Nature Environment and Pollution Technology
An International Quarterly Scientific Journal
p-ISSN: 0972-6268
(Print copies up to 2016)
e-ISSN: 2395-3454
Vol. 25 | No. 2 | Article ID B4382 | 2026
Original Research Paper
https://doi.org/10.46488/NEPT.2026.v25i02.B4382
Open Access Journal

Prediction of Residual Chlorine in Water Distribution Network Using Artificial Neural Network (ANN)

S. R. Lolapod† and S. J. Mane
Department of Civil Engineering, D. Y. Patil College of Engineering, Akurdi, Pune, Maharashtra, India
†Corresponding author: Santosh R. Lolapod: santoshlolapod1@gmail.com

Abbreviation: Nat. Env. & Poll. Technol.
Website: www.neptjournal.com

Received: 29-07-2025
Revised: 29-09-2025
Accepted: 08-10-2025

Key Words:

Artificial Neural Network
Chlorine dosage
NeuroSolutions v6
Residual chlorine
Water distribution network
Rural water quality

Citation for the Paper:

Lolapod, S. R. and Mane, S. J., 2026. Prediction of residual chlorine in water distribution network using artificial neural network (ANN). *Nature Environment and Pollution Technology*, 25(2), B4382. https://doi.org/10.46488/NEPT.2026.v25i02.B4382

Note: From 2025, the journal has adopted the use of Article IDs in citations instead of traditional consecutive page numbers. Each article is now given individual page ranges starting from page 1.

ABSTRACT

Protecting public health in rural water distribution networks requires reliable and safe disinfection. Although chlorination is the most widely used disinfection approach, determining the optimal chlorine dosage remains challenging because of environmental and distribution-related variations. This study presents an artificial neural network (ANN)-based predictive model for estimating residual chlorine in the Rui and Shingave Water Supply Scheme in Maharashtra, India. Field data, including variables such as pH, temperature, and distance from the Elevated Storage Reservoir (ESR), were collected from several nodes. A total of 250 samples were collected between 5 and 15 December 2024, covering winter-period variation. The min-max normalization method was used to standardize the dataset, and the NeuroSolutions v6 software was used for processing. The Levenberg-Marquardt algorithm was used to develop and train a Multilayer Perceptron (MLP) model, using 70% of the data for training and 30% for testing. Strong correlation coefficients, low MSE (mean squared error), and minimal MAE (mean absolute error) values across all phases showed the model's high level of accuracy. Specifically, the model achieved R = 0.902, MAE = 7.18, and MSE = 114.25 on the test dataset. The results show that the ANN model can successfully learn the dynamics of chlorine degradation in the distribution network. With initiatives such as the Jal Jeevan Mission, this predictive method offers a practical tool for optimizing chlorine dosage in real time and strengthening water quality management in rural systems. Future integration with SCADA or IoT monitoring platforms may further enhance operational efficiency.

INTRODUCTION

The supply of microbiologically safe drinking water is fundamental to public health, particularly in developing countries where infrastructure and water quality surveillance are underdeveloped. Chlorination is the most commonly employed and efficient method of disinfection to ensure water quality in the distribution system, as studied in previous research (Wadkar et al. 2024). Nevertheless, its efficiency is challenged by factors such as contact time, water pH, temperature, organic matter, and the length of travel in the pipe system, making accurate prediction complex (Batista et al. 2024). The miscalculation of chlorine dose, in terms of either deficient or excessive dosing, could cause unintended consequences, such as the production of toxic disinfection by-products or incomplete microbial control.

Ensuring that the correct level of chlorine is retained is especially difficult in rural and small-scale water distribution networks (WDNs). These systems usually depend on manual chlorination operations without effective monitoring or automation. Therefore, the presence of free chlorine residual may show marked spatial and temporal variation, posing a serious threat to the safety of drinking water and to public health. In rural areas, where continuous monitoring infrastructure is often limited, predictive models can significantly contribute to maintaining disinfection levels. Previous evaluations have shown that such empirical practices often lead to inconsistent outcomes, either underdosing or excessive chlorine residuals (Zaghini et al. 2024, Satish et al. 2024).

In such scenarios, intelligent data-driven models become increasingly important. Applications of ANNs for forecasting have been observed in basin and river studies, such as the Ganga and Godavari Basins, highlighting the versatility of these approaches across water environments (Bisht et al. 2019, Nagalapalli et al. 2022). However, applications of ANN to decentralized rural distribution systems, particularly in Maharashtra, remain scarce, representing a clear research gap that this study addresses. In this study, an attempt is made to develop a prediction model for the estimation of residual chlorine at different nodes of the Rui and Shingave Water Supply Scheme located in Maharashtra, India, based on an artificial neural network. The selected input parameters were pH, temperature, and distance from ESR. The overall objective of the exercise is to develop a practical and scalable model to facilitate evidence-based management under the Jal Jeevan Mission and Har Ghar Jal.

Artificial Neural Network

Artificial Neural Networks (ANNs) are adaptive computational systems modeled after the structure and function of biological neural networks. They are made of interconnected nodes, or artificial neurons, arranged in layers. Every neuron receives inputs, applies an activation function to them, and passes the results on to the next neurons. It generally consists of three types of layers: the input layer, hidden layer, and output layer, as illustrated in Fig. 1.

Since ANNs can approximate complex nonlinear interactions between water quality parameters, enabling accurate predictions in both treatment and distribution contexts (Chen et al. 2020, El Shebli et al. 2023), without the need for explicit mathematical formulations, they have shown significant efficiency in environmental modeling, including water quality and treatment operations. MLP (multilayer perceptron), a popular ANN type utilized in these applications, allows information to flow from input to output in a single direction. ANNs, including GRNN and MLP variants in early studies (Michel et al. 2006), and their later use in distribution systems, have demonstrated successful predictive power. Every connection in the network has a weight, and in order to reduce the prediction error during the training phase, these weights are iteratively changed using optimization methods (Bisht et al. 2019, Enríquez et al. 2023). Water distribution systems can predict chlorine decay more effectively using ANN models than traditional statistical methods (Michel et al. 2006, Riyadh et al. 2024).

A 3-12-1 MLP architecture was chosen for this investigation and implemented using NeuroSolutions v6 software. The performance of an ANN depends on the model architecture and the size of the data. However, there are significant differences among MLP, recurrent, and other network types depending on dataset characteristics (Hua et al. 2018, Isık & Akkan 2024). One output neuron represents the expected residual chlorine concentration, twelve neurons make up the hidden layer, and three input neurons represent pH, temperature, and distance from ESR.

The network was trained over 1000 epochs with the Levenberg-Marquardt backpropagation technique. Compared to simple gradient descent techniques, this method offers faster convergence and higher accuracy in prediction tasks, making it particularly useful for small- to medium-sized datasets. The model was trained using known input-output pairs obtained from field sampling carried out in December 2024 using supervised learning. To assess generalization, the

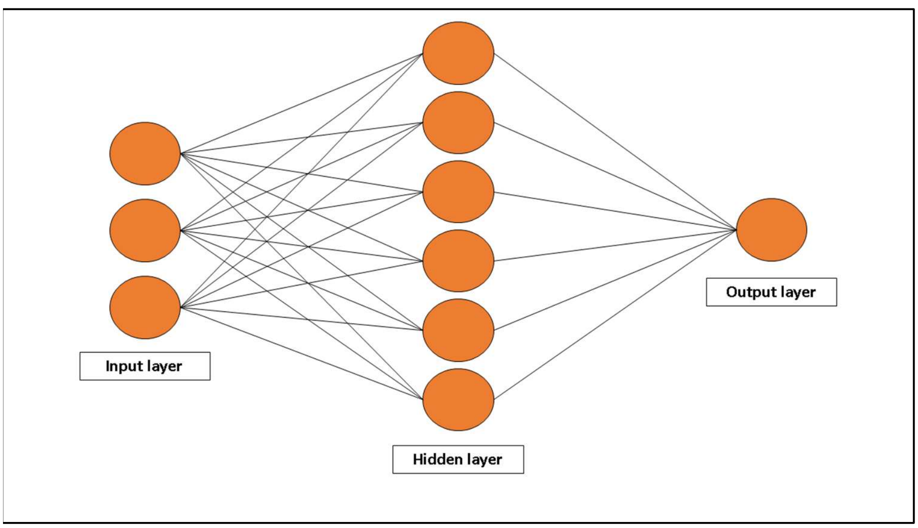

Fig. 1: Neural network architecture.

dataset was divided into training and testing subsets. During training, normalization methods like minimum and maximum scaling were used to improve convergence. Metrics like the correlation coefficient (R), MSE (mean squared error), and MAE (mean absolute error) were used for evaluating the ANN's performance.

ANN techniques have been utilized worldwide for modeling chlorine decay in urban and rural settings, including Brazilian rural communities (Batista et al. 2024) and refugee settlements (De Santi et al. 2021). Regional studies in India have utilized ANN-based models for forecasting river water quality and coagulant dose prediction, indicating their ability to adapt to local environmental and operational conditions (Wadkar et al. 2021, Nagalapalli et al. 2022). The research highlights the potential of ANN in various settings to enhance water quality control. While there has been a lot of progress to date, gaps remain in the application of ANN for rural distribution networks with sparse monitoring due to environmental variability and operational constraints (Onyuth & Kwio 2022, Li et al. 2024). Recent studies (Riyadh et al. 2024, Isık & Akkan 2024) further underline ANN's potential for small-scale or resource-limited water systems, yet evidence from Indian rural WDNs is still very limited.

In rural water systems, where datasets may be limited and unpredictable, artificial neural networks (ANNs) are particularly beneficial. They are ideal for forecasting chlorine decay impacted by different pipe lengths, temperature gradients, and inconsistent dosing because of their capacity to learn from sparse data and model nonlinear behavior. The created ANN model, therefore, has a great chance of being included in rural water quality management systems, allowing for more accurate and adaptable chlorination techniques.

STUDY AREA

The Rui and Shingave Water Supply Scheme, located in Ahilyanagar District, Maharashtra, India, was the subject of the current investigation. This area is located in western India's semi-arid climatic tract, which is distinguished by high evapotranspiration, irregular rainfall, and recurring water stress. Because of these factors, local communities face the important challenge of obtaining continuous access to safe and microbiologically acceptable drinking water. Between 5 and 15 December 2024, field observations were made.

A total of 250 water samples were collected from 15 sampling sites during this period. Sampling was conducted once at each site between 5 and 15 December 2024; therefore, the dataset represents a short-term campaign rather than seasonal monitoring. This limitation is acknowledged in the Discussion section. The dataset was preprocessed before model training. Outliers were identified using two simple checks: (i) values that were much higher or lower than most of the other measurements, and (ii) values that were more than three standard deviations away from the average. After this screening, the accepted dataset was scaled using a normalization method. The scheme's distribution system can be seen in Fig. 2.

The Maharashtra Jeevan Pradhikaran (MJP), a state-level public utility in charge of organizing, carrying out, and

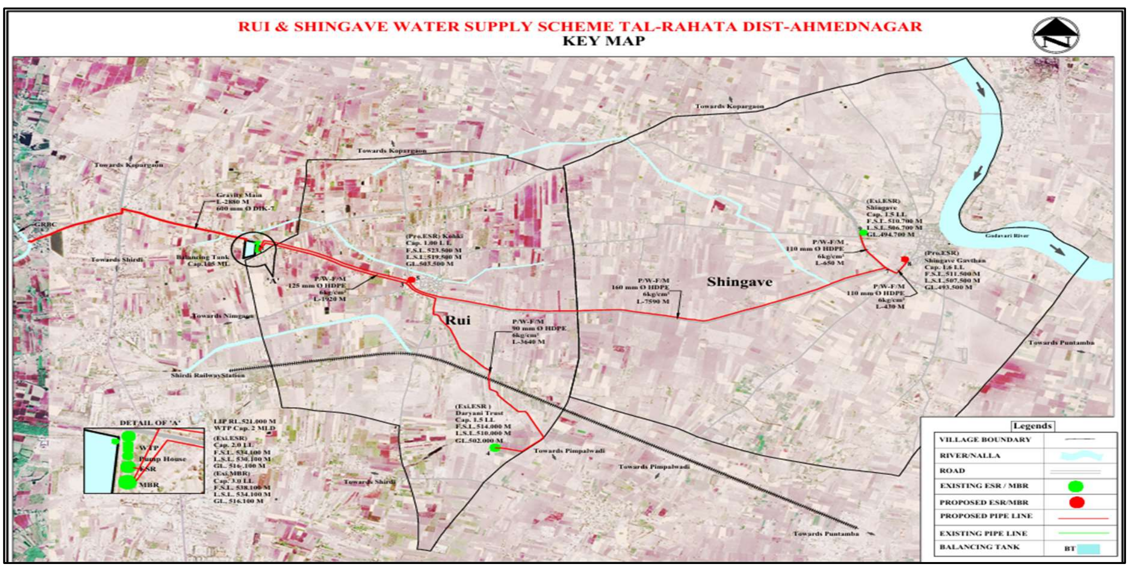

Fig. 2: Water distribution layout of Rui and Shingave water supply scheme.

maintaining rural water infrastructure, oversees the water supply scheme. The program supplies a population dispersed among the villages of Rui and Shingave with piped water, mostly from seasonal surface reservoirs and groundwater. Effective chlorine disinfection is necessary to stop microbial contamination and epidemics of waterborne diseases because there is less water available during dry months.

Elevated Storage Reservoirs (ESRs), which act as centralized dosing and distribution locations, are part of the distribution infrastructure in both settlements. Water gets transported from these ESRs to public stand post outlets and households via a network of interconnected HDPE and PVC pipelines. With pipe lengths ranging from a few hundred meters to several kilometers and elevation variations causing differential hydraulic pressures and residence periods, the network shows major geographical variations.

Without the aid of real-time monitoring equipment, chlorine dosing is now done manually at the ESR outflow that follows simple guidelines. Despite being more economical, this manual method causes large variations in the network's residual chlorine concentrations, particularly at the nodes near the tail end.

Inconsistent dosing raises concerns regarding the development of disinfection by-products in the event of overdosing, in addition to the potential of under-disinfection. Field samples were taken from 15 sites with varying elevations, pipe materials, and distances from the ESRs in order to evaluate the spatial variation in chlorine degradation. Following the same procedures used in previous ANN applications to water systems, field sampling locations and node-level monitoring were selected, which enabled field-driven model training (Wadkar et al. 2021, Kote & Wadkar 2019).

To generate a dataset suitable for building the ANN-based chlorine prediction model, parameters like temperature, pH, and residual chlorine were monitored. Residual chlorine was measured using two methods. The orthotolidine (OT) test was used in the field because it is simple and has been the traditional practice of local operators. At the same time, the N, N-diethyl-p-phenylenediamine (DPD) colorimetric method was applied, which is internationally recommended (APHA) and more accurate. Most of the readings, when observed, were the same from both methods; when there was any difference between the two readings, the DPD value was taken as the reliable result for model development.

MATERIALS AND METHODS

To learn more about the behavior of chlorine decay in the water distribution system, field sampling was carried out in December 2024 at fifteen typical sites in the villages of Rui and Shingave in Ahilyanagar District, Maharashtra. Different pipeline materials (HDPE and PVC), elevation gradients, and distances from Elevated Storage Reservoirs (ESRs) were taken into consideration when selecting the sampling locations. In order to replicate real-world settings, important water quality indicators such as temperature, pH, and residual free chlorine were evaluated during hours of high consumption. Residual chlorine was measured by both the orthotolidine (OT) method and the more accurate DPD (N, N-diethyl-p-phenylenediamine) method.

A digital thermometer was used to record temperature readings on the spot, and a calibrated portable digital meter was used to assess pH. The distance from ESRs was determined from official pipeline drawings and verified with Google Earth Pro and GPS tracking. For every parameter, duplicate readings were gathered, averaged for accuracy, and entered into field sheets before being converted to digital format and analyzed in Microsoft Excel.

The ANN model was fed with the preprocessed dataset for the sake of uniformity and continuity. Outliers were detected and removed by box plot, and features were normalized between 0 and 1 by min-max scaling in order to facilitate the training process. The preprocessing of data (Rustam et al. 2022, Jafari et al. 2023), such as duplication averaging and outlier rejection, is commonly used in water-quality ANN work to stabilize training. The main influencing factors chosen for the model were pH, temperature, and distance to ESR, because they are very influential on chlorine stability within a rural gravity-fed network.

The cleaned dataset was partitioned into training and testing subsets. While a 70:30 split was used for final performance reporting, 5-fold cross-validation was also applied during the tuning stage to reduce overfitting risk, given the limited dataset size. These datasets were saved as a .csv file that was imported into NeuroSolutions v6. Artificial Neural Networks (ANNs), based on the human brain, are very much compatible with the nature of nonlinear and uncertain systems such as chlorine decay in water networks.

A feed-forward multilayer neural network (MLP) with a 3-12-1 structure was trained. It consisted of an input layer with 3 neurons (pH, temperature, and distance), a hidden layer with 12 neurons, and an output layer with 1 neuron representing residual chlorine concentration. The selection of 12 hidden neurons was based on comparative testing with alternative configurations (8, 10, and 15 neurons). The 12 neuron architecture consistently demonstrated the most favorable trade-off between accuracy and model stability, yielding lower validation errors while avoiding overfitting. Based on best practice and chlorine prediction studies that emphasize small to medium datasets (Wadkar et al. 2024, Chen et al. 2020). The model was trained for 1000 epochs with the Levenberg–Marquardt algorithm. This model was then compared to the performance using cross-validation and standard metrics, Coefficient of Determination (R), Mean Squared Error (MSE), and Mean Absolute Error (MAE).

To check the reliability of the reported performance, 95% confidence intervals for MAE and MSE were calculated using bootstrap resampling with 1,000 repetitions. These intervals are presented in the Results section. Which are in line with more recent studies (Batista et al. 2024), which evaluated the effectiveness of chlorine in various scenarios. The network was trained for 1000 epochs with the Levenberg Marquardt algorithm, Here one epoch refers to a complete pass of the training dataset through the network, meaning the model updated its weights after seeing all samples once. The architecture and its epoch internal configuration were designed and tested in NeuroSolutions v6 using performance graphs for predicted and measured chlorine during training and testing processes.

RESULTS

An artificial neural network model was used in this study to predict residual chlorine at different nodes of the Rui and Shingave distribution water network. The feed-forward MLP, the most commonly used network type, was developed using three significant input variables: pH, temperature, and distance from the Elevated Storage Reservoir (ESR). Since these parameters have a well-defined, direct impact on chlorine decay in rural gravity-fed water systems, they were selected. Chemical stability of free chlorine is pH dependent, reaction kinetics are temperature dependent, and the distance of the sample from the ESR in the distribution system represents the age of the water and transit time.

This dataset was divided into 70% training and 30% testing to improve model development and evaluate predictive accuracy on unseen data. NeuroSolutions v6 software was used to develop the model, and the Levenberg-Marquardt backpropagation algorithm was used for training. This algorithm is renowned for its excellent accuracy and quick convergence, especially when applied to small to medium-sized datasets with nonlinear relationships.

A wider set of comparative experiments was conducted across multiple ANN types, including Generalized Feed Forward (GFF), Time-Lag Recurrent Network (TLRN), General Regression Neural Network (GRNN), and Multilayer Perceptron (MLP), with architectures ranging from 3-5-1 to 3-15-1 and training epochs from 500 to 5000.

Table 1: Comparative performance of different ANN models.

Network	Architecture	Epochs	R best	MAE	MSE
GFF	3-5-1	5000	0.875	8.49	216.95
TLRN	3-5-1	5000	0.860	8.70	219.55
GRNN	3-5-1	2000	0.880	8.72	208.30
MLP	3-12-1	1000	0.902	7.18	114.25

Since the overall performance patterns were consistent across these variations, only the best-performing configurations are presented in Table 1 for clarity, while the broader results confirmed the superiority of the MLP 3-12-1 architecture. The network weights were updated during 1000 training epochs in order to reduce their prediction error (MSE cost function). The identified architecture and structure proved to be promising for application in rural water supply systems in that they were successfully able to grasp the complexity and nonlinearity of chlorine decay. The training convergence behavior was stable, with the error drop being dramatic after a few hundred epochs. Regularization methods were implemented to avoid overfitting and enhance the model's generalization during training.

The MLP architecture 3-12-1 gave the best correlation coefficient (R=0.902) and the lowest errors (MAE=7.18, MSE=114.25). This superior performance can be attributed to its ability to balance complexity and generalization: the hidden layer with 12 neurons was sufficient to capture the nonlinear effects of pH, temperature, and residence time without overfitting. In contrast, smaller networks underfit the data, while larger or recurrent structures tend to become unstable on this relatively small dataset.

The trained MLP learned and generalized faster than other models and produced more accurate results (Wadkar et al. 2024, Michel et al. 2006). Converging with recent comparative analyses of ANN architectures for water quality (Isík & Akkan 2024). It demonstrated its stability in various trials and data partitions. The GFF and GRNN configuration presented medium R values (0.875–0.884), but the MAE and MSE rates were large. The TLRN model performance differed among iterations, indicating the problem of chlorine decomposition modeling in various spatial situations. The discrepancies are likely to originate from the complex dynamic feedback mechanisms in TLRN that are sensitive to small disruptions in time series inputs.

Fig. 3 shows how the model's predictions were checked by comparing the predicted outputs with the actual residual chlorine values. The trend lines were very close together, which showed that the ANN was able to learn and reproduce how chlorine behaved at different sampling sites. The fact that predicted values match up so well with observed field data shows that the chosen network design is strong and accurate.

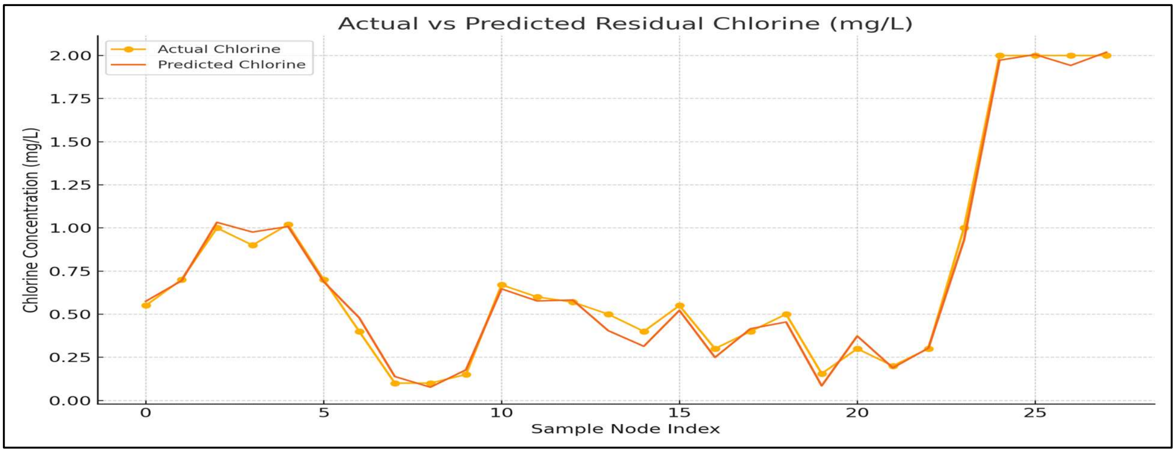

Fig. 3: Comparison of predicted and observed residual chlorine concentrations at 25 sampling nodes using the best-performing ANN model (MLP 3-12-1). Units: residual chlorine (mg/L).

The way the model acted was in line with what is known about chlorine decay chemistry. As the distance from the ESR increased, the levels of chlorine dropped noticeably. Based on kinetic and hydraulic influences (Hua et al. 2018, Vrachimis et al. 2021), reported in the literature, residual chlorine was most strongly associated with distance from ESR and water temperature as their strongest predictors of reaction. This is in line with the longer residence time and wall interactions in the pipe network.

Elevated pH, particularly above 8.0, was associated with more rapid chlorine dissipation, lowering observed field residuals. This non-linear learning was able to mimic such behavior of the system very well by the model. Furthermore, the lowest temperatures registered at the beginning of the sampling hours were associated with greater chlorine retention (which the ANN also represented in the predictions). The model worked reasonably well for most of the nodes.

Slightly underpredicted results were noted for the far-end nodes. To better illustrate this effect, the residual error (predicted – observed chlorine) was plotted against the distance from the ESR (Fig. 4). The scatter plot shows a small but consistent downward trend ($r \approx -0.32$, $p < 0.05$), indicating that underprediction became more noticeable at greater distances.

The downward trendline confirms this tendency, indicating that prediction errors become more negative with distance. This finding supports the observation of slight underprediction at the far-end nodes. This may have been due to the presence of unmodelled effects such as biofilm build-up, nonuniform water demand, or pressure loss (Li et al.

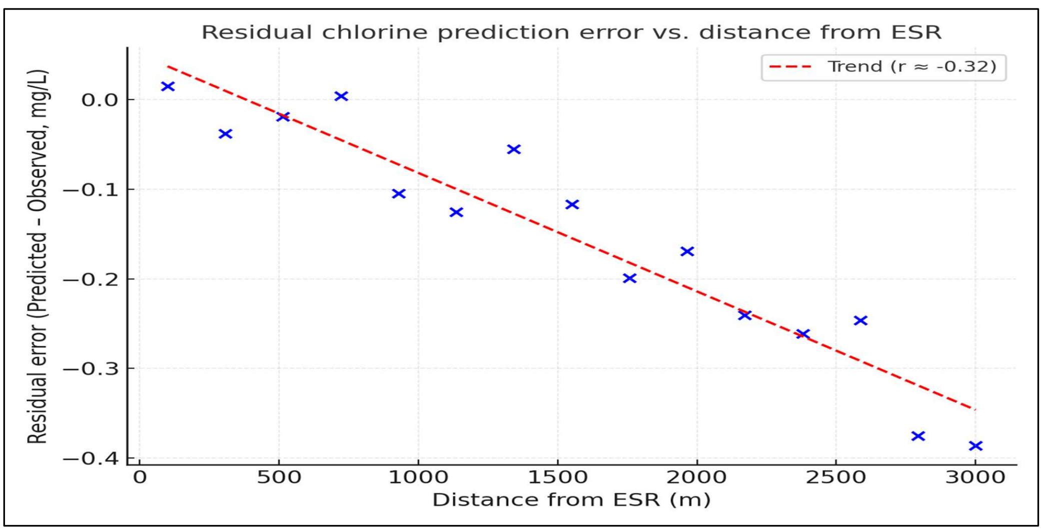

Fig. 4: Residual error (Predicted-Observed, mg/L) plotted against distance from the ESR (m) using the best performing ANN model (MLP 3-12-1).

2024). These results imply that the simple ANN can predict chlorine with relative confidence, which can then be built upon with real-time or seasonal parameters in other studies.

DISCUSSION

In this paper, the application of ANN to chlorine prediction was extended by incorporating node-level data gathered from households and field locations in both Rui and Shingave villages. This contrasts with the previous study by Wadkar et al. (2021), which focused on the treatment plant and ESR under an urban scenario (PCMC). The study incorporates chlorine decay in the rural distribution network (Tinelli & Juran 2024) and provides a more realistic model, which was operationally more relevant.

Traditional dosing rules often treat chlorine decay as a simple, fixed process, but in reality, it depends on several interacting factors such as pH, temperature, and residence time in the network. The ANN approach was able to reflect these nonlinear relationships, which explains why it gave more reliable predictions than methods based only on fixed assumptions. By learning directly from the field data, the ANN adapted better to the variable conditions found in rural water supply systems.

Incorporating household-level residual chlorine measurements was important in providing an adequate spatial resolution for ANN to represent the actual situation at end users (an aspect not available in the previous studies). This methodological advantage increases the model's capability in predicting differences due to manual dosing and long distribution lines, as in rural areas.

For rural water operators working under the Jal Jeevan Mission, this type of model can be directly useful. It can provide advanced estimates of chlorine levels at different points in the network, helping operators adjust dosing at ESRs more effectively. This reduces the risk of under-dosing, which can allow microbial contamination, and also avoids unnecessary overdosing, which wastes chlorine and can create by-products. In this way, the model can support safer and more efficient day-to-day management of rural water supply schemes.

Other research (Alsulaili & Refaie 2021, Nagalapalli et al. 2022) corroborated the ability of ANN to model complex water quality dynamics but did not account for the unique distribution of water quality variability in rural Indian networks. This study addresses that gap and shows the potential benefits of including such models in future decentralized monitoring systems.

The performance achieved in this study (R = 0.902, MAE = 7.18 mg/L, MSE = 114.25 mg/L^2) is in line with, and in some cases better than, results reported in other contexts. For instance, studies in Brazilian rural systems (Batista et al. 2024) found R values of about 0.88, while (Ogwueleka et al. 2023, Riyadh et al. 2024) reported R close to 0.90 in small-scale networks. ANN models applied to other water quality parameters, such as turbidity (Yan et al. 2021) and ammonia (Rustam et al. 2022), usually reported R values between 0.85 and 0.91. Placing our findings in this range shows that the model performed at the higher end of what has been achieved with ANN for water quality prediction.

This can be further developed, such as seasonal datasets (Yan et al. 2021, Rustam et al. 2022, Onyutha & Kwio-Tamale 2022), turbidity, ammonia as covariates, and the model can also be applied to other villages with a similar water supply system. It is important to note some limitations of the present work. The dataset was collected during a single campaign in December 2024, and therefore, seasonal changes in chlorine decay were not captured. Only three input variables, pH, temperature, and distance, were used, while other factors like turbidity, organic matter, or pipe-wall effects could also play a role and may improve predictions if added. Finally, because the model is data-driven, it may need to be recalibrated if applied to other rural schemes with different conditions. Future work should therefore extend monitoring to different seasons and consider additional input parameters to strengthen the model.

CONCLUSIONS

The present study successfully demonstrated the feasibility of an ANN-based model for predicting residual chlorine in a rural water distribution system. With pH, temperature, and distance from the ESR as model inputs, the decay of chlorine in decentralized and manual water supply distribution systems was well described with its often nonlinear behavior.

The best architecture discovered was a Multilayer Perceptron (MLP) with a 3-12-1 configuration, providing good performance (R value = 0.902). Chlorine residuals are affected by a wide range of complex and distributed spatial and environmental variations, and the ANN model showed its predictive power through statistical and graphical analyses in both the training and testing stages. This predictive ability can help rural water operators make better dosing decisions and reduce risks from both under-dosing and overdosing, which is especially important for schemes under the Jal Jeevan Mission.

This research highlights the capability of ANN models as dependable soft computing instruments to improve water quality monitoring and decision-making in rural locations. The model could, in the future, be linked with online monitoring systems or SCADA platforms to automate dosing, but such integration would require further testing and operational support. Its flexibility also means it can be adapted to other rural water supply systems with different hydraulic and environmental conditions.

Future studies should extend monitoring across different seasons, add other predictive factors such as turbidity, organic matter, and pipe material, and also explore the use of hybrid models that integrate ANN with other AI algorithms like fuzzy logic or genetic algorithms for better performance. In the longer term, simple digital interfaces or mobile apps could be developed based on this model to give field operators easier access to chlorine dose recommendations. While this is still a suggestion for future development, such tools, supported by policy and institutional capacity, could strengthen rural water safety and public health through data-driven chlorination management.

ACKNOWLEDGMENTS

The author states acknowledgement to the MJP (Maharashtra Jeevan Pradhikaran) staff and the Rui and Shingave village Gram Panchayat officials for their assistance and collaboration during the field data collection and site access. Their technical and administrative support was crucial to this study's successful completion.

REFERENCES

Alsulaili, A. and Refaie, A., 2021. Artificial neural network modeling approach for the prediction of five-day biological oxygen demand and wastewater treatment plant performance. *Water Supply*, 21(5), pp.1861–1877. [DOI]

Batista, G.S., Lacerda, M.C., Aragão, D.P., Cabral de Araújo, M.M. and Rodrigues, A.C.L., 2024. Modeling the decay of free residual chlorine in water distribution networks in Brazilian rural communities using ANN. *Journal of Water Process Engineering*, 59, 105312. [DOI]

Bisht, A.K., Singh, R., Bhutiani, R. and Bhatt, A., 2019. Artificial neural network based water quality forecasting model for Ganga River. *Applied Water Science*, 9(8), p.1. [DOI]

Chen, Y., Song, L., Liu, Y., Yang, L. and Li, D., 2020. A review of the artificial neural network models for water quality prediction. *Applied Sciences*, 10(17), p.5776. [DOI]

De Santi, M., Khan, U.T., Arnold, U. and Ali, S., 2021. Forecasting point-of-consumption chlorine residual in refugee settlements using ensembles of artificial neural networks. *npj Clean Water*, 4, 35. [DOI]

El Shebli, M., Sharrab, Y. and Al Fraihat, D., 2023. Prediction and modeling of water quality using deep neural networks. *Environment, Development and Sustainability* (advance online). [DOI]

Enríquez, L., Álvarez, B. and Vega-Moreno, D., 2023. Using artificial intelligence models to support water quality prediction in water distribution networks. *IOP Conference Series: Earth and Environmental Science*, 1136(1), 012009. [DOI]

Hua, P., de Oliveira, K., Cheung, P., Gonçalves, F.V. and Zhang, J., 2018. Influences of model structure and calibration data size on predicting chlorine residuals in water storage tanks. *Science of the Total Environment*, 634, pp.705–714. [DOI]

Isık, H. and Akkan, T., 2024. Water quality assessment with artificial neural network models: performance comparison between SMN, MLP and PS-ANN methodologies. *Arabian Journal for Science and Engineering* (early view). [DOI]

Jafari, I., Luo, R., Lim, F.Y., Hui, N.S. and Jiangyong, H., 2023. Machine-learning-assisted prediction and optimized kinetic modelling of residual chlorine decay for enhanced water quality management. *Chemosphere*, 341, 140011. [DOI]

Kwio-Tamale, J.C. and Onyutha, C., 2024. Space-time prediction of residual chlorine in a water distribution network using artificial intelligence and the EPANET hydraulic model. *Water Practice & Technology*, 19(1), pp.231–245. [DOI]

Li, Z., Liu, H. and Zhang, Y., 2024. Real-time water quality prediction in water distribution networks using graph neural networks with sparse monitoring data. *Water Research*, 250, 121018. [DOI]

Michel, R., Dandy, G.C. and Nixon, J., 2006. Forecasting chlorine residuals in a water distribution system using a general regression neural network. *Journal of Water Resources Planning and Management*, 132(2), pp.128–137. [DOI]

Nagalapalli, S., Anmala, J. and Varma, M.R.R., 2022. Prediction of stream water quality in Godavari River Basin, India using statistical and artificial neural network models. *H2Open Journal*, 5, pp.621–641. [DOI]

Ogwueleka, T.C., Mohammed, M.N. and Ezeh, C.E., 2023**.** Modeling the factors affecting residual chlorine decay in a water distribution network of Abuja, Nigeria. *Water Quality Research Journal*, 60(3), pp.482–493. [DOI]

Onyutha, C. and Kwio-Tamale, J., 2022. Modelling chlorine residuals in drinking water: a review. *International Journal of Environmental Science and Technology*, 19(11), pp.11613–11630. [DOI]

Riyadh, A., Zayat, A., Chaaban, A. and Peleato, N., 2024. Improving chlorine residual predictions in water distribution systems using recurrent neural networks. *Environmental Science: Water Research & Technology*, 10(10), pp.2533–2545. [DOI]

Rustam, F., Ishaq, A., Kokab, S.T., de la Torre Diez, I., Mazon, J.L.V., Rodriguez, C.L. and Ashraf, I., 2022. An artificial neural network model for water quality and water consumption prediction. *Water*, 14(21), 3359. [DOI]

Satish, N., Anmala, J., Rajitha, K. and Varma, M.R.R., 2024. A stacking ANN ensemble model of ML models for stream water quality prediction of Godavari River Basin, India. *Ecological Informatics*, 80, 102500. [DOI]

Tinelli, L. and Juran, I., 2024. Intelligent chlorination in water distribution networks: integrating Bayesian optimization for booster placement. *Science of the Total Environment*, 922, 170650. [DOI]

Vrachimis, S.G., Eliades, D.G. and Polycarpou, M.M., 2021. Calculating chlorine concentration bounds in water distribution networks: a backtracking uncertainty approach. *Water Resources Research*, 57(8), e2020WR028684. [DOI]

Wadkar, D.V., Chikute, G.C., Patil, P.S., Wadkar, P.D. and Chikute, M.G., 2024**.** Effectiveness of different artificial neural network models in establishing the suitable dosages of coagulant and chlorine in water treatment works. *Nature Environment and Pollution Technology*, 23(4), pp.2273–2281. [DOI]

Wadkar, D.V., Nangare, P. and Wagh, S., 2021. Evaluation of water treatment plant using artificial neural network (ANN): case study of Pimpri Chinchwad Municipal Corporation (PCMC). *Sustainable Water Resources Management*, 7, 52. [DOI]

Yan, J., Liu, J., Yu, Y. and Xu, H., 2021. Water quality prediction in the Luan River based on 1-DRCNN and BiGRU hybrid neural network model. *Water*, 13(9), 1273. [DOI]

Zaghini, A., Gagliardi, F., Marsili, V., Mazzoni, F., Tirello, L., Alvisi, S. and Franchini, M., 2024. A pragmatic approach for chlorine decay modeling in multiple-source water distribution networks based on trace analysis. *Water*, 16(2), 345. [DOI]