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A Dynamic Flow Forecast Model for Urban Drainage Using the Coupled Artificial Neural Network

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Abstract
Dynamic flow forecast, which is one of the critical technologies in the field of future Intelligent Drainage, has great potential for mitigating the damages resulting from extreme rainfalls. This study aims to develop a coupled neural network called RBF-NARX Forecast Model (RNFM) to predict urban drainage outflow. RNFM integrates the architecture advantages of the radial basis function neural network (RBFNN) and the nonlinear autoregressive with an exogenous inputs neural network (NARXNN). By calculating the Square Sum of Error (SSE) between RNFM predictions and SWMM simulations, the network parameters are optimized and the optimal coupling site of RBFNN and NARXNN is found. The urban drainage in Tianjin is presented to justify the feasibility of RNFM, and the average SSE in test rainfalls is only 0.273. Based on the Monte Carlo simulations (MCS), the uncertainty analysis is quantified and the SWMM simulations lie within the 95% prediction confidential interval, which proves that RNFM have great potential in predictions and management of urban runoff.

Keywords Artificial neural network (ANN) · Outflow prediction · Network coupling · Monte Carlo simulation · Uncertainty analysis

1 Introduction

As a consequence of rapid urbanization and climate change, the traditional urban runoff management is facing complicated challenges. More and more severe flooding events have occurred frequently under extreme rainfall conditions. To attenuate the flooding impacts, the

Highlights
1. RNFM performs well in the dynamic prediction of drainage flow.
2. The advantages of RBFNN and NARXNN are integrated to RNFM.
3. The method of time coordinate segmentation for RNFM is found to achieve high prediction accuracy.
4. RNFM can be used in the dynamic prediction of environmental variables.

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concept of 'Sponge City' provides a feasible and efficient measure to mitigate the risk of urban floods (Cunha et al. 2016). Among the various technical measures adopted to 'Sponge City' construction, the real-time control is one of the critical intelligent technologies in the urban runoff management. Thus, the dynamic forecast of urban runoff has become the key technology in both engineering and research community to realize future Intelligent Drainage.

During the last 20 years, the radial basis function feed-forward neural network RBFNN (Huang et al. 2005), was utilized for dynamic forecast in several critical variables such as water quality (May et al. 2008; Wu et al. 2014), reservoirs operation rules and daily watershed runoff (Wang et al. 2010; Safari et al. 2016). From the above approaches, the prediction of RBFNN is found to be high accurate for the non-monotonic section, but it is not accurate enough for the monotonous one (Nourani and Mousavi 2016; Wu et al. 2015; Soleymani et al. 2016).

Compared to static neural network such as RBFNN, the nonlinear autoregressive with exogenous inputs neural network (NARXNN) is a recurrent dynamic neural network with the functions of memory and global feedback (Siegelmann et al. 1997; Maier and Dandy 2000; Lee et al. 2017). Recently, NARXNN was designed for the time series prediction of groundwater levels, coastal water and ozone concentration (Chang et al. 2016; Guzman et al. 2017; Siegelmann et al. 1997; Maier and Dandy 2000; Gao et al. 2018), and the prediction uncertainty analysis of ANN modeling was quantified by Monte Carlo Simulations (MCS) (Dehghani et al. 2014). Contrary to RBFNN, NARXNN performs well in the prediction of monotonic process variables, but it has poor performance in the prediction of non-monotonic process variables (Wunsch et al. 2018). Therefore, it is quite necessary to integrate the advantages of RBFNN and NARXNN to realize the prediction of both monotonic and non-monotonic process variables and the topic is less reported in previous literatures.

In this study, the dynamic forecast model for drainage outflow is proposed by implementing a coupled neural network in MATLAB software. The dynamic prediction model, named RBF-NARX Forecast Model (RNFM), combines the prediction features of RBFNN and NARXNN on the functions with different monotonic properties. The developed RNFM is validated to perform well in the dynamic prediction of the runoff from urban drainage systems (USDs) and the MCS technique is applied for uncertainty analysis in this paper. With the availability of RNFM in dynamic prediction, it is expected that RNFM could contributes to a state-of-the-art technology of urban real-time runoff management and even serve for future intelligent drainage.

2 Methodology and Study Area

To better understand the coupled neural network, the schematic of RNFM plotted in Fig. 1 is divided into two stages: the establishment of RBFNN and NARXNN, and the search of optimal coupling site.

2.1 Artificial Neural Networks

Figure 2 shows the topologies of RBFNN and NARXNN. The modeling methodology of the artificial neural networks built in this paper can be found in Chen et al. (1991), Wunsch et al. (2018). The network parameter settings of RBFNN and NARXNN can be developed as

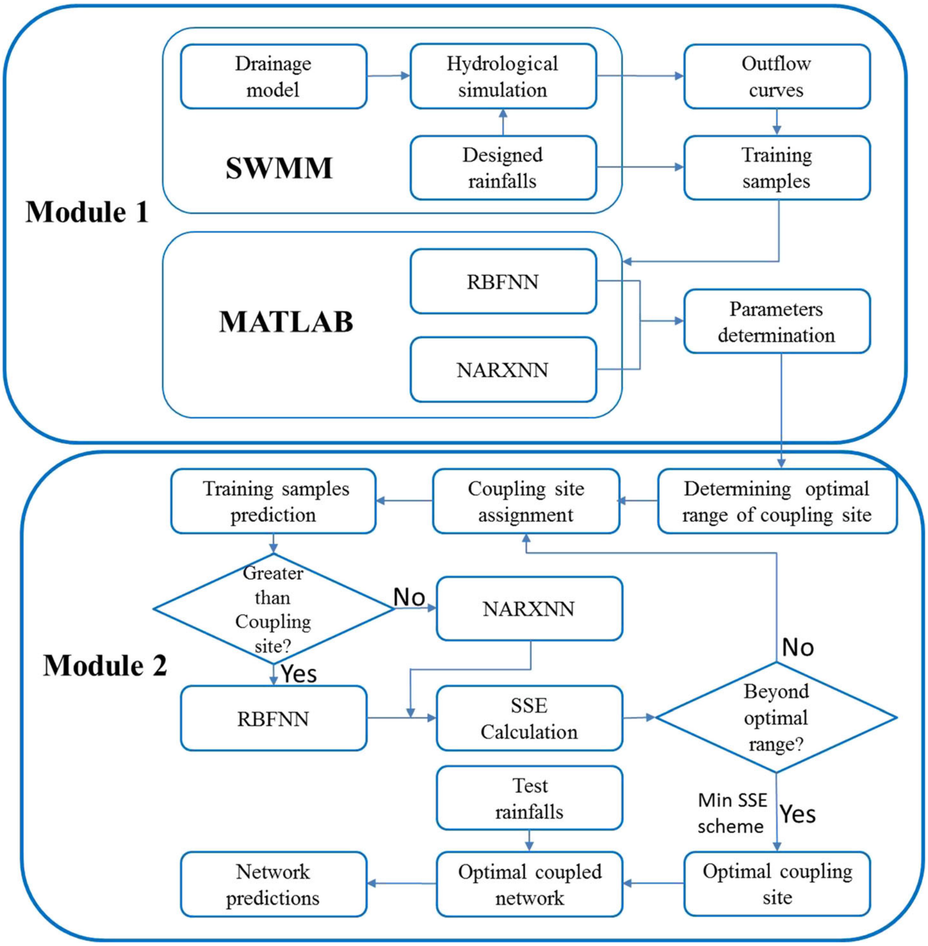

Fig. 1 Algorithm schematic of RBF-NARX forecast model

previous methods (see Chen et al. 1991; Lee and Sheridan 2018). As the available datasets are limited, the Monte-Carlo simulations (MCS) are employed to generate the training, validation and test datasets without subjectivity. After the training stage, the architecture of NARXNN is transformed into the "Parallel" (closed-loop) to achieve the multi-step forecasting of the time series, which will be coupled with RBFNN at the next stage.

2.2 Network Coupling

According to the previous NARXNN studies (see Section 1), NARXNN has the high prediction accuracy for monotonic functions. However, the monotonicity of the runoff curve is unknown before prediction, and it is difficult to divide the predicted function into several monotonous functions with respect to time for NARXNN prediction. The recent studies confirmed that the non-monotonic function could be well predicted by RBFNN. Thus, RBFNN is adopted to couple with NARXNN in our study in order to take the advantages of both methods.

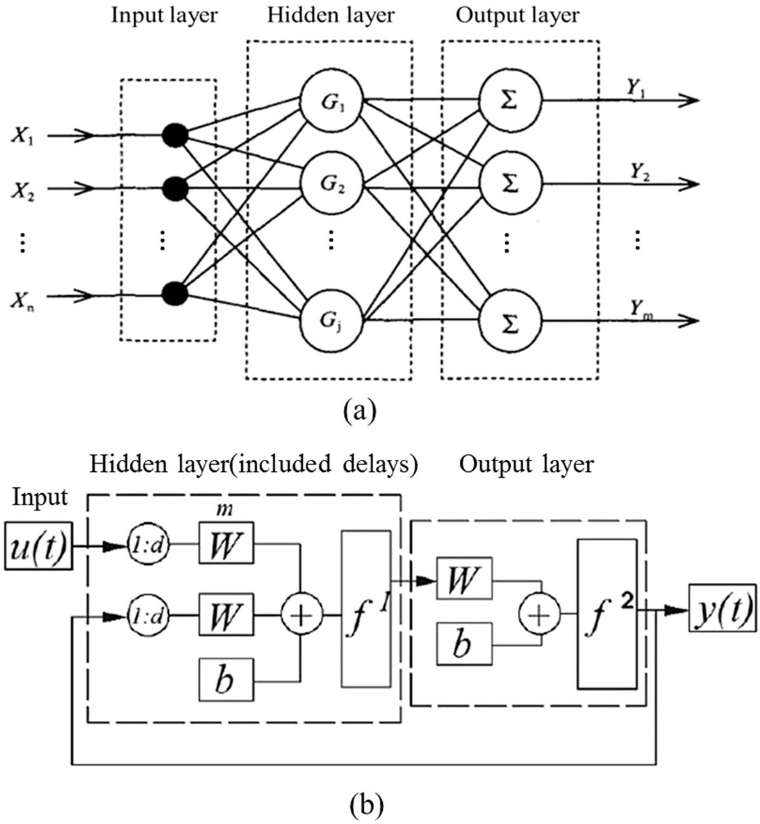

Fig. 2 Neural networks of RBF-NARX Forecast Model: **a** RBFNN; **b** NARXNN

An example of single peak curve is presented in Fig. 3 and the coupling site A is defined as the line parallel to the X axis, which separates the monotonous function (below A) and the non-monotonous function (above A). It is noted that the position of coupling site A affects the prediction accuracy of non-monotonic function by RBFNN. The time interval for non-monotonic function should be taken to the appropriate length to make sure that there are enough samples for RBFNN training.

After networks training, RBFNN and NARXNN are coupled to predict the value of the function for the whole time series in MATLAB software. As a metric, the Square Sum of Error (SSE) is used to evaluate the performance of RNFM predictions. The SSE between the target outputs and the prediction results of RNFM can be written as follows:

$$\mathrm{SSE} = \sum_{i=1}^{n} (y_i - l_i)^2 \tag{1}$$

Where y_i and l_i are the output of target and the result of RNFM at the same time, n is the total number of time step.

For different coupling site and parameters of RNFM, the SSE is calculated during the training process. The optimal value of coupling site A and parameters are determined until the SSE of the training process reaches a minimum value.

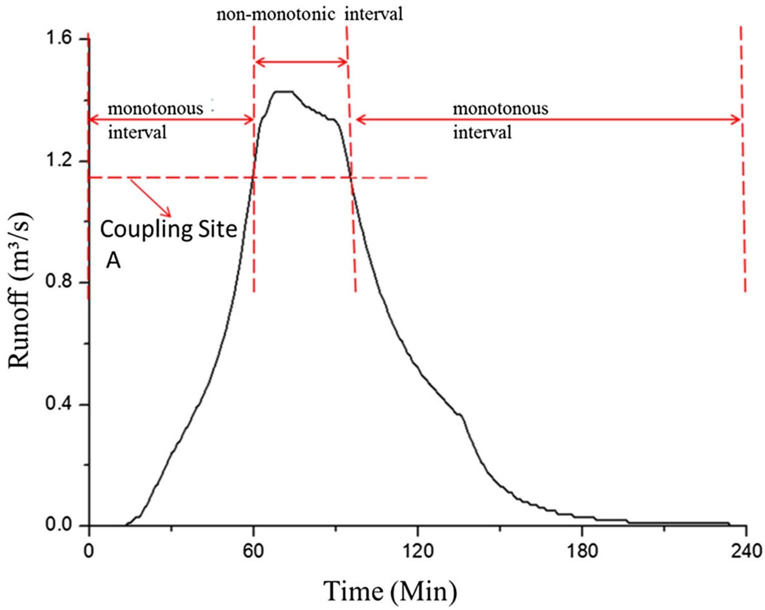

Fig. 3 Example of curve division and coupling site A

2.3 Case Study

In this paper, an urban drainage system located in Tianjin, the municipality of China, is used to validate the prediction performance of RNFM. As shown in Fig. 4, the urban drainage system

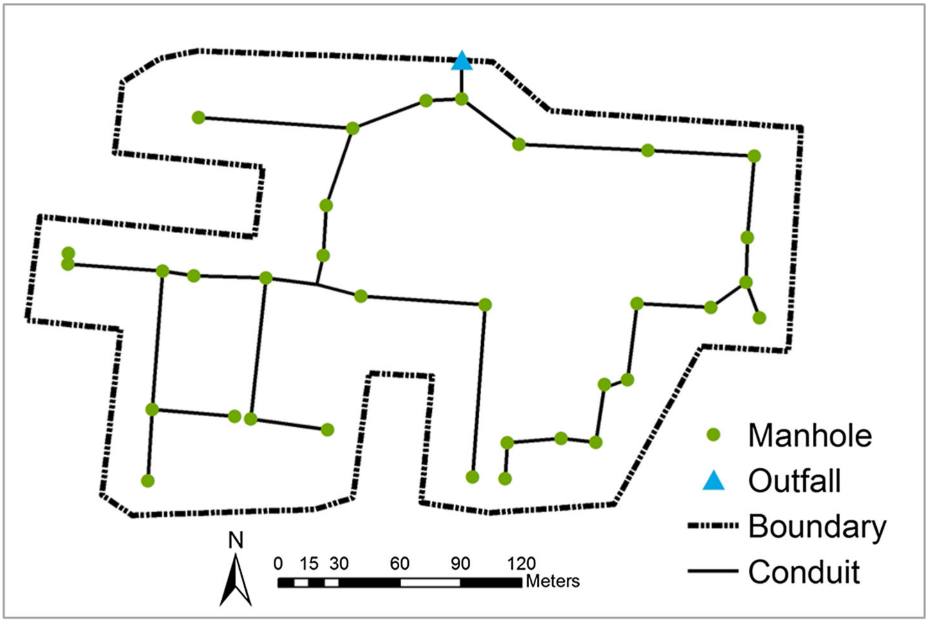

Fig. 4 Drainage system of the case study

with an area of 13.14 ha is composed of 33 nodes, 33 pipes, 21 subcatchments, 1 outfall and 1 pump, which is one of the pilot projects for 'Sponge City' construction in Tianjin.

In previous studies of runoff prediction, the rainfall data is proved to be the appropriate input of artificial neural networks. In this study, the input dataset consists of several time series of rainfall events. The return periods and durations of rainfall events are generated by MCS randomly and the time series of calibration and test rainfalls are created by the Chicago Hydrograph Model (CHM).

3 Results and Discussion

3.1 ANN Parameters

Based on the rainfall with different return periods and durations, the outflow-time series under different rainfall conditions are simulated by EPA-SWMM. The designed rainfall intensities and drainage outflow series are regarded as the inputs and target outputs during the training process of RNFM, respectively. The rainfall events of training listed in Table 1 are imported to EPA-SWMM to compute the UDS outflow in sequence. The routing model in SWMM model is set as Dynamic Wave and the simulation time is 6 h.

The RBF-NARX Forecast Model is set up in MATLAB software. The network architectures of both RBFNN and NARXNN present six input nodes and one output nodes for the time series of the rainfall intensities and the predicted outflows, respectively. Levenberg-Marquardt function is employed as the training function and a normalized Gaussian function is used as the radial basis function of RBFNN. After several trials, the number of nodes in hidden layer and the time step delays of NARXNN are presented in Table 2. Depending on the prediction function, the range of coupling site is set well in [0.8, 1.2]. Figure 5 shows the SSE at different coupling sites. The minimum SSE is achieved when the coupling site is at 1.10.

Table 1 also provides the test rainfall events generated by CHM randomly. The outflow curve is predicted by the proposed RNFM under 3 test rainfalls. The results would be compared with those of EPA-SWMM simulation in order to check the performance of the proposed coupled network.

Table 1 CHM parameters for simulated rainfall

Return period (a)	Total duration (min)	Type
3.4	91	TRAIN
4.1	109	TRAIN
7.6	131	TRAIN
9.5	87	TRAIN
11.1	106	TRAIN
13.3	71	TRAIN
16.6	177	TRAIN
17.7	113	TRAIN
18.7	99	TRAIN
19.5	124	TRAIN
5.1	98	TEST
6.8	132	TEST
11.5	195	TEST

Table 2 The parameters of RBF-NARX forecast model

Section	Parameter	Optimal value
RBFNN	Hidden neurons numbers	64
	Spread	0.6
NARXNN	Hidden neurons numbers	10
	Delay order	4
RNFM	Coupling point	1.10

3.2 Prediction Result

The outflow curves predicted by RNFM and the results of EPA-SWMM simulation are shown in Fig. 6. It is found that all predicted curves show good correlations with the result of SWMM simulation and the peak runoffs and peak times are also predicted with great accuracy. Due to the strong randomness of precipitation data at the initial stage, RNFM requires several time steps to adjust the weights matrix, so the predicted outflow lags behind the SWMM simulation at the beginning of rainfalls. Considering that the threshold of urban runoff control is usually set to be a higher value, the error of RNFM prediction at the initial period is acceptable. After the runoff increases to above $0.2m^3/s$ for our case, the predicted outflows fit the trend of the simulation with high precision until the outflows rate decreases again. The average SSE in the three test rainfalls between RNFM predictions and SWMM simulations is only 0.273, which is acceptable in engineering applications. It is noted that the test rainfall with large return period may exceeds the capacity of USD and RNFM has the potential for managing the high risk events.

3.3 Uncertainty Analysis

In order to conduct the uncertainty in the prediction of USD outflow, MCS can be added in the ANN forecasting procedure, so that the uncertainty analysis could be quantified by estimating the confidential bands of the RNFM results (Gao et al. 2018). MCS involves the repeated

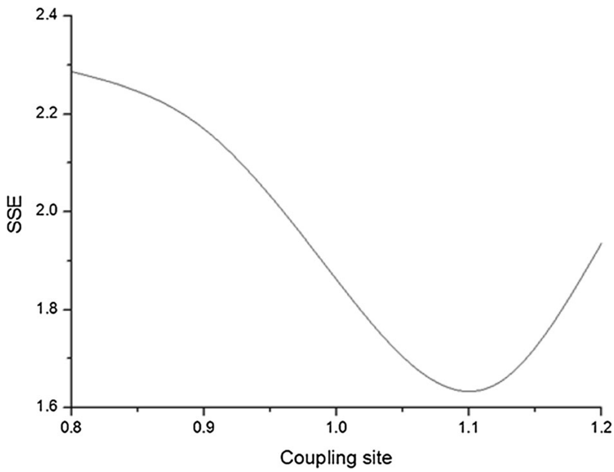

Fig. 5 The SSE with respect to different coupling sites

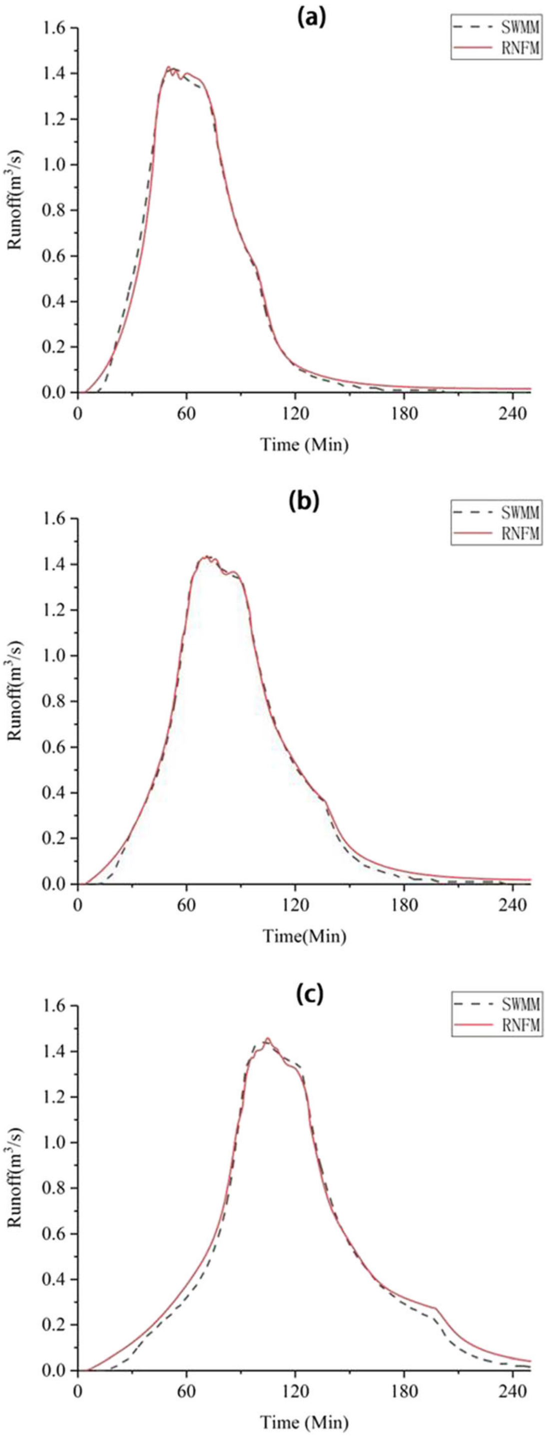

Fig. 6 Comparison of the RNFM prediction and SWMM simulation for 3 test rainfalls of different return periods. **a** 5.1 years; **b** 6.8 years; **c** 11.5 years

generation of random parameters from their probability distributions, and then computing the statistics of the output (Dehghani et al. 2014). Firstly, the return period and duration of rainfall events are limited in 0–20 year and 30–180 min. The input databases are randomly re-sampled for 1000 times and divided into 100 groups of input databases without replacement.

The test rainfall (Table 1) is selected as the representative for uncertainty analysis. Figure 7 shows the 95% confidence intervals for the RNFM results and the EPA-SWMM simulations. Generally, the EPA-SWMM simulations lie within the 95% confidence intervals and this phenomenon is more obvious in non-monotonic part. Compared to the monotonic part, the non-monotonic part has the wider confidence intervals. The wider the interval is, the smaller the accuracy of the forecast is and vice versa (Dehghani et al. 2014). It is concluded that the results of monotonic part can be predicted more accurately than those of non-monotonic part in RNFM. Moreover, it is found that the EPA-SWMM simulations are below the lower bound at the initial stage, which means the current RNFM has limitation to predict the generation of UDS outflow.

4 Conclusions and Future Work

This study proposes the RBF-NARX Forecast Model to predict the real-time urban drainage outflow with high accuracy. The NARXNN and RBFNN are coupled to integrate their architecture advantages. The network parameters and coupling site are optimized by calculating the SSE between target outputs and predictions and the average SEE in the test rainfalls is only 0.273. Based on MCS, the uncertainty analysis of RNFM predictions can be quantified by confidence level. It is proved that the EPA-SWMM simulations lie within the 95% confidence intervals and the current RNFM has limitation to predict the process of runoff generation.

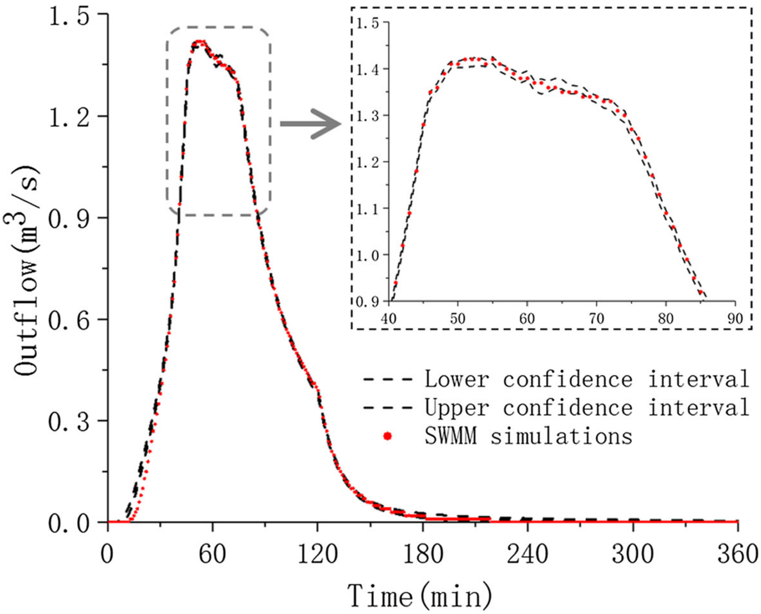

Fig. 7 Confidence intervals for RNFM forecast and SWMM simulations

RNFM is a flexible, dynamic and non-linear autoregressive "black box" model and it can be further developed in the prediction of other real-time process as well. In this work, the dynamic prediction of the RNFM is only validated in the single-peak rainfall events created by CHM. The application of RNFM to multi-peak rainfall events is required to be studied in the future. Furthermore, the combination of RNFM with the sensors, network and real-time control strategy to reduce the urban flooding and to establish future intelligent drainage system are also necessary.

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Compliance with Ethical Standards

Conflict of Interest The authors declared that they have no conflicts of interest to this work.

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