Time series prediction using artificial neural networks: single and multi-dimensional data

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***Abstract*—**The paper studies time series prediction using artificial neural networks. The special attention is paid to the influence of size of the input vector length. Furthermore, the prediction of standard single-dimensional data signal and the prediction of multi-dimensional data signal are compared. The tested artificial networks are as follows: multilayer feed-forward neural network, recurrent Elman neural network, adaptive linear network and radial basis function neural network.

***Keywords*—**Artificial neural network, benchmark, prediction, time series, multi-dimensional data.

I. Introduction

ONE of the most exciting challenges in human researching is the future forecasting. The need of the knowledge of the future does not come only from the natural human curiousness, but also from the necessity to improve the current technologies and methods.

The term prediction, which often substitutes the term forecasting, is very wide. It compromises the methodologies for the weather forecast [1], [2], [3], [4] the financial data prediction [5], [6], [7], the predicting of the biological characteristics [8], technological parameters [9], horse racing results [10], energy grid behavior [11], etc. However, it can be said that the prediction is always based on the model of the process to be predicted.

The model can be based on the predicted signal only or on the other information. Generally, the two main approaches to modeling are possible – the white box modeling and the black box modeling. The first method uses a priori knowledge about the predicted system. Typical white box model is mathematical model based on physical and chemical laws. The black box modeling is based on the identification data that allows update initial predictor to obtain proper results. Typical black box models are artificial neural networks (ANNs).

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There have been published many applications of artificial neural networks in prediction. For example Memmedli and Ozdemir in their paper [12] test linear networks, multilayer feed-forward neural networks, radial basis function neural networks and generalized regression neural networks. Guresen et al. compares performance of the multilayer feed-forward neural network with the DAN2 (dynamic architecture for artificial neural networks), autoregressive conditional heteroscedasticity (ARCH) model and EGARCH–MLP model on the prediction of NASDAQ index [13]. Samek and Manas compare six different types of artificial neural network on the CATS benchmark [14]. Maqsood et al. applies multilayer feed-forward neural networks, Elman neural networks, radial basis function neural networks and Hopfield neural networks in weather forecasting [35]. The chaotic time series were predicted by Diaconescu [36] NARX neural networks based models. Brion et al. compare viruses in shellfish predictions of multilayer feed-forward neural networks to the multivariate logistic regression (MLR) [37]. Pasomsub et al. use multilayer feed-forward neural networks for the phenotypic drug resistance prediction and compare them with other systems [38].

Nevertheless, the choice of proper artificial network and its settings is usually not trivial. There are many parameters that influence the quality of prediction. One of them is the number of input neurons (in the so called zero layer), in other words the length of the input vector of the predictor.

Generally, the size of the input vector relates to frequency of the signal. Some authors mention phrase memory which refers to the correlation of a prediction back to n previous intervals of time [15], [16]. Though, an exact methodology that would provide strict rule for designing zero layer of specific artificial neural network type does not exist.

The motivation of this contribution comes from our previous research and the paper studies the influence of the input vector size for six selected artificial neural network structures. This paper extends research from paper published in [34] and puts importance to the influence of predicted data dimension.

This paper is organized as follows. Section 2 provides some background on time series to be predicted. Section 3 describes the design and implementations of the tested artificial neural network structures. Section 4 presents methodology of simulations, batch program algorithm and results of the testing. In addition, this part describes the evaluation methods and comparison of the results. The paper is finished by the section 5 that consists of some concluding remarks.

II. Testing Time Series

There have been selected two different data sets from the Santa Fe Competition [17]. The first data set contained one signal only while the second consisted of the three signal data. They were selected due its competition usage it became a common way of predictor testing and benchmarking.

A. Data set A

The data set A from the Santa Fe Competition [17] was selected as the signal to be predicted (see Fig. 1). This time series was generated by NH3 laser and it is good example of realistic data.

The measurements were made on an 81.5-micron14NH$_3$ cw (FIR) laser, pumped optically by the P(13) line of an N$_2$O laser via the vibrational aQ(8,7) NH$_3$ transition. The intensity data was recorded by a LeCroy oscilloscope. No further processing happened. The experimental signal to noise ratio was about 300 which means slightly under the half bit uncertainty of the analog to digital conversion [18].

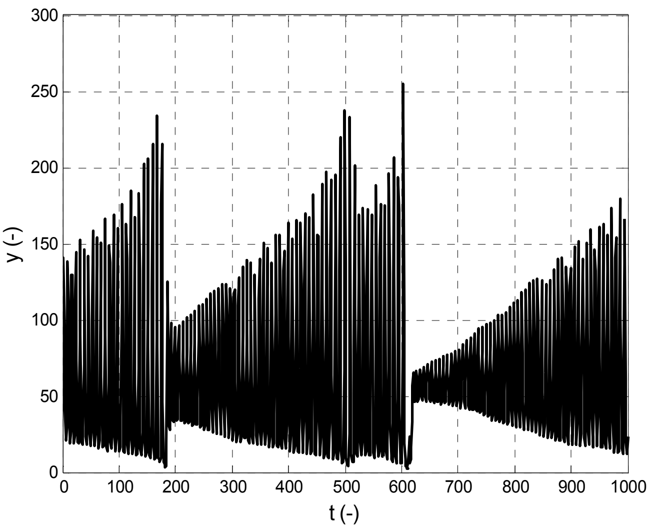

Fig. 1 The predicted signal from data set A

B. Data set B1

This is a multivariate data set recorded from a patient in the sleep laboratory of the Beth Israel Hospital in Boston, Massachusetts. The values are sampled with sampling interval 0.5 second. As can be seen from Fig. 2-4, the data set consists of three different signals: the heart rate, the chest volume (respiration force) and the blood oxygen concentration (measured by ear oximetry) [18]. The signals are non-stationary and the ANN based predictor was to model and predict all three signals at once. They will be in the following text denoted as B1a (heart rate), B1b (chest volume) and B1c (blood oxygen concentration).

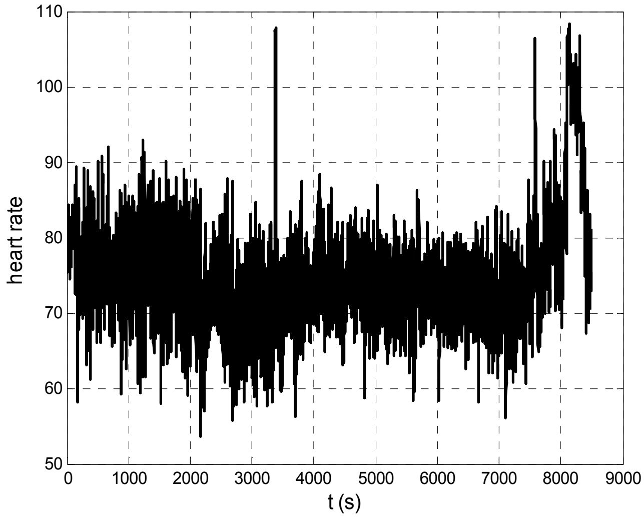

Fig. 2 The predicted signal from data set B1 – heart rate

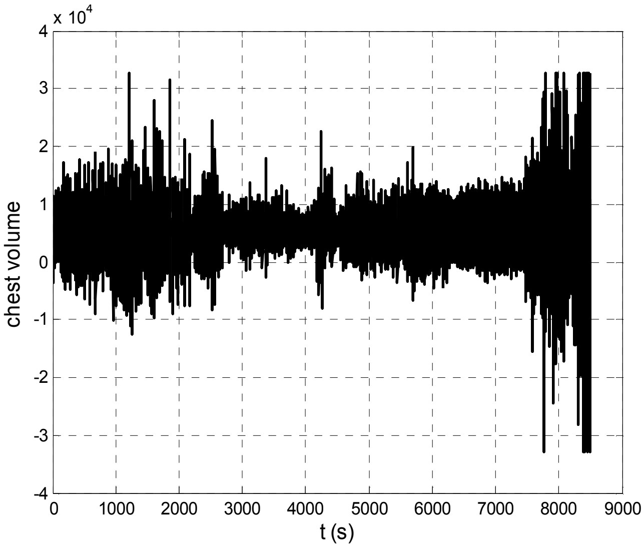

Fig. 3 The predicted signal from data set B1 – chest volume

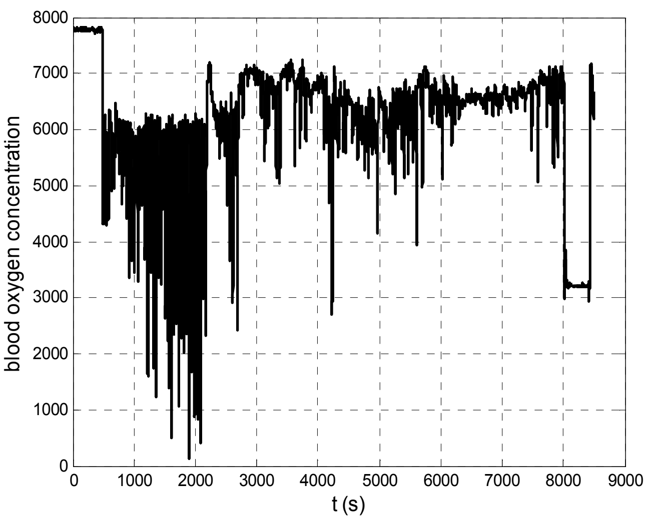

Fig. 4 The predicted signal from data set B1 – blood oxygen concentration

The heart rate was determined by measuring the time between the QRS complexes in the electrocardiogram, taking the inverse, and then converting this to an evenly sampled record by interpolation. There were no premature beats - sudden changes in the heart rate are not artifacts. The respiration and blood oxygen data are given in uncalibrated A/D bits [18].

III. Tested Artificial Neural Networks

There are inexhaustible variety of types and structures of artificial neural networks, but not all of them are capable to model and predict time series. However, there are some popular artificial neural networks that are mostly used. One of the most popular is multilayer feed-forward neural network (MFFNN). These networks are very versatile and have been already applied in many applications in the prediction task. Even the special case of MFFNN - simple adaptive linear network (ADALINE) - can model and predict various systems. When the temporally/sequentially extended dependencies over unspecified (and potentially infinite) intervals should be modeled [19], the recurrent neural networks are often applied. It is worth of noticing the radial basis function neural networks (RBFNNs). RBF networks are popular due to its very fast training [20].Obviously, the list of artificial neural networks would be long, but it is necessary to mention also functional networks [21], Kohonen networks [22], [23] and probabilistic fuzzy neural network [24].

In this paper, there were chosen following structures of artificial neural networks to be tested: two variants of multilayer feed-forward neural network, because of its wide usage, adaptive neural network due to its simplicity, Elman neural network as the representative of the recurrent neural networks, two structures radial basis function neural network, because it provides simple training with good prediction performance and adaptive neural network due to its simplicity.

A. Multilayer feed-forward neural networks

Multilayer feed-forward neural networks have neurons structured in layers and the information flows only in one direction (from input to output). Typically, all neurons in specific layer have same transfer function, while variety of transfer functions is used. It has been proved [25], [26] that two layer MFFNN can approximate any function with certain accuracy while non-polynomial transfer function in the hidden layer is used. In this paper two variants of MFFNN were tested.

The first tested structure had five neurons with hyperbolic tangent transfer function in the hidden layer and one neuron with linear transfer function in the output layer. This network will be denoted as *mffnntp* in the following text. The second structure had same hidden layer, but one neuron in the output layer utilized hyperbolic tangent as a transfer function. This network will be denoted as *mffnntt*.

Both networks were trained using Levenberg-Marquart algorithm built in Matlab Neural Network Toolbox.

B. Adaptive linear neural network

Adaptive linear neural networks can be regarded as a special (simple) case of multilayer feed-forward neural networks. They have typically only one layer with linear transfer function. Despite its simplicity they have many applications [27], [28], [29].

Very often (in case of need of one output value) adaptive linear networks have only one neuron. This methodology is accomplished in the paper and such structure will be called *adaline* hereinafter.

For the creation and training of adaptive linear neural networks were used newlin and adapt functions from Matlab Neural Network Toolbox. Nevertheless, the standard approach to network training as it was applied for other types of ANN was not effective. The adaptive linear neural networks had to be adapted recursively using sliding adaptation method.

C. Recurrent neural networks

Elman neural networks were selected as a representative of large group of recurrent neural networks. Typical Elman network has one hidden layer with delayed feedback. In this article the hidden layer contained ten neurons with hyperbolic tangent transfer function and the output layer of the Elman neural network used linear transfer function (this structure is below denoted as *enn*). The backpropagation algorithm was used for the *enn* training.

D. Radial basis function neural networks

Typical RBFNN contains two layers, while the hidden layer utilizes radial basis transfer function and output layer employs linear transfer function.

Radial basis function neural networks are popular for their fast training. Unfortunately, this advantage is balanced with higher memory requirements because the network has as many RBF neurons as many training vectors are used (Matlab Neural Network Toolbox function newrbe). This network is below denoted as *rbf*.

However, in the Matlab Neural Network Toolbox is available the second approach to RBFNNs – the function newrb. This methodology is much more computational demanding but it is the only solution how to model with large amount of training data. Such structure will be in the following text indicated as *rbfu*. Due to long training times the maximum number of RBF neurons was set to 500.

IV. Simulations and Results

The tested number of inputs from which the prediction is to be performed is as follows: 2, 3, 4, 5, 6, 7, 8, 9, 10, 50, 100. The original signal was processed into training matrixes according to number of values in the input vector. For each combination of the tested artificial network type and the input vector size were created 100 simulations and average values were used for the consequent evaluation and comparison.

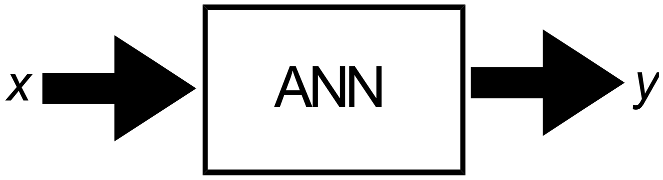

Fig. 5 The simplified scheme of the ANN

The all tested artificial neural networks have two variants – one for the data set A, second for the data set B1. In the data set A the single signal was modeled / predicted, therefore the ANN based model had as many input neurons as was the length of the input signal. In the output layer was only one neuron, because the one-step-ahead prediction strategy was used. Thus, the variable x in the Fig. 5 was equal to 2, 3, 4, 5, 6, 7, 8, 9, 10, 50, 100 and y = 1. In the Fig. 6 is depicted example of the *mffnntp* that predict signal from data set A from 10 input values and in the Fig. 7 is shown example of the *rbf* network that was used for the prediction of the data set A with 50 input values.

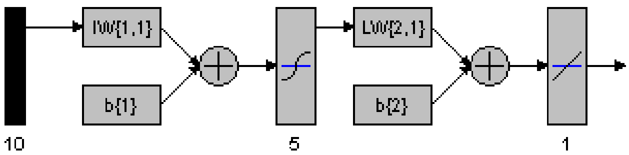

Fig. 6 Example of the *mffnntp* with the 10 input values of the data set A

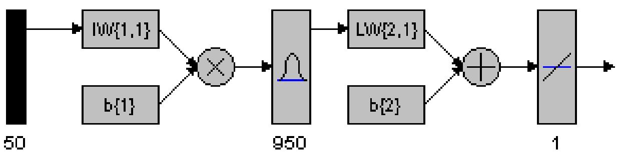

Fig. 7 Example of the *rbf* with the 50 input values of the data set A

On the other hand, in the case of multi-dimensional data set B1 the predictor had predict all three signals at once, hence the y = 3. Then, the number of the input neurons x was 6, 9, 12, 15, 18, 21, 24, 27, 30, 150, 300. In the Fig. 8 is depicted example of the *mffnntt* that predict signal from data set B1 from 10 input values, while the Fig. 9 shows the example of the adaline that was used for the prediction of the data set B1 with 5 input values.

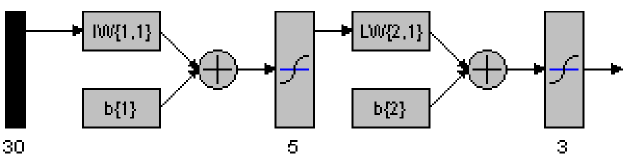

Fig. 8 Example of the *mffnntt* with the 10 input values of the data set B1

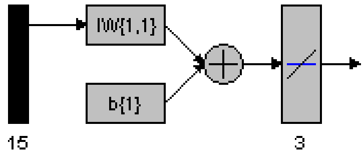

Fig. 9 Example of the *adaline* with the 5 input values of the data set B1

All simulations were done in Matlab using Neural network toolbox. General algorithm of the batch program is shown in the Fig. 10.

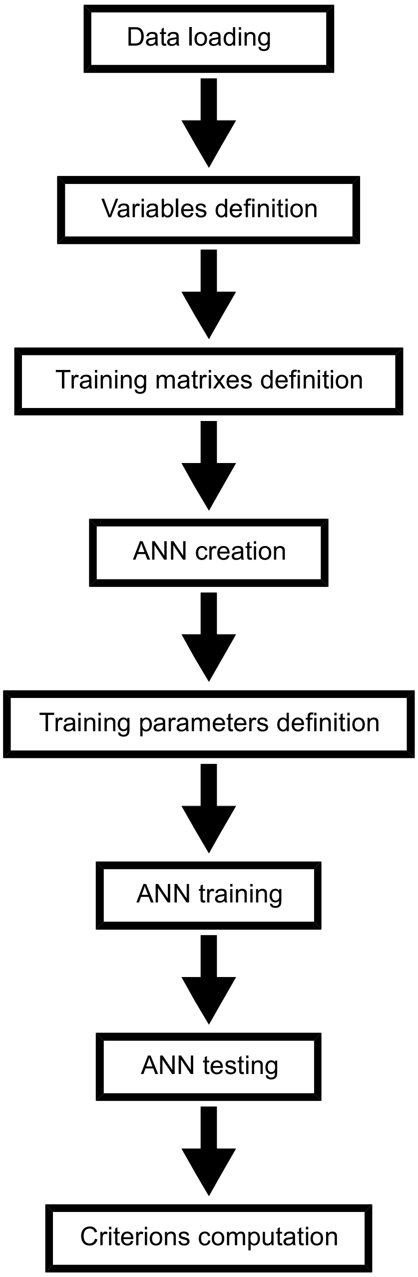

Fig. 10 General algorithm of the Matlab programs

A. Data set A

For better comparison two prediction quality criterions were defined. The first criterion *ABS* describes total sum of absolute values of prediction errors relative to number predictions whilst the second criterion function *SQR* characterizes total sum of squares of prediction errors relative to number predictions.

$$ABS = \frac{\sum_{i=1}^{N} \left| t(i) - p(i) \right|}{N} \tag{1}$$

$$SQR = \frac{\sum_{i=1}^{N} \left(t(i) - p(i) \right)^2}{N} \tag{2}$$

Where N is number of predictions (length of predicted signal), t stand for target (original) signal, p denotes predicted signal and i is number of the prediction.

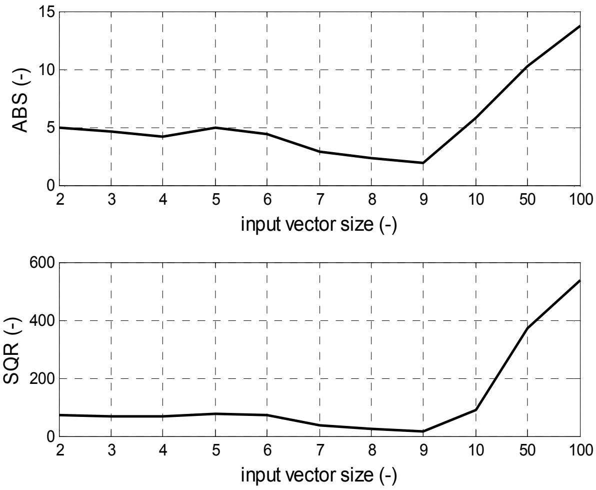

Fig. 11 Prediction of signal A using *mffnntp*

The *ABS* criterion gives same importance to all errors. On the other hand *SQR* emphasizes higher errors and lower prediction errors are suppressed. This can be used for evaluation and comparison of the prediction errors with varying magnitude.

As can be seen from Fig. 11-16, the best results provided *rbf*. This is caused by the fact that *rbf* networks have so many neurons. In other words each neuron in the hidden layer works as an exclusive predictor for one input vector.

It is worth of noticing that *rbfu* performed reasonable good results with markedly less neurons (maximally 500).

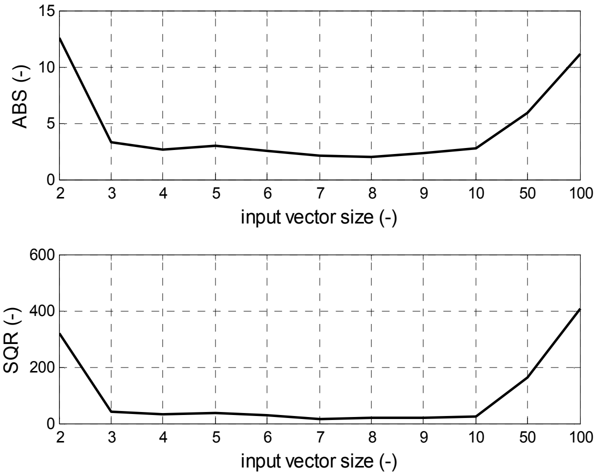

Fig. 12 Prediction of signal A using *mffnntt*

On the contrary, the worst results were obtained using enn. Elman neural network have apparently problems to model this kind of signal. The second worst was *adaline*, if predictions for 50 and 100 input values were omitted. The criterions *ABS* and *SQR* for two largest input vectors were too high to display them in the Fig. 13.

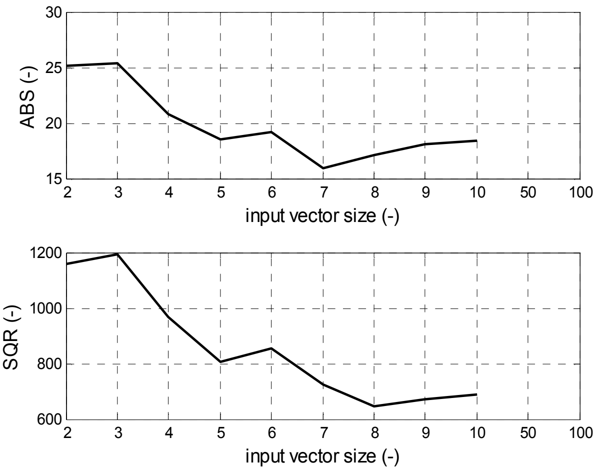

Fig. 13 Prediction of signal A using *adaline*

Multilayer feed-forward neural networks lie in the middle of results chart. Their prediction accuracy verges to *rbfu* as far as *ABS* criterion is concerned. However, as can be seen from *SQR* course in Fig. 11, 12 and 16, the *mffnntp* and *mffnntt* produce significantly more high prediction errors.

The influence of the size should be assessed separately for *rbf* and the rest of tested structures. The radial basis function neural network *rbf* due its exact design converges to zero prediction error with increasing length of input vector.

The prediction error for the rest of tested artificial neural networks generally slightly decreases in the beginning but after certain interval rises approximately around 10 values in the input vector. It can be concluded that the optimal length of input vector lies between 3 and 10 with the exception of *rbf* network.

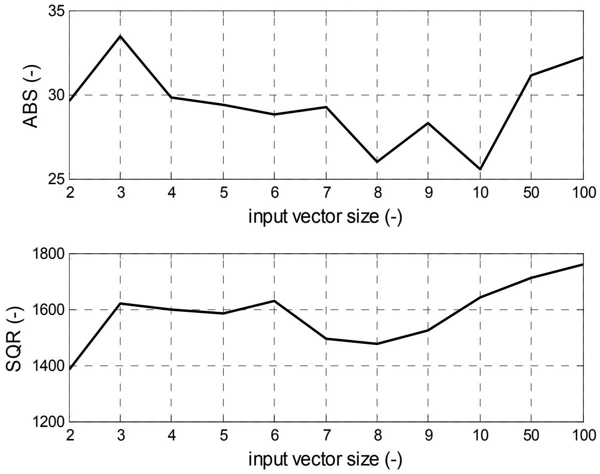

Fig. 14 Prediction of signal A using *enn*

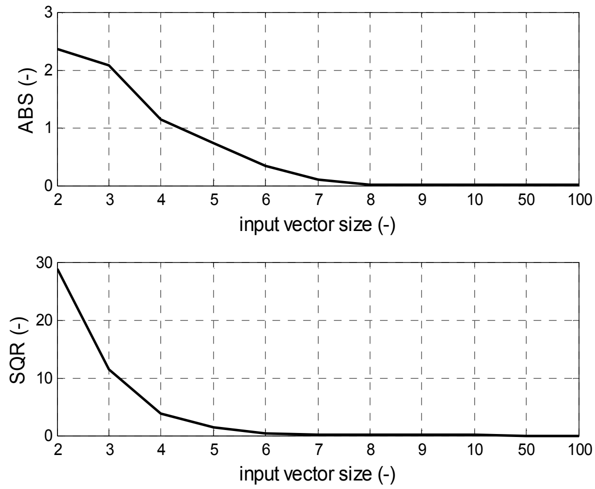

Fig. 15 Prediction of signal A using *rbf*

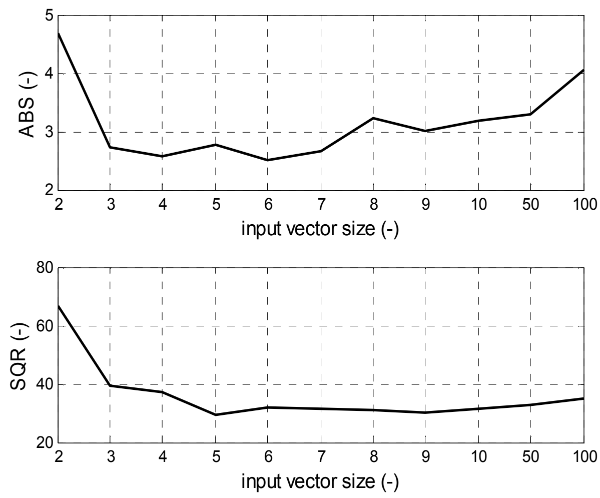

Fig. 16 Prediction of signal A using *rbfu*

B. Data set B1

Because of multivariable data in the set B1, it was necessary to compute overall criterions for the all three signals. Then, the *ABS* and *SQR* criterions are computed as the arithmetical mean of the all individual criterions:

$$ABS = \frac{ABS_{B1a} + ABS_{B1b} + ABS_{B1c}}{3} \tag{3}$$

$$SQR = \frac{SQR_{B1a} + SQR_{B1b} + SQR_{B1c}}{3} \tag{4}$$

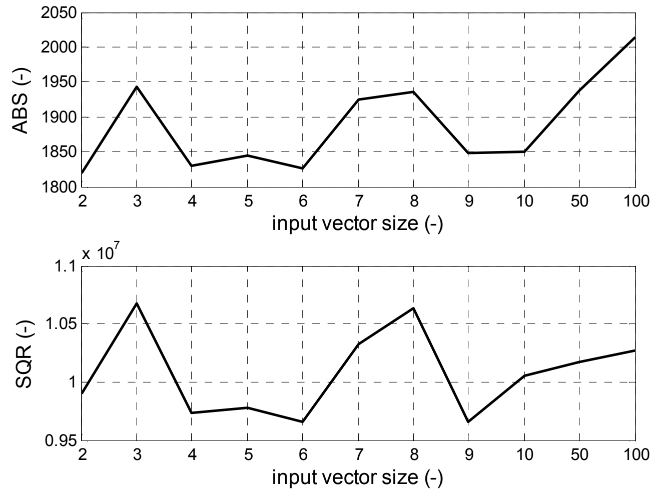

Fig. 17 Prediction of signals B1 using *mffnntp*

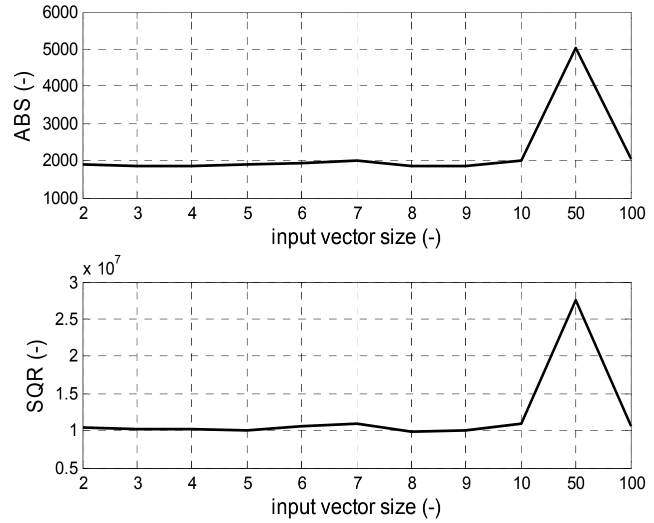

Fig. 18 Prediction of signals B1 using *mffnntt*

Because the length of the signal was 17000, it was not possible to use the *rbf* network due to the memory requirements of the training algorithm. Thus, in the Fig. 17-21 are presented prediction errors for the *mffnntp*, *mffnntt*, *adaline*, *enn* and *rbfu* only. It can be seen that the courses of the both criterions are not as unambiguous as in the case of the data set A. It is probably caused by the fact that the predicted signals were non-stationary and by the multi-dimensionality of the data, because the artificial neural network had to predict three different signal at once. This behavior is significant especially for *mffnntp* and *enn*.

The definitely best results were obtained using *rbfu* network that provided the lowest values of the both criterions between 5 and 10 input values. The second best are multilayer feed-forward neural networks, while *mffnntp* provided slightly better results, but *mffnntt* had more steady accuracy that was not so dependent on the input vector size.

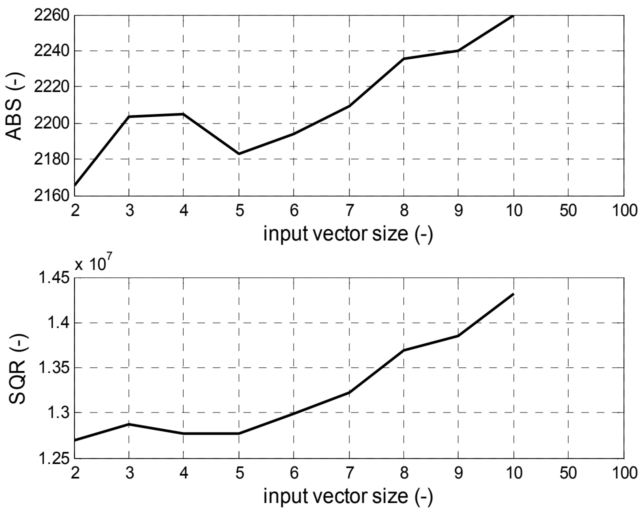

Fig. 19 Prediction of signals B1 using *adaline*

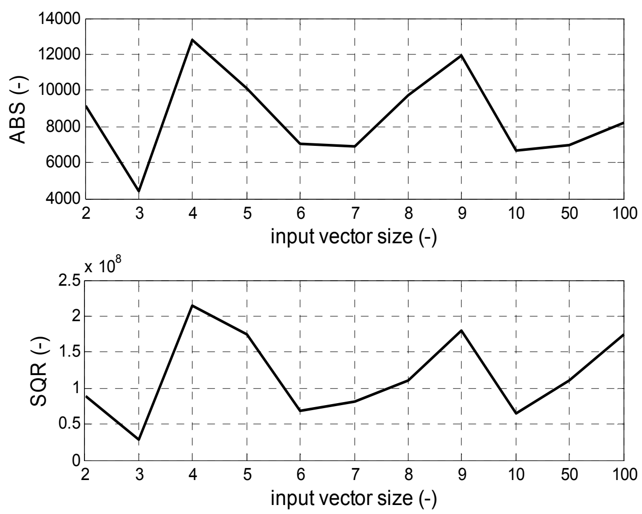

Fig. 20 Prediction of signals B1 using *enn*

Surprising results performed *adaline* network that has increasing trend of the inaccuracy. The acceptable (comparable) prediction quality is in the range 2 – 5 input values. More or less unsatisfying results were achieved using Elman neural network *enn*, because the accuracy has not unambiguous trend and its values are significantly higher than in case of the *rbfu* network, as can be seen in the Fig. 20.

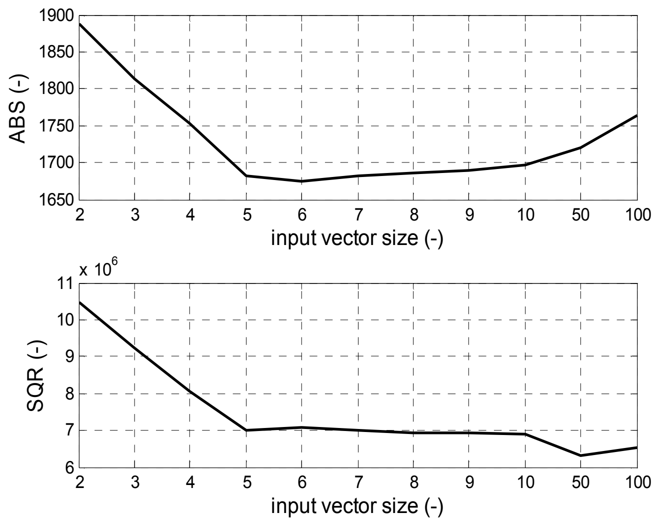

Fig. 21 Prediction of signal A using *rbfu*

V. Conclusion

The paper showed the case study of artificial time series prediction using various artificial neural network structures. There has been tested prediction of non-artificial data from the Santa Fe benchmark. The presented simulations showed dependencies of prediction accuracy on the number of values in input vector.

Furthermore, there have been observed prediction of single and multi-dimensional data. From the results it can be concluded that artificial neural networks are able to predict both single-dimensional data and multi-dimensional data. The prediction accuracy is lower when the one model for more signals is used, despite the multi-output artificial neural network was applied. The selected multi-dimensional data were strongly nonlinear and non-stationary which lead to the varying trend of the both criterions in some cases (see Fig. 17, 18 and 20).

It can be concluded that selection of optimal input vector size is not trivial and it depends on the selected artificial neural network type and the predicted system / signal. As was presented hereinbefore, it was typical for most of the tested networks that the prediction error decreases in the beginning, and then, after reaching minimum, the prediction error rises up. Therefore, the optimal number of inputs usually lies between 3 and 10. Exception to this behavior is the rbf network that due to its "exact training" has descending prediction error trend.

The best prediction quality was obtained using radial basis function neural network with exact design *rbf* in the case of the single-dimensional data (data set A). However, this artificial neural network type was useless for the second testing data (multi-dimensional data set B1), because of the high memory requirements. The best prediction of the data set B1 was gained by radial basis function neural network with classic iterative supervised learning *rbfu*. On the other hand, the training times were incredibly long.

Therefore, it can be deduced that radial basis function neural networks can be recommended as one of "the first to try" methods for the signal prediction, no matter if its single-dimensional data or multi-dimensional data. Moreover, the classic (exact) design of RBFNN can be powerful in the case of short data set. For the longer data sets the improved design with limited number of RBF neurons is recommended with the remark, that such network training is much longer.

As the reasonably good (means exact) and fast predictors can be regarded multilayer feed-forward neural networks. Both tested variants *mffnntp* and *mffnntt* provided moderate prediction accuracy for the both tested data sets, while there is known a lot of training algorithms which enable to reduce the computational times during the network training.

As future research, results presented in this paper will be compared with neural networks optimized by Self-Organizing Migration Algorithm (SOMA). This evolutionary algorithm seems promising as it has many successful implementations on multiobjective optimization problems, e.g. [30 - 33].

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