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Gap Filling of Daily Sea Levels by Artificial Neural Networks

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ABSTRACT: In the recent years, intelligent methods as artificial neural networks are successfully applied for data analysis from different fields of the geosciences. One of the encountered practical problems is the availability of gaps in the time series that prevent their comprehensive usage for the scientific and practical purposes. The article briefly describes two types of the artificial neural network (ANN) architectures - Feed-Forward Backpropagation (FFBP) and recurrent Echo state network (ESN). In some cases, the ANN can be used as an alternative on the traditional methods, to fill in missing values in the time series. We have been conducted several experiments to fill the missing values of daily sea levels spanning a 5-years period using both ANN architectures. A multiple linear regression for the same purpose has been also applied. The sea level data are derived from the records of the tide gauge Burgas, which is located on the western Black Sea coast. The achieved results have shown that the performance of ANN models is better than that of the classical one and they are very promising for the real-time interpolation of missing data in the time series.

1 INTRODUCTION

The integration of various databases is a prerequisite for studying and predicting different Earth's processes, like climate changes, sea level rise, etc. Further analysis and modeling of the natural phenomena suggest an updating, harmonization and standardizing of the various measured parameters for the preparation of scientifically based assessments and forecasts. This requires the available primary measurements and preliminary analyzed data to be subjected to a qualitative and quantitative check. Recent advances in processing of the large amounts of data concern the developing of algorithms to extract the hidden and potentially useful knowledge from them, suggesting that they are complete and reliable.

One common problem in the time series analysis is the presence of gaps (a sequence of missing values or omitted observations) that disrupts or makes it impossible to use them for research and practical purposes. In practice, different mathematical models and methods for filling of ("recovery") missing values are applied. Often, when these values are for a short interval, the linear interpolation is enough. Commonly used methods for reconstruction of the missing values in time series are:

1 Substitution by the mean value - new information is not added to the time series as the Root Mean Square Error (RMSE) is reduced;
2 Single linear, multiple linear or nonlinear regression, with which the available information is accounted, the dimensionality of the sample is increased and the RMSE is reduced;
3 Multiple filling, the so-called Monte Carlo algorithms with Markov chains in which the missing value is filled with the estimated size values;

4 Kalman filter - a recursive two-step method. It allows processing of time series on the principle of prediction-correction, etc.

If there is a long sequence of missing values, the method used to fill gaps need to be chosen very carefully due to its effect on the sub-sequential analysis of time series. Any method that can be used in such case has its advantages and disadvantages. Sometimes, when missing data are not rare and they are in different segments of the time series, a suitable compromise between computational speed and quality of results has to be made. The choice of procedure depends mainly on the properties of time series and the main purpose of their analysis. Comparison of different fill-in methods of the missing values in time series are presented in (Dergachev et al., 2001; Kondrashov & Ghil, 2006; Moffat et al., 2007; Musial et al., 2011).

Artificial neural networks (ANN), as innovative approach greatly enhanced the opportunities for analysis and treatment of information because they have less restrictive requirements with respect to available knowledge about the character of relationships among processed data, functional models, type of distribution, etc. They provide a rich, powerful and robust nonparametric modeling framework with proven and potential applications in many fields of the sciences. The advantages of ANN encouraged many researchers to use the neural network models in broad spectrum of real-world applications. Sometimes, the ANNs are a better alternative, either substitutive or complementary, to the traditional computational schemes for solving many scientific and engineering problems (e.g., Wenzel & Schröter, 2010; Pashova & Popova, 2011). Multilayer ANN with feed forward connections that are trained using the backpropagation algorithm (Feed-Forward Back-propagation Network - FFBP) is one of the first neural architectures that are widely used for modeling of nonlinear dependences (Rumelhart and Clelland, 1986; Allende et al., 2002). For modeling of dynamic dependences, however, it is often needed to use recurrent ANN (RNN). One such modern architecture, called "echo" (Echo State Networks - ESN) offers simplified training algorithm and become widely used for studying the nonlinear dynamical dependencies (Jaeger, 2003; Lukosevicius & Jaeger, 2009; Koprinkova-Hristova et al., 2011). These ANNs are recognized as the best models for time series analysis and prediction (Zang & Behera, 2012).

The near-shore sea level variations are of great importance for studying the relative sea level change, practical realization of the height reference surface in geodesy, many coastal engineering applications, etc. These variations are registered by tide gauges, whose continuous registrations of the sea level represent a superposition of many stochastic and nonlinear processes. Missing observations in the time series of such type of data are very common. This requires the application of various methods of interpolation and/or extrapolation, which allow filling the incomplete time series with necessary accuracy for further analysis. The article presents the results obtained after applying two types of the artificial neural networks and a multiple linear regression (MLR) for filling gaps in the time series of daily sea levels. Data from the tide gauge in Burgas, which is located on the western Black Sea coast spanning the period 1985 - 1989 are analyzed to model the maximum, mean and minimum sea levels. Comparison of the performances of the two ANN and MLR models for filling gaps in the daily sea levels is also presented.

2 ARTIFICIAL NEURAL NETWORK MODELS USED IN THE STUDY

Since the sea level variations can be represent as nonlinear dynamic process, ANN architectures were considered as appropriate candidates for its modeling. Application of different approaches of ANNs applications for the sea level analysis can be seen in (Tsai et al., 2009; Pashova & Popova, 2011). There are several network architectures, which can be used for modeling and filling the missing values of the sea levels. A multiple linear regression is another method often used for filling the missing values in time series. In this study we applied FFBP and ESN architectures in comparison with MLR model. The ANNs and MLR performance were assessed in terms of the root mean square error (RMSE) and the correlation coefficient R (or coefficient of determination R^2).

2.1 *Feed forward back-propagation (FFBP) ANN*

Feed-forward (FF) or layered ANNs are one of the first neural network architectures with typical structure is shown on Figure 1. They consist of several consecutive layers of nonlinear units called neurons. Connections are allowed only between neighbor layers directed from the first (input) to the last (output) layer. The specification of FF model structure includes a determination of the number of the input and the output neurons (depending on the specifics of the function that will be modeled); a choice of the number of hidden layers and the number of neurons in each one of them, and of the non-linear processing functions of all neurons (usually a kind of sigmoid-shaped nonlinearity). "Neurons" in the first layer, showed by squares, are not typical non-linear units. They only distribute the input vector to the first hidden layer (marked by circles on the Figure 1). It is well known that usually one hidden layer is sufficient to model any complex nonlinear dependence between the input and output vector. The training algorithm of this type of neural networks is usually performed applying the error backpropagation (BP), from which their popular name has been shortened to FFBP.

The output of each hidden layer of neurons is calculated by nonlinear dependence of the linear combination of outputs of the neurons in the previous hidden layer:

$$x_j(t) = f\left(W_{ij} x_i(t)\right) \tag{1}$$

For the input and the first hidden layer dependences are:

$$\begin{aligned} x_1(t) &= \left[in(t) \quad in(t-\Delta t) \quad \cdots \quad in(t-n\Delta t)\right]^T \\ x_2(t) &= f\left(W_{in} x_1(t)\right) \end{aligned} \tag{2}$$

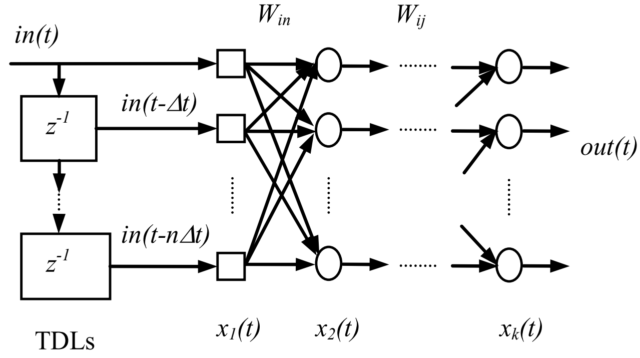


Figure 1. Neural network with feed-forward back-propagation (FFBP) architecture.

Here t denotes a discrete moment in time, Δt is (sampling) discretization step and f is a monotonically increasing function, usually nonlinear sigmoid (logistic sigmoid or hyperbolic tangent) for the hidden layers and usually a linear function for the output layer of the network.

This architecture represents a static dependence model between its input and output vectors of the network. To be able to model a dynamical process' dependence, lines of time delay elements (briefly TDL) are inserted at the network input, that keep "memory" of the past states of the modeled process.

2.2 *Echo state network (ESN)*

Echo state networks (ESN) are a relatively new class of RNNs that belong to the so called "reservoir" approach (Lukosevicius & Jaeger, 2009). The main idea of this approach consists in a generating of rich "reservoir" of dynamic neurons with nonlinear activation functions and with recurrent connections between them. The network output is calculated as a linear combination between current states of the "reservoir" neurons. Training of this type of architecture is simplified by setting the parameters of the linear combination (i.e. the weights of the connections between the "reservoir" and the output) using the least squares algorithm. Hence the RNN training is significantly faster and the application of the recursive version of training algorithm allows on-line training too.

Echo State Network (Jaeger, 2003) is a simplified version of the "reservoir" architecture with sigmoid output nonlinearity of the "reservoir" neurons (usually hyperbolic tangens). Figure 2 shows the structure of ESN network. Its output layer calculates a linear combination between the current state of the network input *in(t)* and the "reservoir" *X(t)* as follows:

$$out(t) = W_{out} \begin{bmatrix} in(t) \\ X(t) \end{bmatrix} \quad (3)$$

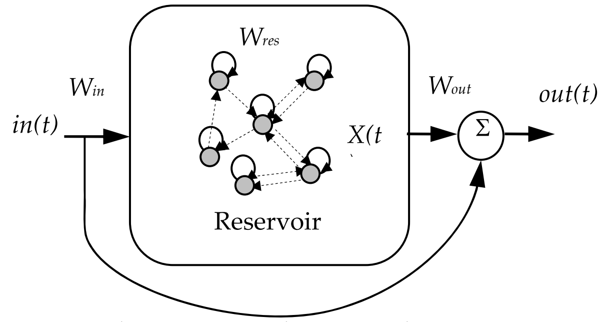


Figure 2. Echo state network (ESN) architecture.

W_{out} is $n_{out} \times (n_{in} + n_X)$ dimensional matrix, where n_{out}, n_{in} and n_X are the dimensions of the vectors *out*, *in* and *X* respectively. The current state of "reservoir" neurons depends on their previous state and on the current network input:

$$X(t) = \tanh\left(W_{in} in(t) + W_{res} X(t - \Delta t)\right) \quad (4)$$

Here W_{in} and W_{res} are matrices containing the weights of connections at the input and inside the "reservoir" with corresponding dimensions $n_{in} \times n_X$ and $n_X \times n_X$. These matrices are randomly generated and are not a subject to training. The recurrent connections inside the "reservoir" create an effect of "memory" about the network past states, that makes such architecture a proper candidate for the modeling of dynamic dependences. Its advantage in comparison to the static layered architectures with TDL neural networks at the input is that there is no necessity to have a priory information about the needed number of TDLs for a particular process that will be modeled.

3 APPLICATION OF DIFFERENT MODELS FOR FILLING UP MISSING DAILY SEA LEVELS

3.1 *Handling incomplete time series of sea levels*

Forecasting the sea level variations in real time is an important activity in the design of coastal engineering structures, decision-making related to navigation of vessels and the construction of offshore platforms in the Black Sea. The main sources of information for studying these variations are the continually operated tide gauges established on the sea coasts. Such information is urgently needed to support the development, calibration and improvement the operational capacity of the integrated systems for forecasting and early warning of dangerous natural phenomena in the sea and coastal areas. Continuous monitoring of the sea level along the Bulgarian Black Sea coast is carried out since 1928 (Pashova & Popova, 2011). Since then, the data on average daily, monthly and annual values of the sea level contain gaps with different time duration. The presence of missing data is due to various factors: technical reasons, failure of recording equipment; interruption of the registration due to defective recording equipment; misuse and incorrect use of records by the field staff; etc. In extreme events like storm surge or high waves the continuous registrations are also terminated due to technical limitations of equipment.

To fill gaps in the time series of sea level the tidal regime in the Black Sea has to be known a priori. The missing values for different time periods are completed for scientific and applied research purposes. Restoration of gaps in observational data used for modeling and forecasting of the natural phenomena should be made at the earliest possible stage of the processing of the original measurements. The classical methods for modeling of the sea level fluctuations (e.g. harmonic analysis) cannot always represent the complex time-varying meteorological effects on sea level, which are produced by weather conditions like wind, atmospheric pressure, rainfall, etc. Therefore, adaptation of the models in real-time is needed, in order to account better for the time-varying environmental changes.

3.2 *FFBP and ESN*

The structure of FFBP neural network model was chosen after repeated testing for the optimal choice of parameters (Pashova and Popova, 2011). For each variable (daily maximum H_max, mean H_mean or minimum H_min sea levels) an individual FFBP model is trained. Increasing the number of neurons and the number of delays requires more computation, and this has a tendency to overfit the data when the numbers are set too high, but it allows the ANN to solve more complicated problems. After several tests, the best number of tapped delay lines (TDLs) is determined to be 6 based on the autocorrelation function of the daily values. Hence the input vector for each model is consisted of the previous 7 daily values of the modeled variable, i. e. its size is 7. The output of the network predicts its current value, i.e. its size is 1. The number of neurons in the rest of layers is determined applying the criteria of the minimum squared error and the highest correlation coefficient between the observed and modeling daily sea levels. The number of neurons in the hidden layer was chosen based on the multiple reruns of different structures of the FFBP models (Pashova & Popova, 2011). One hidden layer is found to be appropriate to model sea levels and the optimal number of neurons in it was found to be 15 neurons. Hence our FFBP model has 7:15:1 architecture. The Matlab programming environment is used for training FFBP models (Demuth & Beale, 2000; Gilat, 2011). The standard training procedure divides the time series randomly into 3 parts with ratio 70:15:15% for training, testing and verification respectively. Training is done with the Levenberg-Marquardt algorithm, which has the fastest convergence for FFBP networks. The criterion for stopping the iterations is when the error of the sample for verification began to increase. This model, evaluation criteria of its applicability and the main characteristics of the time series of daily sea levels and factors influencing the sea level change are described in detail in previous studies presented in (Pashova & Popova, 2011; Pashova et al., 2012).

The structure of the ESN model also contains 15 neurons in the "reservoir" to be comparable with the FFBP ANN model. It was find that the difference in the prediction results of sea level data between 15 and 100 neurons ware insignificant. To evaluate the effect of "memory" of the "reservoir" two versions of ESN model was trained - with 1 input and with 7 inputs respectively for one step back in time and for 7 steps back in time for the modeled daily sea values of the three variables. The training of the ESN model is made using free available Matlab toolbox (http://www.reservoir-computing.org/software). In comparison with the FFBP model the time series are divided into training and test samples in a ratio of 85:15%. Since the ESN was trained by a non-iterative procedure that applies linear regression with a single representation of each element of the teaching sample, there is no need to define stopping criteria for its training.

In the case of batch training of ESN, the all training data for model input are presented consecutively to the network and the corresponding output is calculated and collected. The weights of the output connections are determined by solving linear regression equation in one step using all network input/output data. Hence the reservoir state “evolves” with each new data as if the “gaps” are missing. In the case of on-line training, each input of the training data is presented to the network. The corresponding output is calculated and the output weights are adjusted using recursive least squares (RLS) method. If “data gap” is reached, the predicted by model output is used to replace the missing data at model input. In this way the reservoir state depends on the ESN model predictions and evolves in dependence on the accumulated by the current moment knowledge about the process dynamics. This will allows more “realistic” predictions, especially for longer data gaps.

The outcomes after training of both types of ANN models are directly dependent on the initial conditions therefore 20 ESN and FFBP models were generated and trained. The averaged mean squared errors (MSE) of the simulation with all the data and coefficients of regression R, as well as errors MSE_b and regression coefficients R_b of the best-trained models are presented in Table 1.

3.3 *MLR model*

The filling of the missing values of daily sea levels for the same period for three time series of study have been completed by the multiple linear regressions (MLR using the following model:

$$\hat{y}(t+1) = \alpha_1 \bar{y}(t) + \alpha_2 y(t-1) + \ldots + \alpha_{s+1} y(t-s) \qquad (5)$$

where $\hat{y}(t+1)$ is the predicted sea level by the MLR model, which will be filled instead the missing daily value, $\bar{y}(t)$ is the current daily mean, and s is a number of backward steps like in the case of ANN models. The predicted missing value is a linear combination of several independent variables - the mean daily sea level and several daily values before it. The unknown coefficients $\alpha_1, \alpha_2, \ldots, \alpha_{s+1}$ are determined initially using all available values for the daily sea levels for a 5-year period.

For filling of the missing daily values with different length of gaps in the time series for all the model types we proceed as follow: if the missing values are several consecutive ones, than each predicted by a model missing value is included as known in the line of the 6 TDLs values used to predict the next one; this operation is repeated moving forward with one step while all the consistently missing values are filled. This process continues until the completion of all missing values for the relevant period.

For all the models the least squares error was a criterion that was minimized by the respective training procedure used to estimate the unknown parameters of the corresponding model. The MATLAB codes are written to train and to test each ANN and MLR model's representation.

4 RESULTS AND DISCUSSION

In this study, the time series of observations of the mean daily sea level is seen as a sequence of discrete values trough regular intervals with the sampling step $\Delta t = 1\,day$. Here the daily maximum H_max, mean H_mean and minimum H_min sea levels are modeled, which are determined with millimeter precision relatively to the "zero" point of the tide gauge Burgas. To test the applicability of the ANN to fill the missing values in the time series of daily sea levels, the period from 1January 1985 to 31 December 1989 is selected. The required numbers of the values in the three time series is totally 1826, 151 (8.3%) of which are missing. Most of the data gaps include time periods from 1 to 3-4 days up to 1 to 3 weeks for a five-year analyzed period.

The results for the full 5-years period of study are presented graphically on Fig. 1. After that for two periods, covering two and three weeks with missing values, the results are presented in details. On Fig. 2 (a, h) these periods are between 1050 and 1110 day and between 1590 and 1660 day of observations respectively. The observed daily sea levels, the modeled, and the predicted by the three models are depicted in details correspondingly for both periods. In Table 1 the estimates of the MSE and correlation coefficient R for all the models are given. These estimates are obtained as results after filling of the missing sea levels in the time series.

The mean value of MSE obtained from averaging of the MSEs of all 20 trained FFBP models and the MSE_b of the best model differ by 0.2-0.4. The corresponding difference between the mean MSE value and the MSE_b of the best obtained ESN model is an order of magnitude smaller. This can be explained by the different algorithms used for training of the two neural networks. While the probability of falling into a local minimum of the gradient algorithm used for FFBP model is great, for the training of ESN models a one-step linear regression is used. Although the generation of "reservoir" is randomly, for all ESN models the similar results are received. The best ones of both ANN models were used to fill in the missing daily sea levels at the three time series.

Comparatively lower accuracy is obtained for online trained ESN model as can be seen in Table 1. This can be explained with the real time training of the network that uses previous predications of the model for next training steps. However, the achieved accuracy is still enough for practical purposes. Besides the on-line procedure has the advantage to train the model in real time with significantly less computational resource compared to the other models. The obtained results for online trained ESN model are very promising for practical applications taking into account the need of real time prediction of sea level variations under the extreme weather conditions. This advantage can be used for modeling and predicting the sea levels with a smaller sampling step (e.g. several minutes), which is crucial in forecasting the coastal storm processes.

The comparison of the obtained estimates of the MSE of FFBP, ESN and MLR models shows that the correlation coefficients differ by ~ 0.05 from the previous work (Pashova et al., 2012). This can be explained by the nature of the modeled process, the volume and the location of missing values in the sample of daily sea levels.

The resulting averaged values of MSE of the 20 trained FFBP models in the previous work (Pashova & Popova, 2011) was for 2-year period while the data in this study refer to the 5-year period 1985-1989. The sample size for the two periods differs; respectively the averaged mean square errors in training of the FFBP neural networks are also different. When a large volume of data is used for training, the generalization ability of the ANN model increases, although the RMSE could increases. This means that the model is able to predict with high accuracy new values for which the network is not preliminary trained.

Comparing the graphs and estimation criteria presented in Table 1, we can make the inferences that:

– The phenomenon of change in daily maximum, mean and minimum sea levels is nonlinear, and both types of ANN architectures can model well this non-linear process. The estimates of the MSE and R values are close, but better statistical estimates are obtained using the ESN neural networks with nTDLs = 6. From numerous experiments with both architectures it becomes clear that the errors of predicted daily sea levels vary from 1 to 8%, and the achieved accuracy in mm is sufficient for prognostic purposes in both cases;
– The trained ESN models with nTDLs = 6 provide forecasting the missed values in the three time series with ~ 8% higher accuracy than FFBP and ESN with nTDLs = 0;
– The MSE of MLR model has similar values as those of on-line trained ESN model. Its correlation coefficient R is the best for H_max in comparison with all other modes. But, for H_mean R of MLR is the lowest and for H_min it is almost the same as for all other models.

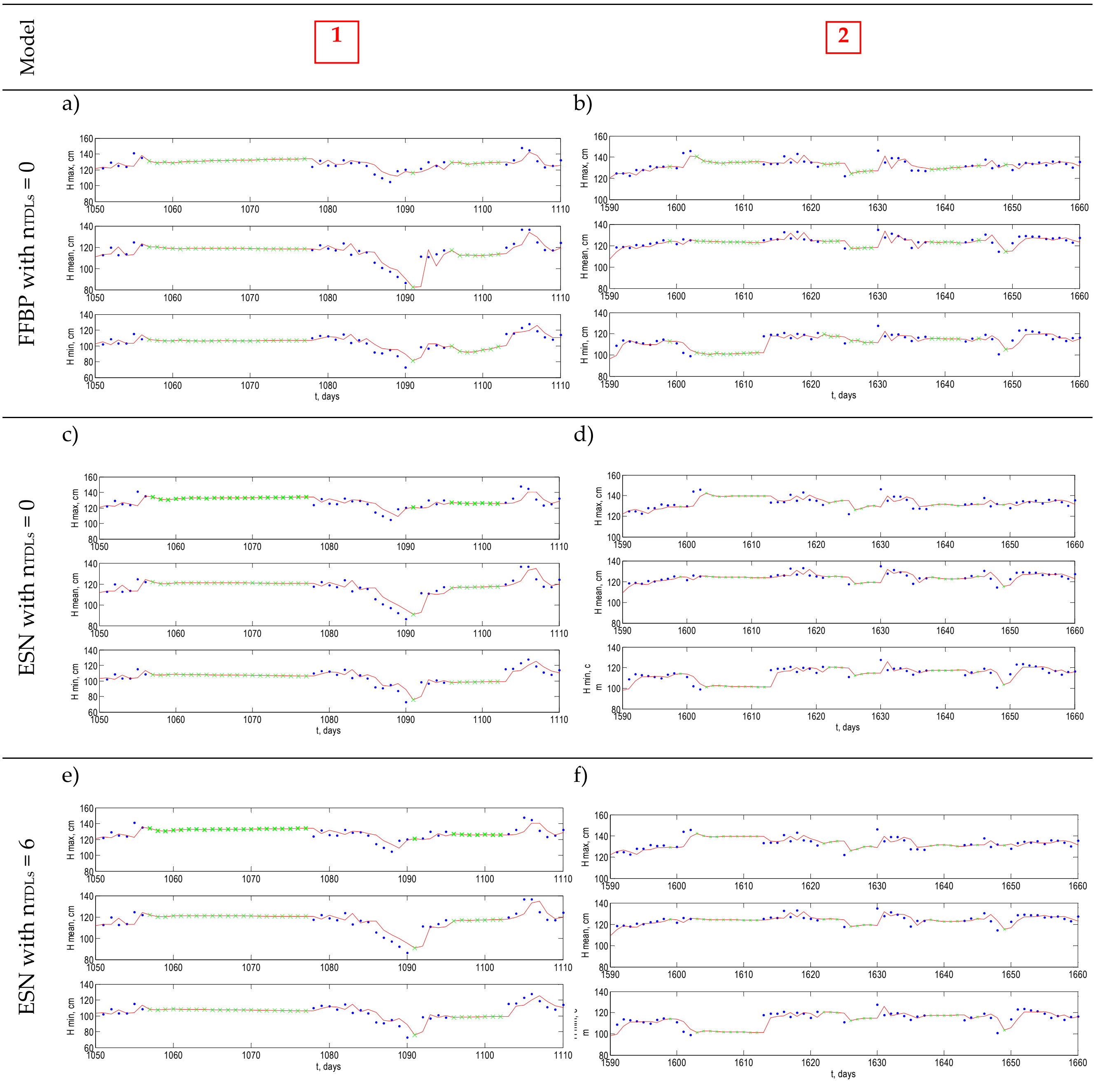
The variations of daily maximum, mean and minimum sea levels for period 1 (from 1050 to 1110 day) and period 2 (from 1590 to 1660 day) are modeled similarly with the FFBP and ESN architectures for gaps larger than 1 to 3 weeks. The MLR model for the two periods represents the same curve as ANNs for the filled missing daily values. On the graphs it can be seen that the non-recurrent ANNs (FFBP) and MLR cannot model in details the non-linear process of daily sea level variations. Further research is needed to fill the gaps with a longer period in the time series using neural networks to account for the dynamics of the modeled process, for example the tidal influence in the Black Sea, various hydro-meteorological and other factors.

5 CONCLUSIONS

In the study two types of the artificial neural network architectures are utilized for filling the missing values in the time series of daily mean sea levels. Subsequently, 20 model tests are generated and the best model is used to reconstruct the missing values for various periods. The comparisons between several tests applying the ANN models have shown that the quality of the filled missing data strongly depends on the number of training data.

Table 1. Estimates of statistical parameters applying FFBP, ESN and MLR models

Model	FFBP				ESN with $n_{TDLs} = 0$				ESN with $n_{TDLs} = 6$				ESN online with $n_{TDLs} = 6$				MLR	
	MSE cm	MSE_b cm	R	R_b	MSE cm	MSE_b cm	R	R_b	MSE cm	MSE_b cm	R	R_b	MSE cm	MSE_b cm	R	R_b	MSE cm	R
H_{max}	5.89	5.64	0.86	0.87	5.88	5.86	0.84	0.85	5.82	5.79	0.85	0.85	6.41	5.99	0.84	0.82	6.10	0.92
H_{mean}	4.86	4.48	0.91	0.92	4.65	4.63	0.91	0.91	4.47	4.43	0.92	0.92	5.25	4.73	0.91	0.88	5.33	0.86
H_{min}	5.48	5.27	0.89	0.89	5.39	5.35	0.88	0.89	5.28	5.24	0.89	0.89	6.20	5.52	0.88	0.84	5.65	0.88



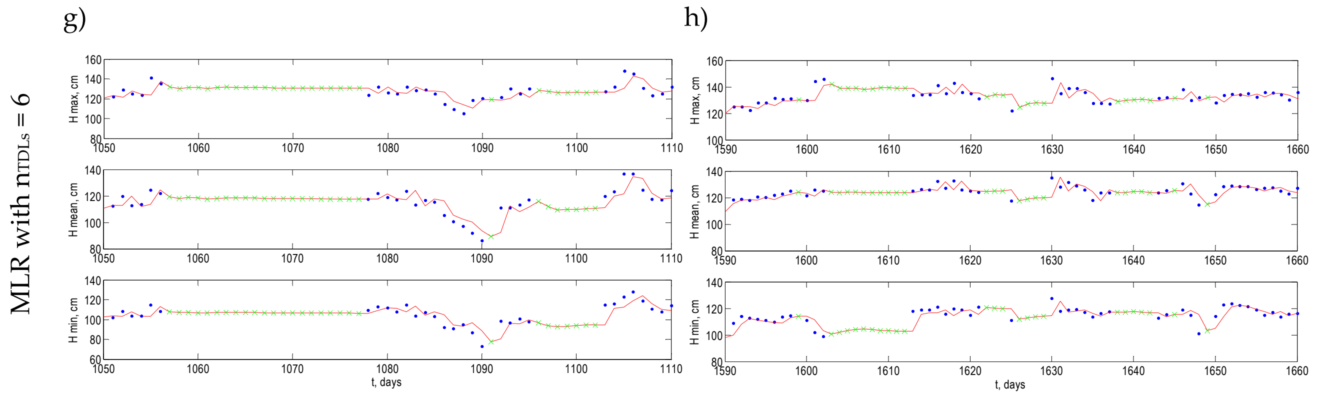


Figure 2. Observed (•), predicted by the model (—) and filled in (×) missing sea levels with FFBP, ESN and MLR models for two sample periods 1 and 2 (marked in Fig. 1)

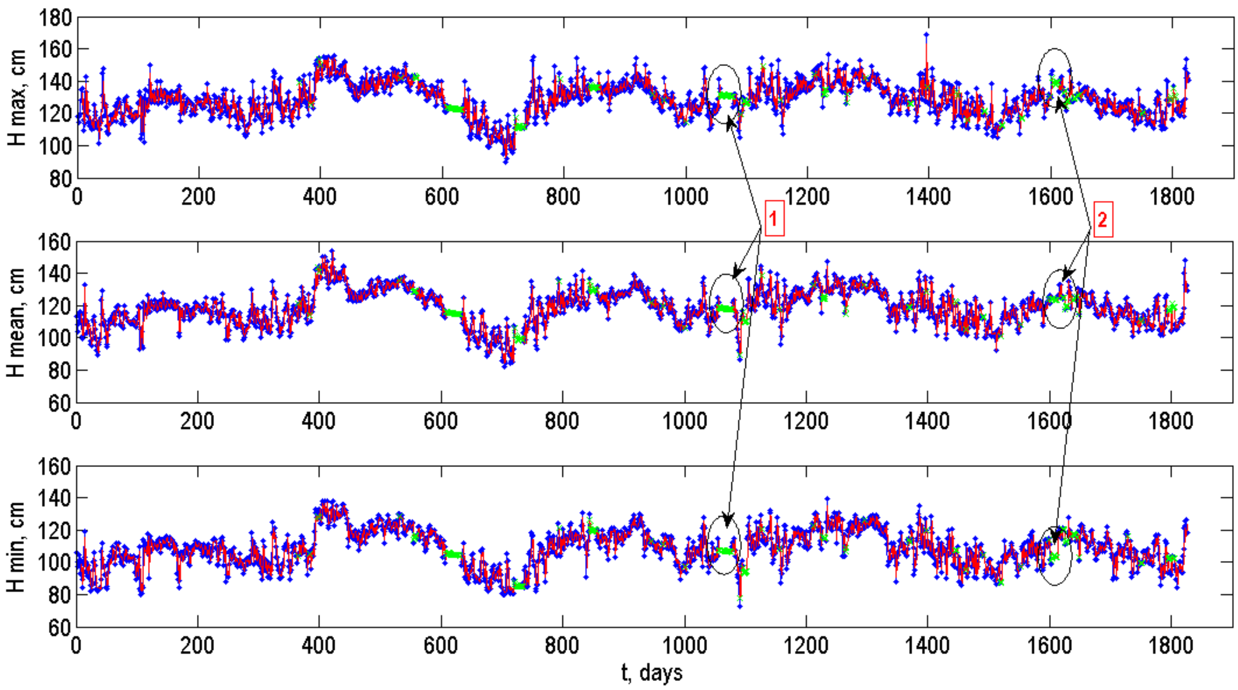


Figure 3. Observed (•), predicted by the model (–) and filled in (×) missing sea levels with FFBP model for the period 1985-1989.

The ANNs and MLR models can be trained with the almost equal MSE and the similar results in predicting the average daily maximum, mean and minimum sea levels are obtained. The recurrent ESN advantage compared to the non-recurrent FFBP and MLR models is due to the significantly faster algorithm for training and weaker dependence of the trained model accuracy on the initial values of the ANN parameters. Furthermore, the ESN model of the sea level variations can be trained in real time with significantly less computational resource compared to the other two models without any further adaptation. It is clear to see, that the ESN architectures deserve a further attention for online applications and the filling data gaps in a consistent way. Thus, the new information obtained by the real-time measurements is possible to be included into the ESN model that will improve its prediction ability. This model can be used for modelling and for predicting the sea level variations with a smaller sampling step of the tide gauge registrations, which is essential for the forecasting of storm surges at the coastal areas.

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