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Battle of Water Demand Forecasting: An Optimized Deep Learning Model †

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Abstract: Ensuring a steady supply of drinking water is crucial for communities, but predicting how much water will be needed is challenging because of uncertainties. As a part of Battle of Water Demand Forecasting (BWDF), this study delves into the application of Long Short-Term Memory (LSTM) networks for water demand forecasting in a city situated in the northeast of Italy. The focus is on forecasting the demand across ten distinct District Metering Areas (DMAs) over four distinct stages. To enhance the performance of the LSTM model, an evolutionary optimization algorithm is integrated, aiming to fine-tune the model's hyper-parameters effectively. Results indicate the promising potential of this approach for short-term demand forecasting.

Keywords: deep learning; demand forecasting; optimization; water distribution network

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1. Introduction

Water distribution networks (WDNs) are critical infrastructure systems that ensure the supply of clean water to urban areas. Water demand is pivotal in efficient operation and planning of WDNs. Accurate water demand forecasting is vital for sustainable water management in the face of population growth, urbanization, and climate change. Forecasting demand models are divided into long-term and short-term models. Long-term demand forecasting is usually based on a yearly and monthly basis, while short-term models are limited to smaller horizons, like one or several days, with daily or hourly time steps. There are a wide range of methods for water demand forecasting, including machine learning techniques such as artificial neural networks, support vector machines and random forests. Regression methods such as multilinear and nonlinear, and genetic programming are other available models [1].

Deep learning models are the next generation of artificial neural networks, which are widely used in many fields such as image processing and natural language processing as well as water demand forecasting [2]. A Recurrent Neural Network (RNN) is a deep learning model which can memorize short-term information. This feature makes the RNN a powerful tool for time series prediction [3]. The Long Short-Term Memory (LSTM) model is a variation of an RNN. It can handle long time series by memorizing long-term information as well as dealing with the vanishing gradient problem [4].

Using the LSTM model requires several hyper-parameters such as the number of units in the hidden layer, batch size, and window size. Using an optimization algorithm for the optimal determination of these hyper-parameters is a common idea [5]. In this study, a coupled Particle Swarm Optimization (PSO) and LSTM model is implemented for short-term water demand prediction, as a part of Battle of Water Demand Forecasting (BWDF) in the third WDSA-CCWI joint conference.

2. Methodology

The proposed model in this study is based on using an optimized LSTM deep learning mode, which is introduced in the following.

2.1. LSTM

Long Short-Term Memory Networks, a type of deep learning sequential neural network, are designed to address the challenge of retaining information over time. Unlike traditional RNNs, LSTM was specifically developed by Hochreiter and Schmidhuber [6] to combat the issue of the vanishing gradient problem encountered in RNNs and other machine learning algorithms. More details can be found in the literature [4,6,7]. In this study, the LSTM module of the TensorFlow library is used in Python.

2.2. PSO

The Particle Swarm Optimization (PSO) algorithm is inspired by the movement of bird flocks and fish schools and is developed based on the concept of swarm intelligence. In this algorithm, each particle represents a possible solution to the optimization problem. Initially, an arbitrary number of particles is produced and evaluated. Then, through an iterative process, the particles move towards the optimal point. The movement of each particle depends on its previous movement direction, the location of its best position so far, and the absolute best location reported so far among all particles. The stopping condition of the algorithm can be defined as a certain number of iterations, no significant change, and/or the reaching of an acceptable solution [8].

2.3. LSTM-PSO

The proposed model is based on using PSO for minimizing the Mean Squared Error (MSE) of the forecasting model, considering LSTM hyper-parameters as decision variables (Figure 1). In other words, PSO tries to find the optimal settings for the LSTM model. Herein, batch size, number of training epochs and number of units are selected as optimized hyper-parameters.

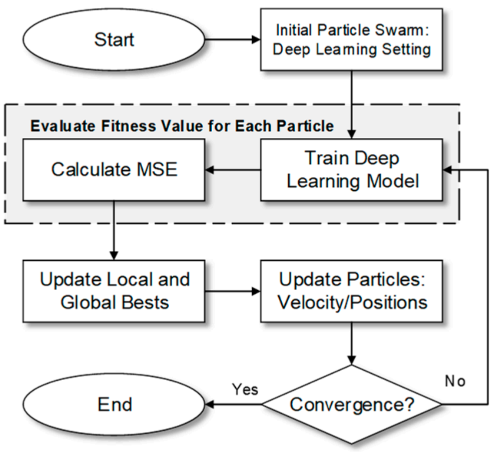

Figure 1. Flowchart for the proposed model.

3. Case Study

A real WDN located in the northeast part of Italy is selected as the case study. It contains ten District Metering Areas (DMAs) and the future forecasting demand for each DMA is the main question. There are four series of available flow data for each DMA, and four prediction models for different periods are required. More details can be found in the BWDF instructions [9].

In this study, 10 parameters in three categories are assumed to be effective in future demand, including:

- Weather data: rainfall depth, air temperature, air humidity, and wind speed.
- Calendar data: the hour of the day, day of the week, day of the month, and month of the year.
- Binary data: holiday or not holiday, and summertime or not summertime indices.

An LSTM model with 10 input nodes (for input parameters) and 10 output nodes (for DMA flow) is created and trained with different settings. To find the optimal setting, a PSO algorithm is implemented, and results are discussed in the next section.

4. Results and Discussion

Results for 10 DMAs' demand forecasting are presented in Figure 2. It contains 10 comparisons for each DMA and two more for training (80%) and testing (20%) data in all DMAs. For each DMA, the train and test data are plotted as blue and black circles, respectively. In addition, the identity line is plotted as a dashed red line for a better comparison.

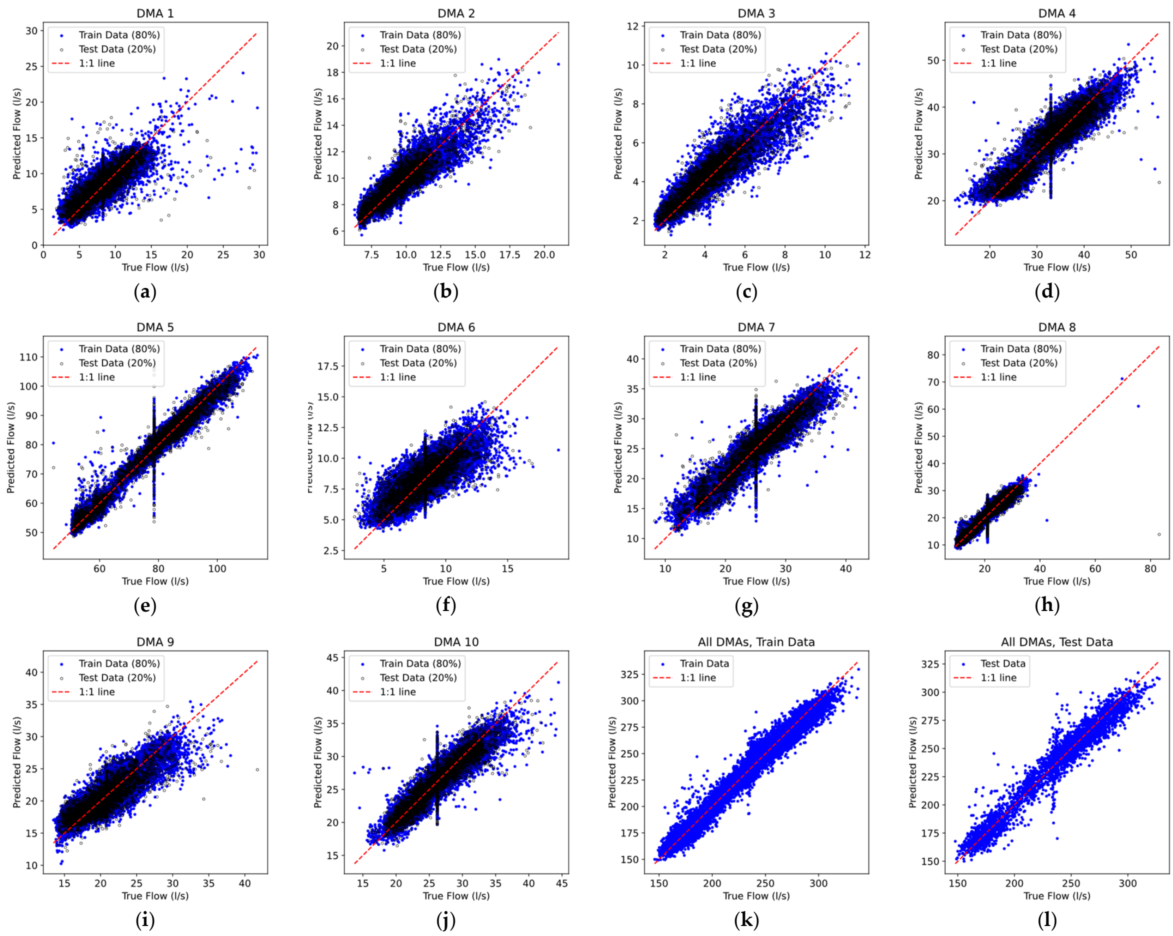

Figure 2. Comparing predicted and actual flow for (**a**–**j**) DMA 1 to 10, (**k**) all DMAs train data and (**l**) all DMAs test data.

As can be seen, the accuracy of the predicted values is almost acceptable for all DMAs. To quantify the comparison, the coefficient of determination (R^2) for each DMA is presented in Table 1. In some cases, like DMA 5 and 8, the agreement between actual and predicted data are at the highest level. In some other cases, like DMA 1 and DMA 6, the model is not able to provide a good estimation of demand. It seems that there are additional important factors influencing demand flow within these DMAs.

Table 1. The coefficient of determination (R^2) for the model evaluation.

Data	DMA 1	DMA 2	DMA 3	DMA 4	DMA 5	DMA 6	DMA 7	DMA 8	DMA 9	DMA 10	All DMAs
Training	0.718	0.802	0.829	0.867	0.972	0.644	0.870	0.938	0.758	0.872	0.9718
Testing	0.622	0.774	0.816	0.814	0.947	0.589	0.840	0.887	0.691	0.852	0.9501
All	0.699	0.796	0.827	0.857	0.967	0.633	0.964	0.928	0.744	0.868	0.973

5. Conclusions

This study has demonstrated the promising potential of an optimized LSTM network as a deep learning model, integrated with a PSO algorithm, for short-term water demand forecasting in a city in northeastern Italy. The analysis of predicted values across various DMAs reveals generally acceptable levels of accuracy. This research contributes to ongoing efforts in efficient water demand forecasting by employing deep learning techniques and optimization algorithms. This methodological framework represents a significant step towards future advancements in water distribution network management, ultimately ensuring the availability of clean water for communities.

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