Clockwork Recurrent Neural Network- M5T: A New Machine Learning Model for Predicting Reservoir Inflow

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Abstract

Reservoir inflow prediction is critical for effective water management. By accurately forecasting these inflows, reservoir operators can make well-informed choices regarding water releases, which can influence both the availability of water downstream and the potential for flooding. This research introduces a novel predictive model called the Clockwork Recurrent Neural Network (CWRNN)-M5T, specifically designed to forecast monthly reservoir inflow. By synthesizing these two models, this study proposes a groundbreaking method that significantly improves prediction accuracy and provides critical insights for effective water resource management. The CWRNN-M5T model can predict inflow for one, two, and three months ahead. This study showcases the model's effectiveness, contributing to advancements in engineering informatics for water resource management and optimal dam operations. It also explores how the model's performance changes with longer prediction horizons, emphasizing its limitations and potential real-world applications. The models utilized the lagged reservoir inflow values as inputs. For one-month predictions, the CWRNN model yielded the best results. However, the CWRNN-M5T model surpassed all others, achieving a Nash Sutcliffe efficiency (NSE) of 0.98, compared to 0.94 for the CWRNN model. Additionally, the CWRNN-M5T model recorded the lowest mean absolute error (MAE) at 0.123, while the CWRNN model had an MAE of 0.210. For two-month predictions, the CWRNN-M5T model achieved the lowest root mean square error (RMSE) of 0.254. Overall, the CWRNN-M5T model has proven to be a highly effective tool for predicting reservoir inflow.

Keywords: Deep learning models, Water resource management, hydrological prediction, hybrid model

1. Introduction

Reservoir inflow prediction is important for effective reservoir management and operation [1]. Inflow predictions also aid in assessing and managing drought conditions. By analyzing long-term inflow patterns, water managers can identify drought-prone periods and develop strategies for water protection, demand management, and alternative water sources. Accurately predicting reservoir inflow can aid in planning water distribution, hydroelectric power generation, flood control, and drought management [2]. It can also aid in decision-making related to irrigation, municipal water supply, and environmental protection [3]. Reservoir inflow is a key factor that affects reservoir water level and storage capacity. In addition, inflow prediction can also reduce the risk of floods and other related disasters. Reservoir inflow prediction can be complex because it relies on different factors such as weather conditions, precipitation patterns, land use changes, and hydrological characteristics of the watershed [1]. Additionally, inflow is often affected by upstream activities such as dam releases or diversions, which can further complicate the prediction process [4]. Therefore, modeling and predicting reservoir inflow requires advanced techniques and a comprehensive understanding of the factors that affect inflow [5]. Machine learning models are useful for predicting reservoir inflow because they can capture complex non-linear relationships between various input variables, such as precipitation, temperature, and water level [6]. These models are able to learn from historical data patterns and produce highly accurate predictions that enable reservoir managers to make informed water allocation [7]. Additionally, machine learning models can process large amounts of data quickly, which is essential for real-time decision-making related to reservoir inflow prediction [8]. The M5Tree model is a machine learning model developed based on the M5 model tree algorithm [9]. It is designed for regression problems and can predict continuous numerical values. The M5Tree model is a type of decision tree algorithm that combines the benefits of decision trees and regression models [10]. The M5Tree model has been effectively used in multiple fields including ecology, hydrology, and meteorology. It can predict various variables such as streamflow, rainfall, and air quality. Esmaeilzadeh et al [11] conducted a study at the Sattarkhan reservoir in Iran to assess the accuracy of different machine learning models for predicting next-day discharge. The study evaluated the performance of several models including artificial neural network (ANN), support vector regression (SVR), wavelet neural networks (WANN), and M5 model tree. The study concluded that wavelet transformation played a significant role in improving the accuracy of the different models. The WANN model, which used temperature, precipitation, and previous discharge as inputs, had the highest accuracy with an RMSE value of 0.31 m^3/s. Yin et al [12] developed accurate and reliable river flow forecasting models using data-driven techniques. The study suggested that the M5Tree method could be used for short-term river flow forecasting in semiarid mountainous regions. Rouzegari et al [13] used the flow duration curve shifting method to estimate the environmental water demand of the Mahabad River in Iran. They used simulated annealing (SA), the M5 tree model, and non-linear programming (NLP) methods to develop an optimal operating model for a reservoir. The M5 tree model was used to determine the optimal values of released water based on optimal water storage values, reservoir inflows, and monthly demands. The SA-M5 tree model extracted the operation rules accurately. These rules were represented as linear if-then statements, which might be useful for future applications. Although the M5 model is robust, it has some limitations. The M5 model tree may not be suitable for all prediction tasks. For example, it may not be effective for predicting complex nonlinear relationships or dealing with high-dimensional datasets. [14]. In addition, M5 can be prone to overfitting when the model is too complex or the data set is too small, resulting in poor generalization performance. Finally, the interpretability of M5 models can be challenging, as the resulting decision trees can become very large and difficult to understand, especially for non-experts [15]. Thus, it is essential to address the limitations of the M5 models. In recent years, deep learning models have been increasingly used to overcome the limitations of classical machine learning models [16]. They have been used to overcome the limitations of classical machine learning models in various fields, including reservoir inflow prediction, weather forecasting, and public health. Deep learning methods can handle larger datasets more efficiently and capture complex non-linear relationships, making them a suitable solution to overcome these limitations [16]. The hybrid deep learning- M5 model is a technique to overcome limitations of the M5 model.

The hybrid deep learning-M5 model can address some of the disadvantages of the M5 model. A hybrid model that combines deep learning techniques with the M5 model can take advantage of both approaches and mitigate the weaknesses of the M5 model. Deep learning algorithms can improve prediction accuracy by capturing subtle patterns and handling complex nonlinear relationships [16-17]. This hybrid model can also address the limitations of the M5 model by reducing sensitivity to noisy data, handling missing data, and improving the scalability and generalization ability of the model. Additionally, the hybrid model can be used to overcome some of the limitations of the M5 model, such as the requirement for pre-processing and feature engineering, and can handle a variety of data types and formats. Additionally, the hybrid model can use techniques such as dropout and regularization to prevent overfitting by reducing the model complexity. A clockwork recurrent neural network (CW-RNN) is one of the most popular deep learning models.

A clockwork recurrent neural network (CW-RNN) is a type of recurrent neural network (RNN) that consists of multiple recurrent layers with different time scales [18]. The architecture of CW-RNN includes multiple modules that process input data at different time scales [19]. Each module has a specific responsibility to process the input data. Each module has its own clock rate, and the output of one module is used as the input to the next module [18]. The CW-RNN model uses different clock rates for different modules to capture different levels of temporal dependencies [20]. Thus, the CW-RNN is a robust deep learning model for handling complex problems. The CW-RNN model has a high potential to address the shortcomings of the M5 model.

The hybrid CWRNN-M5 model can improve the performance of the M5 model by combining the advantages of both models. In addition, the CW-RNN model can avoid overfitting by effectively learning the relevant features of the time-series data and ignoring the noise and irrelevant features. By combining these two models, the hybrid model can capture both the structured and temporal information in the data, resulting in improved accuracy and better prediction performance. In this study, we use the CWRNN-M5 model to predict monthly reservoir inflow. Thus, the main innovation of the current paper is to develop a new model for predicting reservoir inflow. The new CWRNN-M5 model can significantly contribute to water resource management by providing more accurate and reliable predictions of reservoir inflow. This information can be used to improve water allocation and distribution strategies, optimize hydropower generation, and support effective flood management planning. By accurately predicting reservoir inflows at various lead times, the CWRNN-M5T model supports hydrological simulations. This information is crucial for simulating and modeling water flow, storage, and distribution within a hydrological system.

2. Materials and Methods

2.1 Structure of the M5 model

The M5 model is a decision tree-based algorithm suitable for regression and classification tasks [9]. It operates by recursively dividing the input space into smaller regions and fitting simple models to each region [21]. The model starts with a root node representing the entire input space.

It selects the best attribute for data division based on the highest variance reduction (Kisi et al., 2022). This is calculated to determine how much the variance of the target variable decreases when data is split by a specific attribute. It is computed as the difference between the original variance and the weighted average of the variances in each subset [14].

The attribute with the highest variance reduction is chosen at each level. Internal nodes represent decisions based on the selected attribute, and the model continues splitting until it meets a stopping criterion, such as a minimum number of instances or maximum tree depth [22]. Each leaf node represents a simple model predicting the target variable for instances in that region, typically using a linear regression model [14]. After constructing the tree, the M5 model prunes it to prevent overfitting by removing unnecessary branches [23]. It evaluates the performance of internal nodes against leaf nodes, replacing non-improving internal nodes with leaf nodes.

To predict new instances, the model compares attribute values with internal and leaf nodes and uses stored coefficients to calculate the predicted target variable. This structured approach enhances the model's generalization capabilities while simplifying its complexity.

2.2 Structure of a clockwork recurrent neural network

The CW-RNN is a type of recurrent neural network that uses multiple clockwork recurrent layers. This architecture allows the model to capture the hierarchical temporal structure of the data, which is particularly useful for hydrological time-series, where the relationships between variables can be complex and non-linear. The CW-RNN-M5T model includes lagged values of the target variable, which can improve the accuracy of the predictions by capturing the historical patterns and relationships between the variables. The CWRNN-M5T model is trained separately for different lead times, which allows it to learn the specific patterns and dependencies for each lead time. The CWRNN-M5T model uses an ensemble learning approach, where multiple models are trained and combined to improve the overall accuracy of the predictions.

A clockwork recurrent neural network (CW-RNN) has a hierarchical structure that consists of multiple modules [18]. The structure of a Clockwork Recurrent Neural Network (CW-RNN) can be explained level by level:

Level 1: Input layer

The input layer of the CW-RNN model receives input data and passes it to the next layer.

Level 2: Clockwork layer

The clockwork layer consists of multiple modules that process input data over different time scales. Each module has its own clock speed and processes the input data at its designated time scale [24]. A clockwork layer is a specialized type of recurrent neural network layer that operates with varying clock rates for different groups of neurons. The modules that have a slower clock speed are designed to manage long-term information, like seasonal trends or yearly cycles. In contrast, the modules with a faster clock speed focus on processing continuous data, such as daily or hourly variations [25]. A clockwork recurrent neural network (CW-RNN) module with a high clock speed processes information over a longer period of time. For example, a module with a clock speed of one week can capture weekly patterns, whereas a module with a clock speed of one day can capture daily patterns.

Level 3: Hidden layer

The hidden layer of the CW-RNN receives input from the clockwork layer and processes it using activation functions [24].

Level 4: Output layer

The output layer of the CW-RNN receives input from the hidden layer and produces the final output.

Level 5: Feedback connections

The network uses feedback connections to connect the output to the input or hidden layer. Feedback connections help the network improve its performance by learning from its own predictions.

2.3 Structure of a hybrid CWRNN- M5Tree model

The CWRNN-M5Tree model combines a Clockwork Recurrent Neural Network (CW-RNN) with an M5Tree model to improve reservoir inflow prediction accuracy. At the first level, input data (e.g. historical inflow data and weather forecasts) are preprocessed and fed into the CW-RNN model. The CW-RNN employs multiple modules that operate at different clock speeds, allowing it to separately manage long-term and continuous information, which sets it apart from traditional recurrent neural networks. In the second stage, the output from the CW-RNN is input into the M5Tree model, which utilizes decision trees to forecast reservoir inflow. The M5Tree model is adept at handling non-linear relationships between the input and output variables. Finally, the output from the M5Tree model undergoes post-processing to yield the final prediction for reservoir inflow. In summary, the CWRNN-M5Tree model combines deep learning and decision tree techniques to effectively capture the intricate relationships between various input factors and reservoir inflow. The Adam optimization algorithm is employed to fine-tune the parameters of the CW-RNN during training. The Adam algorithm includes momentum and regularization terms that prevent overfitting and improve generalization performance [26]. The algorithm uses a momentum term that dampens oscillations in the optimization process, leading to faster convergence. The weights and biases of the CWRNN model are randomly initialized. Clockwork layers and feedback connections are used to learn and predict patterns in the data. During each training iteration, the optimizer computes the gradients of the loss function with respect to the model parameters [26]. The optimizer uses the gradients to update the parameters using a combination of the first and second moments of the gradients. The updated parameters are then used to compute the next set of predictions. The structure of the CWRNN-M5T is presented in Fig.1.

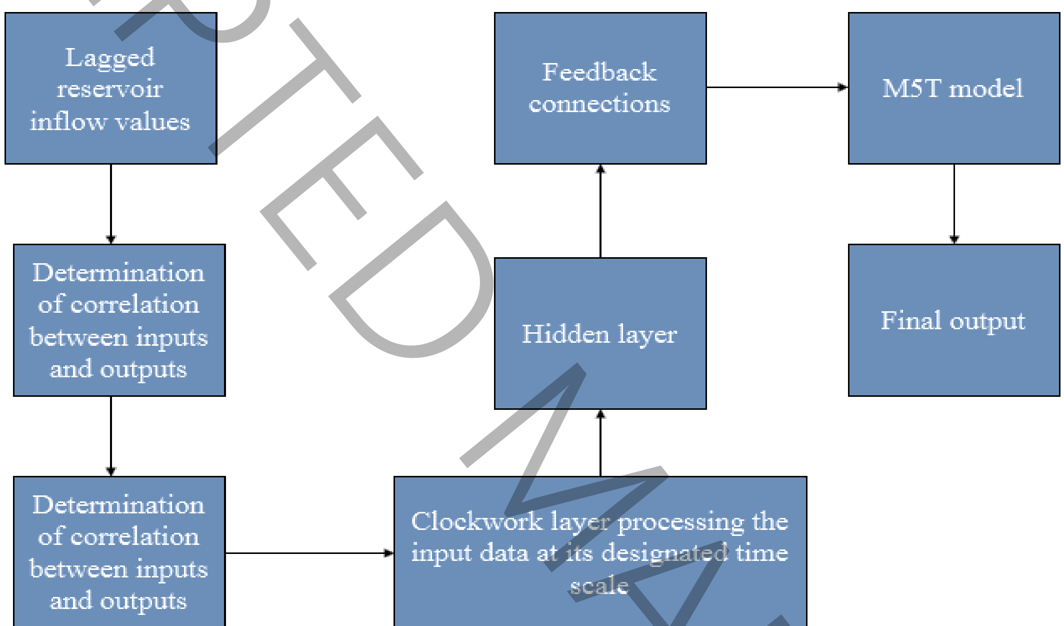


Figure 1. Structure of the CWRNN-M5T

2.4 Benchmark models

A multilayer perceptron (MLP) is a type of artificial neural network (ANN) featuring one or more hidden layers [27]. Each neuron in the MLP receives inputs, computes a weighted sum, applies an activation function, and passes the result to the next layer [28]. The hidden layers enable the network to learn complex patterns through nonlinear transformations. MLPs are utilized for tasks like classification, regression, and time-series prediction [29]. Another type of ANN is the radial basis function neural network (RBFNN), where the input layer sends values to a hidden layer consisting of radial basis functions. These functions transform input data into a higher-dimensional space based on their distance from center points. The output layer then produces the final results. RBFNNs learn weights and centers using optimization methods like gradient descent, evaluated through metrics such as mean square error or classification accuracy [30].

The Backpropagation algorithm is commonly used for training ANNs. It computes the gradient of the loss function relative to the network's weights, adjusting them to minimize prediction errors. During training, input data is processed to generate output, errors are calculated, and these errors are propagated back through the network to update the weights, thus reducing loss.

3. Case Study

The Aidoghmoush Dam is a large arch dam located in the northwest of Iran, near the city of Maragheh. The Aidoghmoush climate is generally characterized as a semi-arid climate with hot summers and cool winters. The region is situated in the northwest of Iran, and it is characterized by its proximity to the Caspian Sea, the Elburz mountain range, and the Mediterranean climate zone. The annual precipitation is approximately 500-700 mm. The summer months are hot and dry, with temperatures reaching up to 40 °C. The climate of the region is an important factor that affects water resources management. The Aidoghmoush dam is used for hydroelectric power generation and water supply. The Aidoghmoush dam is one of the largest dams in Iran and is an important source of power and water for the region. The average annual discharge and rainfall are 190 $*10^6$ m^3 and 378 mm, respectively. Accurate inflow prediction can help optimize water release, plan for droughts and floods, manage water for irrigation and generate hydropower. Additionally, inflow prediction can be useful in maintaining the ecological health of downstream river systems and ecosystems. The dam crest has a length of 297 m and a width of 12 m. Its height is 1,350 m above sea level. In this study, researchers used past reservoir inflow values with different time lags to predict reservoir inflow for periods of one, two, and three months ahead. Using lagged inflow values as inputs reduces the number of variables required for the predictive model, making it simpler and more efficient. This is especially important for real-world applications where the number of input variables may be limited due to data availability or computational constraints. Lagged inflow values are directly related to current reservoir inflow, whereas climate parameters may have indirect or complex relationships with reservoir inflow. Lagged inflow values provide a more accurate representation of historical inflow patterns, which can improve the accuracy of the model. Figure 2 shows the location of the case study. Figures 3a, 3b, and 3c show time-series data for one, two, and three months ahead. The monthly data were collected from 2005–2015.

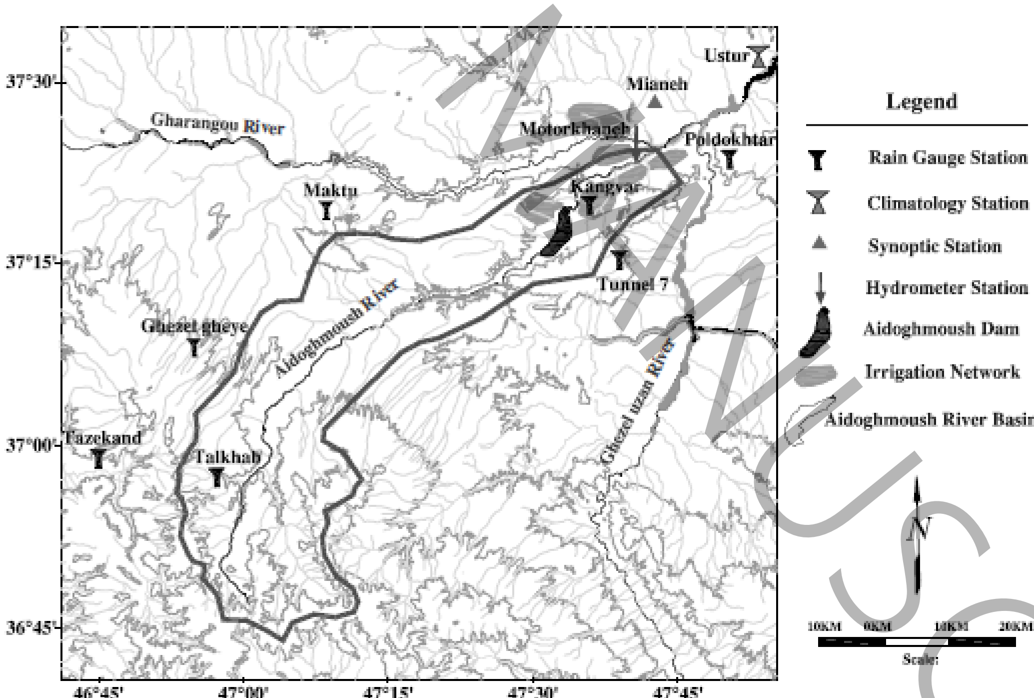


Figure 2. Location of case study (Ashofteh et al [31])

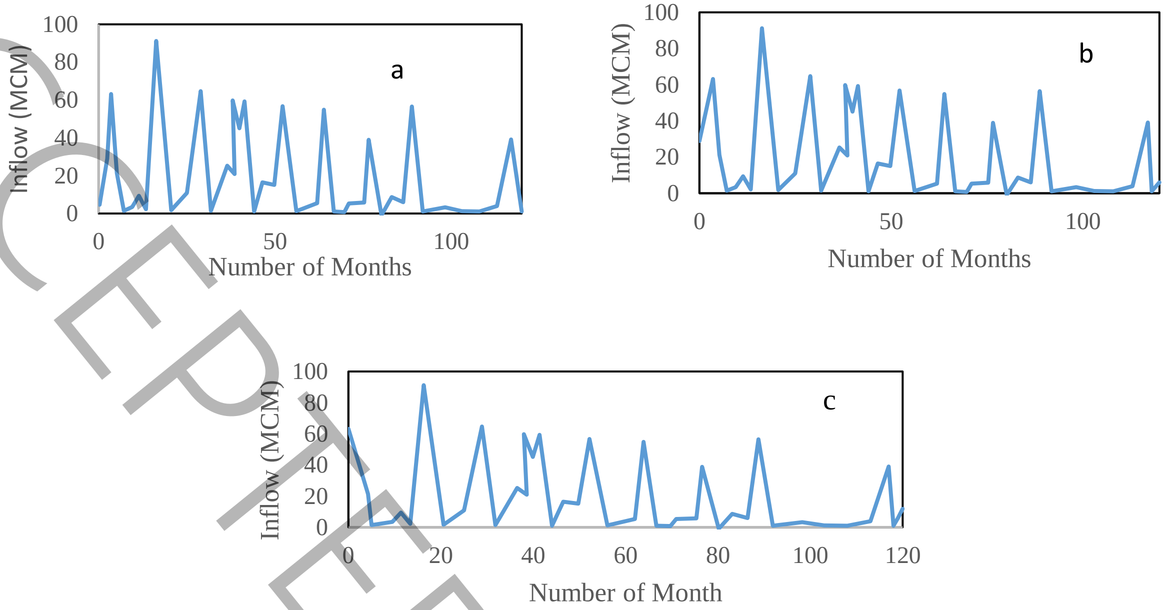


Figure 3. Inflow time-series for a: one-month ahead, b: two-month ahead, and c: three-month ahead

4. Discussion and Results

4.1 Selection of input parameters

Lagged reservoir inflow refers to the historical inflow values of the reservoir in previous periods. Lagged reservoir inflow can affect current reservoir inflow because the inflow to a reservoir at any given time is influenced by various factors, including precipitation, evapotranspiration, and runoff from upstream areas. By analyzing previous inflow values, it is possible to identify patterns and trends over time. Lagged reservoir inflow values can provide insights into the historical trend of water inflow into the reservoir, improving the accuracy of predicting the current reservoir inflow. By adding lagged inflow values as predictors to a prediction model, the model can account for the historical water inflow pattern, which can enhance prediction accuracy for the current period. Table 1 shows correlation values between target variables and lagged inflow values. Predictor variables with a correlation coefficient greater than 0.90 with the target variable are selected. A correlation coefficient greater than 0.90 indicates a strong positive linear relationship between the predictor variable and the target variable. By selecting predictor variables with high correlation, the model can better capture the underlying patterns and relationships, resulting in more accurate predictions.

Table 1. Correlation values between inputs and outputs (bold values=selected inputs)

Target variable	t	t-1	t-2	t-3	t-4	t-5	t-6	t-7	t-8	t-9	t-10	t-11	t-12
	Precipitation	Evapotranspiration	Runoff	Temperature	Snow Water Equivalent	Wind Speed	Wind direction	Reservoir Water Level	Soil Moisture	Soil Permeability	Area of Catchment	Slope of Catchment	Vegetation Coverage
$INF_{t+\Delta t}$ $\Delta t=1$	**0.98**	**0.96**	**0.94**	**0.90**	0.87	0.85	0.85	0.84	0.80	0.78	0.77	0.70	0.68
$INF_{t+\Delta t}$ $\Delta t=2$	**0.97**	**0.94**	**0.92**	**0.90**	0.86	0.84	0.82	0.80	0.78	0.77	0.76	0.68	0.67
$INF_{t+\Delta t}$ $\Delta t=3$	**0.97**	**0.94**	**0.90**	0.89	0.86	0.85	0.84	0.80	0.78	0.76	0.75	0.70	0.68

4.2 Evaluation of the accuracy of the models

Table 2a shows training results for one-month ahead. The performance of five different models for reservoir inflow prediction can be compared. The CWRNN-M5T model outperformed the other models with an RMSE of 0.245, while the CWRNN model had the second-best performance with an RMSE of 0.35. The MLP model had the highest RMSE of 0.56, followed by the RBFNN model with an RMSE of 0.654, and the M5T model with an RMSE of 0.671. The CWRNN-M5T model again outperformed the other models with an NSE of 0.98, followed by the CWRNN model with an NSE of 0.94. The MLP, RBFNN, and M5T models had NSE values of 0.92, 0.90, and 0.89. The CWRNN-M5T model had the lowest MAE value of 0.123, followed by the CWRNN model with an MAE of 0.210. The MLP model had the highest MAE of 0.45, followed by the RBFNN model with an MAE of 0.555, and the M5T model with an MAE of 0.567. The CWRNN-M5T model had the lowest PBIAS value of 5, followed by CWRNN with a PBIAS of 7. The MLP model had the highest PBIAS of 9, followed by RBFNN with a PBIAS of 12, and M5T with a PBIAS of 15. The M5T model had the highest RMSE and MAE values among all models.

Table 2b shows testing results for the one-month ahead. Based on the performance metrics of NSE, PBIAS, MAE, and RMSE, the CWRNN-M5T model outperforms the other models, including CWRNN, MLP, RBFNN, and M5T. The CWRNN-M5T model had the highest NSE value of 0.97, indicating a high accuracy level. It also had the lowest PBIAS value of 6, indicating a low bias level. The CWRNN-M5T model had the lowest MAE and RMSE values of 0.224 and 0.248, respectively, indicating a high precision level.

Table 2c shows training results for two-month ahead. The CWRNN-M5T model had the lowest RMSE (0.251), followed by the CWRNN model (0.372), the MLP model (0.591), the RBFNN model (0.666), and the M5T model (0.679). The CWRNN-M5T model had the highest NSE (0.96), followed by the CWRNN model (0.91), the MLP model (0.89), the RBFNN model (0.87), and the M5T model (0.86). The CWRNN-M5T model had the lowest MAE (0.226), followed by the CWRNN model (0.314), the MLP model (0.472), the RBFNN model (0.578), and the M5T (0.615) model. The CWRNN-M5T model had the lowest PBIAS (8), followed by the CWRNN model (9), the RBFNN model (16), the M5T model (17), and the MLP model (15).

Table 2d shows testing results for predicting two-month ahead inflow. Based on the given table, the CWRNN-M5T model had the lowest RMSE value (0.254) compared to other models. The MLP and RBFNN models had the highest RMSE values (0.592 and 0.667, respectively). The CWRNN-M5T model had the highest NSE value (0.95), indicating a better agreement between observed and predicted values. The CWRNN-M5T model had the lowest MAE value (0.236), while the RBFNN model had the highest MAE value (0.625). The CWRNN-M5T model had the highest PBIAS value (9), followed by the CWRNN model (10). The M5T model had the lowest PBIAS value (18), indicating a better fit than the other models.

Table 2e shows training results for the next three months. The CWRNN-M5T model outperformed the other models with a PBIAS of 10. The CWRNN model had the second-best PBIAS value of 11, followed by the MLP model with a PBIAS of 17, the RBFNN model with a PBIAS of 18, and the M5T model with a PBIAS of 19. Overall, the CWRNN-M5T and CWRNN models showed the smallest PBIAS values. The CWRNN-M5T model outperformed the other models with the lowest RMSE of 0.259, followed by the CWRNN model with an RMSE of 0.381. The MLP and RBFNN models had RMSE values of 0.594 and 0.669, respectively. Based on MAE values, the CWRNN-M5T model had the lowest MAE (0.236), followed by the CWRNN model (0.319), the MLP model (0.487), the RBFNN model (0.589), and the M5T (0.625) model. Based on NSE values, the CWRNN-M5T model outperformed the other models, followed by the CWRNN model.

Table 2f shows testing results for three-month ahead. Based on the NSE metric, CWRNN-M5T had the highest value of 0.92, followed by CWRNN with a value of 0.88. The CWRNN-M5T model had the lowest PBIAS value of 11, followed by CWRNN with a PBIAS of 14, MLP with a PBIAS of 18, RBFNN with a PBIAS of 19, and M5T with a PBIAS of 22. Based on the RMSE values, the CWRNN-M5T model had the lowest value of 0.262, indicating the highest level of accuracy. The next best performing model was CWRNN with an RMSE of 0.394, followed by MLP with an RMSE of 0.599, RBFNN with an RMSE of 0.673, and M5T with an RMSE of 0.694.

The CWRNN-M5T model had the lowest MAE value of 0.241, followed by CWRNN with an MAE of 0.320, RBFNN with an MAE of 0.599, MLP with an MAE of 0.498, and M5T with an MAE of 0.632.

Table 2g shows Uncertainty at 95% (U95) of training and testing results for three-month ahead. U95 quantifies the width of the 95% prediction interval around the model's forecasts. Here U95 calculated by ($U95 = 1.96\left(SD^2 - RMSE^2\right)^{0.50}$) which SD is standard deviation and RMSE is root mean square error. It should be mentioned in this table a lower U95 indicates that the model is more confident in its predictions, while a higher U95 suggests greater uncertainty

Table 2. Comparison of the accuracy of the models based on a: training results at one-month ahead, b: testing results at one-month ahead, c: training results at two-month ahead, d: testing results at two-month ahead, e: training results at three-month ahead and f: testing results at three-month ahead, g: U95 training and testing results at three-month ahead

a

Model	RMSE	NSE	MAE	PBIAS
CWRNN-M5T	0.245	0.98	0.123	5
CWRNN	0.350	0.94	0.210	7
MLP	0.560	0.92	0.450	9
RBFNN	0.654	0.90	0.555	12
M5T	0.671	0.89	0.567	15

b

Model	RMSE	NSE	MAE	PBIAS
CWRNN-M5T	0.248	0.97	0.224	6
CWRNN	0.371	0.92	0.312	8
MLP	0.587	0.90	0.471	12
RBFNN	0.654	0.89	0.567	14
M5T	0.671	0.87	0.612	15

c

Model	RMSE	NSE	MAE	PBIAS
CWRNN-M5T	0.251	0.96	0.226	8

CWRNN	0.372	0.91	0.314	9
MLP	0.591	0.89	0.472	15
RBFNN	0.666	0.87	0.578	16
M5T	0.679	0.86	0.615	17

d

Model	RMSE	NSE	MAE	PBIAS
CWRNN-M5T	0.254	0.95	0.236	9
CWRNN	0.377	0.90	0.319	10
MLP	0.592	0.88	0.487	15
RBFNN	0.667	0.86	0.589	17
M5T	0.682	0.82	0.625	18

e

Model	RMSE	NSE	MAE	PBIAS
CWRNN-M5T	0.259	0.94	0.245	10
CWRNN	0.381	0.89	0.321	11
MLP	0.594	0.87	0.490	17
RBFNN	0.669	0.84	0.591	18
M5T	0.691	0.82	0.627	19

f

Model	RMSE	NSE	MAE	PBIAS
CWRNN-M5T	0.262	0.92	0.241	11
CWRNN	0.394	0.88	0.320	14
MLP	0.599	0.85	0.498	18
RBFNN	0.673	0.82	0.599	19
M5T	0.694	0.80	0.632	22

g

Model	**U95-training**	**U95-testing**
CWRNN-M5T	5	4
CWRNN	10	10

MLP	15	14
RBFNN	22	20
M5T	25	22

Based on the provided information, it appears that the accuracy of the CWRNN-M5T model decreases as the prediction lead time increases. Specifically, the training RMSE values for one-month ahead, two-month ahead, and three-month ahead predictions were 0.245, 0.251, and 0.259, respectively. Based on the provided RMSE values, it can be observed that the accuracy of CWRNN-M5T decreases as the prediction lead time increases. The RMSE values for one-month ahead, two-months ahead, and three-months ahead were 0.248, 0.254, and 0.262, respectively.

Here it should be emphasis on reason of the RMSE decreasing by longer lead times. The decline in prediction accuracy from 0.245 to 0.262, is something which often see in hydrological modeling. There are a few reasons for this producer. One major factor is error accumulation—small mistakes that happen early on can build up over time, making predictions less reliable as we look further into the future. Additionally, hydrological systems are influenced by many complex and sometimes chaotic factors, such as changes in rainfall, temperature, and upstream flows. These elements introduce a lot of unpredictability and non-linearity, which makes accurate long-term forecasting particularly challenging.

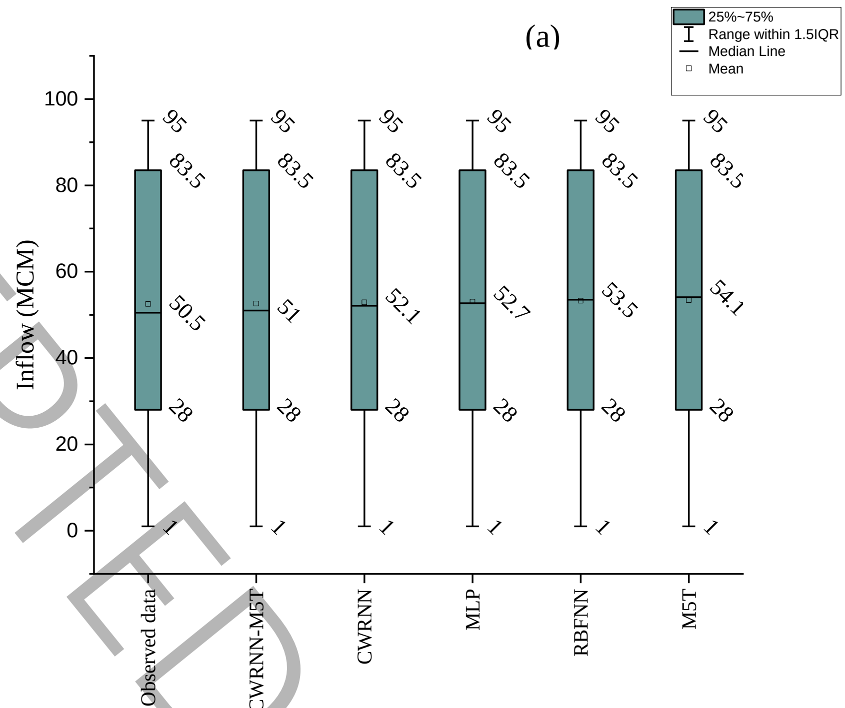
The testing NSE value decreased from 0.97 for a one-month ahead prediction to 0.92 for a three-month ahead prediction. As the prediction lead time increases, it becomes harder to accurately predict the target variable. In the short term, the CWRNN-M5T model may be able to capture patterns and relationships between the input variables and the target variable and make accurate predictions based on those patterns. As time goes on, unexpected changes or variability in the input data can accumulate and produce inaccurate predictions. For example, weather patterns can change, and external factors such as economic or political conditions can affect the target variable. Predictions can be inaccurate if these factors are not accurately captured and incorporated into the model. Therefore, as the prediction lead time increases, the model may not be able to capture all the relevant factors that affect the target variable. As the lead time increases, the input data becomes more uncertain and variable.

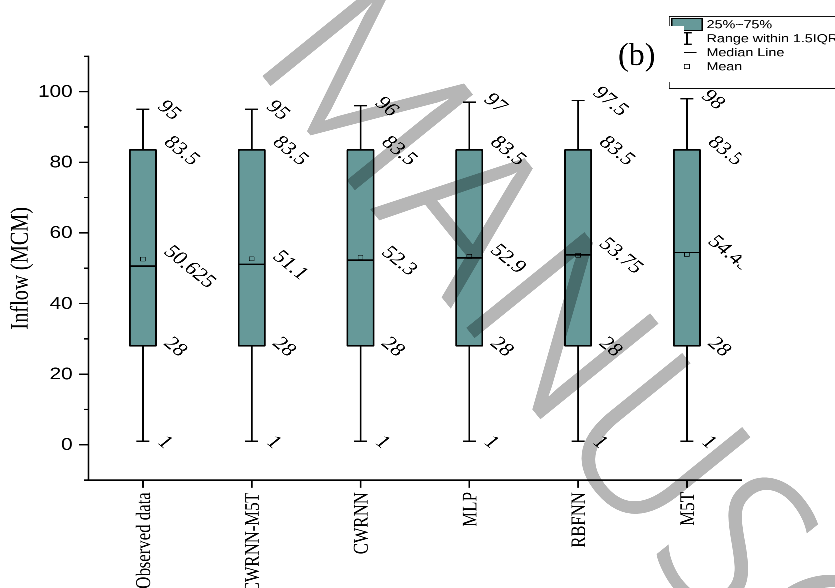
The Clockwork Recurrent Neural Network (CW-RNN)-M5T was developed to model the temporal dependencies, making it a suitable model for hydrological forecasting. One reason why it may outperform other models is that it can capture complex patterns of the time-series data that other models may miss. This model includes multiple time scales in its architecture. This mechanism allows it to capture both short-term and long-term temporal relationships in the input data, resulting in more precise predictions. While the M5Tree model can identify certain patterns and relationships within the data, it struggles to capture more complex temporal dynamics that are crucial for accurate predictions. In contrast, the CWRNN-M5T model is a hybrid approach that effectively captures these temporal patterns and dependencies in the input data. By combining the strengths of both models, the CW-RNN-M5T can deliver more precise predictions than the M5Tree model.

There are several reasons the M5T model may not perform as well as the MLP and RBFNN models. One such reason is its difficulty in capturing non-linear relationships effectively. Additionally, since the M5T model is based on a decision tree structure, it may lack the flexibility of the neural network architectures found in MLP and RBFNN models. The M5T model is also sensitive to outliers or noisy data, which can adversely impact its performance. In contrast, the CWRNN model excels in managing long-term dependencies, which may contribute to its superior performance compared to the MLP, RBFNN, and M5T models.

CWRNN uses multiple modules with different clock speeds to process information at different time scales. CWRNN model can handle larger datasets more efficiently, which can be especially beneficial for predicting reservoir inflow. The results provide insights into water resource management by providing information on the accuracy of different predictive models used for predicting reservoir inflow. Accurate inflow predictions are essential for effective water resource management, as they help decision-makers plan and allocate water resources, such as drinking water and irrigation water, more effectively. Accurate inflow predictions can help water managers better understand how much water will be available for various uses such as irrigation, public utilities, and hydropower generation. By comparing the accuracy of different models, water managers can choose the best model for inflow prediction and use it to optimize reservoir operations. Accurate prediction of reservoir inflow can help water managers make informed decisions about water allocation, drought management, flood control, and hydropower generation. By comparing the performance of different models, the study provides insights into which models are most accurate for predicting different lead times. Overall, the study provides a foundation for developing advanced engineering informatics that can improve water resource management in the future. The CWRNN-M5T model can help optimize the operation of dam reservoirs by providing accurate predictions of reservoir inflow. Additionally, the predictions can be used to develop early warning systems for potential floods, which can help reduce the risk of damage to property and infrastructure. Figure 4a shows boxplots of models for one-month ahead. The median value of observed data, the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T was 50.5 MCM, 51 MCM, 52.1 MCM, 52.1 MCM, 53.5 MCM, and 54.1 MCM, respectively. Figure 4b shows boxplots of models for two-month ahead. The median value of observed data, the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T was 50.625 MCM, 51.1 MCM, 52.3 MCM, 52.9 MCM, 53.75 MCM, and 54.4 MCM, respectively. Figure 4c shows boxplots of models for three-month ahead. The median value of observed data, the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T was 50.69 MCM, 51.175 MCM, 52.325 MCM, 52.92 MCM, 53.95 MCM, and 54.4 MCM, respectively. The maximum value of the observed data, CWRNN-M5T model, CWRNN model, MLP model, RBFNN model, and M5T model was 95 MCM, 95 MCM, 96.50 MCM, 97.25 MCM, 97.55 MCM, and 99.00 MCM, respectively.

The Taylor diagram is a graphical method for comparing and visualizing the similarities and differences between the spatial patterns of different datasets. It is a type of scatter plot that compares multiple datasets by showing their correlation coefficients, root mean square errors (RMSEs), and standard deviations relative to a reference dataset. The reference dataset is typically plotted at the origin of the graph, while the other datasets are represented by points on the graph. The correlation coefficient is represented by the distance from the origin, while the RMSE is represented by the radial distance from the reference dataset. A perfect model or dataset will fall on the reference point, while a poor model or dataset will be located far away from the reference point.


(a)
25%~75%
Range within 1.5IQR
Median Line
Mean
Inflow (MCM)
0
20
40
60
80
100
95
83.5
50.5
51
52.1
52.7
53.5
54.1
28
1
Observed data
CWRNN-M5T
CWRNN
MLP
RBFNN
M5T


(b)
25%~75%
Range within 1.5IQR
Median Line
Mean
Inflow (MCM)
0
20
40
60
80
100
95
96
97
97.5
98
83.5
50.625
51.1
52.3
52.9
53.75
28
1
Observed data
CWRNN-M5T
CWRNN
MLP
RBFNN
M5T

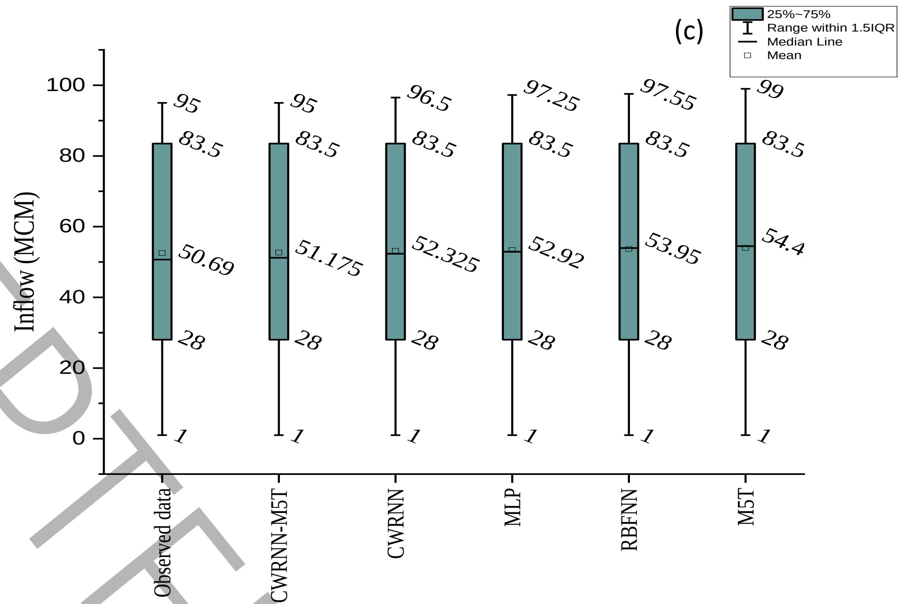


Figure 4. Boxplots of models for a: one-month ahead b: two-month ahead, and c: three months ahead

The CRMSE of the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T models was 0.066, 0.14, 0.23, 0.33, and 0.39, respectively. The correlation coefficients of the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T models were 0.99, 0.98, 0.97, 0.94, and 0.92, respectively. Figure 5a shows a Taylor diagram for one-month ahead prediction. Figure 5b shows a Taylor diagram for a two-month ahead prediction. The CRMSE of the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T model was 0.11, 0.19, 0.30, 0.41, and 0.51, respectively. Figure 5c shows a Taylor diagram for three-month ahead prediction. Thus, the CWRNN had the best performance among the other models. The CRMSE of the CWRNN-M5T, CWRNN, MLP, RBFNN, and M5T model was 0.20, 0.29, 0.45, 0.54, and 0.72, respectively.

By addressing the challenge of predicting reservoir inflow, the CWRNN-M5T model plays a significant role in advancing engineering informatics. A key area of research in this field involves creating accurate and dependable predictive models for managing water resources. The CWRNN-M5T model seeks to fill this void by leveraging the strengths of both the CW-RNN and M5Tree models to deliver more accurate predictions of reservoir inflow.

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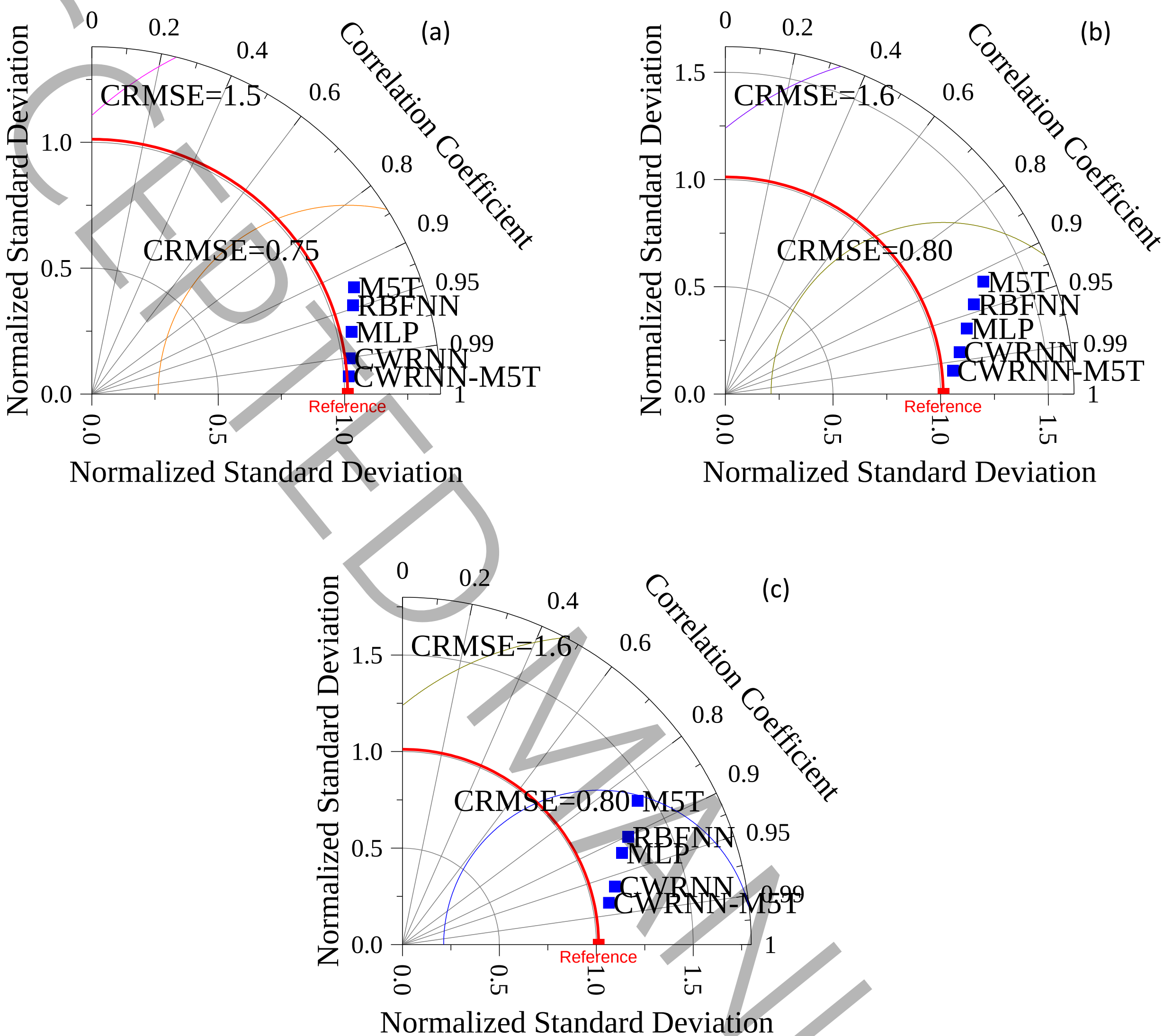

Figure 5. Taylor diagram for a: one-month ahead, b: two-month ahead, and c: three-month ahead

The CWRNN-M5T model can help optimize the operation of dam reservoirs and provide accurate predictions of reservoir inflow. These predictions can also be used to develop early warning systems for potential floods, which help reduce the risk of damage to property and infrastructure. The results show that this model has higher accuracy in predicting reservoir inflow compared to other models (CWRNN, MLP, RBFNN, and M5T). Taylor diagram is used as a graphical method to compare and visualize the similarities and differences in spatial patterns of different data and can help in more accurate analysis of the performance of the models. Overall, the CWRNN-M5T model is an effective tool for water resources management and climate change-related risks by providing accurate predictions.

The CWRNN-M5T model also contributes to advanced engineering informatics by improving understanding of complex hydrological processes and enabling more accurate simulations. By analyzing and interpreting large amounts of data, it provides valuable information for water resource planning, reservoir operation, and flood control. A CWRNN-M5T model also addresses the need for real-time monitoring and control in water systems. By incorporating the concept of clockwork layers and utilizing the M5Tree algorithm, the CWRNN-M5T model effectively captures temporal dependencies and nonlinear patterns in reservoir inflow data. Thus our study fills a gap in the field of advanced engineering informatics by providing a more robust and efficient method for reservoir inflow prediction, which is crucial for water resource management and the optimal operation of dams. The CWRNN-M5T model bridges the gap between advanced machine learning techniques and the specific needs of water resource management, contributing to the advancement of engineering informatics in this field.

Recent developments in engineering informatics have led researchers to adopt hybrid approaches to address the challenges posed by traditional machine learning models [17]. By combining machine learning techniques with established frameworks, they can enhance the accuracy, efficiency, and scalability of their analyses. Predictive models also come with inherent uncertainties, which stem from various sources. One significant source of uncertainty is the input parameters, while model parameters contribute as well [16].

It is worth mentioning that, considering the impact of sources of uncertainty (input parameters and model parameters) on the results of models, efforts have been made to reduce the influence of these sources of uncertainty as much as possible by integrating M5T models with the CWRNN model.

Advanced soft computing models like the M5T and CWRNN provide numerous benefits, particularly their ability to manage uncertain and imprecise data, enhancing their usefulness across different fields. Additionally, they typically demand fewer computational resources than conventional models, making them more efficient. However, a notable downside is their potential lack of interpretability, which can impede comprehension and trust in the outcomes. Moreover, these models may be sensitive to the settings of their parameters, which can influence their effectiveness. Employing hybrid models and addressing uncertainties can help mitigate this limitation to some degree.

5. Conclusion

Reservoir inflow prediction is crucial for effective water resource management. Accurate inflow forecasts can help determine how much water to release from the reservoir for various purposes, including irrigation, drinking water, hydroelectric power generation, and flood control. In this study, we developed a hybrid model for predicting reservoir inflow. The CWRNN was integrated with the M5T model to enhance inflow predictions. From this investigation, the results are as follows:

- The CWRNN-M5T model shows greater accuracy in predicting reservoir inflow than other models like MLP, RBFNN, and M5T.
- Its design includes multiple modules with different clock speeds, which allows it to process short-term and long-term dependencies at the same time.

- The model can be adjusted for various lead times, making it suitable for short-term and long-term forecasts.
- For one-month predictions, the CWRNN-M5T achieved a root mean square error (RMSE) of 0.245, outperforming the CWRNN model (0.35), MLP (0.56), RBFNN (0.654), and M5T (0.671).
- In two-month predictions, it also performed exceptionally well, recording the lowest RMSE of 0.251, followed by the CWRNN model (0.372), MLP (0.591), RBFNN (0.666), and M5T (0.679).
- This study offers important insights for water resource management, helping managers make better decisions regarding water release and retention using the most accurate predictive model available.
- The research points out the advantages of employing the CWRNN model for predicting reservoir inflow and highlights the need to identify key input variables and their relationships.
- By effectively capturing both short-term and long-term dependencies, the CWRNN-M5T model can uncover complex patterns that may be missed by traditional models, resulting in more precise predictions.
- The findings stress the importance of carefully selecting input variables and being aware of how unexpected changes in input data can affect the accuracy of the model.

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