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Autoregressive prediction analysis using machine deep learning

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ABSTRACT

Regression analysis, in statistic a modelling, is a set of statical processes that can be used to estimate the relationship between a dependent variable, commonly known as the outcome or response, and more independent variables generally called predictors of covariant. On the other hand, autoregression, which is based on regression equations, is a sequential model that uses time to predict the next step data from the previous step. Given the importance of accurate modelling and reliable predictions. in this paper we have analyzed the most popular methods used for data prediction. Nonlinear autoregressive methods were introduced, and then the machine deep learning approach was used to apply prediction based on a selected input data set. The mean square error was calculated for various artificial neural networks architecture to reach the optimal architecture, which minimized the error. Different artificial neural network (ANN) architectures were trained, tested, and validated using various regressive models, a recommendation was raised according to the obtained and analyzed experimental results. It was shown that using the concepts of machine deep learning will enhance the response of the prediction model.

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1. INTRODUCTION

In statistics, random data cannot be fully evaluated by visual inspection. While there are many types of regression analysis, at their core all methods examine the effects of one or more independent variables on a dependent variable. The regression analysis model (RAM) is the simple and effective model used to predict an output based on a selected input data set [1]-[3]. The implementation of RAM leads to a calculated regression coefficient, which was used in forming the predicted output equations as shown in Figure 1 [4], [5].

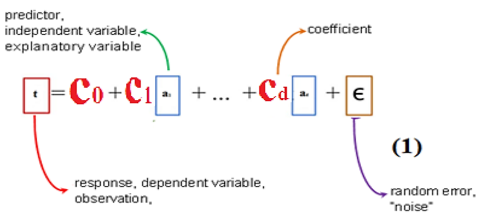

Figure 1. RAM equation

The regression means square error tells us how close the line is to a set of points. It was called the mean square error as it's used in finding the average set of errors. Squaring was needed to eliminate the negative signs in MSE. The lower the MSE the better the forecast. The regression means square error (MSE) between the calculated and the target outputs may be high, causing a poor effective prediction. thus, the machine deep learning approach can be used to minimize MSE and enhance the prediction process accuracy [6], [7]. The machine deep learning (MDL) approach is a process of using an artificial neural network (ANN) [8]-[10] as a prediction tool. MDL can be treated using complicated ANN models, more calculations and big input data set, as shown in Figure 2 [11]-[14].

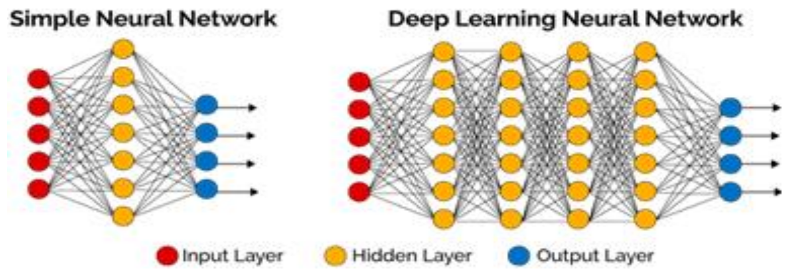

Figure 2. ANN using MDL

The minimum description length principle (MDL) is based on the concept of describing the data in full using fewer symbols. MDL, which was originated from algorithmic coding theory in computer science, regards both the model and the data as codes. The idea of MDL was to reduce redundancies by compression algorithms [15], [16]. Therefore, we can uncover irregular data and enhance the MSE results. In MDL the big input data set can be divided into training, testing, and validating data sets as shown in Figure 3. Artificial Neural Networks (ANNs) are computational algorithms s. Originally, it was intended to simulate biological systems composed of "neurons". ANN is capable of machine learning and pattern recognition based on the model of human neurons. The interconnected neuron can compute values from inputs. ANNs are information process techniques that can be used for classifications and regression of continuous target attributes [17], [18]. This work will have a complicated architecture with a big number of neurons in the hidden layer, the selected number of training iterations must lead to MSE minimization [19]-[21].

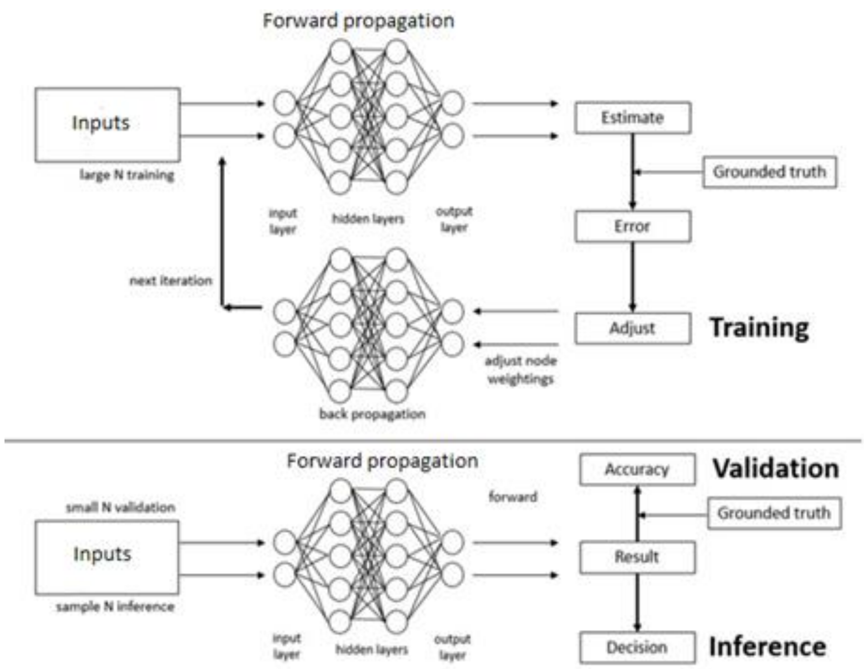

Figure 3. ANN deep learning

A nonlinear autoregressive model (NARM) can be built based on (1) and (2). In (1) the predicted output can be treated as a function of previous inputs and outputs as shown in Figure 4, while in (2) the predicted output is treated as a function of previous inputs only. We can see that there's a feedback connection between the input and the output to get previous input [22], [23].

$$y(t) = F(x(t), x(t-1), x(t-2), \dots, x(t-d), y(t-2), \dots, y(t-d)) \quad (1)$$

$$y(t) = F(x(t), x(t-1), x(t-2), \dots, x(t-d)) \quad (2)$$

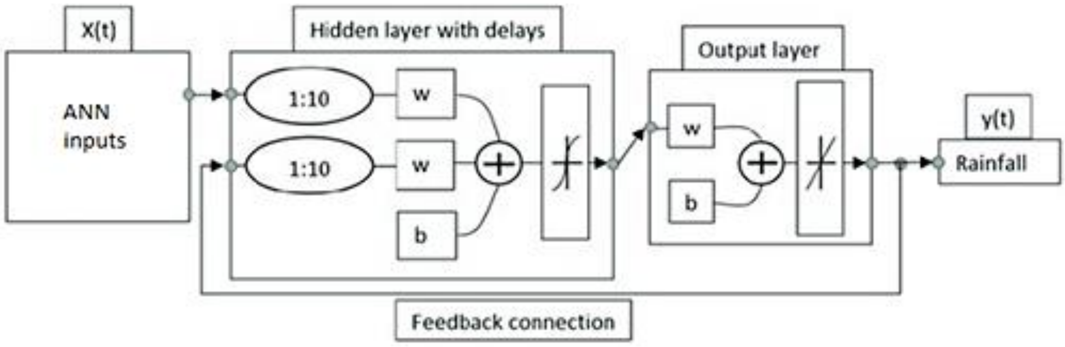

Figure 4. NARM based on equation 1

2. RESEARCH METHOD

A pollution input data set was selected [2]–[5]. This data set contains a 2D matrix with 8 rows and 508 columns, each column represents the values of PM (temperature, relative humidity, carbon monoxide, sulfur dioxide, nitrogen dioxide, hydrocarbons, ozone) [24], [25], The target data is a 2D matrix with 3 rows and 508 column, each row represents the values of the pollution negative effects (total mortality, respiratory mortality, cardiovascular mortality), Figure 5 shows a sample of the input data set. The input data set was divided into 3 parts: training, testing and validating data, the various ANN architectures were selected to be trained and used as a prediction tool. Figure 6 shows the steps required to test each selected ANN.

Inputs

a1	a2	a3	a4	a5	a6	a7	a8
72.3800	29.2000	11.5100	3.3700	9.6400	45.7900	6.6900	72.7200
67.1900	67.5100	8.9200	2.5900	10.0500	43.9000	6.8300	49.6000
62.9400	61.4200	9.4800	3.2900	7.8000	32.1800	4.9800	55.6800
72.4900	58.9900	10.2800	3.0400	13.3900	40.4300	9.2500	55.1600
74.2500	34.8000	10.5700	3.3900	11.9000	48.5300	9.1500	66.0200
67.8800	66.7800	7.9900	2.5700	10.1100	48.6100	8.8000	44.0100
74.2000	35.1600	10.5100	2.3500	9.4900	38.7600	7.4200	47.8300
74.8800	55.8600	9.8400	3.3800	10.7200	45.1900	10.6800	43.6000
64.1700	52.6800	6.6100	1.5000	5.7700	31.6500	5.8500	24.9900
67.0900	50.9400	7.9000	2.5600	7.4300	40.2000	7.6300	40.4100

Targets

t1	183.6300	191.0500	180.0900	184.6700	173.6000	183.7300	171.7900	177.9500
t2	11.9000	10.7500	9.3300	9.5400	8.2700	7.5500	9.1200	7.7600
t3	97.8500	104.6400	94.3600	98.0500	95.8500	95.9800	88.6300	90.8500

Figure 5. Samples of the input data set

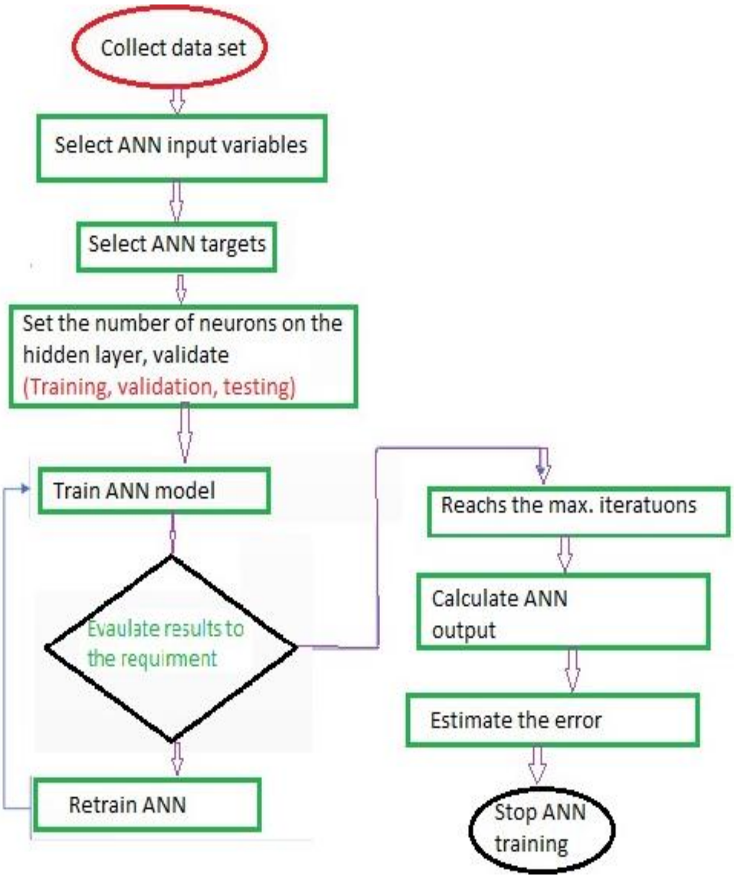

Figure 6. Training process

3. RESULTS AND DISCUSSION

The selected input data set and targets were treated using the regression model presented by Matlab code, Figure 7 shows the obtained regression coefficients, using these coefficients the targets formulas were calculated and the value of MSE was around 5.37425, as shown in Figure 8. To reduce MSE value NARM was built and tested. First, we used (1), where the output is a function of the previous inputs and outputs, and Figure 9 shows the architecture of the used ANN. Here we changed the number of neurons in the hidden layer and the number of delays, Figure 10 shows one of the responses of the executed model. The previous model was treated using a variant number of neurons in the hidden layer and various numbers of delays, Table 1 shows the obtained values for MSE

Coeffecients

t1	t2	t3
220.3519	15.3448	134.3318
-0.8580	-0.1126	-0.6681
-0.2183	-0.0158	-0.1815
1.3875	0.0779	1.0582
2.4728	-0.0530	3.4070
-0.9017	-0.0227	-0.6651
0.1590	0.0216	0.0169
0.7085	0.0199	0.2887
0.0725	0.0183	0.0169

Figure 7. Calculated regression coefficients

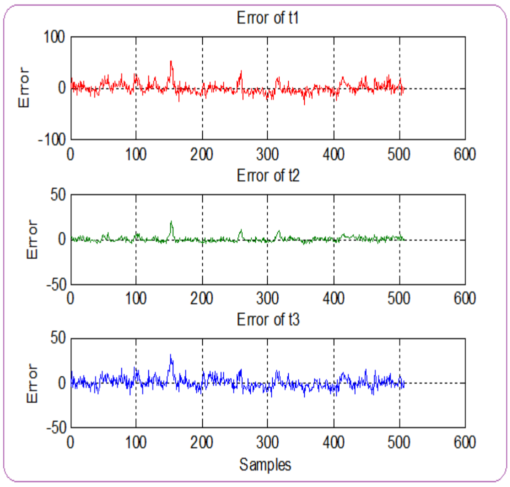

Figure 8. Regression errors between the targets and calculated outputs

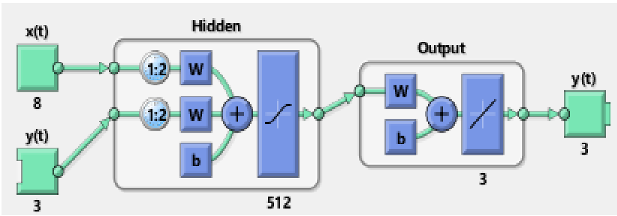

Figure 9. NARM based on (1)

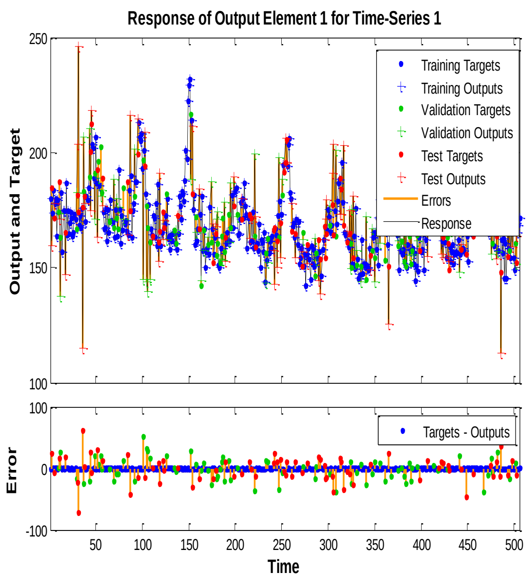

Figure 10. Model-based on (1) response

Table 1. Obtained results of executing model 1

Neuron /delay	8	4	2
128	0.004428	0.216104	**7.07005*e-14**
64	1.30904	0.144605	31.89164
32	1.80656	23.46777	14.88772
16	4.29606	12.18773	29.02915
8	15.30561	16.25447	29.33317

From Table 1 we can see that increasing the number of neurons keeping the delay equal to 2 will enhance the model response by decreasing the MSE value, this is also shown in Table 2. Another model was built and tested based on (2), where the outputs were calculated as functions of the previous inputs, Figure 11 shows the basic architecture of the used model. Here we also changed the number of neurons in the hidden layer and the number of delays, Figure 12 shows one of the responses of the executed model. This model was treated using a variant number of neurons in the hidden anandrousarious numbers of delays, Table 3 shows the obtained values for MSE. From Table 3 we can see that increasing the number of neurons in the hidden layer with a bigger number of delays will enhance the model response by decreasing MSE values.Examining the obtained result using the regression model, model 1 and model 2 we can see the following facts: i) both NAR models enhance the regression performance compared with the regression model; ii) applying MDL by increasing the number of neurons in the ANN hidden layer will enhance the model response by decreasing MSE values; iii) it is better to use model 2 for prediction by increasing the number of neurons in the ANN hidden layer and keeping the number of delays small; and iv) model 1 has a better performance compared with mode 2.

Table 2. Effects of an increasing number of neurons keeping delay equal to 2

No of Neuron	MSE
128	7.07005*e-14
256	1.43335*e-14
512	1.77292*e-26

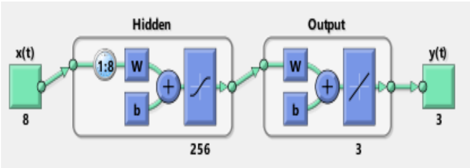

Figure 11. NARM based on (2)

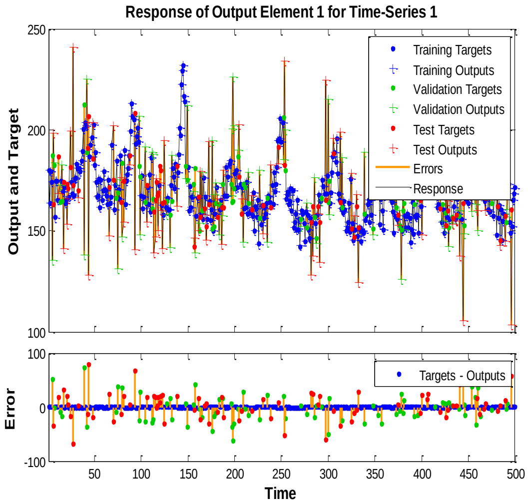

Figure 12. Model-based on (2) response

Table 3. Obtained results of executing model 1

Neuron /delay	8	4	2
256	**7.32080e-4**	2.88122 e-2	1.49598
128	1.02681e-2	1.051855	37.54507
64	1.85082	13.86173	1.41662
32	3.21381e-3	21.91815	11.36876
16	53.68127	19.18600	39.52439
8	57.53899	53.65321	38.15894

4. CONCLUSION

A pollution data set was selected, the various target prediction models were built and tested, and the experimental results were examined and analyzed. It was shown that using the concepts of machine deep learning will enhance the response of the prediction model. Based on the obtained experimental results we recommend using either model 1 or model 2 for target prediction, increasing the number of neurons in model 1 and keeping the number of delays small will lead to better performance by minimizing MSE values.

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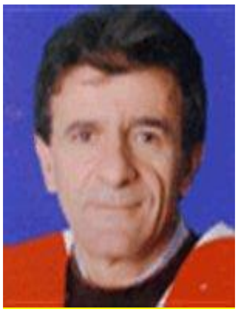

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