World Journal of Environmental Research

Volume 12, Issue 1, (2022) 33-42

www.wjer.eu

Forecasting of daily dam occupancy rates using LSTM networks

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Suggested Citation:
E. Ayyıldız & M. Erdoğan (2022). Forecasting of daily dam occupancy rates using LSTM networks. *World Journal of Environmental Research*. *12*(1), 33-42. https://doi.org/10.18844/wjer.v12i1.7732

Received from January 02, 2022; revised from March 21, 2022; accepted from May 10, 2022;
Selection and peer review under responsibility of Prof. Dr. Murat Sonmez, Middle East Technical University, Northern Cyprus Campus, Cyprus

Abstract

Due to unconscious consumption of natural water resources and climate change, a water crisis is expected in the upcoming years. At this point, it is necessary to know the water levels in the dams and develop strategies for water-saving applications in the coming periods. This study aimed to propose the artificial neural network models for forecasting the water in the dams that provide usable water for the future. For this reason, long short-term memory (LSTM) networks that are a type of recurrent neural networks are employed to make future forecasts. The daily dam occupancy rate data between 2005 and 2021 for İstanbul is used to train the LSTM network. Then, the developed models are used to forecast over the next 30 days. The data are used in ARIMA to model the daily dam occupancy time series, for a fair comparison. The forecast values gained by the proposed LSTM network are compared with the traditional methods using RMSE and MAPE for all the forecast horizons. The results show that the LSTM-based forecast model always has a better accuracy rate than the ARIMA.

Keywords: ANNs, dam, forecasting, occupancy, LSTM, RNNs;

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1. Introduction

The rate of usable water in the world is rapidly decreasing due to unconscious consumption of natural water resources and climate change [1]. It is estimated that this water demand will increase further in the coming years, and as a result of this increasing demand, a water crisis is expected in the coming years. It should even be mentioned that water resources are an important input that directly affects the living standards and economic structure.

The annual amount of available water per capita in Turkey is around 1,350 m^3; however, this number is estimated to be 1,000 m^3 with a growing population in the future [2]. It is unlikely to increase the amount of usable water economically. There is a way it would come to mind, which is to get fresh water from seawater, but this way is quite costly. Therefore, it is strategically important for countries to use the available water resources effectively and sustainably. Since the 1980s, it is on the water sector reform agenda in Turkey and has turned in some presentative applications [3]. However, the first national policy for the efficient use of natural water resources in Turkey is expressed in the Sixth Development Plan [4]. In order to encourage the sustainable use of existing water resources throughout the country and determine water needs and form effective policies, it is very essential to determine and monitor the existing water reserves, as well as make estimates and plans for the coming years.

Istanbul is the most populated city in the country and its water consumption rate is quite high, depending on the development and population. In Istanbul, which has gone through a low rainy period, 77% of the dams supplying water to the city are empty, and there is a significant increase in water consumption compared to the previous year due to the coronavirus [5].

1.1. Related studies

In the related literature, dam occupancy rates have been generally used within the scope of predicting and preventing floods. For example, [6] proposed an automated system for monitoring the water level in reservoirs to prevent the bursting of dams and dams. By developing software and hardware for this system, the authorities have been provided with the opportunity to monitor instantly. Shibuo *et al*. [7] performed real-time flood prediction for dam operations and the performance of their proposed procedure was evaluated for three typhoons on Honshu Island in Japan.

Bocchiola and Rosso [8] applied real-time flood prediction for the case study of the St. Giustina dam in Italy. Simaityte *et al*. [9] focused on extreme floods over 200 years in the Kaunas dam water level control during the flood period and developed a risk-based control approach. Pidal *et al*. [10] proposed a process that allows hydrological estimates of the inflow of reservoirs in the mountainous regions of Spain to support the establishment of dam's shelters during periods of floods. Along with these studies, Leitão and Castilho [11] simulated the heat transfer and boundary conditions required to obtain a representative behaviour at the first filling of the dam and identified the main issues related to structural and geotechnical modelling. Salawy *et al*. [12] examined Aswan high dam reservoir operation under the influence of different climate change scenarios.

Cheng *et al*. [13] conducted a sensitivity analysis that included factors such as land resource use, water occupancy of the city, reservoir sediment accumulation, reservoir temperature structure and water reservoir structure identified as environmental impact factors for the Songyuan Water Dam in China. Guo *et al*. [14] simulated the deformation properties of the rockfill dam to investigate and predict the effects of the change in water level upstream of the rockfill dam on the deformation properties of the dam. In this paper,

we firstly apply long short-term memory (LSTM) networks to forecast the dam occupancy rate by considering the sustainable consumption of usable water.

1.2. Purpose of the study

At this point, it is necessary to estimate the water levels in the dams feeding Istanbul and develop strategies for water-saving applications in the coming periods. In this study, we have made the forecast of the water in the dams that provide usable water to Istanbul for future periods. For this reason, the LSTM method is utilised to forecast the daily dam occupancy rate.

2. Materials and Method

This section explains the models and methods that were used for the experiment.

2.1. Artificial neural networks (ANNs)

ANNs are systems consisting of interconnected processing elements with different weights, inspired by the structure of nerve cells in the human brain. ANNs are artificially designed network systems inspired by the structure of neural networks in the brain. These networks are a system consisting of simple processor elements (neurons) and parallel connections (synapses) between each other to use and store the knowledge gained through experience later. Haykin [15] defined the ANNs as follows: it is a processor with a natural tendency to store and use experience-based information. The ANNs are similar to the human brain in two respects: the information is obtained by a network through a learning process and the so-called synaptic weight between the nerve cells is used to store information [15]. The structure of an ANN is shown in Figure 1.

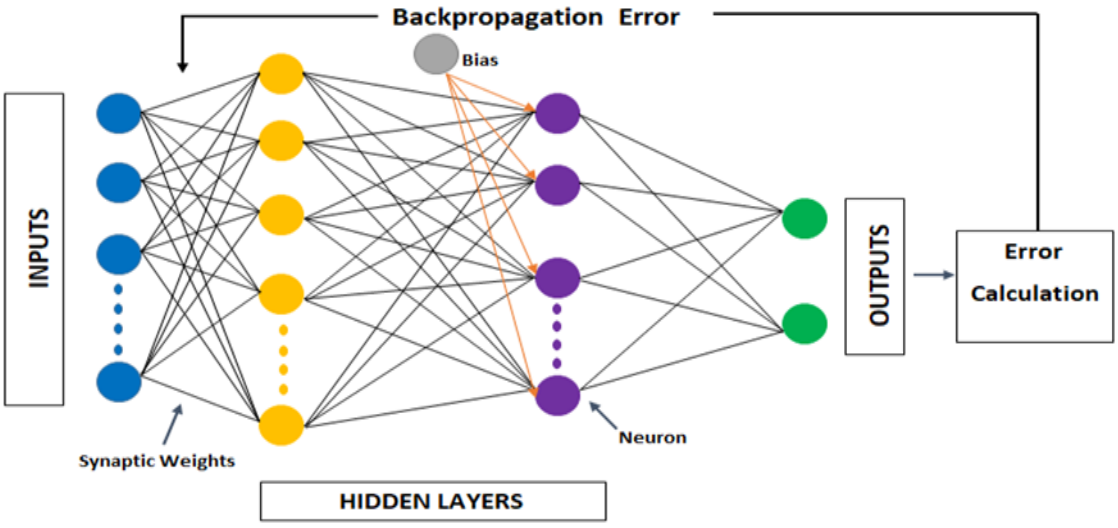

Figure 1. Example of an ANN structure

The ANNs have the capability to learn 'by example'. Here, a set of input and output variables is presented to set the rules that regularise the relationship between variables [16]. ANNs are widely used for many applications and studies because of their certain special advantages. Some of these advantages are listed as [16–23]: self-learning ability, storing information, handle with incomplete information, adaptability, real-time operation, fault tolerance ability, parallel processing capability, multiple task ability, easy implementation and low cost.

2.2. Recurrent neural networks (RNNs)

ANNs can be either feedback (recurrent) networks or feed-forward networks. RNNs are a special case of neural networks and one of the feed-forward network types. RNNs have memory, parameter sharing and tour integrity features and can learn non-linear properties of arrays with high efficiency. RNNs contain a self-connecting hidden layer and the connections between nodes form a directed graph along a temporal sequence. The basic logic in RNNs is to make predictions using sequential information. RNNs use previous steps to predict the next step RNN method has memory. While the RNNs make predictions for time step x in the future, it advances it step by step by estimating all the intermediate time steps up to that time from the data from the past periods; then, it performs the prediction for time step x using intermediate time steps. RNNs are affected by all the information learned before while making predictions. This situation can lead to information pollution in RNNs.

2.3. Long short-term memory

The LSTM deep learning algorithm is known as a RNN introduced by Hochreiter and Schmidhuber [24] to eliminate the disadvantages of the RNN architecture [25]. LSTM can also be expressed as a memory-added RNN to evaluate whether the information is useful [26]. With these features, the LSTM network is effective in capturing long-term relationships between temporarily separated data points in sequential data [27]. LSTM is recommended for sequential or time series problems as it can learn long-term dependencies with its memory transitive mechanism. The LSTM model is arranged as a chain structure [28]. However, the repeating module has a different structure. Instead of a single neural network like a standard RNN, it has four interactive layers with a unique communication method. A typical LSTM network consists of memory blocks called cells. Cell states are transferred to the next cell. The cell state is the main data flow chain that allows the data to proceed without change.

LSTM performs exceptionally in learning high-level temporal patterns with time series data, and prediction accuracy increases as the number of information increases in LSTM [29]. In the LSTM network, the data is divided into training and test data, and the network is expected to learn both long-term and short-term properties of the training data.

The memory cell of the LSTM model consists of three non-linear gate units, an input gate (Eq. 1), forget gate (Eq. 2), an output gate (Eq. 4) and memory cells (Eq. 3) [30]. The forget gate and output activation function are the most critical components of the LSTM block structure. Removing any of these significantly reduces LSTM performance. The processing functions of the gates and cells of the neural network are given below.

$$i_{\mathrm{t}} = \sigma(W_{\mathrm{xi}}X_{\mathrm{t}} + W_{\mathrm{hi}}h_{\mathrm{t-1}} + W_{\mathrm{ci}}C_{\mathrm{t-1}} + b_{\mathrm{i}}) \quad (1)$$

$$f_{\mathrm{t}} = \sigma\left(W_{\mathrm{xf}}x_{\mathrm{t}} + W_{\mathrm{hf}}h_{\mathrm{t-1}} + W_{cf}c_{\mathrm{t-1}} + b_{\mathrm{f}}\right) \quad (2)$$

$$C_{\mathrm{t}} = f_{\mathrm{t}} \odot C_{\mathrm{t-1}} + \mathrm{it} \odot \tanh\left(W_{\mathrm{xc}}X_{\mathrm{t}} + W_{\mathrm{hc}}h_{\mathrm{t-1}} + b_{\mathrm{c}}\right) \quad (3)$$

$$O_{\mathrm{t}} = \sigma\left(W_{\mathrm{x_o}}X_{\mathrm{t}} + W_{\mathrm{h_o}}h_{\mathrm{t-1}} + W_{\mathrm{CO}}C_{\mathrm{t}} + b_{\mathrm{O}}\right) \quad (4)$$

$$h_{\mathrm{t}} = O_{\mathrm{t}} \odot h(\mathrm{ct}) \quad (5)$$

where i, o, f, c, W represent the input gate, exit gate, forget gate, cell activation vector and weight matrix, respectively. The definition of a sigmoid function $\sigma(x)$ is shown in Equation 6.

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (6)$$

3. Results

In this study, the daily dam occupancy rate data between 2005 and 2021 for İstanbul is used to train the LSTM network. Figure 2 shows the daily dam occupancy rate for İstanbul for the last 15 years [31].

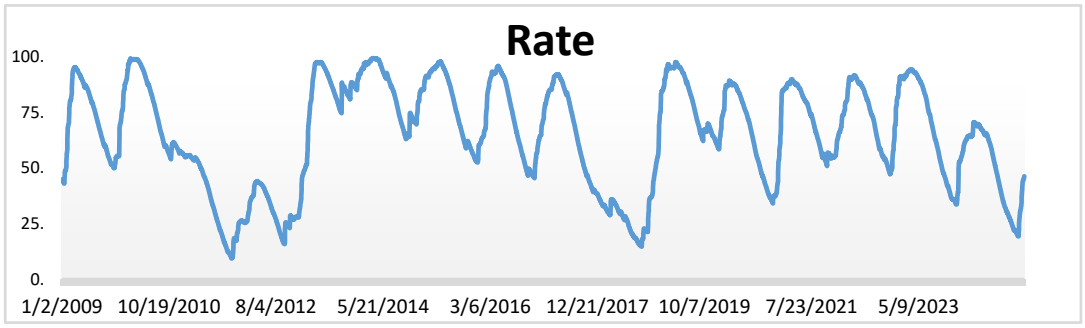

Figure 2. The daily dam occupancy rate data

The LSTM is implemented in Python by using the Keras library with the TensorFlow backend. The number of epochs is determined as 100 in the LSTM structure. 80% of the time series data is used to train the network and 20% of the data is used to test the network. Additionally, to achieve better performance the lag is analysed between 7 and 14. Besides, different numbers for LSTM units are tested. The results of the LSTM models are presented in Table 1.

TABLE 1. The LSTM results

LAG	LSTM units	RMSE	MAPE	LAG	LSTM units	RMSE	MAPE
7	32	0.906	1.266	11	32	0.490	0.499
7	64	0.704	0.877	11	64	1.064	1.361
7	128	0.434	0.386	11	128	0.653	1.022
7	256	2.635	3.664	11	256	0.510	0.696
7	512	0.586	0.658	11	512	1.655	2.598
8	32	0.387	0.325	12	32	0.620	1.036
8	64	0.384	0.325	12	64	0.402	0.317
8	128	0.439	0.561	12	128	0.450	0.476
8	256	0.466	0.650	12	256	0.381	0.289
8	512	0.509	0.573	12	512	1.279	2.077
9	32	0.411	0.339	13	32	0.569	0.895
9	64	0.472	0.528	13	64	0.414	0.448
9	128	0.411	0.348	13	128	0.385	0.303
9	256	0.455	0.529	13	256	0.659	0.655
9	512	0.466	0.601	13	512	2.284	3.698
10	32	0.565	0.725	14	32	0.515	0.590
10	64	0.436	0.363	14	64	1.146	1.823
10	128	0.400	0.296	14	128	0.703	1.046
10	256	0.424	0.459	14	256	1.180	1.619

10	512	0.443	0.412	14	512	0.387	0.296

Different error measures are used in this study to evaluate the accuracy of the proposed methodology from a variety of perspectives [32]. One of the most popular error measurements, MSE, can be calculated as follows [33]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{j=1}^{m} \left(y_j - \hat{y}_j\right)^2} \quad (7)$$

MAPE is another one of the most common measures used to determine estimation accuracy [34] (due to its features such as scale independence and interpretability [35], [36]. MAPE is calculated as [37]:

$$\mathrm{MAPE} = \frac{1}{m}\sum_{j=1}^{m} \left|\frac{y_j - \hat{y}_j}{\hat{y}_j}\right| \quad (8)$$

In this paper, we adopted RMSE and MAPE to determine the performance of our proposed model. The best performance is determined as 12 lags with 256 LSTM units for both RMSE and MAPE. After the best structure was determined, the network was trained using this structure. Figure 3 shows the training and test results obtained.

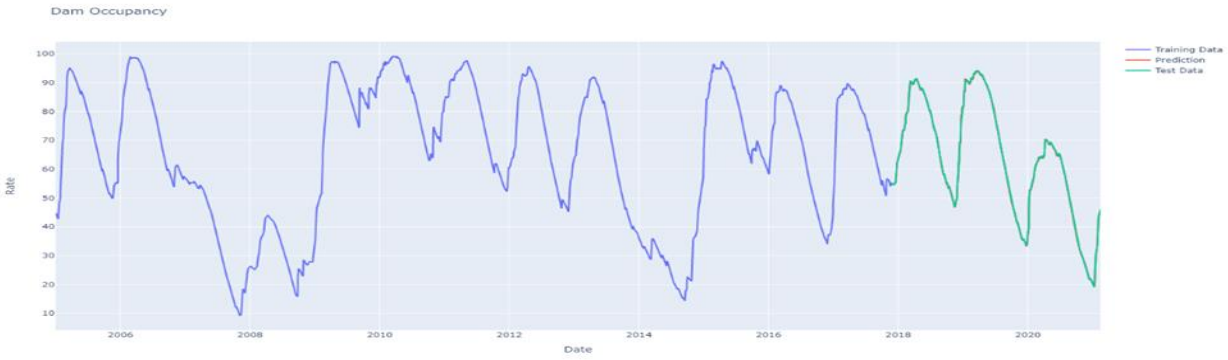

Figure 3. The training and test results of LSTM

Then, the network is then simulated and forecasts are made for the next 30 days. Figure 4 shows the forecasted values for 30 days.

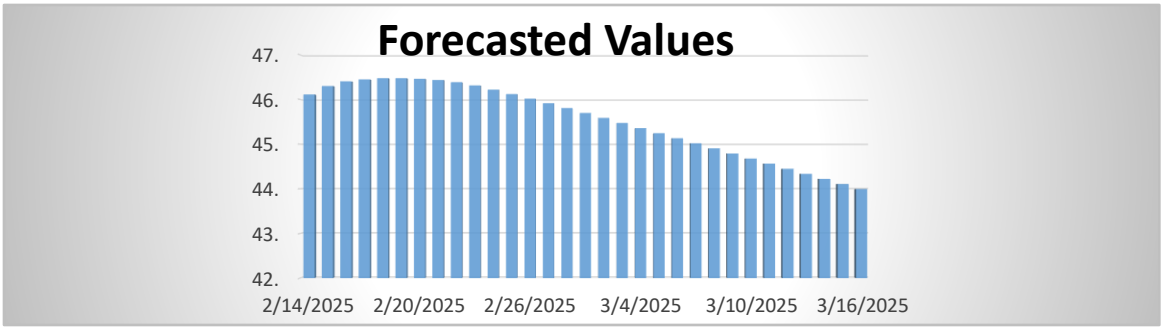

Figure 4. Forecasted values for the next 30 days

With the increase in the consumption of limited resources in the world and the effect of global warming, the occupancy levels in the dams are decreasing. Especially the changes in precipitation patterns and temperature averages affect the amount of water in the dams significantly. With this forecasting methodology, we proposed a model in which the water level in the dams can be predicted by making future predictions. In this study, as seen in the graph shown in Figure 3, it is forecasted that the water level will decrease for the following months. Thus, managers should take necessary precautions.

3.1. Comparative analysis with ARIMA

ARIMA is one of the most used techniques for parametric univariate time series modelling. ARIMA models are applied to non-stationary series but converted to stationary by difference-taking. ARIMA makes a strong assumption that future data values are linearly dependent on current and past data values, similar to other linear methods [38]. In this way, ARIMA gives high accuracy results in stationary time series forecasting. The ARIMA method uses autoregressive (AR) and moving average (MA) models. AR includes lagged terms and MA includes lagged terms on the residuals or noise [39]. ARIMA is uses the stationary time series data with no missing values. So, time series data can be modelled as stationary or can be transformed to stationary by differencing. Whether the series is stationary is tested with the Dickey–Fuller statistics [40]. Thus, the 'I' (Integrated) letter in ARIMA means that the first-order difference is applied to transform time series into stationery. The general representation of the models is ARIMA (*p*, *d*, *q*). Here, *p* and *q* are the degrees AR model and MA model, respectively, and *d* is the degree of difference. The equation to represent the ARIMA model for the time sequence Y_t is given in Equation 9. ε_t is a normal random variable white noise sequence with zero mean and variance σ^2 and *B* is the backshift operator whose effect on the Y_t can be represented as: $B^d Y_t = Y_{t-d}$.

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t \quad (9)$$

Different models are tested to achieve a better forecasting performance. The results of the ARIMA are presented in Table 2.

TABLE 2. Results of ARIMA

p	*q*	RMSE	*p*	*q*	RMSE
0	0	0.532	3	0	0.423
0	1	0.449	3	1	0.414
0	2	0.436	3	2	0.414
0	3	0.432	3	3	0.414
0	4	0.429	3	4	0.414
0	5	0.428	3	5	0.414
1	0	0.427	4	0	0.421
1	1	0.427	4	1	0.414
1	2	0.416	4	2	0.414
1	3	0.414	4	3	0.414
1	4	0.414	4	4	0.414
1	5	0.414	4	5	0.414
2	0	0.427	5	0	0.420
2	1	0.416	5	1	0.414
2	2	0.414	5	2	0.414
2	3	0.414	5	3	0.414
2	4	0.411	5	4	0.414
2	5	0.414	5	5	0.413

The best results with respect to MSE are determined as the (2, 1, 4) model. The best model is determined with a 0.411 RMSE value. The best LSTM network is determined with 0.381 as mentioned before. So, LSTM shows better forecasting performance than ARIMA.

4. Discussion

This study aimed to estimate the dam occupancy rate by using the LSTM method. For this purpose, the occupancy rates of the dams in Istanbul are discussed. A time series LSTM model is developed and trained using data on daily occupancy rates between 2005 and 2021. Different LSTM models have been developed to obtain higher forecasting performance. With the help of the best model determined, the next 30 days are estimated with a 0.381 RMSE error. The obtained results were compared with ARIMA on the same dataset. As a result, it was seen that the LSTM method was more successful than ARIMA in estimating daily dam occupancy.

In parallel with the increase in the world population, the water need is also increasing. Due to the fact that the main source of water is precipitation and these precipitations are not regular, and especially as a result of events such as climate change, the decrease in precipitation amounts can put countries in a very hard situation [41]. Therefore, it is very important to determine the dam occupancy rates and to make predictions for the future.

5. Conclusion

In conclusion, sustainable water consumption should be ensured all over the world. In this period, where water resources are decreasing and the importance of precipitation is increasing, studies on rainwater storage (rain harvesting) and active use will provide a more sustainable approach to eliminate the problems in water need. Effective and sustainable use of water resources should be ensured by determining the pressure on water resources with domestic and industrial water use analysis. Finally, even in cases where the dam occupancy rate is 100%, the awareness of the efficient and sparing use of water should continue.

In the future study of the proposed LSTM model, the data set will be expanded and replicated with the obtained data. With the increase in the number of data, the model will be retested and the increase in the success rate will be monitored. In addition, the proposed model will be compared with different time series estimation methods.

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