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Particle swarm optimization based LSTM networks for water level forecasting: A case study on Bangladesh river network

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ABSTRACT

Floods are one of the most catastrophic natural disasters. Water level forecasting is an essential method of avoiding floods and disaster preparedness. In recent years, models for predicting water levels have been developed using artificial intelligence techniques like the artificial neural network (ANN). It has been demonstrated that more advanced and sequenced-based deep learning techniques, like long short-term memory (LSTM) networks, are superior at forecasting hydrological data. However, historically, most LSTM hyperparameters were based on experience, which typically did not produce the best outcomes. The Particle Swarm Optimization (PSO) method was utilized to adjust the LSTM hyperparameter to increase the capacity to learn data sequence characteristics. Utilizing water level observation data from stations along Bangladesh's Brahmaputra, Ganges, and Meghna rivers, the model was utilized to estimate flood dynamics. The Nash Sutcliffe efficiency (NSE) coefficient, root mean square error (RMSE), and MAE were used to assess the model's performance, where PSO-LSTM model outperforms the ANN, PSO-ANN, and LSTM models in predicting water levels in all stations. The PSO-LSTM model provides improved prediction accuracy and stability and improves water level forecasting accuracy at varying lead times. The findings may aid in sustainable flood risk mitigation in the study region in the future.

1. Introduction

The most destructive natural catastrophes in the world are floods. Floods can have either natural or artificial origins, yet people are responsible for the destruction in both scenarios. River water level forecasting is essential to reduce the loss of life and property [1]. Reliable monitoring and cutting-edge river water level detection are essential to protecting the lives and property of those living near the river basin. For this need to be met, highly precise river water level forecasts are essential [2]. The World Health Organization (WHO) estimates that more than 2 billion people were affected by floods between 1998 and 2017. This organization also claims that between 80% and 90% of the natural catastrophes that have occurred in the previous 10 years have been caused by floods [3].

More than 300 rivers run across Bangladesh's territory, which covers an area of around 1,47,000 km^2. Major rivers like the Ganges, Brahmaputra, and Meghna often create floods across the majority of the nation because of the substantial monsoon rainfall in the upper catchments [4–6]. Bangladesh continuously experienced extreme floods in 1954, 1955, 1974, 1987, 1988, 1998 and 2007 [4,7]. In the last decade, several flood incidents occurred in this country in 2017, 2018, and 2019 [8]. In terms of human suffering and financial loss, floods are one of Bangladesh's most expensive natural disasters. Annually, 20% of the country floods, while more than 50% of the country has been drowned by devastating floods in the past [9]. Additional layers of constraints that affected regions must bear after the floods include loss of human life and farm animals, value escalation, social insecurity, and the expenses of infrastructure repair, as well as asset diversion for quick attention and retrieval. The Ganges, Brahmaputra, and Meghna rivers have highly seasonal flows that are significantly affected by the monsoon season. As a result, during the monsoon season, these rivers rise to embankments and often overflow. This is most noticeable in the lower reaches,

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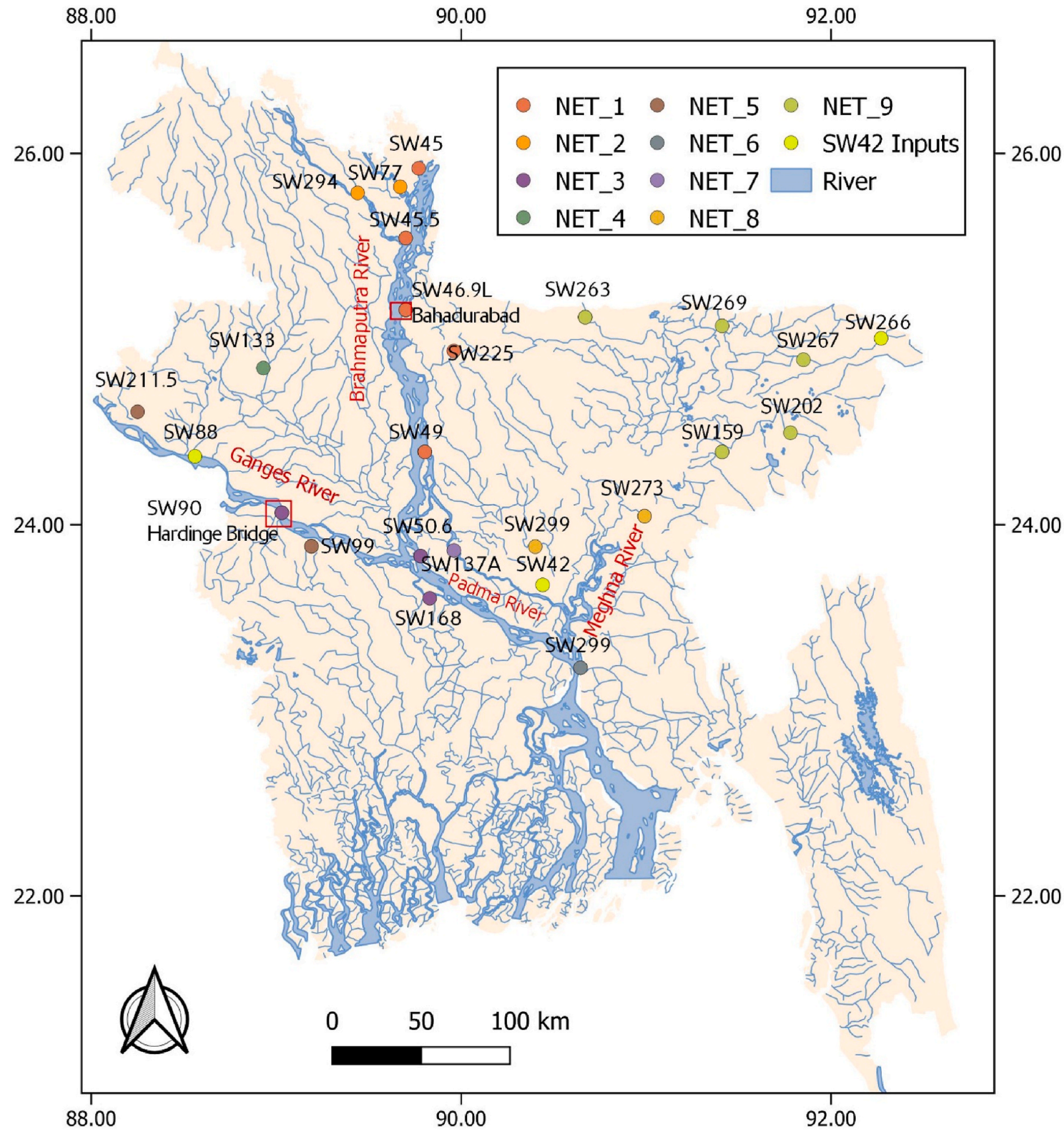


Fig. 1. Water station locations of different rivers.

Table 1
Input and output station list used in the study.

Network Name	Input Station	Output Station
Net_1	SW46.9L	SW45, SW45.5, SW225, SW49
Net_2	SW45.5	SW294, SW77
Net_3	SW90, SW46.9L	SW50.6, SW168
Net_4	SW50.6, SW49	SW133
Net_5	SW90	SW211.5, SW99
Net_6	SW46.9, SW90	SW277
Net_7	SW50.6, SW49	SW273
Net_8	SW277	SW299, SW273
Net_9	SW273	SW159, SW202, SW267, SW269, SW263
SW42	SW45.5, SW88, SW99, SW263, SW266, SW159	SW42

especially in Bangladesh, the country with the fewest floodplains [10]. Accurate flood forecasting appears to be hampered by uncertainties in observed and expected water levels, which calls for a forecasting lead time of five to ten days to improve flood response and readiness for key river basins. Without taking functional utility into account, much effort is being put into developing mechanical hydrological models as well as statistical, satellite, and other approaches to enhance lead-time predictions [11]. A hydrodynamic model such as MIKE-11, MIKE-21 or MIKE-SHE is used worldwide for water level prediction, real-time flood forecasting or rainfall-runoff data simulation [12,13]. Hydrodynamic models have been used in Bangladesh since the nineteenth century for water level forecast [14]. As most of the rivers in Bangladesh are connected to India, both countries follow a similar flood control method [15]. Analysis and forecasting of seasonal and annual precipitation, temperature, river flow and water table are important for local water resource practices [16].

Estimating future values in a sequence using previous data is known as time series forecasting. Machine learning approaches are sometimes a

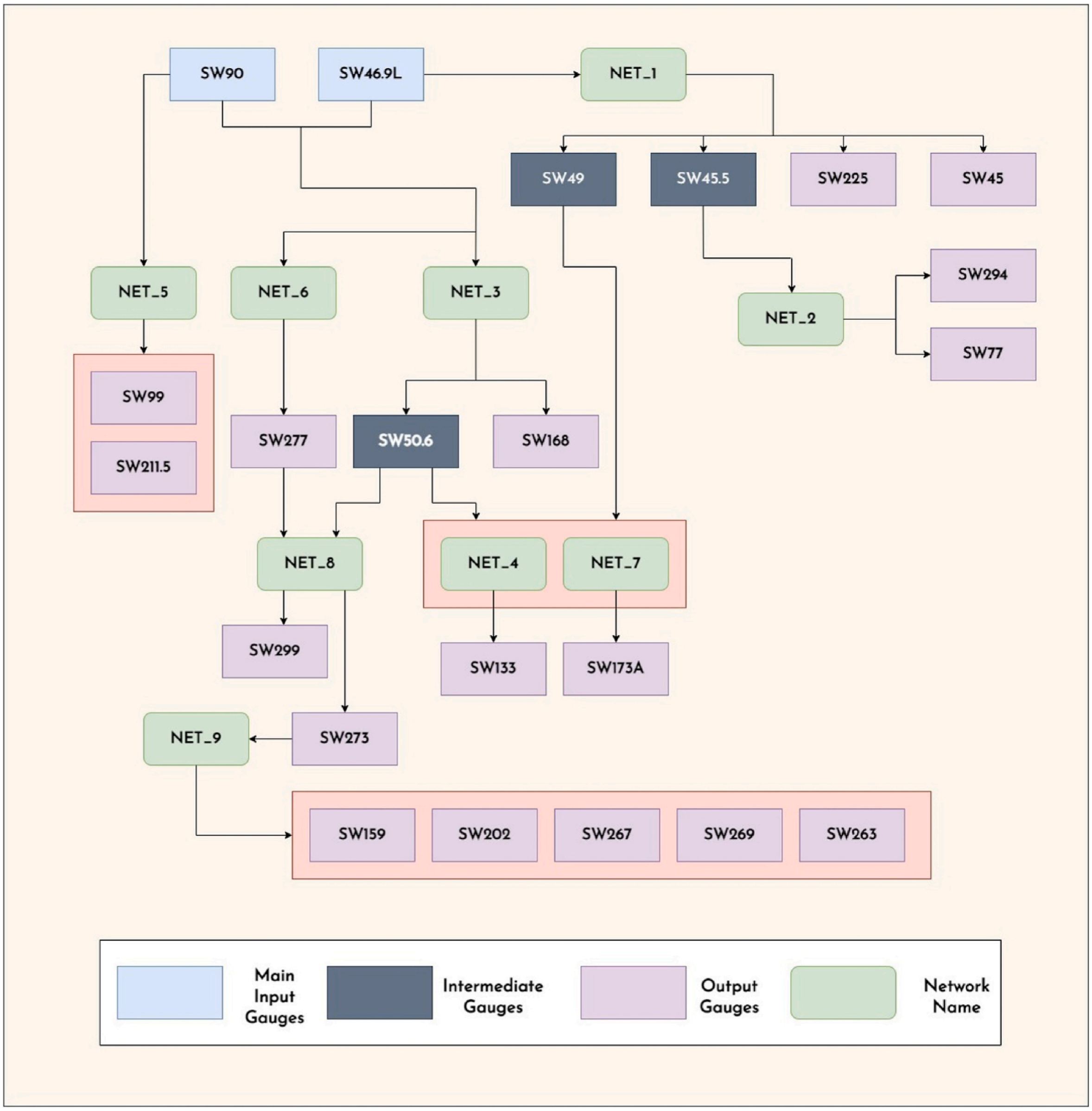


Fig. 2. Structure of river Network (Reproduced from Siddiquee and Hossain [6]).

better choice to solve the constraints of traditional forecasting approaches, which are time-consuming and difficult. Different methods have been applied to forecast water data for last two decades such as fuzzy technique, Soil and Water Assessment Tool (SWAT) model, machine learning models, deep learning techniques and so on [7,17,18]. The LSTM approach performs better than the SARIMA and RF methods, according to the findings of the floodwater level forecast in the Red river of the North [19]. Water level forecasting in Bangladesh using an artificial neural network was first introduced by Liong et al. in the early twentieth century [18]. The author later studied Dhaka gauge stations using a fuzzy model [7]. Biswas et al. worked on the Surma river of Bangladesh to predict the water levels of the rivers for water management and flood control [20]. Five stations along the Ganges, Brahmaputra and Meghna rivers in Bangladesh's border region were chosen as input nodes for the neural network, with Dhaka on the Buriganga river serving as the output node. The model was developed using river stage data from 1998 to 2004 and verified using data from 2005 to 2007 [21]. Several works have been done using fuzzy logic using ANFIS time series forecasting, where a recent work reported on Jamuna river data [22].

Recent work has been done on Someshwari-Kangsa Sub-watershed which is connected to India and Bangladesh [23]. In this study, Decision Tree regression performs better than other machine learning techniques for 10 days of forecasting. In some cases, XGboost algorithm outperforms as demonstrated in that research. Siddiquee and Hossain worked on cascaded channels of Brahmaputra and Ganges water levels in Bangladesh which introduced artificial neural network in a faster method [6]. Later in the Bahadurabad transit, deep learning models were applied using 15 years of recent data where RNN provided the most accurate result in the case study [24]. The LSTM model was built and tested to anticipate one-day, two-day, and three-day flood flow in Vietnam stations [25]. Rahman et al. proposed a hybrid method combining ANN, LR, and frequency ratio where the integrated LR-FR model gives the highest predictive value in water level data [26]. For estimating the water levels of 17 harbors in Taiwan, a forecasting model based on the long short-term memory (LSTM) recurrent neural network was constructed [27]. Multistep river flow is also forecasted by Hayder using NARX and LSTM model combination and applied in the Malaysian basin [28]. To estimate flood susceptibility, appropriate feature engineering technique with LSTM is applied in different studies [29,30].

Some recent works have been done on stream flow forecasting on

Table 2
Standard Deviation of all the water stations.

Water Stations	Standard Deviation
SW46.9L	1.417276
SW45	1.558242
SW45.5	1.521192
SW45	1.467837
SW49	1.531403
SW294	0.763729
SW77	1.086790
SW90	2.270603
SW50.6	1.51194
SW168	1.4187
SW133	1.412321
SW211.5	2.63937
SW99	2.4408
SW277	0.702169
SW173	2.302046
SW299	1.113187
SW273	1.113187
SW88	3.064279
SW263	0.785723
SW266	3.521559
SW159	0.919631

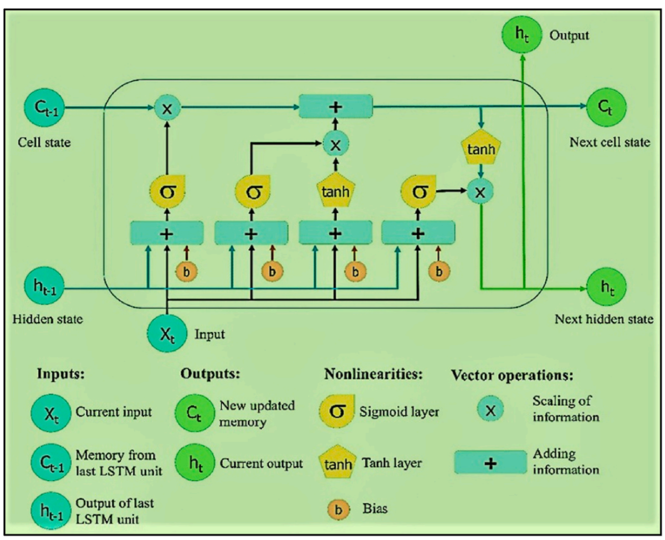


Fig. 3. Conventional LSTM model architecture.

Orontes Basin in Turkey and rainfall-runoff simulation in China using particle swarm optimization on neural networks [31,32]. Song et al. [31] used only rainfall-runoff data and introduced daily stream flow forecasting where different lead day forecasting is missing. Xu et al. [32] showed maximum 12 h forecasting in daily rainfall-runoff. Yan et al. [33] also applied the particle swarm based long short term memory on water quality data to improve the performance over the previously reported work. Another particle swarm based LSTM work was done for predicting moisture, where results were compared using several evaluation metrics [34]. For multi-step ahead flood forecasting, various recurrent neural network models are used for flood forecasting networks [35]. Multiple works are done based on specific river basins and also with a limited number of river station data. In our current study, we have incorporated a total of 24 water stations that constitute a river network. In this network, nine sub-networks are connected where output from a network is fed as input to the other network. To the best of our knowledge, the application of hybridized models on such a complex river network has not been applied yet.

The contributions of the research are as follows.

(1) Introduce particle swarm-based neural network models to predict the water level of different river stations in Bangladesh.
(2) Apply different lead times and analyze the behavior of PSO based Neural Network models for different lead time forecasting.
(3) Find the best model for various river networks by comparing the prediction performance of different neural network models.

The rest of the paper is organized as follows. Data set, study area, the structure of river network is described in Section 2. It also presents different data preprocessing techniques and various artificial intelligence techniques that include sequence based modelling like LSTM, hybridized models like PSO based LSTM, and ANN based techniques used in this research. Different performance metrics used to evaluate the models are also discussed subsequently. Section 3 showcases the results and Section 4 presents a discussion on them. Finally, Section 5 concludes and gives direction of future research.

2. Materials and methods

2.1. Study area

Fig. 1 is the visualization of the whole river network of Bangladesh and the water station locations we have used in our study. We have considered a total of 24 river station data in our work. Here we tried to select most of the water station data related to the Ganges, Brahmaputra and Meghna (GBM) river that are highly responsible for flash floods or extreme floods in Bangladesh.

2.2. Dataset

We have collected water level data from the Bangladesh Water Development Board (BWDB) from different gauge stations [36]. All the water related data are managed by Flood Forecasting & Warning Center and the organization uses the hydrodynamic model MIKE-11 to calculate the water level. This model has been running in Flood Forecasting and Warning Center (FFWC) since 1998 [36]. We used data from 1979 to 2009 for time series forecasting of our model. We did not get all of the stations' data we used in our study after the year 2009. Later, we added data till 2014 and used the new augmented data for the prediction of water level. The major river tidal data has been used in this study. The major inputs are taken from SW90 and SW46.9L channel data. In our study, Chittagong Hill tracks water section parts have been discarded due to the low amount of data availability and also because of not a part of Ganges, Brahmaputra and Meghna (GBM) river of Bangladesh. We also covered the water stations of Dhaka and forecasted Buriganga station water level in our research.

Table 1 shows the input and output stations that we have taken in our study. The stations for Net 1- Net 9 are the same as reported in Ref. [6]. These stations cover the Meghna, Brahmaputra and Ganges River. We additionally introduce a new network of rivers by including the water stations of Dhaka as input to forecast Buriganga station (SW42) water level in our research.

2.3. Structure of applied river network

We need to input the SW46.9L and SW90 tidal data which will sequentially use the outputs to feed the inputs of the other networks. But when we try to predict SW42 water station output, we will take the output of Net_1 (SW45.5 prediction) and also the other listed water stations. These water station data will cover the major rivers' water stations of Bangladesh which will help in flood forecasting in different lead times. Here, Net_1, Net_3 and Net_6 are independent from the other networks.

Fig. 2 is the representation of the major sequencing river network based on water station channels. Here, Light Blue color is the symbol of the major input station, light purple is the symbol of output gauges, dark

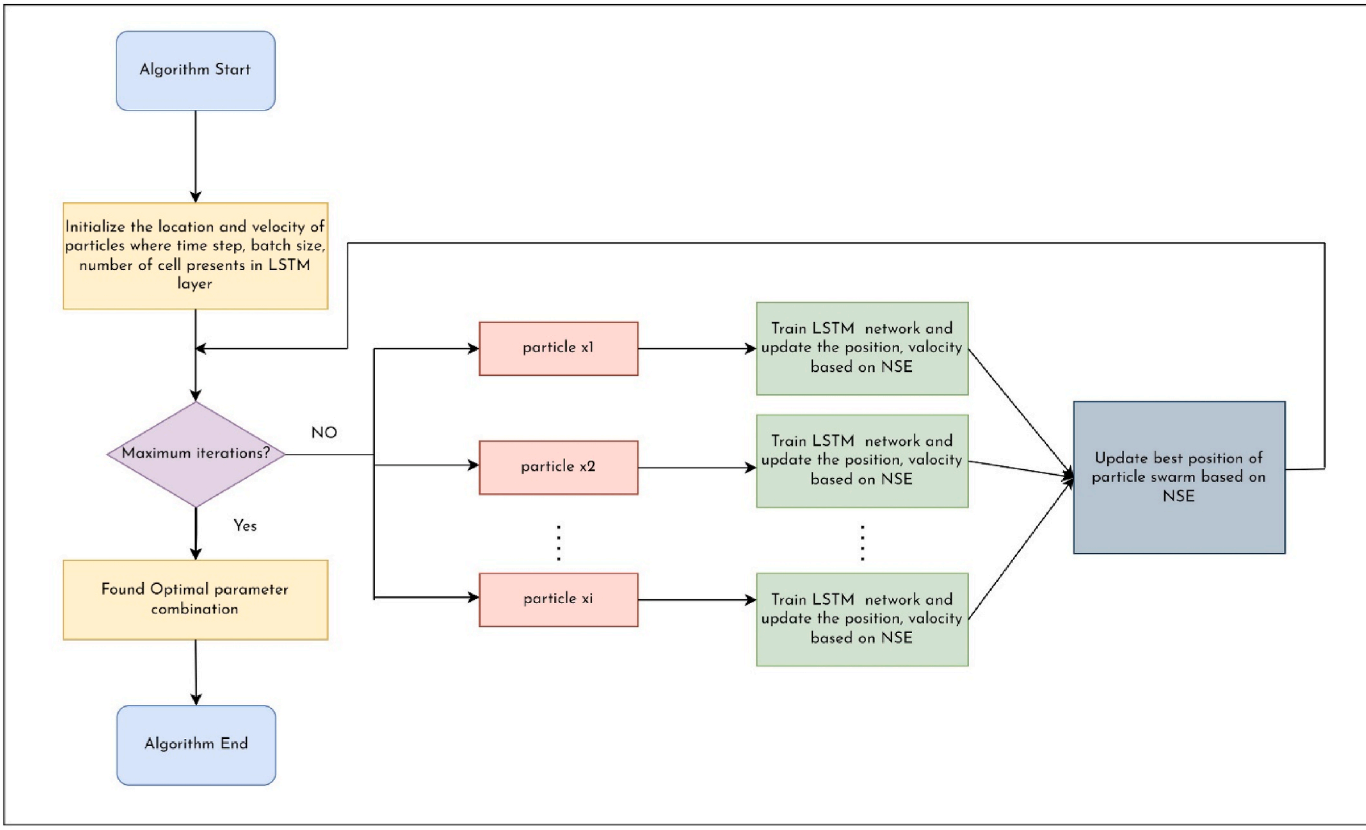


Fig. 4. Applied particle swarm based LSTM algorithm (inspired from Xu et al. [32]).

Table 3
PSO-LSTM model NSE value in 1-day lead time with various time steps, batch size and number of cells (Net_1 result is listed here).

Iterations	Time Steps	Batch Size	Number of Cells	NSE
10	13	124	124	0.9524
20	14	124	128	0.9577
40	17	164	128	0.9644
60	19	164	224	0.9698
80	19	198	224	0.9779
100	21	221	254	0.9892

Table 4
Comparison of predicting R values using PSO-LSTM approach with previously listed work of different sub network.

Network	R value (Siddiquee and Hossain [6])	R value (Applied PSO-LSTM approach)
Net 1	0.99538	0.99729
Net 2	0.98789	0.99006
Net 3	0.96357	0.97114
Net 4	0.75955	0.76021
Net 5	0.99333	0.99410
Net 6	0.93113	0.94237
Net 7	0.95357	0.95519
Net 8	0.91356	0.91455
Net 9	0.91248	0.91398
SW42	–	0.99371

grey is the symbol of intermediate gauges and light green is shown for the created network name. The major input gauges we selected here are SW90 and SW46.9L. SW90 is the channel of Hardinge Bridge and is situated in the Ganges River. This station gives the incoming water level data of the Ganges river [37]. Another major input channel used in this study is SW46.9L which is placed in Bahadurabad transit. The Brahmaputra River Basin's exit was thought to lie near the Bahadurabad gauging station [38]. Both Hardinge bridge channel (SW90) and Bahadurabad (SW46.9L) are the major gauges for the Ganges and Brahmaputra rivers, respectively. The total Bangladesh river system is covered by the sequential network where some sub networks are created for the completion of this task.

In NET_1, input is the Bahadurabad transit data (SW46.9L) and four output gauges are selected. SW45 and SW45.5 are the upstream and SW49 is the downstream, which is placed at Shirajganj. Here, SW225 is the affluent river station for Bahadurabad transit. In the presented sequential network, the output of NET_1 SW45.5 Chilmari station located on the Brahmaputra-Jamuna River will be the input of NET_2. The output of NET_2 selected SW294 (Kaunia Station) and SW77 (Kurigram Station). Both of the stations' data predict the Teesta and Dharla river water levels, respectively.

When we move forward to NET_3 and NET_6 networks, we take both of the major input gauges data SW90 and SW46.9L as the input and for NET_3, SW50.6 and SW168 as the output. The gauges for the output stations are downstream of the gauges for the input stations, with SW50.6 related to the Brahmaputra-Jamuna river and SW168 related to the Faridpur station. NET_4, NET_7 and NET_8 are dependent on the intermediate input station SW50.6 which we got from NET_3 output. SW50.6 is considered as an intermediate gauge because it is related to Brahmaputra river. In this case, NET_4 takes only one input and predicts SW133, which is Naogaon Station and is related to the Jamuna River. Another network, NET_7 covers the Sylhet area and takes both SW50.6 and SW49 as input and SW173A (Sheola Station) is the output. NET_6 output covers the Chandpur station, which is related to Surma-Meghna river.

Later in this research, we added SW277 and SW50.6 as input of NET_8 and then the output of this network selected SW299 (Tongi) and SW273 (Bhairab Bazar). This SW273 gauge output data is inserted as the

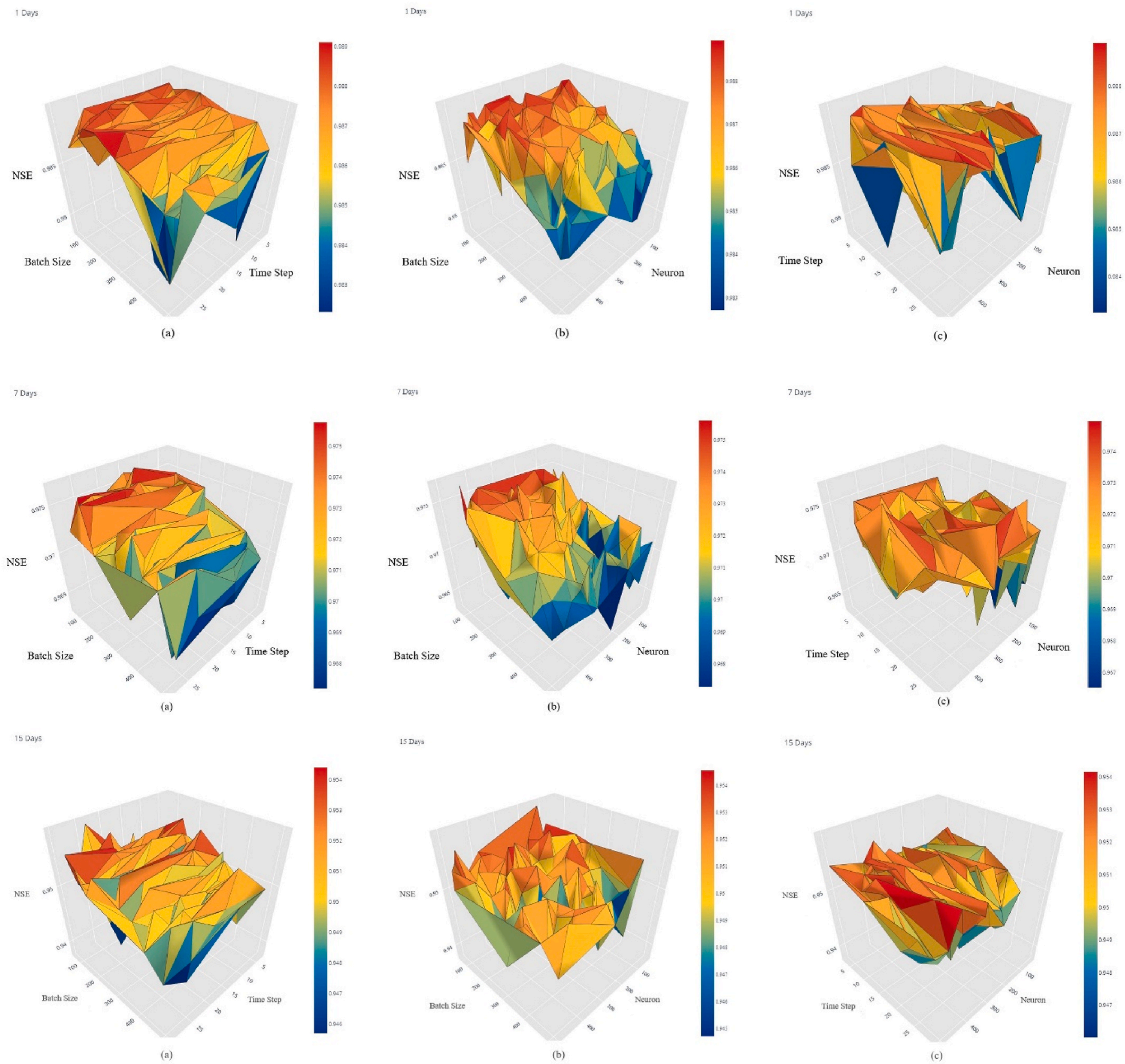


Fig. 5. NSE result with (a) time step values and batch size, (b) Number of cells and batch size and (c) number of cells and time cells, first row (1 day lead), second row (7 days lead) and third row (15 days lead) (Net_1 results).

input of NET_9 and gives SW159 (Habiganj), SW202 (Moulvi Bazar), SW267 (Sylhet), SW269 (Dirai_on Kalni) and SW263 (Madhanagar). All of the input and output of the NET_9 cover the Sylhet district of Bangladesh for water level forecasting. Another independent network NET_5 is only dependent on the main input gauge SW90 and predict the SW99 (Gorai Railway Bridge) and SW211.5 (Chapai Nawabganj) in the output.

The sequential networks are planned to execute from NET_1 to NET_9 one by one because some of the inputs are dependent to the other NET outputs. The sequence of net building. e.g., from NET_1 to NET_9 tracked the flow of the river via the branches. In this river networking system, NET_1, NET_3, NET_6 and NET_5 are independent to the other network's outputs.

We have additionally incorporated Dhaka station in current research to predict SW42 channel of Dhaka_Mill Barrack (Buriganga River) to cover the major water station of the city of Bangladesh. To get the output, we considered one previous intermediate gauge output (SW45.5) and the other stations SW88, SW99, SW263, SW266, and SW159 as input. The inputs of this network are related to the Meghna and Ganges basin which helps to predict the Buriganga river water level.

2.4. Data analysis

The standard deviation of the water stations data that we evaluated was determined. Table 2 depicts all the results.

2.5. Data preprocessing

In the first step of preprocessing the data, we applied the data imputation technique to fill in the missing values. For the data impu-

Table 5
Average performance comparison of different water stations on 15 days lead time.

Network	Model	NSE	RMSE	MAE	MAPE
Net 1	ANN	0.9036	1.1994	0.9671	0.0707
	PSO-ANN	0.9216	1.1812	0.9432	0.0682
	LSTM	0.8753	1.5914	1.4148	0.0883
	PSO-LSTM	0.9475	1.1143	0.9531	0.0595
Net 2	ANN	0.7136	0.8701	0.7356	0.02987
	PSO-ANN	0.7411	0.8633	0.7305	0.02899
	LSTM	0.7122	0.8635	0.739	0.02997
	PSO-LSTM	0.7687	0.8567	0.7291	0.02781
Net 3	ANN	0.7804	1.036	0.9691	0.1604
	PSO-ANN	0.7921	1.005	0.8847	0.1575
	LSTM	0.7811	1.104	0.9572	0.1589
	PSO-LSTM	0.84021	0.9135	0.7016	0.1488
Net 4	ANN	0.7743	1.301	0.40	0.315
	PSO-ANN	0.7896	1.117	0.394	0.294
	LSTM	0.7782	1.275	0.413	0.302
	PSO-LSTM	0.7948	1.0051	0.28	0.259
Net 5	ANN	0.8013	1.73	1.46	1.42
	PSO-ANN	0.8354	1.61	1.38	1.29
	LSTM	0.8299	1.47	1.39	1.33
	PSO-LSTM	0.8506	1.22	1.17	1.28
Net 6	ANN	0.8301	1.79	0.921	0.98
	PSO-ANN	0.8398	1.36	0.835	0.87
	LSTM	0.8219	1.73	0.798	0.87
	PSO-LSTM	0.8653	1.29	0.702	0.83
Net 7	ANN	0.7251	1.88	0.724	0.1788
	PSO-ANN	0.7593	1.78	0.717	0.1525
	LSTM	0.7313	1.91	0.728	0.1713
	PSO-LSTM	0.7873	1.69	0.691	0.1269
Net 8	ANN	0.7327	1.95	0.736	0.1698
	PSO-ANN	0.7391	1.76	0.731	0.1407
	LSTM	0.7309	1.91	0.749	0.1533
	PSO-LSTM	0.7598	1.70	0.727	0.1335
Net 9	ANN	0.7376	1.246	0.708	0.0296
	PSO-ANN	0.7578	1.29	0.738	0.0289
	LSTM	0.7387	1.361	0.719	0.0301
	PSO-LSTM	0.7692	1.102	0.726	0.0282
SW42	ANN	0.8981	0.991	0.8534	0.119
	PSO-ANN	0.9024	0.903	0.8567	0.118
	LSTM	0.8891	0.921	0.932	0.130
	PSO-LSTM	0.9287	0.847	0.842	0.113

tation technique, we used the *k*-nearest neighbor approach. After that, we used the following equation, Eq. (1), to conduct min-max normalization on the input features since different stations had varying absolute values of water level. The dataset is first separated into the train and test sets, and then normalization is used to avoid losing information from the training set.

$$Normalised\ data = \frac{q - Q_{min}}{Q_{max} - Q_{min}} \tag{1}$$

We used the initial 80% of data for training and the remaining 20% data to validate our applied model. In our case study, we introduced multivariate multi-step time series forecasting with particle swarm optimization.

2.6. Hybridization of long short term memory (LSTM)

In this section, we have discussed the algorithms, i.e., Particle Swarm Optimization (PSO), Long Short Term Memory (LSTM), Traditional Back Propagation Neural Network and their hybrid models. Additionally, we also addressed the hyperparameters, model construction, and performance measures used to assess the models.

2.6.1. PSO algorithm

Many global optimization techniques built on a metaphor inspired by nature have been developed over the years. Kennedy and Eberhart [39] discuss the idea of using a particle swarm technique to optimize nonlinear functions based on observations of bird migration and eating behavior. According to the technique, people are viewed as particles in a multidimensional search space, with each particle standing in for a potential answer to the optimization problem. Location, velocity, and fitness value are used as the three variables to characterize the particle attributes. The fitness value is determined by the fitness function. Based on the ideal global fitness value, the particle independently alters its direction of motion and its distance, eventually choosing the optimum [40].

The PSO system is configured with random variables and updated after each cycle in order to identify the best choice. Each potential solution, denoted as a particle, is represented by a point in the multidimensional solution space. As they search for the ideal solution, the particles move at a set speed into the solution region. According to its experiences and those of its neighbors, each particle changes its location and velocity. Correctly, each particle follows the optimum solution path. Personal best representative, or *pbest*, is the name of this solution. The system also keeps track of the global best path for all swarms, known as gbest. At each repeat, the primary principle of PSO is to alter the velocity of each swarm towards the pbest and gbest places [41]. During balancing exploration and exploitation, the PSO system combines a local search method with global techniques.

Assume k particles in an M-dimensional space form a group A = a_1, a_2, a_k, with $a_i = [a_{i1}, a_{i2}, a_{iM}]$. The following are the present properties of the i-th particle:

$$A_i = \left(a_{i1}^t, a_{i2}^t, \ldots, a_{iM}^t\right)^T \tag{2}$$

$$V_i = \left(v_{i1}^t, v_{i2}^t, \ldots, v_{iM}^t\right)^T \tag{3}$$

$$P_i = \left(p_{i1}^t, p_{i2}^t, \ldots, p_{iM}^t\right)^T \tag{4}$$

$$P_g = \left(p_{g1}^t, p_{g2}^t, \ldots, p_{gM}^t\right)^T \tag{5}$$

In equations (2) and (3), a_i^t and v_i^t are the current location and the current velocity, where P_i^t and P_g^t are the optimum location in the particle's and the overall particle swarm's history. The velocity and the position changes per iteration using following conditions (7) and (8).

$$v_i^{t+1} = wv_i^t + C_1R_1^t\left(p_i^t - a_i^t\right) + C_2R_2^t\left(p_g^t - a_i^t\right) \tag{7}$$

$$a_i^{t+1} = a_i^t + v_i^{t+1} \tag{8}$$

Here, v_i^{t+1} and a_i^{t+1} shows the how velocity update after each iteration and position after the iteration respectively. C_1 and C_2 represents the constants and R_1 and R_2 are arbitrary integers between (0, 1).

In the recent works, PSO is used for optimal sizing of the parameter. It produces better result than other optimization method in forecasting application [42]. This algorithm is also applied for optimization of artificial neural network model parameters for prediction [43].

2.6.2. LSTM algorithm

Hochreiter and Schmidhuber [44] introduced long short term memory which includes forget gate, memory cell, output gate. A conventional LSTM model is presented in Fig. 3. A long short term memory neural network is a RNN that allows previously entered data to be kept inside the network without impacting the output. Zhang et al. [45] shows in their study that the gradient vanishing is an exponential explosion that hinders typical RNNs from learning long-term relationships in data. The LSTM model's structure enables it to manage short data dependencies and also massive ones.

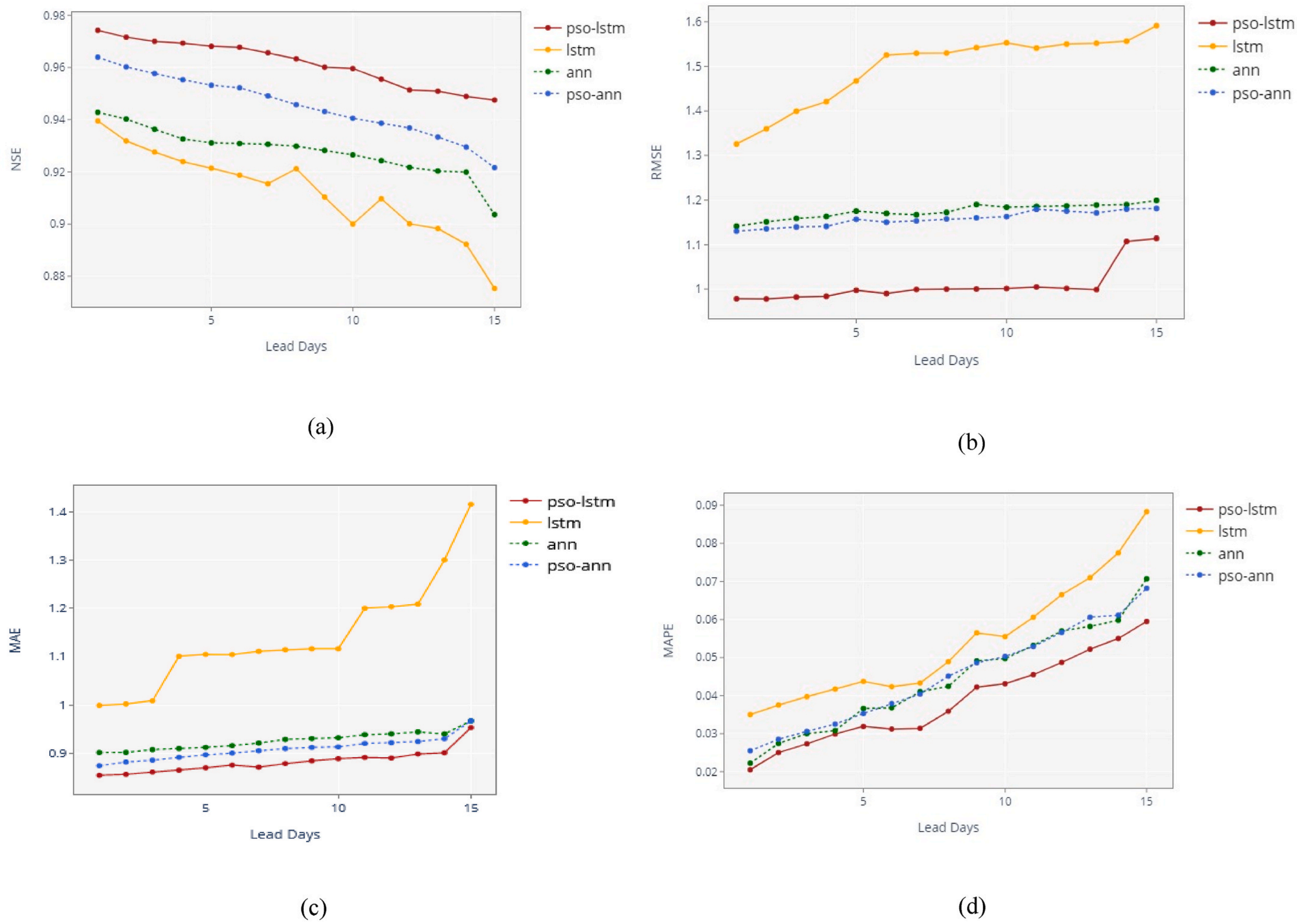


Fig. 6. Water level prediction models (a) NSE, (b) RMSE, (c) MAE and (d) MAPE values of 15 days forecasting using all the applied models (Net_1 is shown here).

We applied stacked LSTM to train our model. LSTM model is preferred for prediction and forecasting of multi class classification studies [46].

2.6.3. *Artificial neural network (ANN)*

ANN is commonly used as a tool for identifying nonlinear systems and is typically employed for learning complicated tasks such as identification, decision making, or forecasting [47]. An input layer, hidden (containing neurons), and output layers make up a typical feedforward neural network. According to recent studies, utilizing ANN is one of the most important ways for simulating hydrological processes [48].

2.6.4. *PSO-LSTM algorithm*

The initial settings of the parameters in the LSTM neural network have a significant impact on the network's efficiency. The PSO technique was used to improve two important LSTM network parameters in this study. The number of buried layer neurons and the learning rate are the two factors. A conventional LSTM network prediction model was done as a priority while developing the suggested model. Following that, PSO was used to improve numerous LSTM model hyperparameters. The PSO algorithm's best outcomes were found, then inserted as a parameter to the LSTM network, and the LSTM model was retrained. We applied PSO to optimize the parameters of LSTM.

Fig. 4 is the illustration of PSO-LSTM algorithm where for a specific iteration, model will find out the best parameter based on Nash–Sutcliffe model efficiency coefficient (NSE).

2.6.5. *Model configuration and parameterization*

We used python 3.9 for the programming language and implemented PSO using python, Tensorflow for model training and testing. Initially, preprocess the data using python libraries that can be used by LSTM networks and forecast 1-day, 5-day, 7-day, 11-day and 15-day ahead water level using different time steps as a sliding window.

For this experiment, we used batch size [64, 512], time step [4,30] and number of cells [64, 512] for the particle swarm to find the optimization for the best combination in river basin data. We also defined learning rate 0.0001, activation function '*tanh*' to build the model. The number of epoch we set to 30 and set the early stopping to avoid overfitting the model. When we trained the model, we also set the *patience* to 5.

2.6.6. *Performance evaluation method*

We applied different methods to evaluate our model. Statistical error metrics such as the root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are used to assess the performance of several models in this study.

In the equations, n represents the total number of test values.

The root mean square error, or RMSE, is a commonly used statistic for assessing predicting accuracy. Equation (9) is the representation of RMSE.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(actual - pred)^2}{n}} \quad (9)$$

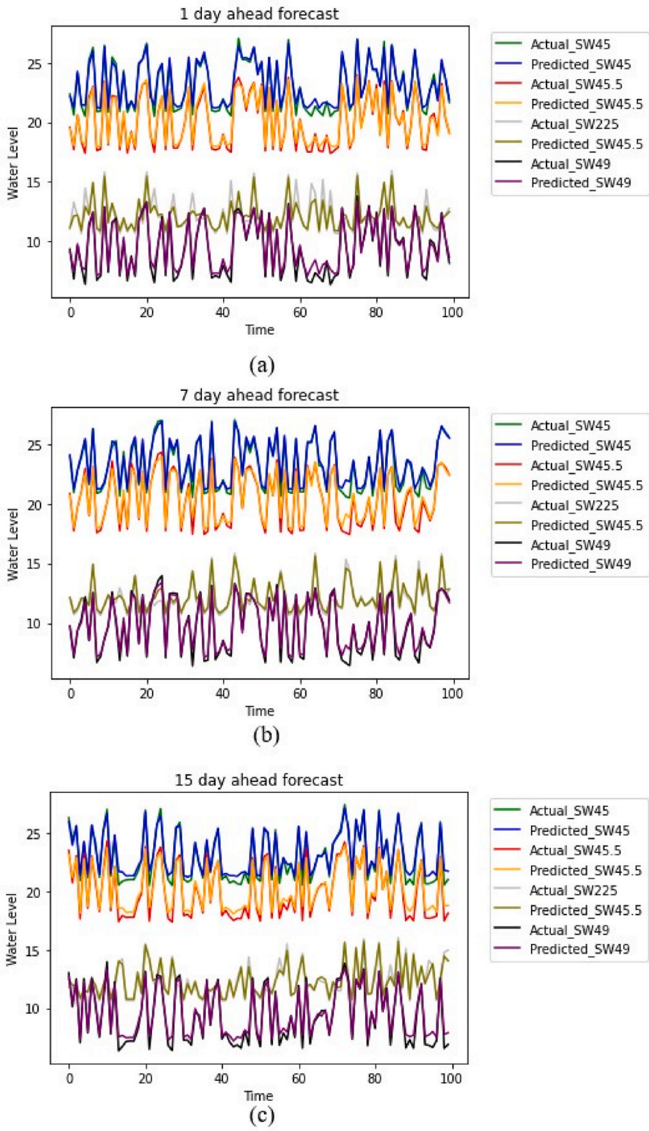


Fig. 7. The predicted water levels (a) 1 day, (b) 7 day and (c) 15 day lead time forecast of four water stations using PSO-LSTM model (NET_1 outputs shown in the graph).

The Nash–Sutcliffe model efficiency coefficient is abbreviated as NSE. The performance of a model is determined using this statistical criterion. Equation (10) is the representation of NSE.

$$NSE = 1 - \frac{\sum_{i=1}^{n} (actual - pred)^2}{\sum_{i=1}^{n} (actual - \overline{actual})^2} \tag{10}$$

The mean absolute error is denoted as MAE. MAE enables us to determine how effectively the models are able to forecast and by what margin these values differ from the real value.

$$MAE = \frac{\sum_{i=1}^{n} |actual - pred|}{n} \tag{11}$$

The above equation (11) shows the calculation method of MAE.

Another evaluation metrics we used in our study is MAPE which denotes mean absolute percentage error. The following equation (12) is the representation of MAPE equation.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{|actual - pred|}{actual} \times 100\% \tag{12}$$

R value is measured for water level prediction by Siddiquee and Hossain in Ref. [6] which is also referred as Pearson's correlation coefficient and shows the equation in equation (13). The correlation coefficient is a measurement of the degree of linear connection between predicted and actual data [49]. R value varies from −1 to +1. R values with +1 indicating a positive connection, −1 indicating a negative correlation, and 0 indicating no relation.

$$R = \frac{\sum_{i=1}^{n} (actual_i - \overline{actual})(pred_i - \overline{pred})}{\sqrt{\sum_{i=1}^{n} (actual_i - \overline{actual})^2 \sum_{i=1}^{n} (pred_i - \overline{pred})^2}} \tag{13}$$

We use the corrected Akaike information criterion (AIC_C) introduced by Suguira [50] to compare the applied sequential models and also the hybridized model performances in our study with different lead time forecasting. equation (14) is the representation of AIC_C where k is the total number of parameters of model. This AIC_C value is also applied by Ren et al. [51] for real-time water level prediction in their study.

$$AIC_C = n.\ \ln \frac{1}{n} \left(\sum_{i=1}^{n} (pred - actual)^2 \right) + 2k + \frac{2k\ (k+1)}{n-k-1} \tag{14}$$

3. Results

We evaluated the parameters using PSO for all the stations we have selected, as shown in Table 1. Here, in Table 3, we can observe the NSE value improvement when iterations of PSO models have been increased. When the iteration value is small, which is 10, batch size value is 124 and number of cells 124 and NSE value we achieved 0.9524 for the input of SW46.9L. Here, we forecasted only 1 day lead values for find out in which iteration step we can get the highest NSE values. The NSE value of the initial iteration value is much lower compared to the other values of NSE. When we have increased the iterations to 20, 40, 60, the NSE value is much higher. Initially, NSE value was 0.9577, but when we iterate the model 40 times, with time step value 17, batch size 164 and number of cells 128 NSE value reaches 0.9644 which is very much higher compared to the initial iteration.

We also observed that if we increase the iteration number and batch size together in this algorithm, NSE value finally reaches to 0.9892. This value is highest for our input station SW46.9 where the output stations are SW45, SW45.5, SW225 and SW49. For our data, PSO provides higher NSE value in 100 iterations and time step 21 and LSTM number of cell assigned to 254.

Later in our experiment, we take the iteration step 100 which provides the highest NSE compared to the lower number of iteration steps (reported in Table 3). In this step, we used all of our gauge station data which is enlisted in Table 1. We reported the NSE values with various lead time in days in Table 3. When the lead time increases the performance of the model slowly decreases. The highest NSE value 0.9892 is reported in 1-day lead time for NET 1. We have listed 5, 7, 11 and 15 days lead time NSE values with different hyperparameter tuned values. When lead time increased in 5 days, time step is increased and NSE value we get here 0.9801 which is quite good in terms of NSE value. Because NSE value larger than 0.75 considered as good model and in between value of 0.75 to 0.5 is considered as average model performance [52, 53]. Finally, when time step is higher among all the previous forecasted output, 24, NSE value is 0.9577 in 15 day lead forecasting in Net_1.

We determined R values for the networks which are listed in Table 4 for prediction. We can see that R value is notably improved throughout the river networks. When we noted the value from Net 1, we observed that R value improved around 0.00191. The listed previous work using ANN NET_1 value reported 0.99538 where in our approached method, we achieved 0.99729. In Net 2, we also improved the R value using

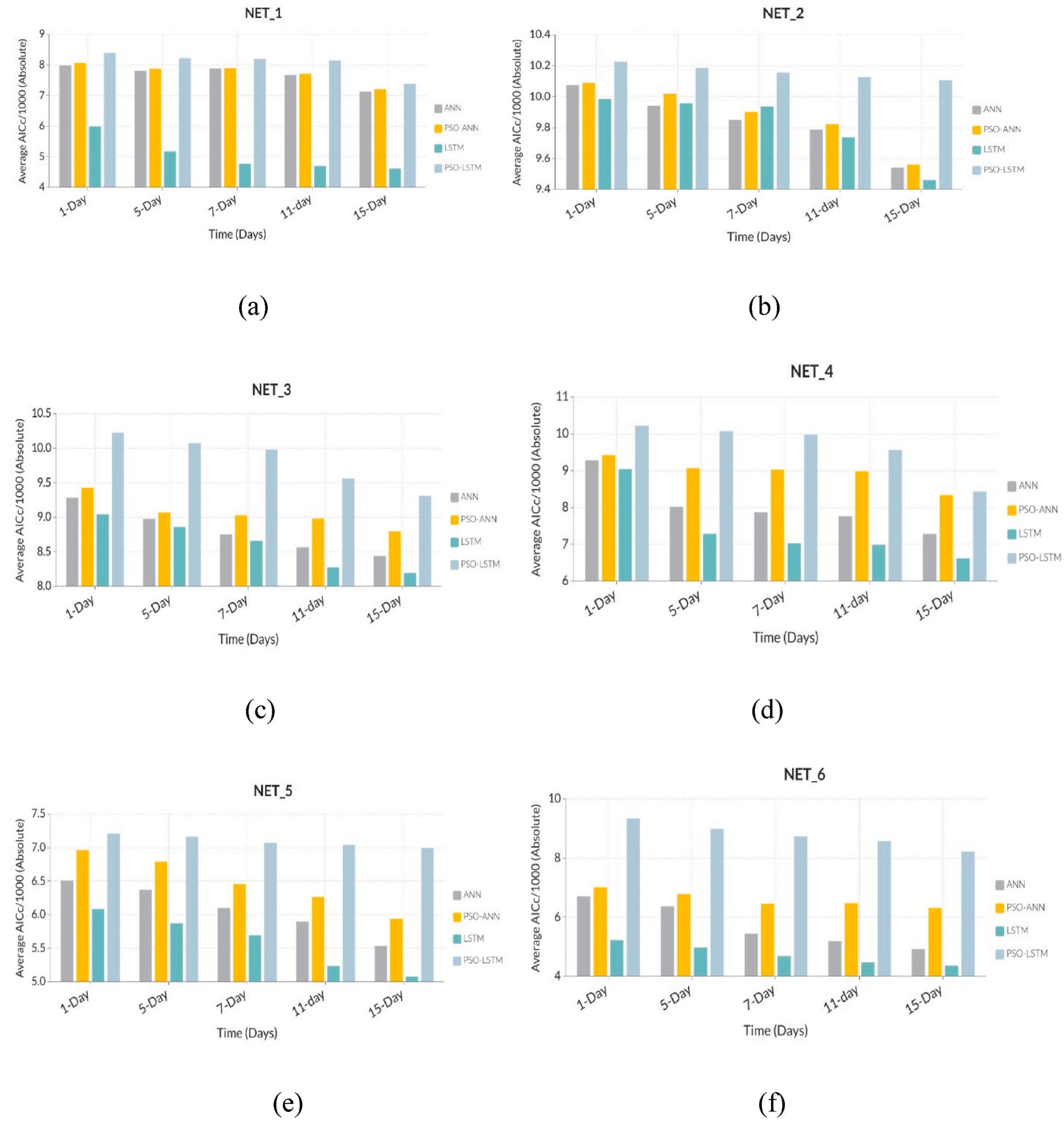
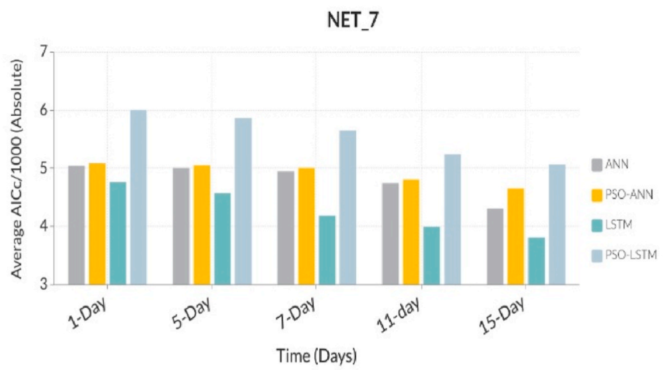


Fig. 8. Water level model prediction comparison using average AICc/1000 values in different river subnetworks in 1-day, 5-day, 7-day, 11-day and 15-day lead time of subnetworks (a) NET 1, (b) NET 2, (c) NET 3, (d) NET 4, (e) NET 5, (f) NET 6, (g) NET 7, (h) NET 8, (i) NET 9, and (j) SW42.

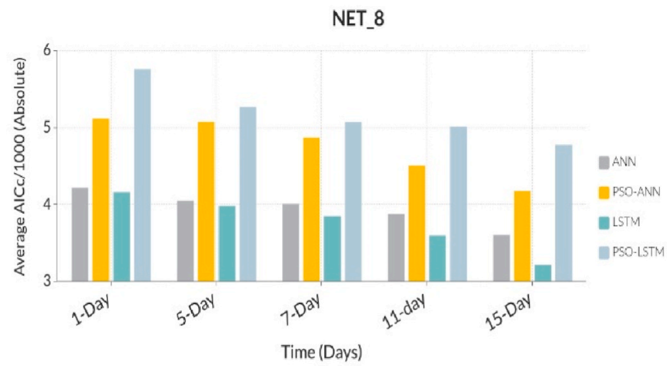
introduced model and get around 0.99006. In Net_3, we improved the R value around 0.00757 that is higher than the previous ones. Almost every networks R value is enhanced by PSO-LSTM model. SW42 gauge station R value we received 0.99371 which is quite good and close to positive 1. The highest improvement we achieved in terms of R values in NET 6 which is 0.01124.

Fig. 5 is the representation of the combination of different time step, number of cells and NSE values with various lead times. From the first row of Fig. 5, we can see that when time step and batch size is higher together the NSE values reaches around 0.988. But when batch size is lower and number of cells are higher, the NSE values low compared to the other values.

When we observed 7 days lead time, the highest NSE value falls down to 0.975. But with a higher number of time step, the number of cell value gives good number of NSE value. In 15 days lead time prediction, NSE value falls down around 0.03 compared to the 1 day ahead forecast. But



(g)



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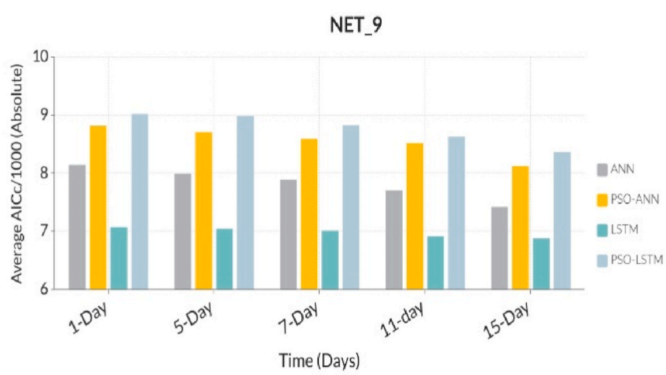
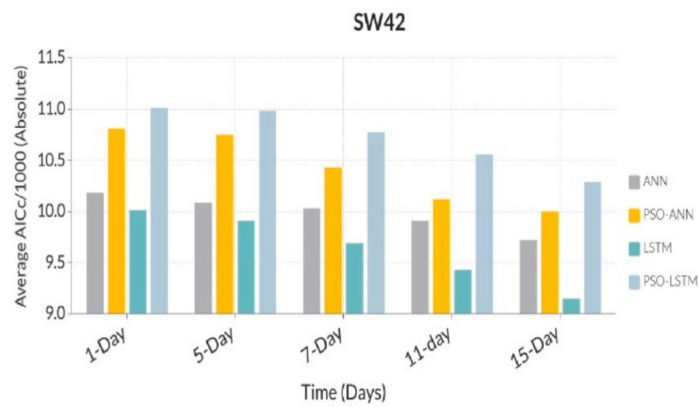


(i)



(j)

Fig. 8. (*continued*).

when we forecasted 15 days ahead forecast for all the number of cells output did not differ much in terms of accuracy.

In the experiment, every water station produced NSE data with different time steps, batch sizes and number of LSTM layer cells.

From all the experiments we used 100 iterations for hyperparameter tuning using PSO, and achieved the highest accuracy when we predicted 1 day ahead water level. But when we increased the lead time, we also observed that we had to increase the time step as the sliding window to forecast the future water level data. For Net 1 we reported the highest forecasted value of NSE, which is 0.957 in 15 days ahead of prediction.

From all the gathered experiment data, we observed that with a high number of cell, time step and batch size, we can get better NSE values which helps to predict the future data much better than the lower number of lag data or time step data. The highest number of the cell we used 398 here by particle swarm optimization in SW42 water station data forecasting.

We compared the PSO-LSTM results for all the sub networks we used in the study with three other neural network models. The results of the comparison with models are listed in Table 5. In terms of NSE value, PSO-LSTM provides higher accuracy compared to all other experiments we conducted. The average NSE value is 0.9475 in 15 days lead forecasting whereas LSTM provides the lowest amongst the other ones which is 0.8753. The PSO optimized ANN gives a much more accurate result than the PSO-LSTM that is 0.9216 but not more than the PSO optimized LSTM model. We also recorded the RMSE, MAE and MAPE values for all the networks. RMSE value for Net_1 is around 0.0423 lower in PSO-LSTM than the LSTM model.

Fig. 6 is the representation of ANN, PSO_ANN, LSTM and PSO-LSTM for different lead time forecasting scenarios. The NSE value of ANN and LSTM is quite closer compared to the PSO applied models. We recorded the highest NSE value when we applied PSO-LSTM algorithm. Initially, LSTM and ANN give similar results, but later, when lead time increased, PSO optimized models perform way better than benchmark models like ANN and LSTM neural networks.

When we recorded RMSE value, initially in 1 day lead time, error value was around 0.9787 in PSO-LSTM. But, when we applied 15 days lead time, error value increased but less than 1.1146. But the RMSE value of LSTM was initially greater than 1.32 and later, when lead time increased, ANN and LSTM error values increased more and reached around 1.1996 and 1.5914. In this case, PSO-ANN provides better performance compared to ANN and LSTM.

Fig. 6(c) shows the MAE values where we observed that PSO-LSTM outperforms compared to other models. Though the MAE value is greater than 0.90 for our network Net_1, the results are comparatively better than the other three experimented models in this study. PSO-ANN model value also performs better than the LSTM and ANN models.

Fig. 6(d) shows the MAPE values we observed throughout a multiple number of lead times using our experimented models. The highest MAPE value obtained using PSO-LSTM in a 15-day lead time is 0.0573, whereas it was lower in a 1-day ahead forecast, at 0.0215. MAPE metric results of PSO-ANN and ANN are slightly overlapping throughout the 15-day forecasting period. But the LSTM result is quite higher compared to

Table 6
Comparative analysis of water level prediction work, forecasting and approaches in different regions.

Study	Research Purpose	Dataset	Method	Findings
Ghorbani et al. [54]	River stage and river flow prediction in Australia	Dulhunty River and Herbert River in Australia	Cascade correlation neural network and the random forest model	0.862 NSE value in Dulhunty River and 0.885 Herbert River
Ren et al. [51]	Real-time water level prediction of cascaded channels	River water level data in China	RWLP model using LSTM as hidden layer	RMSE 0.008790 in 6 h lead time using LSTM model
Pan et al. [55]	Water Level Prediction	Yangtze River in China 30 years data	CNN-GRU model	5-day ahead forecast and 0.9747 NSE values
Palash et al. [11]	A Model for Forecasting Streamflow and Water Levels on the Ganges, Brahmaputra, and Meghna Rivers	GBM streamflow or WL data of Bangladesh	ReqSim QQ + ObsR + ForeR model	Flood forecasts up to 10 days for the GBM basins. 0.95 R^2 value 0.95 and 0.92 for Ganges and Brahmaputra respectively.
Noor et al. [56]	Water Level Forecast of Bangladesh River	Dhaka and Sylhet gauge station river data	Spatio-temporal LSTM model	7 days ahead forecast of Dhaka and Sylhet stations
Siddiquee and Hossain [6]	River water level prediction	Major rivers of Bangladesh except Chittagong Hill tracks related river data	Artificial Neural network model	R value 0.99538, 0.98789, 0.96357, 0.75955, 0.99333, 0.93113, 0.95357, 0.91356, 0.91248 for all the nine river network respectively.
Our Study	Water level prediction case study of Bangladesh river network	24 river stations data of Bangladesh with cascaded network	PSO optimized hybridized LSTM model and performance evaluated using AIC_c metric with ANN, PSO-ANN and LSTM	1–15 days water level prediction. R value 0.99729, 0.99006, 0.97114, 0.76021, 0.99410, 0.94237, 0.95519, 0.91455, 0.91398 for all the subnetworks respectively and 0.99371 for SW42 river network.

the other three models we used in this case study.

We have applied 2010–2014 years data for predicting the water levels. Fig. 7(a) depicts the 1-day lead time forecasting values with actual data and the PSO-LSTM optimized prediction, demonstrating that the SW45 output is much closer than the other station outputs. When we increased the lead time to 7 days (Fig. 7(b)), the difference between actual and predicted values was higher than the 1-day lead time. If we increase the lead time to 15 days (Fig. 7(c)), the error between forecasted and actual water level data becomes high.

In order to determine which model fits the applied river network the best, we compared the applied models using AICc values. We have tallied the values of various lead periods, with 1-day lead times having higher values than 15-day lead times.

For the simplicity of explanation, we compared the results using the absolute value, and based on the AICc criterion value from Fig. 8, the PSO-LSTM model is a better option.

4. Discussion

From the overall performance of the applied model, LSTM model gives poorer prediction results compared to other hybridized models and ANN model. But ANN model gives a much better AICc criterion value but is slightly lower than the PSO optimized ANN model results. But in all the subnetworks, hybridized LSTM model outperforms and is proved as the best fit after optimizing the parameter based on NSE values. Though 15-day lead time performance is not as good as 1-day lead time results according to other evaluation measure metrics but still our optimized model can predict the better values.

From Table 6, we can see the comparative results of the water level prediction works and methodologies. It is clearly shown that, compared to previously reported work on cascaded water level prediction in Bangladesh, we built a model that performs way better in terms of R values. And also, it provides 15 day forecasting ahead, which was not reported in the previous work. We have also evaluated the hybridized model using 2010 to 2014 data that also provided better results after optimization. Different works have been listed for short term water level forecasting but a long term forecasting like 15 day ahead using hybridized model in Bangladesh river network was not applied yet.

According to previous works, no other experiments till now can perform better than the applied hybridized model in the large and complex river network in Bangladesh. The optimized model is also evaluated using the AICc metric, which also ensures the effectiveness of the applied architecture. The models we applied in our study listed sequentially in terms of NSE values for all the sub networks is LSTM - > ANN- > PSO-ANN - > PSO-LSTM where LSTM gives inferior performance and the PSO optimized LSTM gives the best performance.

5. Conclusion

The current research uses the PSO method to improve the LSTM network hyperparameters. The hyperparameter sizes are adjusted based on the NSE value, so the model can handle different situations. To get better results from the PSO algorithm, different hyperparameters are chosen. The batch size is over 256, the timestep is kept around 24, and the lead time is varied with the number of cells in the hidden layer. The lead time and river basin data qualities both have an impact on the hyperparameter selection. The built-in neural network can effectively learn the input data and prevent overfitting during training. We have compared the results of subnetwork predictions using the R-value with previous studies performed using artificial neural networks. Nearly all of the tested subnetworks show greater R-values when the suggested model is used. This NSE-optimized PSO-LSTM algorithm performed better while covering Bangladesh's river network. This is useful for 15 days ahead flood forecasting.

The PSO-LSTM model provides higher performance values such as NSE, RMSE. We have applied only water level data to find out an optimal model which can provide better results compared to conventional neural network models. We investigated time series analysis utilizing the PSO deep learning approach, which hasn't been done before in this part of Bangladesh. Further study can be done on other station data of Bangladesh to find better results. This study can be enhanced by using weather, and rainfall data to predict flood more accurately.

Contribution

Jannatul Ferdous Ruma: Conceptualization, Methodology, Software, Formal analysis, Validation, Writing - Original Draft, Writing - Review & Editing, Visualization; **Mohammed Sarfaraz Gani Adnan**: Methodology, Formal analysis, Software; **Ashraf Dewan**: Data curation, Visualization; **Rashedur M. Rahman**.: Investigation, Resources, Funding acquisition, Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rineng.2023.100951.

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