Artificial Neural Network Utilization for FSO Link Performance Estimation

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Abstract. *This paper describes FSO link performance prediction based on available meteorological data using different Artificial Neural Network (ANN) approaches. Several types of ANNs were compared and their performance was evaluated. The paper introduces an ANN application utilizing delayed real data. This approach has been validated to be more precise than common feed-forward neural networks.*

Keywords

Artificial neural networks, free-space optics, weather influence.

1. Introduction

The influence of weather is an important factor when planning Free Space Optical (FSO) links [1]. Some electromagnetic energy transmitted in the atmosphere is absorbed and scattered by molecules and particles present in the air. Aerosols in size rating from 0.01 μm and 100 μm (typically fog) cause severe disturbances to the propagation of optical waves since their dimensions are extremely close to the transmitted wavelengths resulting in Mie scattering. Since this phenomenon causes major optical link degradation, several models derived from theoretical analyses [2],[3] up to published results from precise measurements like [4] or [5] are found in the literature. Thermal turbulences inside the propagation medium cause the deviation and defocusation of propagating optical beams depending on the size of the eddies (non-homogeneous areas of different refractive index). Turbulence effects were theoretically dealt with in [6],[7] and several other papers including recent experiments published e.g. in [8].

The main task in this paper was not to focus on particular atmospheric influence separately, but to create a model usable for the estimation of FSO link fadings caused by concurrently changing weather conditions. Since, typically, only a fraction of meteorological data (sensors) can be accessed at particular measurement sites, we focused on the general adaptation of Artificial Neural Networks and their further utilization for estimating FSO fades. Statistics of temporal link attenuation changes (time-series of fades) were also evaluated using ANNs. The paper, moreover, deals with different approaches to measured data-set processing to highlight the improved ANN responsethan for a classical multilayer perceptron.

2. Experiment Description

Two measuring FSO links located on a building of the Czech Technical University in Prague and its surrounding campus were used. The first link, where initial data for ANN adaption were gathered, has a length approximately 120 meters and is situated between two building blocks on the 8th floor (approximately 30 meters above ground). This link uses an older 100 Mbps FSO heads WaveBridge 500 by Plaintree. The first FSO link is situated in a north-western direction, and, therefore, background noise caused by sunlight in daily measured data is observed. This was also considered within data processing.

The second link is approximately 450 meters long and is situated in a similar direction as the first link. New four-beam FlightStrata-G FSO heads with 1 Gbps interfaces were utilized. Measured data from the link are used later in this paper when describing the validation of the derived neural model.

Both measuring links on the university building are accompanied by meteorological stations. Data from two meteorological stations WS981 by Anemo corporation, Czech Republic, located in the middle of the first link and one of the FSO transceivers, respectively, were used for further analyses. The first station collected data recording the temperature and humidity (a temperature sensor -30 to +70 °C and hygrometer), as well as atmospheric pressure (a barometer with a range of 800 - 1200 hPa), precipitation (heated tipping-bucket rain gauge with a collecting area of 500 cm^2, and rain measured in an amount of 0.1 mm per tip), and the speed and direction of the wind (anemometer AN 955C). The second station gathered temperature, atmospheric pressure and precipitation data. There is a Vaisala PWD 20 visibility sensor (visibility up to 20 km) installed and data are used for fog influence analyses. Data were captured every second. It has to be emphasized in this case that visibility data was omitted because a high correlation of fog-caused attenuation and other atmospheric influences were found. This leads to an excessively large influence on the final FSO link attenuation estimation. The second reason why measured visibility data were not used in this experiment results from the cost of such sensors. We wanted to derive a more versatile tool based on typical weather sensors available from other measuring sites. The processed data set, therefore, consists of quantum of precipitation, relative humidity, temperature, wind direction, speed and wind blasts and the quality of links in terms of received power levels as taken from two FSO transceivers measuring differently.

3. Neural Network Modeling

In the past it was proved (in landmark publications [9] and [10]), that multilayer feed-forward neural networks with sigmoid activation function can act as an universal approximator, but there is a lot of freedom afforded in the design of those networks, their interconnections and in preparing input data. Each problem requires a unique approach to get the best results. In this paper the architecture of the multilayer feed-forward neural network with nonlinear sigmoid activation function with bias is used. The architecture of the neural network is depicted in Fig. 1, where every circle in the hidden and output layers represent a basic perceptron (for a detailed description of the basic principles of the perceptron see [11]). The input layer consists only of distribution elements. All input data used in this network are described in the previous section.

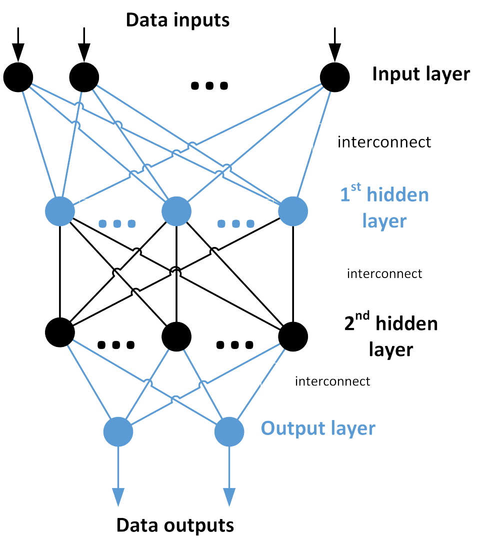

Fig. 1. Typical architecture of a fully connected feed-forward ANN used for data processing in this article.

Neural network processing of data in this paper consisted of four of these consecutive phases:

1. Manual data preparation
2. Normalization and dataset creation
3. ANN training
4. ANN validation

All networks were successfully trained, then the results of each network were evaluated. Each step of the above-mentioned processing is described in-depth in the following paragraphs.

3.1 Data Preparation

All data involved in the ANN simulation (all meteorological and FSO link attenuation data described in the previous paragraph) have to be first normalized into the interval $< 0,1 >$. This is required by neural network architecture which is based on a LOGSIG function. For data normalization the following logistic function has been used:

$$f(x|\mu,\sigma) = \frac{e^{\frac{x-\mu}{|\sigma|}}}{\sigma\left(1+e^{\frac{x-\mu}{|\sigma|}}\right)^2}, \quad x \in \mathbb{R} \tag{1}$$

where parameters σ and μ represent standard deviation and mean value computed from each type of all measured data to filter out general fluctuations caused by A/D converters on RSSI output and the error of measuring voltmeter which are not caused by atmospheric influences. This approach also helps to change the distribution of input data sets, where the standard (mean - defined by μ) FSO link quality (also average values of meteorological data) occurs most frequently, to emphasize other special states of the link, such as link blackouts and substantial link quality decreases. Therefore, it is important to detect the time intervals when the FSO link is most influenced. Such a feature can be illustrated as a change of histogram before normalization in Fig. 2 and after normalization in Fig. 3 where the change of distribution of measured data and normalized data is shown.

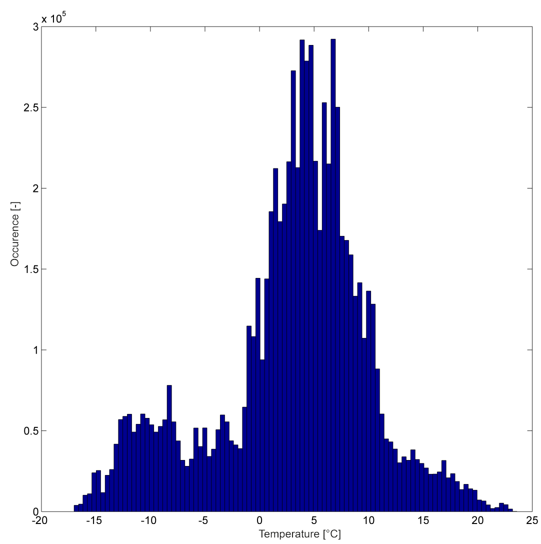

Fig. 2. Example of measured temperature histogram before normalization process.

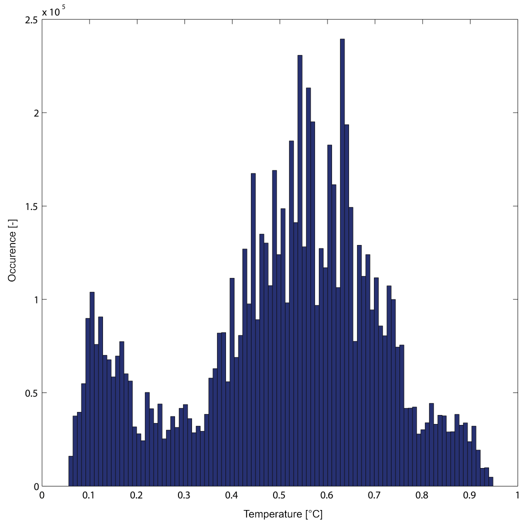

Fig. 3. Temperature data after process of normalization using logistic function.

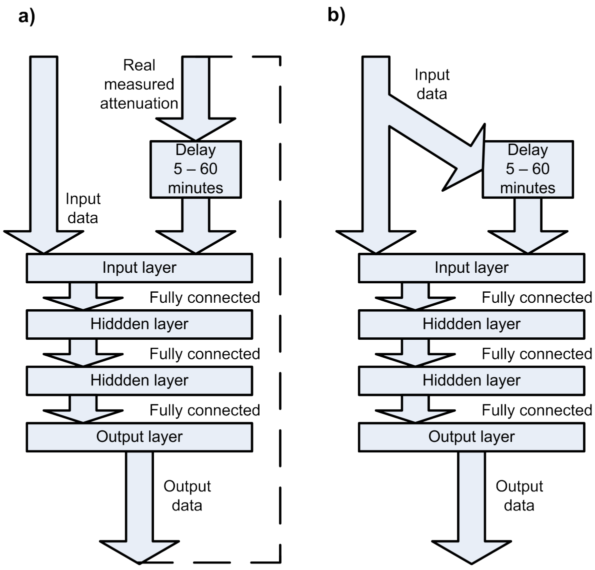

Fig. 4. Architecture of neural network with a) delayed real link attenuation, b) delayed weather data.

3.2 Neural Network Architectures

The primary aim of this paper was to build new feed-forward neural networks based on the cluster analysis results which were published in a previous work (the first attempts towards this approach were published in [12]). Together with an improved cluster analysis and simple ANN prediction we tried to apply suitable architectures of ANNs. The main idea is that the weather status of parallel events is constantlychanging both in time and space. Therefore some past data sets (previously measured) should be included in an ANN classification of actual influences. It has to be emphasized that ANN can be applied without any preceding learning mechanism.

In this paper a time delay is used before the ANN input layer (Fig. 4b). Different lengths of delay were used and evaluated. A second experiment was performed to introduce the previously measured FSO link received power to the input layer with defined delay (see applied architecture in Fig. 4a). This approach can later lead to a regular, nonlinear, auto-regressive network with exogenous inputs (NARX) architecture [13], which is a recurrent neural network used for time series prediction. In this experiment the feed-back was realized by real measured data. The neural network used in this article utilizes an input layer responsible for distributing input data without any transfer function or weights. The network is fully connected (each layer with the preceding layer). Hidden layers use perceptrons with log-sigmoid transfer function, weights for each input of each perceptron and bias for all perceptrons. The output layer consists of two log-sigmoid perceptrons which produce the final FSO link attenuation estimation.

3.3 Data Selection and Evaluation

After normalization, continuous blocks (approximately 4 hours blocks) of data (approximately 30 % of all measured data) were selected and duplicate inputs were removed. The shapes of training data histograms (FSO attenuation, as well as all meteo data) were checked to correspond to the whole dataset. After training, the performance of the ANN was evaluated by denormalization - the inverse logistic function was used with the same deviation and mean value as derived during normalization. The performance of each network (details of neural network sizes and architectures are described in the following paragraph) was computed as: desired FSO link quality measured in the whole dataset - data represented by the ANN. An example of the error histogram for the best networks is shown in Fig. 5.

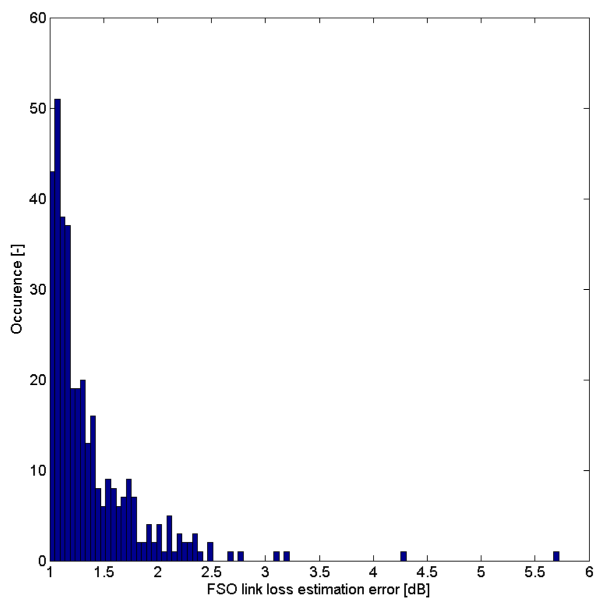

Fig. 5. Histogram of error distribution for ANN estimation of FSO link quality.

3.4 Network Learning and Validation

The neural network was taught using Gradient descent with a momentum training algorithm [14]. This algorithm is considered to be more proof against being stuck in local minima as it uses recent changes in the error surface of examined functions. The training was performed for approximately 5000 epochs, and the learning rate of the algorithm was progressively lowered from 0.3 to 0.05. The momentum constant was kept in the range of 0.9 to 0.6. Note that a momentum close to 1.0 can lead to problems when determining the global minimum of error function. Therefore, a higher span was not used during the training stage. A validation training set consistings of 15 % of all measured data was also introduced. This validation set is used to check overfitting of the ANN a well-known method used also in [15]. The training should be stopped before the MSE (Mean Squared Error) of the validation set starts to rise, but it is not the only thing which has to be accomplished to avoid overfitting. Thus, all networks used in this paper were stopped early – before the validation MSE started to rise.

4. Results

Table 1 presents results from the testing of fully trained neural networks of size 14×9 (first and second hidden layers). The 17×11 and 9×6 networks were also trained and evaluated, but the results were only slightly worse than for the 14×9 network (further in the text only the best results are discussed). These sizes were selected with respect to a recommendation [16]: the Baum-Haussler rule for neural network size determination. This rule is considered to be the only recommendation for network construction, but ANN size can be problem-dependent. The larger network in our case several times oversizes recommendation assumptions. The numbers of input configurations in tables are:

C1 - only meteorological data on the input layer
C2 - meteorolog. data + 5 min delayed meteorolog. data
C3 - meteorolog. data + 15 min delayed meteorolog. data
C4 - meteorolog. data + 30 min delayed meteorolog. data
C5 - meteorolog. data + 60 min delayed meteorolog. data
C6 - meteorolog. data + 5 min delayed link attenuation
C7 - meteorolog. data + 15 min delayed link attenuation
C8 - meteorolog. data + 30 min delayed link attenuation
C9 - meteorolog. data + 60 min delayed link attenuation

In Tab. 1 and Tab. 2 the number of errors (each value corresponds to one second of measurement) is shown, depending on error size in dB and the neural network input configuration mentioned above. In Tab. 1 errors smaller than 0.7 dB – the error size which is considered as negligible – are omitted. On the other hand, in Tab. 2, errors for all inputs (also one ocurrence corresponds to one second of measurement) and configurations to demonstrate very low functionality on such coarse grained values (steps of size approximately 6 dB) are shown.

As can be seen in Tab. 2, contrary to precise FSO estimation from the first FSO link, the network is not able to estimate the quality of the FlightStrata link correctly and has low resolution between the measured levels corresponding to RSSI (Received Signal Strength Indication) levels. Although it is possible to select the best configuration for the FlightStrata link, differences in the results are too small to detect any statistical significance. However, the WaveBridge link estimation can be considered to be precise for all sizes of ANNs used (estimation of ongoing events with error less than 1 dB). The best estimation was achieved in dataset configuration C6 (Tab. 1 and Fig. 4a). The best achieved result involved only approximately 500 errors higher than 0.7 dB. It means the neural network gave an inaccurateestimation less than 9 minutes in 3 months. This error was distributed over time throughout the 3-month period (Fig. 7), i.e. without clusters of error estimations. Significant errors usually occur in short periods of time and they are followed by longer period of smaller errors (0.7 to 2.2 dB).

From the analyzed meteorological data histograms of error cases the following statistics of meteorological data webe found:

- During strong winds (average 5 m/s during 1 minute and 6 to 8 m/s in boosts) almost 50 % of all errors of ANN applications were found.
- The greatest number of errors was found during very weak rain - approx 0.1 to 0.2 mm/min in 5-minute intervals.
- The greatest number of errors from a humidity point of view was in 81 – 83 % rH (almost 50 % of all errors)
- In 50 % of error cases the wind was from a northerly direction (the meteo sensors are approximately 5 meters from the northern wall of the building).
- From a temperature point of view the error was greatest for a temperature of approximately 3.5 °C which is also the median of all measured data.
- An atmospheric pressure of 990 hPa was found in 2/3 of error cases.

There were, as well, evaluated doubles of measured input data sets for each simulation case, when an error was higher than 1 dB. Only weak correlations in atmospheric pressure and wind were found. It is also possible to see clusters in those doubles of input data; there should be some other influence on the FSO link which is not covered by measured meteo data. Another scattering is shown in Fig. 6. Most error cases are found when wind speeds are higher.

The worst ANN performance was found in configurations C1, C4 and C5. There are high differences in the results of these different sized network configurations. It could be the result of a training problem as it was difficult to overcome all local minima in which the training process could get stuck in these situations.

5. Conclusions

This paper describes a neural network method to estimate the influence of weather on FSO links. The performance of different network snes was shown and it was proven that the size of hidden layers has a much smaller impact on estimation performance than when using feedbacks and delays in the neural network input layer. Statistics of inputs which led to inaccurate estimations were also shown. These statistics can be later used in the methodology for improved neural network architecture construction to achieve even better estimation results. The importace of having an extremely fine-grained scale of FSO detection has been proven. ANN estimation based on the RSSI of FlightStrata is almost unusable, even if the error occurs only 6 – 7 % of the time.

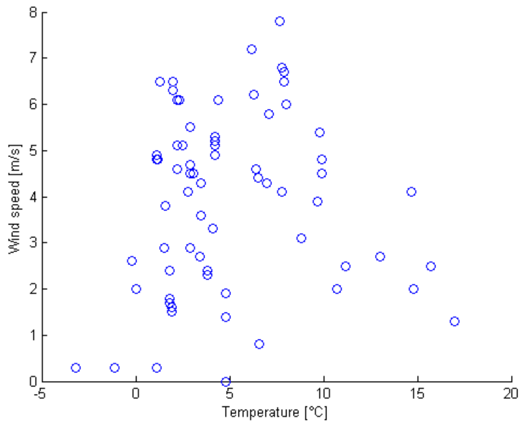

Fig. 6. Average wind speed vs. temperature scattering for simulation error greater than 1 dB.

Network 14 × 9	Error size [dB]								Sum
Configuration	-21.0	-7.0	-4.2	-2.2	-1.5	(±0.8)	+1	+1.5	
C1	0	2	6	573	641	8040	447	0	9709
C2	0	2	5	697	323	52	0	0	1079
C3	0	1	6	554	305	2248	1299	0	4413
C4	0	2	6	566	386	3480	350	0	4790
C5	0	1	7	623	518	2153	96	0	3398
C6	0	2	12	366	119	1	1	0	501
C7	0	1	10	456	183	0	0	0	650
C8	0	1	14	545	236	0	0	0	796
C9	0	1	14	553	292	0	0	0	860

Tab. 1. Simulation of neural network error distribution for 14 × 9 sized neural network in hidden layers for WaveBridge FSO link.

Network 17 × 11	Error Size [dB]							
Config.	-24	-21	-12	-6	0	6	12	Sum Err
1	0	22408	39106	357416	7369656	64850	11027	494807
2	0	22408	39109	357443	7369399	64777	11027	494764
3	0	21939	38491	355851	7354742	81813	11027	509121
4	0	22408	39109	357129	7363552	69438	11027	499111
5	0	22408	39109	357427	7365706	65186	11027	495157
6	0	22408	39109	357443	7369399	64777	11027	494764
7	13	22424	39205	358792	7367926	64812	10691	495937
8	0	22061	38539	350346	7363529	77159	11029	499134
9	5	22352	36235	350409	7367653	73165	11044	493210

Tab. 2. Simulation of neural network error distribution for best trained neural network in hidden layers for FlightStrata FSO link.

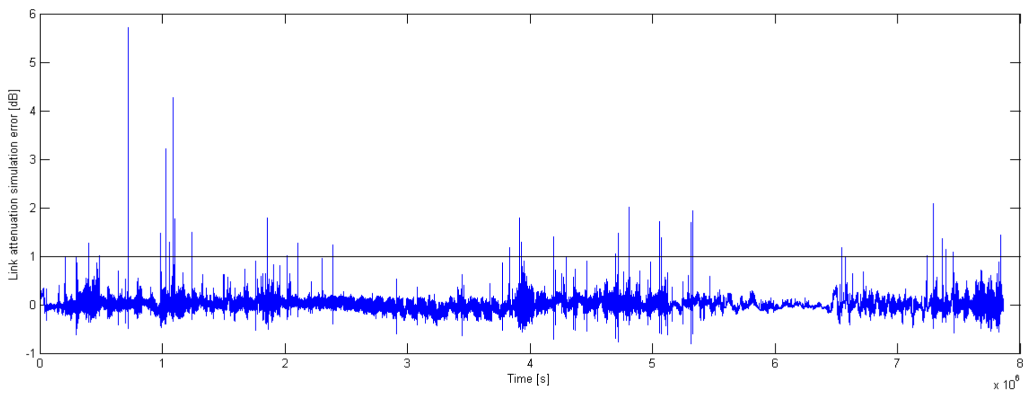

Fig. 7. Network (size 14 × 9) simulation error in dB for three months. Simulation each second, based on measured data; error of 1 dB is marked.

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References

[1] BOUCHET, O., SIZUN, H., BOISROBERT, C., DE FORNEL, F., FAVENNEC, P.-N. *Free-Space Optics: Propagation and Communication*. Wiley, 2006.

[2] KIM, I., McARTHUR, B., KOREVAAR, E. J. Comparison of laser beam propagation at 785 nm and 1550 nm in fog and haze for optical wireless communications. *SPIE Proceedings*, 2001, vol. 214, p. 26 - 37.

[3] NABOULSI, M. A., DE FORNEL, F., SIZUN, H. Fog attenuation prediction for optical and infrared waves. *Optical Engineering*, 2004, vol. 43, no. 2, p. 319 - 329.

[4] GRABNER, M., KVICERA, V. The wavelength dependent model of extinction in fog and haze for free space optical communication. *Journal of Optics Express*, 2012, vol. 19, p. 3379 - 3386.

[5] IJAZ, M., GHASSEMLOOY, Z., PEREZ, J., BRAZDA, V., FISER, O. Enhancing the atmospheric visibility and fog attenuation using a controlled FSO channel. *IEEE Photonics Technology Letters*, 2013, vol. 25, no. 13, p. 1262 - 1265.

[6] FRIEDLANDER, S. K., TOPPER, L. (Eds.) *Turbulence: Classic Papers on Statistical Theory*. Wiley-Interscience, 1961.

[7] ANDREWS, L. C., PHILLIPS, R. L. *Laser Beam Propagation through Random Media.* 2nd ed. SPIE, 2005.

[8] ZVANOVEC, S., PEREZ, J., GHASSEMLOOY, Z., RAJBHANDARI, S., LIBICH, J. Route diversity analyses for free-space optical wireless links within turbulent scenarios. *Journal of Optics Express*, 2013, vol. 21, p. 7641 - 7650.

[9] HORNIK, K., STINCHCOMBE., M. AND WHITE, H. "Multilayer feedforward networks are universal approximators," *Neural Networks*, vol. 2, pp. 359–366, 1989.

[10] STINCHCOMBE, M. WHITE, H. Universal approximation using feedforward networks with non-sigmoid hidden layer activation functions. In *International Joint Conference on Neural Networks (IJCNN).* 1989, vol. 1, p. 613 - 617.

[11] MINSKY, M. L., PAPERT, S. A. *Perceptrons*. Cambridge (MA, USA): MIT Press, 1969.

[12] MUDROCH, M., LIBICH, J., ZVANOVEC, S., MAZANEK, M. FSO link performance modelling using artificial intelligence. In *Proceedings of the 5th European Conference on Antennas and Propagation (EuCAP).* Rome (Italy), 2011, p. 1715 - 1718.

[13] SIEGELMANN, H., HORNE, B., GILES, C. Computational capabilities of recurrent NARX neural networks. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 1997, vol. 27, no. 2, p. 208 - 215.

[14] HAGAN, M., DEMUTH, H., BEALE, M. *Neural Network Design*. Boston (MA, USA): PWS Publishing, 1996.

[15] WADA, Y., KAWATO, M. Estimation of generalization capability by combination of new information criterion and cross validation. In *International Joint Conference on Neural Networks*. Seattle (USA), 1991. vol. 2, p. 1 - 6.

[16] BAUM, E., HAUSSLER, D. What size net gives valid generalization? *Neural Computation*, 1989, vol. 1, no. 1, p. 151 - 160.

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