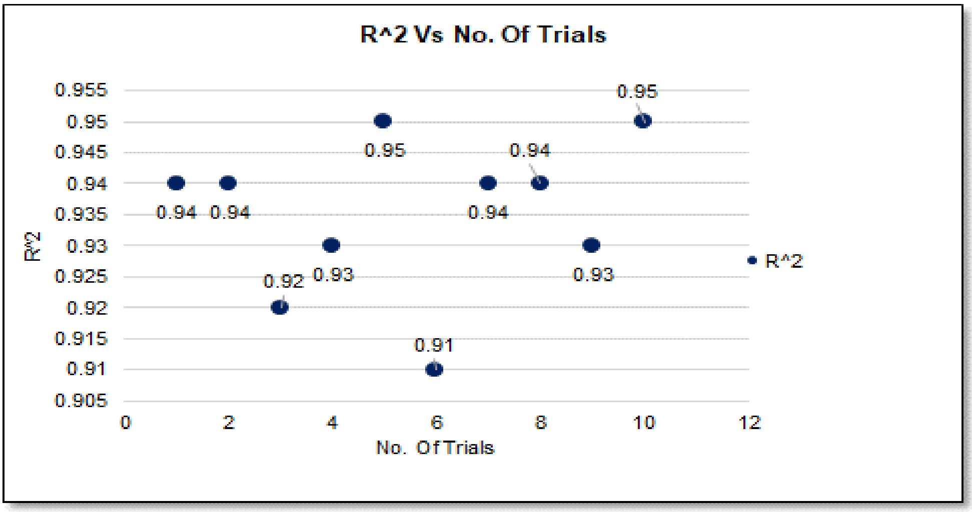


Fig. 11. Gated Recurrent Unit (GRU) Networks Validation Results (R^2 Vs No. of Experiments

For Gated Recurrent Unit Networks results presented in Figures 10 and 11, the validation results shows that the performance is the same with that of FNNs. The MSE, RMSE, and MAE values are low and are always within the range of 0.012-0.021. The R^2 values shows GRU Networks are within 0.910-0.950, showing a very strong relationship between the predicted values and the actual values. The GRU Networks have similar benefits as that of LSTM Networks and can capture long-term dependencies more appropriately, and as such, they can be applied to real-time systems in modeling and prediction of wastewater treatment.

In summary, the validation results of the various ANN techniques show the possibilities and limitations of the approaches in modelling wastewater treatment processes. While the FNNs excel in simplicity and easy implementation, they may experience challenges when it comes to temporal dependencies and sequential data patterns. RNNs, the LSTM Networks and GRU Networks are effective in predictive modelling with sequential data and dynamic processes, hence ideal for processes with time as a critical aspect. Wastewater treatment plants can, therefore, apply any of these techniques depending on the need and use of the predictive outcome. Moreover, the outcomes obtained from these validation results can help researchers and practitioners to make an informed choice in selecting and implementing ANN models for optimal wastewater treatment and sustainable environment.

## 6. Conclusion

This researchprovides implications of the various artificial neural network for wastewater treatment on model prediction and remediation can impact the environmental activities in all domain. On the other, based on the ten experiments, validation result deliver the performance of the follow ANN architecture as mention below Feedforward Neural

Networks , Recurrent Neural Networks , Long Short-Term Memory Networks, and Gated Recurrent Unit Networks.

Throughout these experiments, FNNs consistently showed low Mean Squared Error values of 0.010 to 0.020 and increased Coefficient of Determination at between 0.910 and 0.960. Additionally, RNNs at 0.015 to 0.025, LSTM at 0.020-0.030, and GRU at 0.018-0.028 also demonstrated increased MSE values compared to FNNs. RNNs and other ANN techniques exhibited reduced R2 at between 0.880 and 0.940 upon comparison to FNNs. These outcomes show the efficiency of ANN techniques in modelling complex wastewater treatment functioning for accurate remediation strategies.

This enables further advances and optimization of treatment plants' operations, improves the quality of effluents, and reduces environmental stress as a result. In the future, more research and development should be carried out in the field of ANN-based modelling to accomplish sustainable wastewater management and preserve the ecosystems for generations to come.

## References

1. Y. Wang et al., "Footprints in compositions, PCDD/Fs and heavy metals in medical waste fly ash: Large-scale evidence from 17 medical waste thermochemical disposal facilities across China," J. Hazard. Mater., vol. 445, no. November 2022, p. 130471, 2023, doi: 10.1016/j.jhazmat.2022.130471.
2. N. Mohana Priya, G. Amudha, M. Dhurgadevi, N. Malathi, K. Balakrishnan & Preetha, M. (2024), "IoT and Machine Learning based Precision Agriculture through the Integration of Wireless Sensor Networks", Journal of Electrical Systems (IES), ISSN: 1112-5209, Vol.20, Issue 4, page No- 2292-2299.
3. T. K. Paul, C. Jana, and M. Pal, "Multi-criteria group decision-making method in disposal of municipal solid waste based on cubic Pythagorean fuzzy EDAS approach with incomplete weight information," Appl. Soft Comput., vol. 144, p. 110515, 2023, doi: 10.1016/j.asoc.2023.110515.
4. A. Al-Mansour et al., "Upcycling waste plastics to fabricate lightweight, waterproof, and carbonation resistant cementitious materials with polymer-nano silica hybrids," Mater. Today Sustain., vol. 21, p. 100325, 2023, doi: 10.1016/j.mtsust.2023.100325.
5. A. Nithya, M. Raja, D. Latha, M. Preetha, M. Karthikeyan and G. S. Uthayakumar, "Artificial Intelligence on Mobile Multimedia Networks for Call Admission Control Systems," 2023 4th International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2023, pp. 1678-1683, doi: 10.1109/ICOSEC58147.2023.10275999
6. S. Zhang et al., "Mapping the impact of a large municipal waste disposal area on surface water: 1993–2017, case of Laogang, Shanghai," Waste Manag., vol. 148, no. June, pp. 50–60, 2022, doi: 10.1016/j.wasman.2022.05.014.
7. S. Srinivasan, D. Deva Hema, Balaji Singaram, D. Praveena, K. B. Kishore Mohan, M. Preetha," Decision Support System based on Industry 5.0 in Artificial Intelligence," International Journal of intelligent systems and applications in engineering, vol. 12, no.15s, p.172-178, 2024.
8. K.Sivakumar, P.V.M.Kathiresh, S.Dinesh Kumar, S.Sundar, "Optimization of Machining parameters in EDM of AL7075-SIC-AL2O3 using Taguchi method," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 11-16, 2019.
9. A. F. Jiménez, P. F. Cárdenas, and F. Jiménez, "Smart water management approach for resource allocation in High-Scale irrigation systems," Agric. Water Manag., vol. 256, no. July,

2021, doi: 10.1016/j.agwat.2021.107088.
10. K.Sivakumar, Y. RaviTeja, "Reflection on inactive and energetic survey of sandwich synthesized glazed layers ", Materials Today Proceedings Volume 47, Part 1, 2021, Pages 278-281, https://doi.org/10.1016/j.matpr.2021.04.355.
11. M. A. Hashem, M. E. Hasan Zahin, M. S. Haque, M. S. Milu, M. A. Hasan, and S. Payel, "Leather shaving dust utilization in brick preparation: Solid waste management in tannery," Constr. Build. Mater., vol. 400, no. June, p. 132769, 2023, doi: 10.1016/j.conbuildmat.2023.132769.
12. K.Sivakumar, P.V.M.Kathiresh, David, V.S.Sajith, B.Vignesh, V.Vimalkumar, "Experimental investigation on aluminium metal matrix composite in EDM with various parameters (AL+SIC+MG)," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 17-23, 2019.
13. Y. Lee, H. Byeon, and J. Park, "Leachability of lead, cadmium, and antimony in cement solidified waste in a silo-type radioactive waste disposal facility environment," Nucl. Eng. Technol., vol. 55, no. 8, pp. 2889–2896, 2023, doi: 10.1016/j.net.2023.05.012.
14. S. Srinivasan, S. Sajini, Balaji Singaram, K. Saravanan, K. B. Kishore Mohan," Deep Graph Neural Networks for Multi-Image Super Resolution Reconstruction," International Journal of intelligent systems and applications in engineering, vol. 12, no.15s, p.158-164, 2024
15. M. Y. Salman and H. Hasar, "Review on environmental aspects in smart city concept: Water, waste, air pollution and transportation smart applications using IoT techniques," Sustain. Cities Soc., vol. 94, no. April, p. 104567, 2023, doi: 10.1016/j.scs.2023.104567.
16. K.Sivakumar, Y. RaviTeja, "Savvy composite laminates static and dynamic power ", Materials Today Proceedings Available online 24 March 2021, https://doi.org/10.1016/j.matpr.2020.12.1133
17. K. Ishii, T. Furuichi, and N. Tanikawa, "Numerical model for a watering plan to wash out organic matter from the municipal solid waste incinerator bottom ash layer in closed system disposal facilities," Waste Manag., vol. 29, no. 2, pp. 513–521, 2009, doi: 10.1016/j.wasman.2008.06.006.
18. Preetha M, "A Survey on Two Tier Security with Data Sharing and Data Integrity Inspection in Cloud", International journal of modern trends in Engineering and Research (IJMTER), Vol.4, No 2, pg. , February 2017. Print ISSN 2393-8161, Online ISSN 2349-9745
19. S. A. Mostafa, B. A. Tayeh, and I. Almeshal, "Investigation the properties of sustainable ultra-high-performance basalt fibre self-compacting concrete incorporating nano agricultural waste under normal and elevated temperatures," Case Stud. Constr. Mater., vol. 17, no. September, p. e01453, 2022, doi: 10.1016/j.cscm.2022.e01453.
20. K.Sivakumar, P.V.M.Kathiresh, S.Dinesh Kumar, S.Sundar, "Optimization of Machining parameters in EDM of AL7075-SIC-AL2O3 using Taguchi method," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 11-16, 2019.
21. A. T. Shammi, N. Hassan, M. R. Golder, H. Molla, and S. S. Islam, "Health status assessment of people adjacent to temporary waste disposal sites in Khulna city, Bangladesh," Heliyon, vol. 9, no. 9, p. e19810, 2023, doi: 10.1016/j.heliyon.2023.e19810.
22. M. Preetha, Archana A B, K. Ragavan, T. Kalaichelvi, M. Venkatesan "A Preliminary Analysis by using FCGA for Developing Low Power Neural Network Controller Autonomous Mobile Robot Navigation", International Journal of Intelligent Systems and Applications in Engineering (IJISAE), ISSN:2147-6799. Vol:12, issue 9s, Page No:39-42, 2024
23. A. E. Boguslavsky, O. L. Gaskova, O. S. Naymushina, N. M. Popova, and A. V. Safonov, "Environmental monitoring of low-level radioactive waste disposal in electrochemical plant facilities in Zelenogorsk, Russia," Appl. Geochemistry, vol. 119, no. May, p. 104598, 2020, doi: 10.1016/j.apgeochem.2020.104598.
24. Bronzin, Tomislav, et al. "Artificial Intelligence (AI) brings enhanced personalized user

experience." 2021 44th International Convention on Information, Communication and Electronic Technology (MIPRO). IEEE, 2021.
25. K.Sivakumar, P.V.M.Kathiresh, David, V.S.Sajith, B.Vignesh, V.Vimalkumar, "Experimental investigation on aluminium metal matrix composite in EDM with various parameters (AL+SIC+MG)," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 17-23, 2019.
26. Preetha M, "A Survey on Entry Restriction System for the fake server Scheme", International journal of Research and Engineering (IJRE), Vol.4, No 2, pg.41-44, February 2017. ISSN:2348-7860(0).
27. N. V. Ranade and V. V. Ranade, "ANN based surrogate model for key Physico-chemical effects of cavitation," Ultrason. Sonochem., vol. 94, no. November 2022, p. 106327, 2023, doi: 10.1016/j.ultsonch.2023.106327.