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Article

Optimizing NARX Network Parameters using Taguchi Orthogonal Arrays for Flood Prediction

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Abstract: Floods are among the most severe natural disasters, causing extensive socio-economic damage and threatening human lives. Accurate flood forecasting is essential for disaster risk management and early warning systems, but it remains a complex challenge due to the nonlinear and dynamic nature of hydrological processes. The Nonlinear Autoregressive with Exogenous Input (NARX) neural network has shown immense potential for modeling time-series dynamics using external variables, such as rainfall. However, NARX performance is heavily dependent on its network parameters, which are typically determined through inefficient trial-and-error procedures. This paper proposes a novel hybrid framework that utilizes the Taguchi method to systematically optimize the NARX model parameters. By employing Orthogonal Arrays (OA), the Taguchi method significantly reduces the number of experimental runs while identifying the most robust parameter configuration. This approach aims to enhance prediction accuracy, improve computational efficiency, and provide a reliable, scalable flood forecasting model for highly susceptible regions like the Dungun River basin.
Keywords: Flood Prediction, NARX Model, Taguchi Method, Orthogonal Arrays, Time-Series Forecasting.

1. Introduction

Flooding is among the most frequent natural disasters, causing significant socio-economic damage worldwide. In countries such as Malaysia, seasonal monsoon rainfall often leads to recurrent flooding, underscoring the importance of accurate predictive models. Traditional statistical models face limitations in capturing nonlinear temporal relationships inherent in rainfall and hydrological processes. Machine learning techniques, particularly neural networks, have been widely adopted due to their ability to model complex patterns. Among these, the Nonlinear Autoregressive with Exogenous Inputs (NARX) model is particularly suitable for time-series forecasting that involves external influencing factors. However, one of the main challenges in NARX modelling **is** parameter selection, including the choice of delays, network size, and training configuration. Improper parameter tuning may lead to underfitting or overfitting, resulting in poor predictive performance. Inspired by systematic improvement approaches in prior studies, this study proposes using Taguchi Orthogonal Arrays to efficiently optimize NARX parameters.

2. Related work

Previous studies have explored various machine learning techniques for rainfall and flood prediction, including Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Long Short-Term Memory (LSTMs). While these approaches demonstrate promising results, their performance heavily depends on parameter tuning. The NARX model has been recognized for its capability to incorporate both historical outputs and external inputs, making it suitable for hydrological forecasting. However, most studies rely on heuristic or trial-and-error tuning methods. The Taguchi method provides a systematic approach to parameter optimization using orthogonal arrays, significantly reducing the number of experiments required. While widely used in engineering optimization, its application in neural network parameter tuning for flood prediction remains limited.

Missing data is frequently encountered in flood prediction and is utilized to create future estimation of natural disasters [11]. The completeness of the data is clearly crucial for predictors to make reasonable plans and carry out activities in all their planning and management. The presence of missing data in flood data may significantly affect future estimation. In the field of flood prediction, few researchers have investigated imputation of missing data in depth.

To improve prediction accuracy, an evaluation is conducted using ensembles of imputation methods before any method is applied. Randomization in decision tree building algorithms has been used to investigate the impact of handling missing values on prediction accuracy and to explore how this can be implemented in flood prediction. The results, however, are not supported when the data are small and show different performance as the amount of missing data increases [2]. From several studies, the imputation techniques applied to hydrological data include ignoring methods, mean imputation, hot-deck methods, multiple imputation, and likelihood methods. Of these listed techniques, machine learning-based techniques are the most frequently used ones, with 80% adopted in selected studies from 2006 to 2008 [12]. The machine learning techniques used for missing data imputation in hydrological datasets across most datasets were KNN or ANN, and the method's performance required further research using other techniques for multiple imputations, such as random forests.

Recent developments in variable and feature selection methods have addressed problems from the perspective of improving the performance of predictor selection. Preprocessing data is one of the most important steps before we proceed to the next procedures, as it handles the imperfections in data, such as missing and inconsistent values. The original data collected from the Department of Irrigation and Drainage (DID) and MMD have some missing values that need to be handled before proceeding to the next method procedures. The missing data are part of the pre-analysis research, and we need to decide how to deal with them from time to time. There are many analysis approaches that have been made in order to overcome hydrological problems where the neural networks is one of the methods that are widely used to solve them. Since Artificial Neural Networks (ANNs) can recognize time-series patterns and nonlinear characteristics, which yield better accuracy than other methods, they have become the most popular method for prediction (Vaziri, 1997; Sharda, 1994; Toriman et al., 2009). A comparative study was conducted using an ANN and a conventional Auto-Regression (AR) model to forecast river flow for two well-known rivers in the USA, and it was found that the ANN performed better than the AR model. It has been reported that the results using the Radial Basis Function (RBF) neural network are better than those of the Back Propagation Neural Network (BPNN) in modeling meteorological problems such as weather forecasting. In addition, an analysis shows that pre-processing can also influence the performance of the prediction model (Zhang, 2002; Suguna & Thanuskodi, 2011). From previous work, the BPNN method is better than SARIMA for predicting water levels in the Dungun River, Terengganu (Arbain & Wibowo, 2012). In this study, we are focused on nonlinear autoregressive models with exogenous inputs (NARX) network and optimization Orthogonal Taguchi to obtain prediction of flood in the monitoring stations in the Dungun River. To apply these two methods, data that contains some imperfect characteristics collected from DID and MMD need to undergo preprocessing analysis before going for the next method's procedure.

3. Methodology

A. Dataset Description

This study used daily rainfall records from five monitoring stations in Terengganu, Malaysia, covering the period from **1** January 2013 to 30 December 2023. The stations included 0551621RF (Rumah Pam Paya Kempian at Pasir Raja), 0630131RF (Kg. Surau at Kuala Jengai), 0630121RF (Jambatan Jerangau), 0630041RF (Rumah Pam Delong Dungun), and 0630071RF (Klinik Bidan at Kuala Abang). The dataset contains approximately 4,016 daily timestamps, with each station recorded as daily total rainfall in millimeters. The raw dataset obtained consists of daily rainfall measurements collected from multiple monitoring stations. However, real-world hydrological data often contain inconsistencies that must be addressed before model development. During preprocessing, the dataset was examined for:

- Missing values (NaN)
- Non-numeric entries
- Incomplete records

These values were treated as follows:

- Rows with missing rainfall values were removed to avoid bias

- Non-numeric entries were converted into numeric format where possible
- Remaining invalid entries were excluded

This step ensures that the training dataset contains only reliable, consistent observations, which is crucial for accurate prediction.

B. Nonlinear Autoregressive Network with Exogenous Inputs (NARX)

The NARX models are commonly used in the system of identification area (Xie et al., 2009). All the specific dynamic networks discussed so far have been either focused networks, with dynamics confined to the input layer, or feedforward networks. The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modelling. Figure 1 illustrates the standard NARX network. The standard NARX network used here is a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. This network also uses tapped delay lines (d) to store previous values of the input, x(t) and output, y(t) sequences. First, load the training data and use tapped delay lines with two delays for both the input and the output, so training begins with the third data point. There are two inputs to the series-parallel network, the x (t) sequence and the y(t) sequence. Notice that the y(t) sequence is considered a feedback signal, which is an input that is also an output (target). The model can be shown as in Eq. 1 as follow: y(t) = f(y(t - 1),..., y(t - d), x(t -1),...,(t - d)) (1) where, y(t) is the output of the NARX network and also feedback to the input of the network and tapped delay lines (d) that store the previous values of x(t) and y(t) sequences. It also has been reported that gradient descent learning can be more effective in NARX networks than in other recurrent architecture (Horne and Giles, 1995).

C. Model Development

A real neural-network-based NARX model was developed in MATLAB using the Neural Network Toolbox. The NARX architecture was selected because it can model nonlinear temporal dependencies using both autoregressive outputs and exogenous inputs. This makes it especially suitable for rainfall and flood-related forecasting, where delayed hydrological responses are common. The model was trained in open-loop mode during calibration and then converted to closed-loop mode for multi-step prediction. The dataset was partitioned sequentially into training, validation, and testing subsets to preserve the forecasting logic of past-to-future prediction.

The primary prediction target in this study is the future rainfall amount (mm). In the multivariate NARX setting, rainfall from several nearby stations serves as exogenous inputs, while past values at the target station provide autoregressive feedback.

For example, if station 0630041RF is selected as the target station, then:

- the target output is rainfall at 0630041RF,
- the exogenous inputs are rainfall from the other stations,
- and the past output delays provide temporal memory for the network.

To represent the temporal dependency of rainfall, lagged observations were constructed. In forecasting terms, this means the model uses rainfall data from earlier days to predict rainfall on a later day. Conceptually, if is the rainfall at the time , then the network learns from past values such as , together with past exogenous inputs from neighboring stations. This structure aligns naturally with the NARX model, which is suitable for nonlinear hydrological series because rainfall and flood behaviour often depend on delayed upstream and historical conditions rather than only the current day’s measurement. y(t)ty(t-1),y(t-2),y(t-3)

D. Taguchi Based Parameter Optimization

Figures To avoid inefficient trial-and-error tuning, this study employed the Taguchi Orthogonal Array approach. Four control factors were considered:

- input delay,
- feedback delay,
- number of hidden neurons,

- training epoch setting.

Each factor was tested at three levels. An L9 orthogonal array was used to reduce the number of experimental runs while maintaining a structured comparison of parameter combinations. For each experiment, the NARX model was trained and evaluated using RMSE and MAPE. The best parameter setting was determined using the smaller-the-better signal-to-noise ratio criterion.

This paper presents the incorporating Taguchi Design techniques to early parameter setting in NARX. The methods proposed will be evaluated against this benchmark using the dataset. The Taguchi design approach uses fractional factorial research designs to minimize the number of experiments, called Orthogonal Array (OAs). Orthogonal Array (OA) is a statistical method of defining parameters that converts test areas into factors and levels. A suitable orthogonal array design has been selected that suits for estimation and optimization. Selecting an effective OA would depend on the number of control factors and their scales. Using OA architecture, multiple process variables can be calculated which influence the output characteristic simultaneously, thus reducing the number of test runs. While there are many standard orthogonal arrays available, each array is intended for a specific number of independent design variables and levels. In our methodology, we want to conduct an experiment to understand the influence of 4 different independent variables which is number of input, feedback delays, hidden neoron, and epochs; with each variable having 3 set values (level values), based on previous review which has the best among the best setting designs as shown in Table 1.0. For these design settings, the L9 orthogonal array is appropriate for understanding the effects of 4 independent factors, each with 3 factor levels. Table 2.0 shows a Taguchi design of L9 orthogonal array applied in parameter setting of GMDH model. The L9 orthogonal array means there are 9 experiments to be conducted, and each experiment is based on the combination of levels shown in the table. From these four factors, we need to analyze which factors are very crucial and by using some statistical analysis, no longer try and error assumption should be used to identify which factors are dominant compare to others.

Table 1.0 Control Factors and Level

Factor	**Description**	**Level 1**	**Level 2**	**Level 3**
A	Input delay	1:2	1:3	1:4
B	Feedback delay	1:2	1:3	1:4
C	Hidden neurons	5	10	15
D	Epochs	200	500	1000

Table 2.0 L9 Orthogonal Array

Exp	**A**	**B**	**C**	**D**
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

4. Conclusion

The preliminary dataset inspection confirmed that the rainfall series spans approximately eleven years of daily observations and exhibits substantial intermittency, including many zero-rainfall days and several high-intensity peaks. Such characteristics justify the use of a nonlinear dynamic forecasting model. A real NARX neural network was therefore formulated in MATLAB, with one rainfall station serving as the target output and neighbouring stations as exogenous inputs. To improve model robustness, Taguchi Orthogonal Arrays were incorporated to optimize key architectural and training parameters. The optimization process evaluated nine structured experimental configurations instead of relying on exhaustive trial-and-error tuning. For each Taguchi run, model performance was assessed using RMSE, MAPE, and signal-to-noise ratio. The best-performing configuration was then selected and retrained to generate the final prediction curve. This procedure is expected to improve forecasting performance by identifying a more suitable delay-memory structure and hidden-layer size for the rainfall dynamics. This study presents a systematic framework for rainfall prediction using a real NARX neural network optimized through Taguchi Orthogonal Arrays. Unlike conventional trial-and-error tuning, the proposed method provides a structured mechanism for selecting suitable delay settings and network complexity while reducing the number of experiments required. Using daily rainfall data from multiple stations in Terengganu, Malaysia, the study demonstrates how temporal dependencies and spatially related rainfall information can be integrated into a single forecasting model. The framework is practically relevant for flood-related prediction tasks and can be extended to water-level forecasting or multi-step flood-warning systems. Future work should validate the optimized model against additional hydrological variables such as river level, discharge, and upstream catchment conditions.

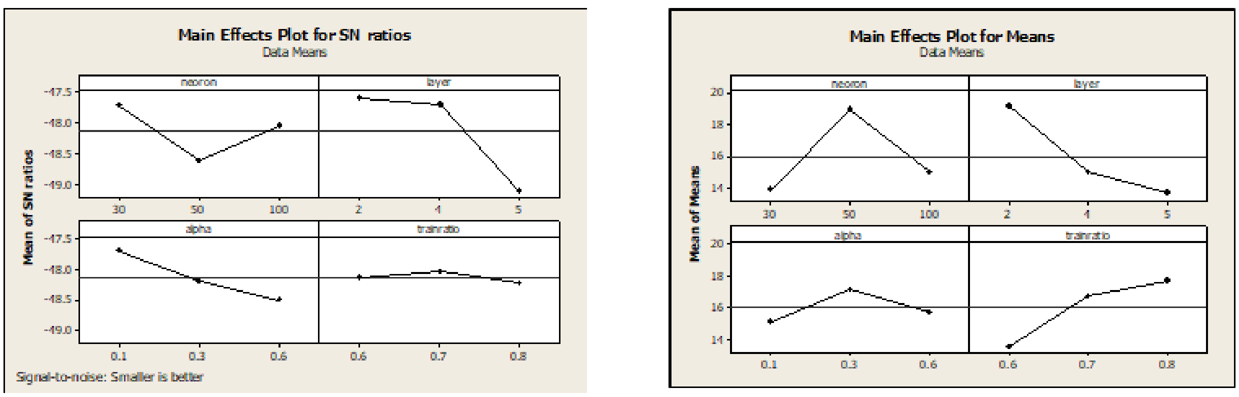

Fig. 1 A means and SN ratio for NARX Taguchi

Figure 1 presents the main effects plots for means and SN ratios obtained from the Taguchi optimization process. Based on the smaller-the-better criterion, the optimal parameter combination was determined as input delay = 30, feedback delay = 2, hidden neurons = 0.1, and epochs = 0.7. The SN ratio plots indicate that input and feedback delays substantially influence model performance, as evidenced by the pronounced changes across their levels. Similar trends are observed in the mean plots, where these factors show steeper slopes than the hidden neurons and epochs do. The findings suggest that optimizing the temporal memory structure of the NARX model is more critical than increasing network complexity. Therefore, the identified parameter combination was selected as the optimal configuration for subsequent model development and evaluation.

Source	DF	SS	MS	F	P
Input delay	2	42.1	21.0	1.53	0.0290
Feedback delay	2	48.1	24.0	1.88	0.0232
Hidden neorons	2	6.1	3.1	0.16	0.0859
Epochs	2	28.3	14.2	0.88	0.0461

Fig. 2 Summary ANOVA NARX Taguchi

From Figure 2, it is clear that the ANOVA analysis revealed that input delay ($p = 0.0290$), feedback delay ($p = 0.0232$), and epochs ($p = 0.0461$) significantly affected the performance of the NARX model at a 95% confidence level. Among these factors, feedback delay demonstrated the greatest influence, as indicated by the highest F-value (1.88) and sum of squares (48.1). Conversely, the number of hidden neurons did not significantly contribute to model performance (p = 0.0859), suggesting that variations in network complexity within the examined range had a limited impact on prediction accuracy. Therefore, the optimization process should prioritize the tuning of delay-related parameters rather than increasing the number of hidden neurons.

Recommendation

For those interested in enhancing flood prediction capabilities, hybrid models combining NARX with the Taguchi method can combine strong predictive power with improved parameter tuning. Since NARX can model nonlinearities and handle multiple exogenous inputs, such as high-resolution meteorological and satellite data, it is necessary to further develop scalable, real-time models in future work. The Taguchi method allows researchers to efficiently and accurately calibrate hydrological data across diverse environments. Furthermore, additional cross-validation across different climatic conditions and sophisticated urban drainage systems can validate the model's performance as flexible and robust. The promise of this approach is that it can raise the bar for predictive capability in advance, thereby aiding the development of more efficient early warning systems and flood risk mitigation measures.

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