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Application of Soft Computing for Time Series Water-Level Prediction in Jamuna River†

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Abstract

Time series analysis is one of the essential and complicated research methods. It is a well-known fact that improving time series prediction accuracy is a vital yet challenging issue. Recently, soft computing has become popular in time series forecasting in various application areas. Soft computing is a fusion of research of evolutionary and genetic algorithms, neural networks, fuzzy set theory, and fuzzy systems and provides rapid dissemination of results. This study investigates a model for time series water-level prediction using soft computing techniques which is reliable and effective. To illustrate the applicability and capability of soft computing, the Jamuna river, Bangladesh, was used as a case study. We used four areas of the Jamuna river (i.e., Aricha, Bahdurabad, Shariacandi, and Sirajganj) water-level and rainfall events with daily data collected in the past 12 years. In experiments, past 2 to 4 days' time-series wa-ter-level with and without rainfall has been applied to predict 1 to 4 days ahead water-level. The experimental results demonstrated that the adaptive neuro-fuzzy inference system (ANFIS) performs superiorly to traditional methods, such as nonlinear autoregressive neural network with external input (NARX) and focused time-delay neural network (FTDNN).

Keywords: Time series analysis, soft-computing, water-level prediction, ANFIS, NARX, FTDNN

1. Introduction

Time series prediction is a widely research and applied area, including weather forecasting, intelligent transportation, trajectory forecasting, and earthquake prediction. Time series analysis is highly complex due to the variation of knowledge, noise, and every observation is somehow dependent upon past remarks. However, the purpose of the forecast is to minimize the risk in decision-making. Time series water-level prediction is vital and essential research. Last few decades, many models have been used, including the general hydrodynamic numerical modeling system (Box et al., 2015). At present, water-level predictions have come to different intelligent methods to make decisions. Consequently, artificial neural networks (ANNs) and fuzzy techniques are employed as an efficient alternative in hydrodynamic numerical simulation studies.

Soft computing is one of the modern approaches for constructing computational intelligent or expert systems. Its ultimate goal is to emulate the human mind as closely as possible. Soft computing is a blend of methodologies designed to solve real-world problems using logic, which do not resolve or are complicated to solve mathematically. It includes neural networks, genetic algorithms, and fuzzy logic. Recently, these techniques identified as emerging alternatives to the standard well-established 'hard-computing' methods.

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The unique property of soft computing is, deep involvement in learning from experimental data makes it suitable for time series analysis. For these reasons, artificial neural networks, fuzzy systems, and adaptive neuro-fuzzy systems are practiced for time series analysis (Michie et al., 1995; Ross, 2010).

The water-level prediction model plays a significant role in providing relevant information on potential impending floods in populated locations. A prototype design can reduce the damage in areas by decreasing the environmental and economic impact of floods. For this reason, water-level variation analysis, as well as prediction, has been the subject of many research activities. We aim to investigate and implement a reliable and effective model for water-level prediction using a soft computing technique. The result of this study can support foretelling water-level or floods. Past time series water-level and rainfall are used to predict the future water-level, i.e., 1 to 4 days ahead. From the Jamuna river, Bangladesh, four stations (areas) are selected to evaluate the performance of the designed framework. We observe that ANFIS provides superior outcomes for time series water-level prediction compared to traditional NARX and FTDNN models.

This paper is organized as follows. We reported related works on water-level analysis in Section 2. Then, Section 3 explores a soft computing framework for time series water-level prediction. Experiment results presented and discussed in Section 4. Finally, we conclude in Section 5.

2. Related works

Time series analysis be classified into two categories: statistical approach and intelligent approach (Gelfand et al., 2019; Michie et al., 1995). Statistical methods utilize the background information by having an explicit underlying probability basis, but the action is supposed without human intervention. Therefore, these techniques show inefficiency for nonlinear and complex problems. The statistical approach includes autoregressive (AR), moving average (MA), and combined AR and MA (ARMA). Recently, experts applied technical-intelligent techniques, such as artificial neural networks (ANNs) and fuzzy logic systems. The intelligent system performs classification terminologies that mimic human reasoning enough to give insight into the decision process (Michie et al., 1995). There are ongoing efforts to integrate ANNs, fuzzy logic, rough set theory, and genetic algorithms (GAs) in the soft computing paradigm. Among these, neuro-fuzzy computing is the most visible.

Soft computing is utilized in many applications, including stock exchange trend prediction, intelligent transportation, trajectory forecasting, and earthquake prediction. ANN is an efficient tool to build expert systems and successfully applied monitoring problems, decision-support technologies, and statistical prediction (Fung et al., 2002; Huang et al., 2009; Seo et al., 2015). ANNs are used to predict water-level by Biswas and Jayawardena (2014) and Guldal and Tongal (2010). The ANN, ARIMA (autoregressive integrated moving average), and NARX (nonlinear autoregressive network with exogenous inputs) models are comparative and better predict water-level than the hydrodynamic models (Grimes et al., 2003). In recent decades, machine learning has become a popular research topic and successfully implemented in research within statistics, including time-series stock exchange price prediction (Abbasi and Abouec, 2008; Abdulsalam et al., 2011; Boyacioglu and Avci, 2010; Castillo-Boton et al., 2020; Chou et al., 2018; Chang and Liu, 2008; Mahmud and Meesad, 2016). Alternatively, the ANFIS provides a novel computational approach, combining the idea of ANN and fuzzy inference learning (Jang, 1993).

Last few decades, many research have been submitted about water-level prediction, each of them used different parameters for comparison (Panda et al., 2010; Seo et al., 2015). Water-level prediction is the act of trying to determine the future condition of water trends. The statistical technique is popular in water-level monitoring and forecast, flood modeling and mapping, and ice-level monitoring. The statistical methods used to determine the likelihood, frequency, and intensity of water discharge affecting floods (Goovaerts, 2019; Zhang et al., 2019). The models and mapping practiced to discover and visualize the extent of possible flooding, abnormal amounts of rainfall, and sudden large amounts of water discharges can be monitored to

provide short-term flood predictions (Pamda et al., 2010).
It can be beneficial when several uncertainties are manifested in a system. Soft computing is employed in many practical engineering situations because of its capability in dealing with obscure and imprecise information (Ahmed et al., 2019; Yue and Kontar, 2020). The powerful aspect of the soft computing model is that most human reasoning and concept formation are transformed into rules. The combination of rough and incomplete information and the imprecise nature of the decision-making process makes the neuro-fuzzy model efficient in modeling complex engineering, control, classification, prediction. This approach consolidates imprecision and subjectivity in model formulation and solution processes (Lu et al., 2017; Ramachandran, 2020). Nevertheless, optimal neuro-fuzzy systems design are complicated tasks, and it builds by determining the most suited number of rules, fitted parameters, and structure of the fuzzy-logic systems (Tekeli et al., 2019).

3. Method

It is challenging to deal with time series temporal data. The aim of this study is time series water-level prediction using soft computing. Past temporal water-level and rainfall data are applied to predict future water-level. The proposed model is shown in Fig. 1.

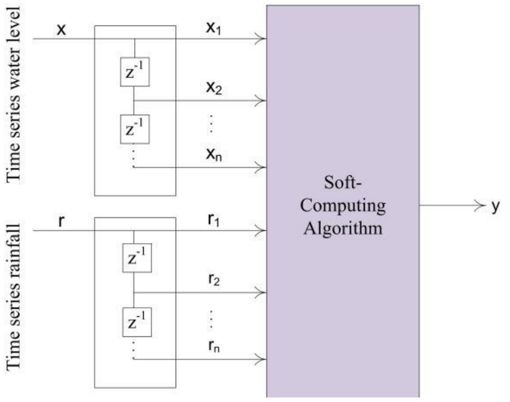

Fig. 1. Architecture of the proposed soft-computing model.

3.1 Workflow

The workflow of the proposed model as follows.
Step 1. Data preprocessing: Time series data sampling as a train and a test set.
Step 2. Parameter selection: To design the framework, we perform the prediction horizons selection and how many ahead have to predict.
Step 3. ANFIS design: In this study, a traditional five-layers ANFIS network is adopted. To design the ANFIS network, we applied two to four inputs, the 'bell-shaped' membership function and fuzzy rules generated from 'genfis1', where 'genfis1' generates a single-output Sugeno-type fuzzy inference system (FIS) for ANFIS using a grid partition on data.
Step 4. Training model: After loading the training data and generating the initial model structure, we start training according to the learning algorithm.
Step 5. Test model: Finally, we test the model against the test sub-dataset and evaluate the result.

3.2 Time series data

Time series is a sequence of records from past to present, denoted by $x(k), k = 1,2,\dots,n$. Extending backwards from time k has time series $x(k), x(k-1), x(k-2),\dots,x(k-n)$. From this, the prediction x is at future time h,

$$x(k+h) = f\big(x(k), x(k-1), x(k-2),\dots,\\ x(k-n)\big) \qquad (1)$$

Assume, in case of $h = 1$, the time series $x(k), x(k-1),\dots,x(k-n)$ as the inputs and the predicting value $x(k+1)$ can be obtained as the output. The prediction error $e(k)$ is the difference between actual value $x(k+1)$ and prediction value $y(k)$ can be expressed as

$$e(k) = x(k+1) - y(k) \qquad (2)$$

3.3 Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS integrates the advantage of the neural network's learning capabilities and fuzzy system's transparency. The basic ANFIS network is illustrated in Fig. 2.

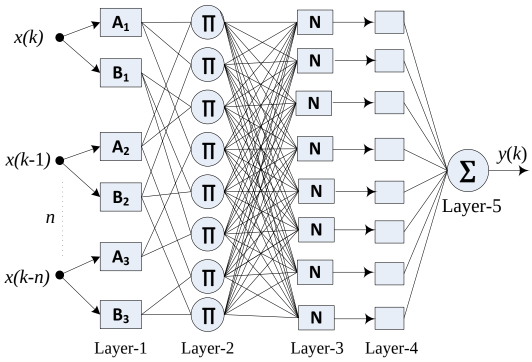

Fig. 2. Jang's ANFIS architecture.

The first layer is the fuzzification layer. Each input node i generates a membership grade of the crisp inputs which belong to each of the convenient fuzzy sets by using the membership functions. There are various membership functions such as 'gaussian', 'sigmoidal', 'triangular', and 'trapezoidal'.

The second layer is the product layer. Every node of this layer (marked as $\prod$) multiplies the incoming signals from the fuzzification layer. The output of each node represents the firing strength of fuzzy rules.

The third layer is the normalization layer. Every ith node (marked as N) computes the ratio of the ith rules firing strength to the sum of all rules strengths.

The fourth layer is the defuzzification layer. Every node i (square node) with a node function computes the contribution of each ith rule toward the total or the model output.

The fifth layer is marked by $\sum$, which calculates the overall output by summing all the incoming signals. Fuzzy results are transformed into a crisp value in this layer by the defuzzification process.

Experimental results and discussions

4.1 Dataset and data preprocessing

In this study, past time-series water-level and rainfall data are adopted to predict water-level. The experiment emphasizes water-level prediction for the Jamuna river, Bangladesh. The dataset has been collected from the Bangladesh Water Development Board (BWDB), which contains water-level and rainfall followed by twelve years of consecutive data from January 2005 to May 2017. We selected four stations of the Jamuna river: Aricha (3,730 days), Bahadurabad (3,270 days), Shariacandi (3,550 days), and Sirajganj (3,430 days), to predict water-level. Among the total dataset, 60% used as a train-set and the remaining 40% used as a test-set.

3.2 Experiment setup

The experiments were set up to predict water-level for 1 to 5 days ahead, using past consecutive 2 to 10 days of time-series data. We observed that significant results are achieved for two to four days of input and one to four days ahead of prediction. The experiment focused on two types of models,

-Type-1 model: predict water-level using past water-level (WL), without applying rainfall.

-Type-2 model: predict water-level using past water-level with rainfall (WLR).

For model comparison, we compared results of dynamic neural networks, such as FTDNN (focused time-delay neural network), NARX (nonlinear autoregressive neural network with external input), and ANFIS (adaptive neuro-fuzzy inference system).

4.3 Result analysis and discussion

In experiment 1, for Aricha station (Table 1), it is found that ANFIS performed significantly better than NARX and FTDNN in all cases, i.e., 1 to 4 days ahead without rainfall. The best accuracy achieved for one-day ahead prediction using the previous three-days input, which is 99.58%, whereas one-day ahead prediction using 2 to 4 days past data accuracy is similar. In applying rainfall, accuracy gained significantly for one-day ahead prediction using 2 to 4 days of previous data, where accuracy is above 99.50%.

In experiment 2 for Sirajganj station, in Table 2, also noticed ANFIS performed significantly better than NARX and FTDNN in all the cases, i.e., 1 to 4 days ahead prediction using with and without rainfall. The highest accuracy is 99.67%, achieved for one-day ahead prediction with the past three days' input. While we applied rainfall, a notable result was gained (99.65%) for one-day ahead prediction using the past two days of water-level with one-day rainfall data input. One-day ahead prediction using 2 to 4 days past input accuracy is quite similar, i.e., higher 99.60%.

Table 1. This Performances for Aricha station. (Acc: Accuracy and bold value indicates best result).

	Models												
		Without rainfall (WL)						With 1 day rainfall (WLR)					
		NARX		FTDNN		ANFIS		NARX		FTDNN		ANFIS	
Prediction	Input series	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc
1 day ahead	2 days WL	0.07	95.86	0.07	95.82	0.07	**99.57**	0.08	95.81	0.07	95.75	0.08	**99.56**
	3 days WL	0.37	94.86	0.08	95.72	0.07	**99.58**	0.07	95.80	0.09	95.71	0.08	**99.56**
	4 days WL	0.13	95.38	0.13	95.45	0.08	**99.56**	0.10	95.58	1.64	88.34	0.11	**99.50**
2 days ahead	2 days WL	0.07	95.84	0.14	91.04	0.14	**99.10**	0.07	95.92	0.14	91.14	0.14	**99.09**
	3 days WL	1.08	92.53	0.94	88.67	0.14	**99.11**	0.08	95.70	0.16	91.27	0.14	**99.09**
	4 days WL	0.08	95.58	0.24	90.48	0.17	**99.07**	0.14	95.28	1.50	85.18	0.21	**98.97**
3 days ahead	2 days WL	0.08	95.53	0.21	86.05	0.21	**98.59**	0.08	95.40	0.20	86.32	0.21	**98.59**
	3 days WL	0.08	95.29	0.20	86.46	0.21	**98.60**	0.12	94.92	0.21	86.24	0.21	**98.59**
	4 days WL	0.11	94.97	0.28	85.28	0.24	**98.54**	0.09	95.28	0.27	85.57	0.32	**98.40**
4 days ahead	2 days WL	0.09	95.01	0.30	80.66	0.28	**98.08**	0.09	95.04	0.27	81.98	0.28	**98.09**
	3 days WL	0.87	94.91	0.28	81.05	0.27	**98.08**	0.99	91.59	0.27	81.40	0.28	**98.07**
	4 days WL	0.11	94.50	0.57	79.24	0.31	**98.00**	0.24	93.54	0.64	78.40	0.43	**97.84**

Table 2. This Performances for Sirajganj station. (Acc: Accuracy and bold value indicates best result)

	Models												
		Without rainfall (WL)						With 1 day rainfall (WLR)					
		NARX		FTDNN		ANFIS		NARX		FTDNN		ANFIS	
Prediction	Input series	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc
1 day ahead	2 days WL	0.13	95.03	0.12	95.25	0.12	**99.65**	0.11	95.26	0.15	94.97	0.13	**99.65**
	3 days WL	0.24	94.35	0.14	95.31	0.12	**99.67**	0.14	95.13	0.13	95.16	0.17	**99.64**
	4 days WL	0.24	94.18	0.35	93.87	0.14	**99.64**	0.30	93.97	0.16	94.88	0.14	**99.63**
2 days ahead	2 days WL	0.18	94.88	0.21	88.90	0.22	**99.20**	0.13	95.26	0.21	89.38	0.25	**99.19**
	3 days WL	0.31	93.69	0.22	89.18	0.21	**99.24**	0.23	94.11	0.19	89.61	0.24	**99.22**
	4 days WL	0.34	93.96	0.21	89.20	0.29	**99.16**	0.12	95.18	0.28	88.50	0.26	**99.15**
3 days ahead	2 days WL	0.13	94.60	0.29	83.34	0.31	**98.71**	0.13	94.57	0.34	82.47	0.39	**98.69**
	3 days WL	1.20	90.62	0.31	82.31	0.29	**98.78**	0.12	94.68	0.29	83.41	0.33	**98.76**
	4 days WL	0.20	93.56	0.30	82.94	0.45	**98.65**	0.13	94.41	0.29	83.53	0.43	**98.60**
4 days ahead	2 days WL	0.13	93.95	0.38	76.68	0.40	**98.27**	0.13	93.73	0.37	77.16	0.52	**98.21**
	3 days WL	0.17	93.45	0.39	76.40	0.37	**98.34**	0.12	94.10	0.36	77.92	0.40	**98.32**
	4 days WL	0.14	93.65	0.65	74.02	0.53	**98.17**	0.15	93.67	0.38	76.54	0.62	**98.06**

Table 3. Performances for Bahadurabad station. (Acc: Accuracy and bold value indicates best result).

	Models												
		Without rainfall (WL)						With 1 day rainfall (WLR)					
		NARX		FTDNN		ANFIS		NARX		FTDNN		ANFIS	
Prediction	Input series	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc
1 day ahead	2 days WL	2.98	75.39	0.29	91.04	0.97	**99.46**	0.53	89.20	0.30	93.16	0.80	**99.48**
	3 days WL	5.74	65.09	0.41	91.94	2.12	**99.06**	0.48	90.59	0.35	91.82	2.35	**98.96**
	4 days WL	0.77	85.42	0.46	89.43	5.83	**98.11**	0.47	88.59	0.09	79.62	3.85	**98.58**
2 days ahead	2 days WL	1.12	60.04	0.45	85.35	1.97	**98.87**	2.00	83.64	0.18	82.29	1.74	**98.90**
	3 days WL	0.72	87.56	0.47	81.66	3.6	**98.32**	0.53	89.76	0.17	83.47	4.21	**98.06**
	4 days WL	0.84	88.16	0.51	82.98	8.94	**96.77**	0.41	90.07	0.17	80.42	7.70	**97.09**
3 days ahead	2 days WL	2.02	76.26	6.71	46.68	2.74	**98.33**	2.13	75.87	0.26	73.92	2.41	**98.33**
	3 days WL	0.47	89.20	0.55	77.17	4.68	**97.74**	1.23	82.56	0.25	75.65	5.66	**97.35**
	4 days WL	5.34	55.95	0.58	77.18	8.41	**96.35**	0.47	90.33	0.25	73.72	10.56	**95.61**
4 days ahead	2 days WL	2.19	73.68	0.73	68.19	3.32	**97.81**	0.34	89.52	0.33	70.15	2.96	**97.80**
	3 days WL	0.30	90.34	0.69	66.26	5.48	**97.27**	0.44	86.95	0.32	63.60	6.67	**96.83**
	4 days WL	0.50	87.64	4.42	47.42	11.49	**94.66**	1.05	80.48	0.32	36.90	16.04	**93.92**

Table 4. Performances for Shariacandi station. (Acc: Accuracy and bold value indicates best result).

	Models												
		Without rainfall (WL)						With 1 day rainfall (WLR)					
		NARX		FTDNN		ANFIS		NARX		FTDNN		ANFIS	
Prediction	Input series	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc	RMSE	Acc
1 day ahead	2 days WL	0.09	95.77	0.09	95.81	0.08	**99.76**	0.10	95.68	0.09	95.66	0.09	**99.75**
	3 days WL	0.87	95.83	0.08	95.94	0.08	**99.76**	0.93	95.52	0.09	95.70	0.09	**99.74**
	4 days WL	0.12	95.57	0.08	96.03	0.08	**99.75**	0.32	94.37	0.09	95.67	0.12	**99.71**
2 days ahead	2 days WL	0.21	95.14	0.18	90.91	0.18	**99.46**	0.14	95.48	0.18	90.85	0.19	**99.45**
	3 days WL	0.08	95.70	0.17	91.03	0.18	**99.46**	0.09	95.69	0.17	90.93	0.18	**99.45**
	4 days WL	0.10	95.59	0.17	91.02	0.18	**99.45**	0.11	95.23	0.19	90.51	0.23	**99.39**
3 days ahead	2 days WL	0.09	95.55	0.38	84.79	0.26	**99.16**	0.10	95.29	0.26	86.15	0.28	**99.16**
	3 days WL	0.10	95.27	0.26	86.13	0.26	**99.17**	0.10	95.10	0.26	85.59	0.27	**99.15**
	4 days WL	0.22	94.50	0.26	85.87	0.28	**99.13**	0.93	95.17	0.27	85.33	0.33	**99.08**
4 days ahead	2 days WL	0.10	94.70	0.36	80.29	0.34	**98.86**	0.10	94.89	0.35	81.34	0.36	**98.86**
	3 days WL	0.10	94.70	0.34	81.06	0.34	**98.87**	0.15	94.27	0.34	80.56	0.35	**98.84**
	4 days WL	0.10	94.54	0.35	80.47	0.36	**98.83**	0.10	94.73	0.34	80.62	0.41	**98.76**

Furthermore, in two other experiments for Bahadurabad and Shariacandi stations, Table 3 and 4, respectively, illustrate that ANFIS performed significantly better comparing NARX and FTDNN in 1 to 4 days ahead prediction. According to the experimental results, we noted including rainfall data as input to the model shows no significant improvement in performance.

In contrast, the RMSE (root mean square error) for the four individual experiments is different because of the variation of data. It also noticed that FTDNN and NARX models have lower accuracy (Acc.). ANFIS provides better prediction, whereas FTDNN and NARX provided poor results for several cases (see Figs. 2-5 for more details). Figures 2, 3, 4, and 5 displayed a time series response length n = 100 generated by the NARX, FTDNN, and ANFIS model for Aricha, Bahadurabad, Shariacandi, and Sirajganj stations, respectively. In the figures, we observed while ANFIS is reasonably good of the actual prediction, the FTDNN and NARX are badly affected and provide a poor estimation for several points. The advantage is, ANFIS and NARX both rely on component adjustment by previous time prediction. Nevertheless, many data points are measured on large-inverse difference prediction in FTDNN and NARX. For a sudden location which is no issue.

Conclusion

This study proposed and evaluated a soft computing model to predict time series water-level. Time series water-level and rainfall are employed to estimate future water-level for one to four days ahead. In this case study, four stations of Jamuna river were experimented with to evaluate the performance of soft computing techniques. Experimental results confirmed that ANFIS provides superior results for time series water-level prediction compared to NARX and FTDNN models. In the experiment, we used twelve (12) years of data. This model can be more reliable and stable if potential to test on more historical data. It is worth to noting that our model is not proficient in predicting the monsoon river floods, storm surge floods, and flash floods because of more features needed, i.e., brute-force and tide force.

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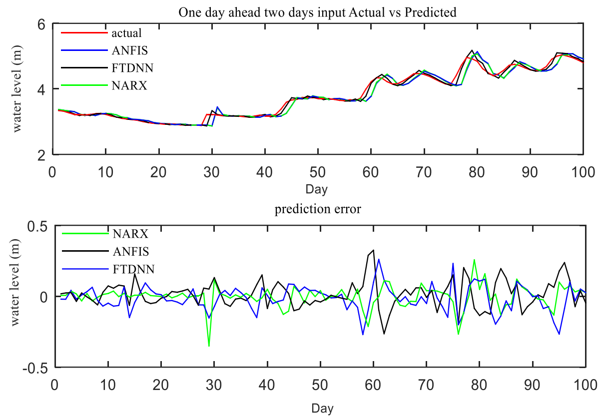

Fig. 3. One day ahead prediction using two days water-level with rainfall of Aricha station.

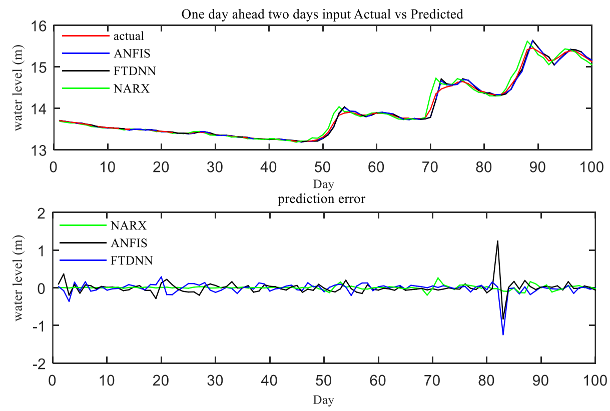

Fig. 4. One day ahead prediction using 2 days water-level with rainfall of Bahadurabad station.

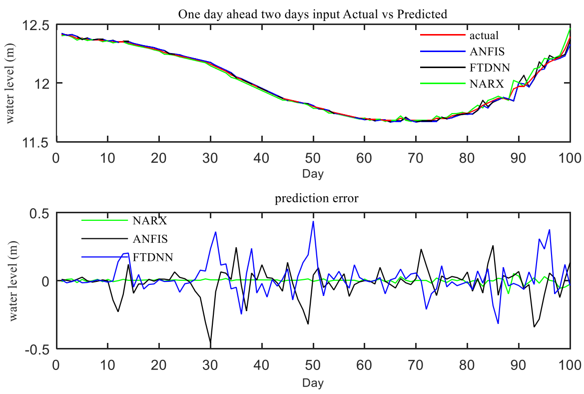

Fig. 5. One day ahead prediction using 2 days water-level with rainfall of Shariacandi station.

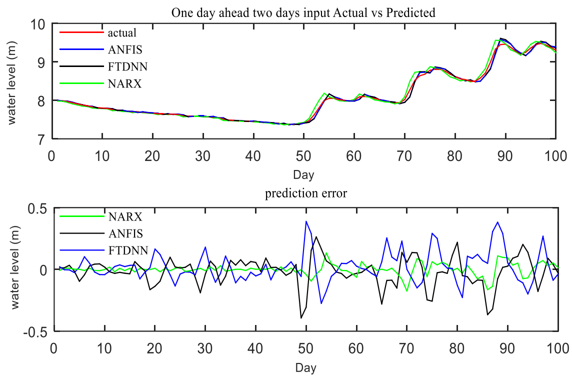

Fig. 6. One day ahead prediction using 2 days water-level with rainfall of Sirajganj station.

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