Modeling of Nonlinear Autoregressive Neural Network for Multi-Step Ahead Air Quality Prediction

Mirza Pasic, Izet Bijelonja, Edin Kadric, Hadis Bajric

Mechanical Engineering Faculty Sarajevo, University of Sarajevo, Vilsonovo setaliste 9, Sarajevo, Bosnia and Herzegovina

Abstract – In this paper five neural network models were developed using NARX-SP neural network type in order to predict air pollutants concentrations (SO_2 , PM_{10} , NO_2 , O_3 and CO) for the 72nd hour ahead for Sarajevo. Hourly values of air pollutants concentrations and meteorological parameters (air temperature, pressure and humidity, wind speed and direction) for Sarajevo were used. Optimal model was selected based on the values of R^2 , MSE and the complexity of models. Optimal neural network model can predict air pollutants concentrations for the 72nd hour ahead with high accuracy, as well as for all hours up to 72nd hour.

Keywords – NARX-SP, neural network, air pollutant concentration, meteorological parameters

1. Introduction

The increasing possibility to collect large amounts of data about particular phenomena, as well as the development of computers and the power of its processors, have enabled usage of scientific methods for analysing and establishing relationships between data, which help better understanding certain phenomena and make adequate decisions. One of the scientific methods that has proven very effective in solving such tasks are neural networks.

DOI: 10.18421/TEM93-03

<https://doi.org/10.18421/TEM93-03>

Corresponding author: Mirza Pasic,
Mechanical Engineering Faculty Sarajevo,
University of Sarajevo, Bosnia and Herzegovina
Email: mirza.pasic@mef.unsa.ba

Received: 07 May 2020.

Revised: 24 June 2020.

Accepted: 01 July 2020.

Published: 28 August 2020.

© 2020 Mirza Pasic, Izet Bijelonja, Edin Kadric & Hadis Bajric; published by UIKTEN. This work is licensed under the Creative Commons Attribution-NonCommercial-NoDerivs 4.0 License.

The article is published with Open Access at www.temjournal.com

Neural networks are based on the work of neurons in humans and are suitable for use in the presence of large amounts of data. They can predict, with great accuracy, certain phenomena based on data related to that phenomena. The development of neural networks has proven to be extremely useful for cases where many other methods have proven insufficient.

Air quality is one of the phenomena where a large amount of data is collected. The prediction of air quality refers to the prediction of the concentration of air pollutants. Poor air quality is associated with a wide range of diseases, from acute to chronic, and from less dangerous to those very life-threatening. This problem is especially present in Sarajevo, where the air quality index is often in the danger zone. Due to the high impact of polluted air on human health, this issue is attracting a lot of public attention.

According to the U.S. Environmental Protection Agency (U.S. EPA), 187 pollutants have been identified that can cause health problems in humans. U.S. EPA has identified 6 most dangerous pollutants for human health and those are particulate matter (PM_{10} , $PM_{2.5}$), ozone at ground level (O_3), carbon monoxide (CO), sulfur dioxide (SO_2), lead (Pb) and nitrogen dioxide (NO_2) [1].

From the literature reviewed, it can be concluded that different types of neural networks for different geographical locations, as well as different combinations of inputs and outputs were used to predict the concentrations of different pollutants in the air. Adams and Kanaraoglou [2] conducted research for the city of Hamilton, Ontario, Canada using ANN. Alimissis et al. [3] analyzed multiple urban sites in Greece. Zhang and Li [4] analyzed air pollution in Xi'an and Shanghai in China.

Kolehmainen, Martikainen and Ruuskanen [5] used feedforward neural network (FFNN) with backpropagation algorithm to predict the concentration of NO_2 in Stockholm. Cai, Yin and Xie [6] used FFNN to predict hourly values of CO , NO_2 , PM_{10} , and O_3 . This type of network was also used by Viotti, Liuti and Di Genova [7] to predict urban pollution.

A review of the literature revealed that one of the most powerful types of neural networks is the nonlinear autoregressive exogenous network (NARX). The NARX neural network is a type of neural network that is adequate in working with data where the values of the predicted outputs depend on their values from the previous period, as well as the values of other inputs from that period [8].

The data required for model development were taken from the Federal Meteorological Institute of Bosnia and Herzegovina and represent hourly values of meteorological parameters (air temperature, pressure and humidity, wind speed and direction), as well as pollutant concentrations (SO_2 , PM_{10} , NO_2 , O_3 and CO) for the period from the beginning of 2016 to the end of 2018.

For the development of neural network models, a code in Python was created using the Keras library.

Neural network models for the prediction of air pollutant concentrations for the 72nd hour ahead from the current hour with a different combination of inputs and outputs for Sarajevo were developed.

For the prediction of concentration of SO_2 , PM_{10} , NO_2 , O_3 and CO , concentration of these pollutants from the previous period, as well as the values of meteorological parameters, month, day and time in that day from the same previous period were used.

Different combinations of inputs and outputs were achieved by different number of hours from the previous period from which data were used to develop neural network models.

Depending on the number of hours from the previous period used in the development of neural networks, 5 different models were developed.

An optimal model was selected based on the values of the coefficient of determination R^2 and the mean squared error MSE for the test data set and the complexity of the model. For the optimal neural network model, the relations between observed and predicted air pollutants concentration values for all data, for each pollutant were graphically presented.

With the optimal model selected, the prediction of the air pollutants concentration for each hour in the next 72 hours can be made relative to the current hour by correctly selecting the referent hour against which the prediction is made.

2. Theoretical Background

In the modern world, in many areas of life, a large amount of data is being collected, and there is a need for new methods of data processing, called machine learning. Neural networks have been shown to be one of the most effective methods of machine learning for prediction of certain phenomena.

Neural networks operate on the principle of biological neuron operation [9], [10]. Using the

principle of work of biological neurons, McCulloch and Pitts created a mathematical model of neurons (MCP).

This simple model of MCP neurons consists of a set of input data x_i , set of weights w_i and activation function. The model works by multiplying the value of each input x_i by the corresponding weight w_i , and then these products are summed up in equation (2.1) [9], [10]:

$$h = \sum_{i=1}^L w_i \cdot x_i \quad (2.1)$$

where:

i - the order number of the input value ($i = 1, \dots, L$).

The resulting sum h enters the activation function, which has its own sensitivity threshold. The MCP neuron has a binary character, because the activation function is binary, so as an output value it can give is only 0 or 1, as shown in equation (2.2) [9], [10]:

$$y = g(h) = \begin{cases} 1, & \text{if } h \geq \theta \\ 0, & \text{if } h < \theta \end{cases} \quad (2.2)$$

Based on the principles of the MCP in 1958, scientist Rosenblatt invented perceptron, the first modern neural network. Perceptron is a set of multiple neurons with multiple weights and multiple outputs. The perceptron consists of an input and output layer and its structure is shown in Figure 1. [9], [10].

Figure 1. Perceptron (adapted from [9])

The importance of Rosenblatt's perceptron is the ability to learn. Learning implies that weights change until the best output results are achieved. This form of perceptron can only solve linear problems, so as the problems are much more complex in reality, more weights have to be introduced. In 1986, Rumelhart, McClelland and Hinton proposed the creation of a multi-layer perceptron (MLP), which has one or more hidden layers between the input and output layers. The correction of weights to their

optimal value, in order to achieve the best performance of the neural network, is achieved using the backpropagation algorithm [9].

NARX neural networks have been shown to be very useful tools for modelling nonlinear systems as it is the case in this paper. The NARX neural network actually has the structure of a recurrent neural network, and it is used to model nonlinear dynamic systems as well as to predict time series [8], [11], [12].

There are two types of NARX neural networks, Serial-Parallel (NARX-SP) and Parallel (NARX-P) neural network. In this paper, the NARX-SP type of neural network was used. As inputs the previous output values and exogenous inputs from the same previous period were used. One area where the NARX-SP neural network can be successfully used is to predict the concentration of air pollutants [13], [14], [15].

Air pollution is the second largest environmental problem in the world after climate change. The importance of this problem has been recognized in the European Union (EU), and in organizations such as the United Nations (UN) and the World Health Organization (WHO). In order to reduce air pollution in the EU countries, various measures have been taken to improve air quality. These measures have resulted in significant improvements in air quality, although pollution is still a major problem. In some areas, such as urban areas, there has even been an increase in air pollution. Air pollution over permitted values increases mortality, shortens life expectancy, causes many diseases, increases medical costs, affects the economy and climate change. Pollutants

in excessive concentration damage buildings and cultural monuments, and negatively affect water, soil, vegetation and wildlife [16].

The problem of air pollution is also present in Sarajevo. The most common air pollutants in Sarajevo are SO_2 , PM_{10} , NO_2 , O_3 and CO . In order to protect human health, it is very important to know the concentration of air pollutants in the coming period, so that citizens can plan their activities accordingly. This can be achieved by accurately predicting the concentration of air pollutants for the coming period.

3. Methodology

The NARX-SP neural network type was used to develop the neural network model, and data were obtained from the Federal Meteorological Institute of BiH. The data consists of hourly values of meteorological parameters, air temperature (T), pressure (p) and humidity (H), wind speed (v) and wind direction (wd) and concentration of air pollutants SO_2 , PM_{10} , NO_2 , O_3 and CO , for the period from the beginning of 2016 to the end of 2018. Data were processed, so the database contains 26304 data for each meteorological parameter and for each air pollutant.

In order to gain a better understanding of the data used in this work for the development of neural network models, Table 1 presents descriptive statistics of these data (mean, median, mode, standard deviation, minimum and maximum values, and units).

Table 1. Descriptive statistics of used data

	H	p	T	v	wd	SO_2	PM_{10}	NO_2	O_3	CO
Mean	71,159	944,222	11,064	1,870	18,635	15,286	41,297	20,914	58,427	0,305
Median	75,000	944,300	11,400	1,600	15,839	6,900	26,100	14,350	53,900	0,170
Mode	88,000	945,000	13,200	0,900	11,000	6,965	24,149	11,098	69,958	0,040
Standard deviation	17,797	6,957	9,058	1,134	8,951	27,061	51,186	21,424	38,491	0,431
Minimum	7,000	841,800	- 22,200	0,000	2,000	0,000	0,000	0,000	0,000	0,000
Maximum	100,000	993,400	44,000	15,500	36,000	872,300	756,100	271,600	434,600	5,760
Unit	%	hPa	°C	m/s		$\mu\text{g}/\text{m}^3$	$\mu\text{g}/\text{m}^3$	$\mu\text{g}/\text{m}^3$	$\mu\text{g}/\text{m}^3$	$\mu\text{g}/\text{m}^3$

The data used to develop neural network models have been previously adequately sorted, normalized and filtered. The values of the concentration of air pollutants and meteorological parameters other than

wind direction (wd) are normalized to the interval [0,1], by the algorithm created in Python shown in Figure 2.

```

df["H"]=((df["H"]-df["H"].min())/(df["H"].max()-df["H"].min()))
df["P"]=((df["P"]-df["P"].min())/(df["P"].max()-df["P"].min()))
df["T"]=((df["T"]-df["T"].min())/(df["T"].max()-df["T"].min()))
df["v"]=((df["v"]-df["v"].min())/(df["v"].max()-df["v"].min()))
df["SO2"]=((df["SO2"]-df["SO2"].min())/(df["SO2"].max()-df["SO2"].min()))
df["PM10"]=((df["PM10"]-df["PM10"].min())/(df["PM10"].max()-df["PM10"].min()))
df["NO2"]=((df["NO2"]-df["NO2"].min())/(df["NO2"].max()-df["NO2"].min()))
df["O3"]=((df["O3"]-df["O3"].min())/(df["O3"].max()-df["O3"].min()))
df["CO"]=((df["CO"]-df["CO"].min())/(df["CO"].max()-df["CO"].min()))

```

Figure 2. Code in Python for normalizing data

The values referring to the month of the year, day of the week, time of a day and wind direction were normalized to the interval $[-1,1]$ using the sin and cos functions. This means that the sin and cos components of the month, day, time of a day and wind direction were used in further work.

These values are normalized in this way because of their cyclic repetition, where the last data in the sequence has an effect on the first data, as shown in Figure 3.

Figure 3. Cyclic repetition for: a) wind direction, b) month, c) day and d) time

The sigmoid function was used as an activation function in the layers of all developed neural network models. The batch size of 10, 500 epochs with early stopping and the Adam optimizer were also used.

The number of neurons in the input layer depends on the selected number of previous hours from which the prediction data were used. In each developed model, meteorological parameters, month of the year, day of the month and time in that day for the hour for which the prediction is made (12 inputs) and meteorological parameters, concentration of air pollutants, month, day and time in that day from the referent hour were used as inputs (17 inputs), and from the referent hour and the selected number of previous hours.

The data is split into three sets, training, validation and test data set. For the developed models the values of the coefficient of determination R^2 and the mean

squared error MSE were calculated. Optimal neural network model was selected based on values of R^2 , MSE and model complexity. Relations between the predicted and observed values of concentration of air pollutants were graphically presented, and conclusions were made about the prediction accuracy of the selected optimal model.

The inputs to the neural network were the values of meteorological parameters, concentration of air pollutants, month in the year, day of the week and time of a day from the referent hour and the referent hour, and previous 23, 35, 47 and 71 hours and values of meteorological parameters, month, day and time for the hour for which the prediction is made.

Structures of models in terms of the number of neurons in the input, hidden and output layers is shown in Table 2.

Table 2. Structures of neural network models for the 72nd hour ahead

Model	Number of previous hours	Structure
1	Referent hour	29-59-5
2	Referent hour + 23 previous hours	432-865-5
3	Referent hour + 35 previous hours	636-1273-5
4	Referent hour + 47 previous hours	864-1729-5
5	Referent hour + 71 previous hours	1296-2593-5

4. Results and Discussion

Model analysis was performed based on the values of R^2 and MSE. The R^2 and MSE values of all 5 models for all data sets and for all pollutants are shown from Tables 3. to 10.

Table 3. R^2 values [%] for training data set

Model	R^2 train	R^2 train SO_2	R^2 train PM_{10}	R^2 train NO_2	R^2 train O_3	R^2 train CO
1	62,805	43,544	59,247	74,858	62,700	73,674
2	96,250	93,877	96,342	96,971	96,303	97,757
3	97,437	95,923	97,241	97,645	97,969	98,408
4	96,921	94,690	96,891	97,644	97,184	98,197
5	96,825	94,143	96,908	97,662	97,852	97,829

Table 4. MSE values for training data set

Model	MSE train	MSE train SO_2	MSE train PM_{10}	MSE train NO_2	MSE train O_3	MSE train CO
1	0,002184728	0,001533912	0,002136510	0,002255586	0,003401855	0,001595778
2	0,000223554	0,000167367	0,000198091	0,000266049	0,000347346	0,000138917
3	0,000151678	0,000115821	0,000151494	0,000204890	0,000189124	0,000097059
4	0,000179314	0,000144191	0,000169546	0,000211200	0,000262457	0,000109173
5	0,000171987	0,000161406	0,000162326	0,000191556	0,000224409	0,000120235

Table 5. R^2 values [%] for validation data set

Model	R^2 val	R^2 val SO_2	R^2 val PM_{10}	R^2 val NO_2	R^2 val O_3	R^2 val CO
1	60,065	42,333	56,511	71,880	61,096	68,504
2	91,693	84,781	93,759	93,686	91,018	95,220
3	93,773	89,498	95,031	94,583	93,271	96,480
4	92,707	86,810	93,624	93,561	93,242	96,299
5	92,522	86,558	94,238	93,133	93,725	94,956

Table 6. MSE values for validation data set

Model	MSE val	MSE val SO_2	MSE val PM_{10}	MSE val NO_2	MSE val O_3	MSE val CO
1	0,002428519	0,001636032	0,002447507	0,0021517785	0,003629123	0,001912149
2	0,000474193	0,000375878	0,000345137	0,000556281	0,000805195	0,000288473
3	0,000368757	0,000251832	0,000266125	0,000484383	0,000632428	0,000209017
4	0,000411553	0,000337954	0,000338350	0,000537356	0,000617833	0,000226270
5	0,000447001	0,000360522	0,000331294	0,000636636	0,000578712	0,000327840

Table 7. R^2 values [%] for test data set

Model	R^2 test	R^2 test SO_2	R^2 test PM_{10}	R^2 test NO_2	R^2 test O_3	R^2 test CO
1	60,852	47,234	56,017	71,235	58,962	70,813
2	92,204	88,017	93,241	93,684	90,884	95,194
3	93,403	89,517	94,364	93,702	92,995	96,439
4	92,862	87,344	93,886	93,459	93,437	96,183
5	93,025	87,101	94,663	93,978	93,338	96,046

Table 8. *MSE values for test data set*

Model	MSE_{test}	$MSE_{test_{SO_2}}$	$MSE_{test_{PM_{10}}}$	$MSE_{test_{NO_2}}$	$MSE_{test_{O_3}}$	$MSE_{test_{CO}}$
1	0,002528202	0,001538079	0,002547798	0,002580728	0,004014633	0,001959770
2	0,000489889	0,000352507	0,000361692	0,000588074	0,000847853	0,000299317
3	0,000402715	0,000263937	0,000298198	0,000586891	0,000636526	0,000228021
4	0,000411997	0,000335452	0,000332844	0,000550051	0,000610238	0,000231399
5	0,000406506	0,000296979	0,000297544	0,000549379	0,000619560	0,000269065

Table 9. R^2 values [%] for all data

Model	R^2_{all}	$R^2_{all_{SO_2}}$	$R^2_{all_{PM_{10}}}$	$R^2_{all_{NO_2}}$	$R^2_{all_{O_3}}$	$R^2_{all_{CO}}$
1	61,849	44,079	57,991	73,538	61,591	72,045
2	94,534	90,939	95,194	95,621	94,180	96,735
3	95,923	93,552	96,234	96,186	96,025	97,615
4	95,291	91,706	95,642	96,048	95,649	97,408
5	95,165	91,347	95,866	95,882	95,944	96,786

Table 10. *MSE values for all data*

Model	MSE_{test}	$MSE_{test_{SO_2}}$	$MSE_{test_{PM_{10}}}$	$MSE_{test_{NO_2}}$	$MSE_{test_{O_3}}$	$MSE_{test_{CO}}$
1	0,002302290	0,001555052	0,002281075	0,002373119	0,003570307	0,001731897
2	0,000327847	0,000246744	0,000260767	0,000389578	0,000540696	0,000201448
3	0,000246215	0,000173210	0,000204258	0,000338426	0,000369066	0,000146116
4	0,000272778	0,000221591	0,000236305	0,000344896	0,000403808	0,000157288
5	0,000275242	0,000229300	0,000223987	0,000354306	0,000376093	0,000192523

It can be seen from Tables 3 to 10 that for all developed neural network models, the values of R^2 and MSE for both training and validation data sets show approximately the same values as for the test set. It can be concluded that the developed neural network models performed the learning process correctly.

Figures 4 and 5 graphically represent the values of R^2 and MSE by models for the test data set. The values of R^2 for the test data set in Table 7 differ very little from each other for models 2, 3, 4 and 5, as can be seen from Figure 4. Only model 1, where the prediction is based on the data from the referent hour and the hour for which the prediction is being made, has significantly lower the value of R^2 than the other models. Sharp increase in the value of R^2 , from 60,852% to 92,204% can be observed between models 1 and 2, because model 2 used more data from the previous period as it is shown in Table 2. It shows the fact that in order to predict the concentration of air pollutants for the 72nd hour, it is necessary to provide more data from the previous period. By comparing models 2, 3, 4 and 5, it can be seen that model 3 has the highest value of $R^2 = 93,403\%$.

Figure 4. R^2 values [%] for test set by models

From Figure 5, and by analyzing the values in Table 8 for the test data set, a sharp decrease in the MSE value between model 1 and model 2 can be observed, from $MSE = 0,002528202$ to $MSE = 0,000489889$. For models 2, 3, 4 and 5, the MSE values are approximately the same, with model 3 having the lowest value of $MSE = 0,000402715$.

Figure 5. MSE values for test set by models

Model 3 has the highest R^2 value and the lowest MSE value, so it was selected as the optimal model for prediction the concentration of air pollutants for the 72nd hour ahead. Based on the values of $R^2 = 93,403\%$ and $MSE = 0,000402715$ for model 3 for the test data set, it can be concluded that model 3 has very high values of R^2 and low values of MSE performance. By analyzing the values of MSE for training and validation data set during the learning process, it was examined whether the network was overtrained for the selected model 3, as shown in Figure 6.

Figure 6. Change of MSE values by epochs for training and validation set (model 3)

Figure 7. Relation between observed and predicted values SO_2 for all data

Figure 8. Relation between observed and predicted values PM_{10} for all data

Figure 6 shows that the learning process stopped in the 175th epoch. Based on the movement of the MSE curves for the validation and training set, it can be concluded that the learning process was done correctly, ie. that the network is not overtrained. For the selected optimal model 3, as the best performing model, the relations of predicted and observed values for all data for each pollutant individually were graphically presented in Figures 7 to 11.

Figure 9. Relation between observed and predicted values NO_2 for all data

Figure 10. Relation between observed and predicted values O_3 for all data

Figure 11. Relation between observed and predicted values CO for all data

It can be seen from Figures 7 to 11 that predicted values are very close to observed values. The observed values of the air pollutant concentration show seasonal changes that are repeated in each of the three years. The predicted values follow the seasonality of the observed values, so it can be said that optimal model 3 is suitable for prediction of the

concentration of air pollutants for the 72nd hour ahead.

In order to reach better visibility and for a randomly selected 72 consecutive hours the relation between predicted and observed values of concentration of all 5 air pollutants individually is graphically presented in Figure 12.

Figure 12. Relation between observed and predicted values of air pollutants concentrations for randomly selected 72 consecutive hours (model 3): a) SO_2 , b) PM_{10} , c) NO_2 , d) O_3 , e) CO

Prediction of concentration of air pollutants for the 72nd hour ahead is a complex task, since it is a further hour ahead. Optimal model 3 can be used to predict the concentration of all 5 air pollutants used in this paper for each hour in the next 72 hours relative to the current hour, with the correct selection of the referent hour. Model 3 for the prediction of air pollutant concentration for 72nd hour ahead shows high prediction accuracy.

5. Conclusion

The NARX-SP neural network has proven to be a powerful tool for air pollutant concentrations prediction. For the selected optimal model the value of R^2 is very high and the value of MSE is very low. It can be concluded that the optimal model can predict concentration of air pollutants for 72nd hour ahead with a very high accuracy. The graphical presentations of the relations between observed and predicted values show that the predicted values deviate very little from the observed values confirming the conclusion that the optimal model prediction is very accurate.

As predicted values follow the seasonal changes of observed values, it can be concluded that NARX-SP neural network recognizes changes in observed values and creates functional dependence of the air pollutants concentration, meteorological parameters, month in the year, day of the week and time of the day. Optimal neural network model can predict with great accuracy sudden changes in the concentration of air pollutants. Therefore, it can be concluded that the use of a NARX-SP neural network can establish functional dependencies, complex and nonlinear relationship between inputs and outputs that do not have a mathematically defined functional dependency.

References:

- [1]. United States Environmental Protection Agency. (n.d.). Initial List of Hazardous Air Pollutants with Modifications. Retrieved from: <https://www.epa.gov/haps/initial-list-hazardous-air-pollutants-modifications> [accessed: 20 February 2020].
- [2]. Adams, M. D., & Kanaroglou, P. S. (2016). Mapping real-time air pollution health risk for environmental management: Combining mobile and stationary air pollution monitoring with neural network models. *Journal of environmental management*, 168, 133-141.
- [3]. Alimissis, A., Philippopoulos, K., Tzani, C. G., & Deligiorgi, D. (2018). Spatial estimation of urban air pollution with the use of artificial neural network models. *Atmospheric Environment*, 191, 205-213.
- [4]. Zhang, B., & Li, W. (2019). Intelligent air quality detection based on genetic algorithm and neural network: An urban China case study. *Concurrency and Computation: Practice and Experience*, 31(10), e4673.
- [5]. Kolehmainen, M., Martikainen, H., & Ruuskanen, J. (2001). Neural networks and periodic components used in air quality forecasting. *Atmospheric Environment*, 35(5), 815-825.
- [6]. Cai, M., Yin, Y., & Xie, M. (2009). Prediction of hourly air pollutant concentrations near urban arterials using artificial neural network approach. *Transportation Research Part D: Transport and Environment*, 14(1), 32-41.
- [7]. Viotti, P., Liuti, G., & Di Genova, P. (2002). Atmospheric urban pollution: applications of an artificial neural network (ANN) to the city of Perugia. *Ecological Modelling*, 148(1), 27-46.
- [8]. AlHamaydeh, M., Choudhary, I., & Assaleh, K. (2013). Virtual testing of buckling-restrained braces via nonlinear autoregressive exogenous neural networks. *Journal of computing in civil engineering*, 27(6), 755-768.
- [9]. Marsland, S. (2015). *Machine learning: an algorithmic perspective*. CRC press.
- [10]. Skansi, S. (2018). *Introduction to Deep Learning: from logical calculus to artificial intelligence*. Springer.
- [11]. Mahmoud, S., Lotfi, A., & Langensiepen, C. (2013). Behavioural pattern identification and prediction in intelligent environments. *Applied Soft Computing*, 13(4), 1813-1822.
- [12]. Kumpati, S. N., & Kannan, P. (1990). Identification and control of dynamical systems using neural networks. *IEEE Transactions on neural networks*, 1(1), 4-27.
- [13]. Karasu, S., Altan, A., Saraç, Z., & Hacıoğlu, R. (2017). Estimation of fast varied wind speed based on NARX neural network by using curve fitting. *International Journal of Energy Applications and Technologies*, 4(3), 137-146.
- [14]. Lin, T. N., Giles, C. L., Horne, B. G., & Kung, S. Y. (1997). A delay damage model selection algorithm for NARX neural networks. *IEEE Transactions on Signal Processing*, 45(11), 2719-2730.
- [15]. Siegelmann, H. T., Horne, B. G., & Giles, C. L. (1997). Computational capabilities of recurrent NARX neural networks. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 27(2), 208-215.
- [16]. European Environment Agency. (2019, October 16). Air quality in Europe – 2019 report. Retrieved from: <https://www.eea.europa.eu/publications/air-quality-in-europe-2019> [accessed: 10 March 2020].