An Experimental Design Frame for Active Dam Reserve Ratio Forecasting Using Neural Networks

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Abstract. Today, one of the important and frequently spoken problems of the world is global warming and climate change. Due to these subjects, water drought and scarcity may become a trouble in the future. To prevent these problems, scientific studies are being carried out, solutions are being recommended and preventive applications are developing. In this study, to examine and foresee the decrease in water resources, active dam reserve ratio is considered and estimated using artificial neural networks. Time series analysis is performed using the active dam reserve ratio of Guzelhisar Dam, located in city of Izmir, Turkiye. Active reserve ratio data between 2012 and 2023 are considered on monthly basis. Since the data set displays high seasonality, this cyclic effect is extracted out of the data to get non-seasonal series. Then, using non-linear autoregressive artificial neural network method, both original seasonal data and non-seasonal data is forecasted. Three parameters are considered for neural network models: Input neurons, middle layer neurons and backpropagation algorithm. Results are compared according to mean absolute percent error. In the result, values of parameters to give minimum error are presented. In addition, performances of backpropagation algorithms are compared.

1 Introduction

In general, it is known that nearly 70% of the earth surface is coated water. However, only 2.5% of this water makes up freshwater resources. In addition, vast amount of freshwater resources are located in glaciers and at inaccessible depths. Accessible, usable clean water resources are only 0.1% of freshwater resources in the world [1]. The annual amount of usable water per person is calculated for countries in the world and is divided into three classes accordingly: Water scarcity countries (annual amount per person is below 1000 tons), water stress countries (annual amount per person is between 1000 and 1700 tons) and water rich countries (annual amount per person is more than 1700 tons). In Turkiye, the amount of water per person per year is nearly 1555 tons. For this reason, Turkiye is included in the class of countries experiencing water stress [2].

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Due to the variability of underground and surface water resources, dams are becoming more important. Since water resources are collected in dams, they are one of the major factors to deal with water scarcity. Considering all these effects, dam active reserve ratio forecasting is considered in this study.

Studies on dam reserves appear in the literature in two categories. The first category includes studies considering amount of water entering dams. The second category includes studies addressing the dam reserve level.

Some of the forecasting studies on the amount of water entering dams belong to Altin [3], Bae et. al. [4], Santos et. al. [5], Hadiyan et. al. [6], Herbert et. al. [7] and Yousefi et. al. [8]. Among these, some studies consider the problem in the form of a time series, and some studies have examined the amount of water entering the dam depending on other meteorological variables (precipitation amount, air temperatures, wind speed, etc.). The methods used include artificial neural networks (ANN), deep learning models, Box-Jenkins models.

On the other hand, among the studies addressing the dam reserve level Akgul and Cetin [9], Zhang et al. [10], Aslan et al. [11], Temiz et al. [12], Stefanon et al. [13] and Filiz et. al. [14] exist. Methods used in these studies include ANN, level estimation with remote sensing systems, simulation, fuzzy inference methods and regression models.

In this study, active reserve ratio of Guzelhisar Dam located in Izmir, Turkiye is handled. Monthly active reserve ratio values from 2012-January to 2023-December are considered as a time series. In literature, some of the studies showing successful ANN results in timeseries forecasting are Semenoglou et. al [15], Egrioglu et. al. [16] and Ari and Ozfirat [17]. Therefore, ANN modelling is used in this study by developing non-linear autoregressive instance of ANN. The three input parameters of the model, namely input neuron number, mid-layer neuron number and backpropagation algorithm, are chosen to be examined. An experimental design frame is developed to test the effects of these three factors. Design points are compared according to mean absolute percent error (MAPE). The design point with the minimum MAPE value is revealed.

2 Case study

Guzelhisar Dam is one of the major dams supplying water to the city of Izmir, Turkiye. Active reserve ratio between 2012 and 2023 is considered on monthly basis. In Figure 1 [18], the data are graphed.

The average active reserve ratio over the 12 years is found to be 72.84%. As seen from Figure 1, data show high seasonality. Reserve ratio is at minimum levels during October, November and December and it is at maximum levels during March, April and May. Variance of whole data is found to be 141.16. Therefore, firstly, seasonal effect is desired to be removed from the data.

To remove seasonal effect, length of a season should be determined. A regular season may be out of 12 months (yearly basis). However, looking at the first three years data (2012-2013-2014 from Figure 1), it can be seen that a season for this case may be longer than a year. Therefore, seasonal decomposition is made using four different season length. The first one considers a season to be 12 months. Then, 24 months, 36 months and 48 months season length are considered. For each case, seasonal factors are computed. Seasonal effect is extracted by dividing data points to seasonal factors. Finally, variance of non-seasonal series is computed for each case. The variances of each case can be seen in Table 1 below.

Table 1. Variances of non-seasonal series.

Length of one season in removing seasonal effect	Variance
12 months	95.65
24 Months	95.51
36 Months	66.44
48 months	87.17

Considering Table 1, it can be said that all seasonal decomposition methods have decreased the variance in a recognizable way compared to the original data series. In addition, seasonal decomposition over 36 months have provided the minimum variance as it has decreased variability nearly by 53%. Therefore, seasonal decomposition over 36 months is used for forecasting. In Figure 1, original series and non-seasonal series can be seen comparatively.

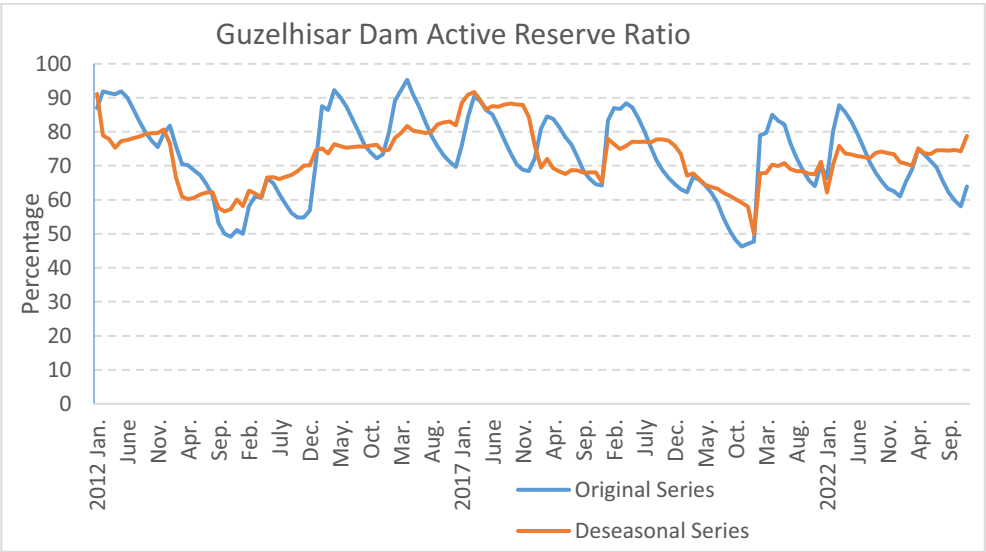

Fig. 1. Active reserve ratio of Guzelhisar Dam between 2012 and 2023 (monthly basis) [18] and non-seasonal reserve ratio

3 Developing experimental design frame

In a neural network model, there are number of parameters. Out of these parameters, input neurons, hidden layer neurons, and backpropagation algorithm are considered for the experimental design frame. The parameters and the tested levels are given in Table 2.

Table 2. Experimental Design Frame

Input Neurons	Hidden Layer Neurons	Backpropagation Algorithm	Test Points
2 up to 15 24, 36, 48	1..15	Levenberg-Marquardt (LM) Bayesian regularization (BR)	510

Active reserve ratio forecasting is made through a time series approach. Therefore, inputs are the reserve ratio values belonging to previous periods. In the design frame (Table 2), number of input neurons is tested from two input neurons (representing the two periods preceding the forecasted period), to 15 input neurons (representing the 15 periods before the estimated period). Furthermore, since the data has a high seasonal effect, 24, 36 and 48 input neurons are also tested in the design frame. In the hidden layer, from one neuron up to 15 neurons are considered. Two different backpropagation algorithms are tried. These are Levenberg-Marquardt (LM) and Bayesian regularization (BR) algorithms respectively. In summary, 510 design points are experimented using ANN approach for forecasting active reserve ratio.

This design frame is applied using the non-seasonal series given in Figure 1. Furthermore, the design frame is also applied using the original series, which shows high seasonal effect. Since ANN approach is advantageous to capture nonlinear relations, it is also possible to see the performance on seasonal time series forecasting. By this way, the results are also compared for seasonal and non-seasonal series.

4 Artificial neural network approach

In the ANN approach, three-layer network is employed. These are input layer, one hidden layer (middle layer between the input and output) and output layer. Input layer neurons in the matches with the preceding period reserve ratios. Number of neurons in the input and hidden layers are tested in the experimental design. In the output layer, there exists only one neuron representing the forecasted period reserve ratio.

In data processing step of ANN, all data are normalized between 0 and 1. Training and validation data are set to be 75% (15% of this part is validation set), test data are set to be 25% (last 36 months) of the whole data respectively. Then, a nonlinear autoregressive NN model is used to experiment the 510 design points defined in Table 2 both for seasonal and non-seasonal reserve ratio data (Figure 1). MAPE levels are used for benchmarking. The values of parameters with best performance in both seasonal and non-seasonal cases can be seen in Table 3 below.

Table 3. Minimum MAPE obtained in experimental design

	Input Neurons	**Hidden Layer Neurons**	**Backpropagation Alg.**	**MAPE**
Seasonal Series	9	10	LM	4.19%
	14	2	BR	4.42%
Non-seasonal Series	**3**	**3**	**LM**	**3.20%**
	2	2	BR	3.26%

From Table 3, minimum MAPE value is 3.20% which is obtained using non-seasonal series with LM backpropagation algorithm, three input neurons and three hidden layer neurons. This means, active reserve ratio of Guzelhisar Dam can be forecasted with 3.20% error using the suggested network which is a significantly beneficial error level. In addition, the other three points in Table 3 also obtained very small MAPE levels. This shows that ANN model used in the study is quite successful to capture the relations in both seasonal and non-seasonal time series and forecast the future values. The forecasted reserve ratios provided by these four points (given in Table 3) are presented in Figure 2.

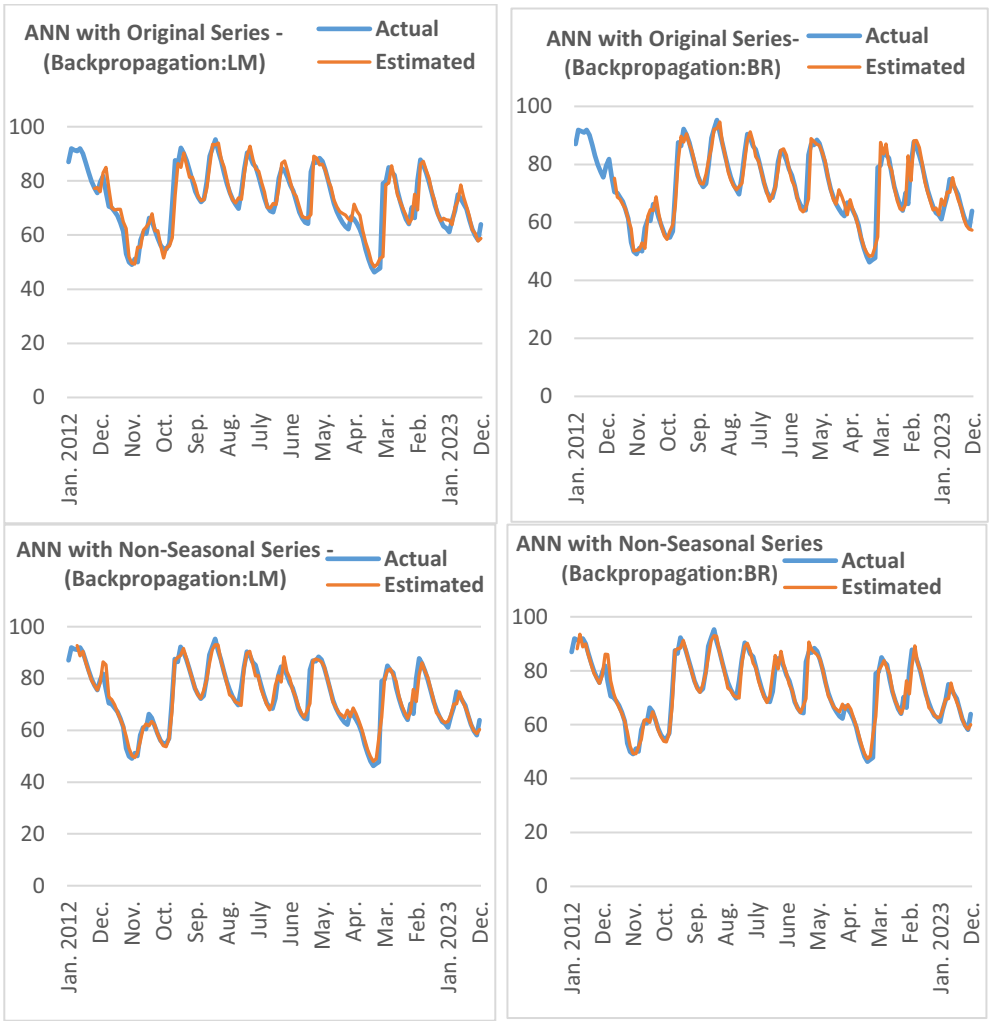

Fig. 2. Estimated reserve ratio by ANN compared to actual reserve ratio.

All four models provide very close forecasts (Figure 2) to real data points. However, the model with minimum MAPE (Table 3) is used to forecast future active reserve ratio of Guzelhisar Dam (Table 4). Although cyclic effect is removed and seasonal series is smoothed, it is seen that the forecasts are not directly affected by this situation and continue the three years fluctuation as seen from the Table 4 when April (highest ratio month) and November (lowest ratio month) are examined. This shows that ANN works realistically and in depth.

Table 4. Future estimates

	Estimated Active Reserve Ratio	**Estimated Active Reserve Ratio**
	Apr. (Highest Season)	**Nov. (Lowest Season)**
2025	92.22	67.87
2026	78.82	61.91
2027	95.57	75.03

The results are further analysed considering not only the minimum but also the average MAPE values of all design points. The average MAPE of all design points using the seasonal and non-seasonal series are found to be 7.32% and 5.14% respectively. Although they are close values, forecasting after removing the seasonal effect obtains smaller MAPE values and it can be suggested. In addition, average MAPE values according to backpropagation algorithm, according to no. of input layer neurons, according to no. of mid-layer neurons are presented in Figures 3, 4 and 5 respectively.

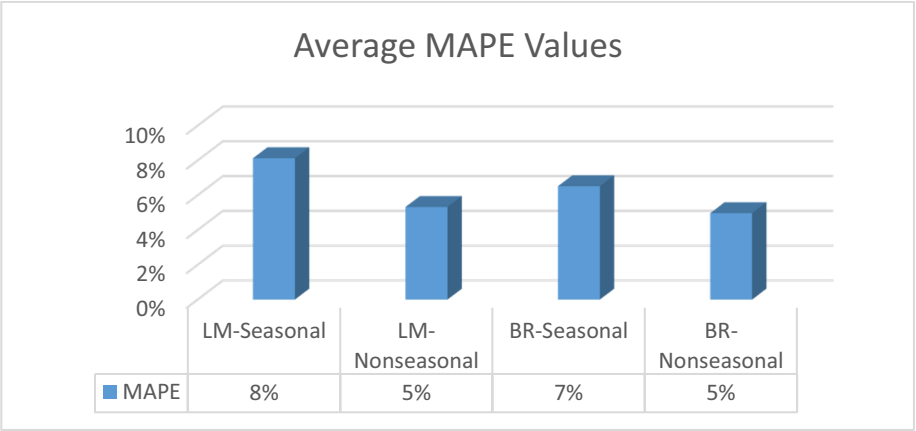

Fig. 3. MAPE values of ANN model according to seasonality and backpropagation algorithm.

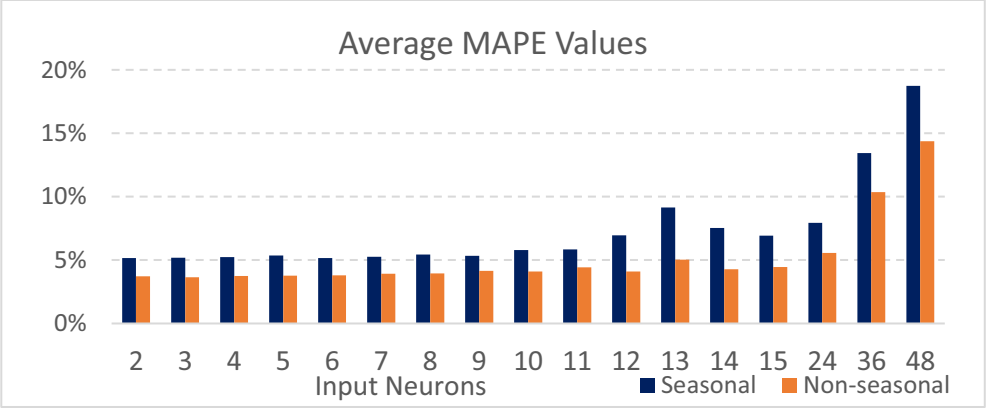

Fig. 4. MAPE values of ANN model according to number of input neurons.

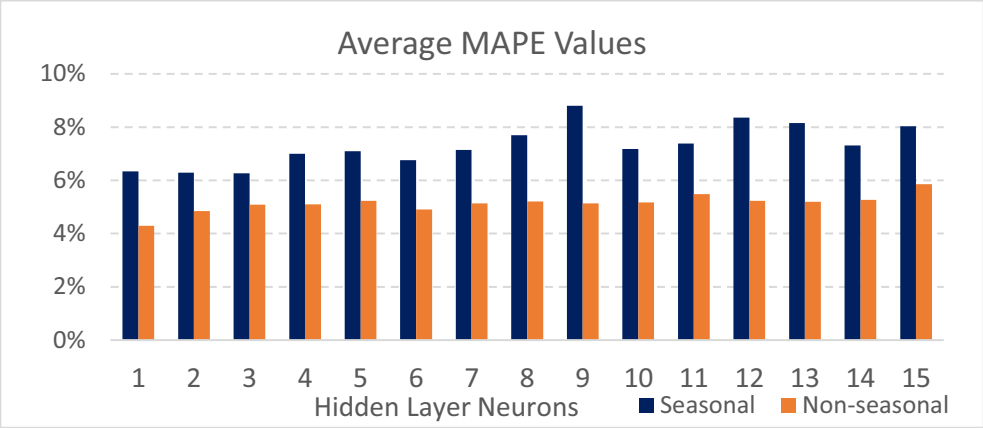

Fig. 5. MAPE values of ANN model according to number of hidden layer neurons.

Looking at Figure 3, it is seen that the non-seasonal series have the lowest average MAPE, and when examined in terms of the backpropagation algorithm, both algorithms are rather close to each other. From Figure 4, it is seen that there has not been much change in MAPE within 2 input neurons to 11 input neurons. However, there is a gradual increase in MAPE from 12 input neurons to 48 input neurons. From Figure 5, in non-seasonal series, it can be seen that, there is not much change in MAPE between different number of neurons. For seasonal series, when no. of hidden layer neurons is more than 3, MAPE is greater. In addition, in all three figures, average MAPE values are smaller in non-seasonal series compared to seasonal series.

5 Conclusion

Fresh water is a vital factor for life. So, consumption, storage and management of fresh water are getting more important with global warming and climate change issues. Dams are major ways to collect, keep and supply fresh water. In this study, active reserve ratio of a major dam in Izmir, Turkiye is considered. Firstly, cyclic effect, which indicates seasonality, is taken-off from data to get non-seasonal series. A non-linear autoregressive ANN model is used to estimate active reserve ratio. The ANN model is experimented on three different factors: input layer neurons, mid-layer neurons and backpropagation algorithm. 510 design points are examined both for original data series and non-seasonal series. Finally, design points providing minimum MAPE values are used to forecast future active reserve ratio for the dam. By interpreting the results, it can be said that by removing seasonal effect from the data, MAPE values are decreased, and neural network model performance is increased.

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