Conference Proceedings of the Academy of Romanian Scientists
PRODUCTICA Scientific Session
ISSN 2067-9564 Volume **9**, Number **1/2017**

ARTIFICIAL NEURAL NETWORK MODELS USED TO PREDICTING DYNAMIC SPINDLE PARAMETERS

Petre-Raul GHENCEA[1], Miron ZAPCIU[2]

Rezumat. Lucrarea prezintă abordarea mai multor tipuri de rețele neuronale artificiale (RNA) cu propagare înainte pentru prognozarea parametrilor dinamici la arbori principali. Obiectivul este de a găsi un altgoritm care să satisfacă obținerea de prognoze cât mai realiste prin utilizarea de parametri dimanici având diferențe între ordinele de mărime foarte mari. Pentru prognozare este utilizat Azure Machine Learning, soft care este capabil să facă legături între diferite arhitecturi de RNA şi prezentarea într-o formă complexă a prognozei. Rezultatul cercetării stabileşte tipul de RNA optim pentru prognozarea parametrilor dinamici în cazul în care avem ca seturi de date de intrare unul sau mai mulți parametri.

Abstract. The paper presents the approach of several types of artificial neural networks (ANN) with forward propagation for the prognosis of dynamic parameters on main shafts. The objective is to find an algorithm that satisfies the most realistic prognoses by using dynamic parameters with very large orders of magnitude. For forecasting Azure Machine Learning is used, which is capable of linking different ANN architectures and presenting it in a complex form of the forecast. The result of the research determines the optimal ANN type for forecasting dynamic parameters if we have one or more parameters as input data sets.

Keywords: Multiclass Neural Network, Two-Class Neural Network, Neural Network Regression, Azure Machine Learning.

1. Introduction

Artificial neural networks (ANN) are a branch of the artificial intelligence science being the main research object for neuroinformatics. ANN's main feature is the ability to learn by example, using previous experience to improve performance, so they are able to implicitly synthesize a particular model of the problem by constructing by learning the algorithm to solve a problem on the basis of measured data sets.

Climate predictions studies use ANN built on data sets with many solar radiation input parameters [1]. The precision and flexibility of an ANN is given by using multiple input parameters.

Research on forecast production indicators (number of finished products and production flow while progress) were made with software Miner Statistica Data,

[1] Ec. raul_petrino@yahoo.com
[2] Prof. PhD. eng., Dept. of Machine Tools and Manufacturing Systems, Politehnica University of Bucharest, Corresponding Member of the Academy of Romanian Scientists, miron.zapciu@upb.ro

based on linear and nonlinear ANN decision tree or random [2]. The software performs an effective analysis, representing a performance assessment tool for policy-makers [3].

ANNs have been applied to predict the production of bioelectricity extracted from glucose (electron donors). ANNs use multilayer perception with good prognostic ability. The sigmoid type (MATLAB) transfer function is used for all neurons due to its better prediction performance than other transfer functions [4].

Designing addressable memories is done with ANN Hopfield using a time-based evolutionary algorithm based on the parallel asynchronous process [5].

ANN models are also used to predict treatment or dental extractions. Collecting a precise set of samples for use in mathematical modelling is required for the diagnosis, given that dental extraction is an irreversible intervention. It is essential to evaluate the treatment performance of an ANN model that predicts the proportion of cases in which the system recommends an extraction or not [6].

This article proposes an ANN prognostic algorithm for temperature/vibration front/back using Azure Machine Learning (AML) [7]. AML uses ANNs with pre-supervised learning algorithms, the software being developed based on modules that can be connected as needed or the researcher's vision. Predictive analysis is based on historical or current data that identifies patterns or trends for forecasting future developments.

The purpose of the article is to use a subcomponent of artificial intelligence, namely ANN propagation supervised learning type before forecasting and dynamic thermal behaviour of spindle on the data sets obtained by measuring.

2. Research method

The forecasting methodology temperature/vibration front/back is based on ANNs with forward propagation. The proposed method uses three ANN models (Multiclass Neural Network, Two-Class Neural Network and Neural Network Regression) which are connected in succession in the basic algorithm to determine which type of ANN model ensures the best prognosis.

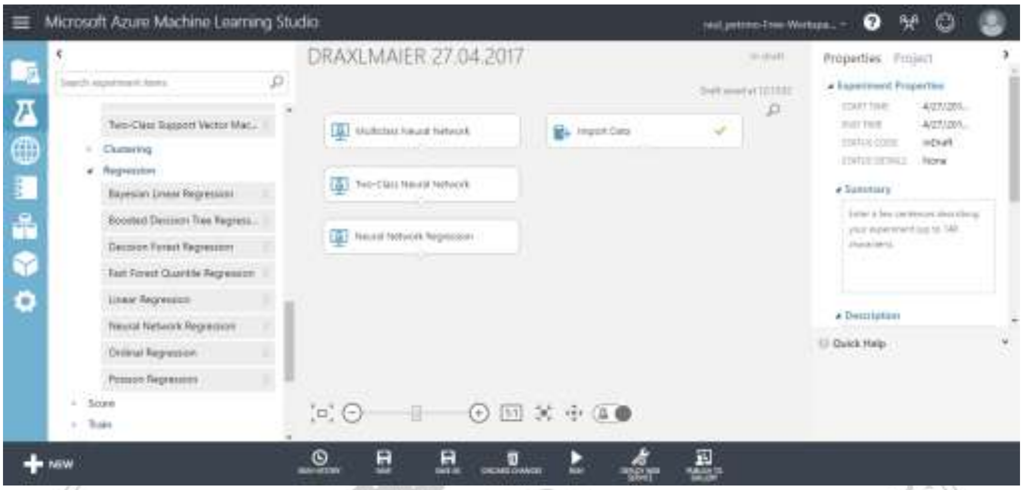

Fig. 1 Selection of ANN models and database import - Azure Machine Learning

The three models are based on the ANN algorithm to create:

- multiclass classification - Multiclass Neural Network (MNN);
- binary classification - Two-Class Neural Network (TCNN);
- regression model - Neural Network Regression (NNR);

Fig. 2 The algorithm proposed with the three ANN - Azure Machine Learning

Table 1 The simulation features of the three ANN models

Setting	MNN	TCNN	NNR
Loss Function	CrossEntropy		
Learning Rate	0.1	0.1	0.005
Number Of Iterations	100		
Is Initialized From String	False		
Is Classification	False		
Initial Weights Diameter	0.1		
Momentum	0		

Neural Network Definition	
Data Normalizer Type	MinMax
Number Of Hidden Nodes	System.Collections.Generic.List`1[System.Int32]
Shuffle	True
Allow Unknown Levels	True

2.1 Simulation with Multiclass Neural Network

With this algorithm simulation was performed for temperature (Fig. 3):

- **front** on 7 levels of class (22, 23, 25, 28, 29, 30, 32);
- **back** on 8 levels of class (21, 22, 23, 26, 28, 29, 30, 31);

from 32 class levels, the smallest errors being achieved for class 28.

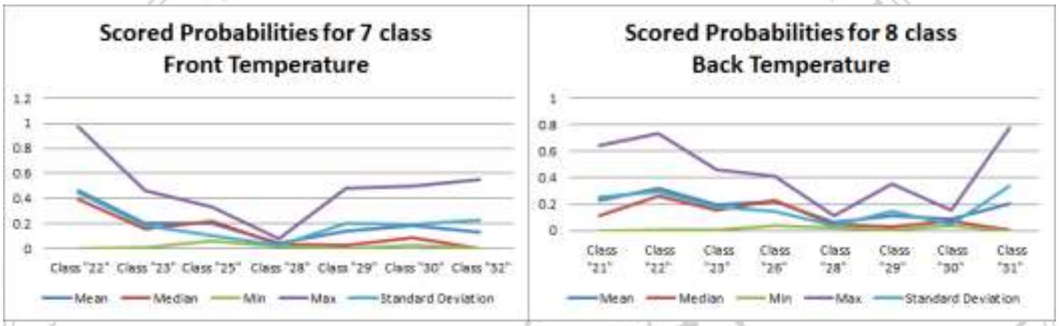

Fig. 3 Scored Probabilities for Temperature Front/Back

At the above-mentioned temperature, a better ANN reading is observed over the whole wavelength of the chaotic trend of the back temperature.

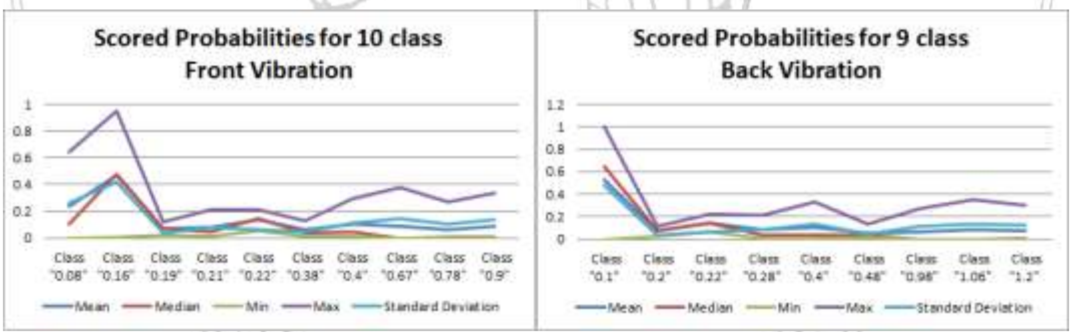

Fig. 4 Scored Probabilities for Vibration Front/Back

The ANN algorithm made the vibration simulation (Fig. 4):

- **front** on 10 levels of class (0.08, 0.16, 0.19, 0.21, 0.22, 0.38, 0.4, 0.67, 0.78, 0.9), to give the smallest error for the class 0.19:
- **back** on 8 levels of class (0.1, 0.2, 0.22, 0.28, 0.4, 0.48, 0.98, 1.06, 1.2);

from 32 class levels, to give the smallest error for the class 0.2.

Conclusion: Vibrations show an inverse behaviour towards temperature, that is, front vibration is chaotic, and for ANN back vibration, good training.

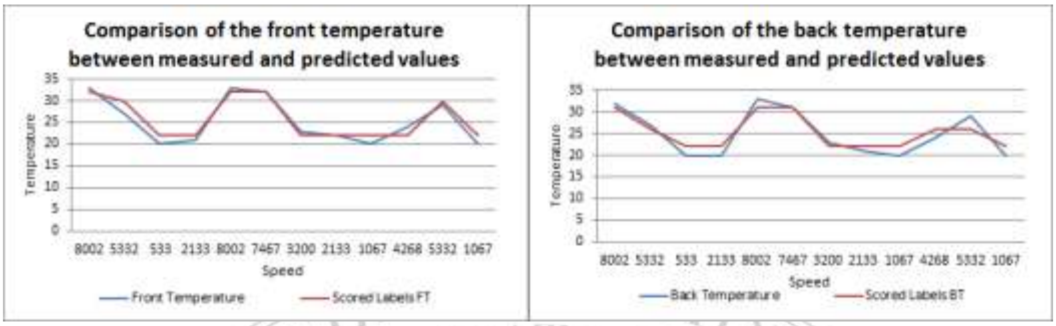

Fig. 5 Temperature comparison between measured and predicted values

The analysis of the temperature front/back (Fig. 5) between the measured and predicted values is observed that if the temperature:

- **front**, we get a maximum overvaluation forecast from 27 [^{0}C] to 30 [^{0}C], so 3 [^{0}C] represents (11%) and a minimum of undervaluation forecast 24 [^{0}C] to 22 [^{0}C], so (-2) [^{0}C] represents (-8%).
- **back**, we get a maximum overvaluation forecast from 20 [^{0}C] to 22 [^{0}C], so 2 [^{0}C] represents (10%) and a minimum of undervaluation forecast 29 [^{0}C] to 26 [^{0}C], so (-3) [^{0}C] represents (-10.34%).

Conclusion: For temperature in case of overvaluations we obtain a maximum deviation of 11% and for undervaluation (-10.34%).

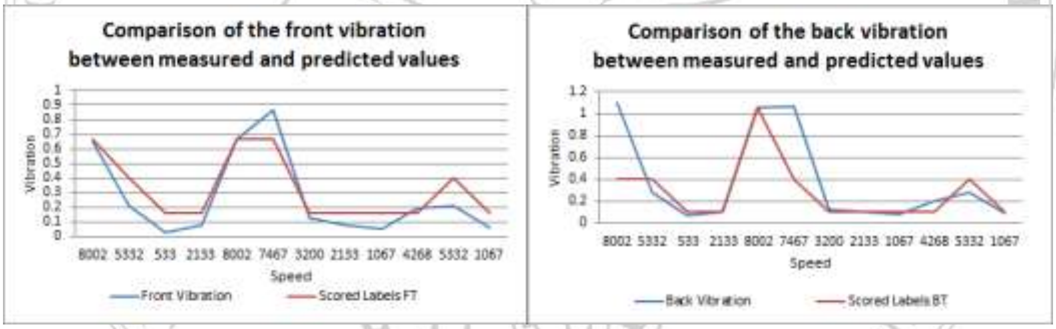

Fig. 6 Comparison to vibration between the measured and predicted values

Analysis of the vibration front/back (Fig. 6) between measured and predicted values lead to the following observations:

- in the case of the **front** vibration we get a maximum overvaluation forecast from 0.21 [mm/s] to 0.4 [mm/s], so 0.19 [mm/s] represents (90.4%) and a minimum of undervaluation forecast 0.87 [mm/s] to 0.67 [mm/s], so (-0.2) [mm/s] represents (-22.99%).
- in the case of the **back** vibration we get a maximum overvaluation 0.28 [mm/s] to 0.4 [mm/s], so 0.12 [mm/s] represents (42.86%) and a minimum of undervaluation forecast 1.1 [mm/s] to 0.4 [mm/s], so (-0.7) [mm/s] represents (-63.3%).

Conclusion: For vibrations in the case of overvaluations we get a maximum deviation of 90.4% and for undervaluation (-63.3%).

2.2. Simulation with Two-Class Neural Network

A second simulation is performed by dividing the measured data sets into two classes random.

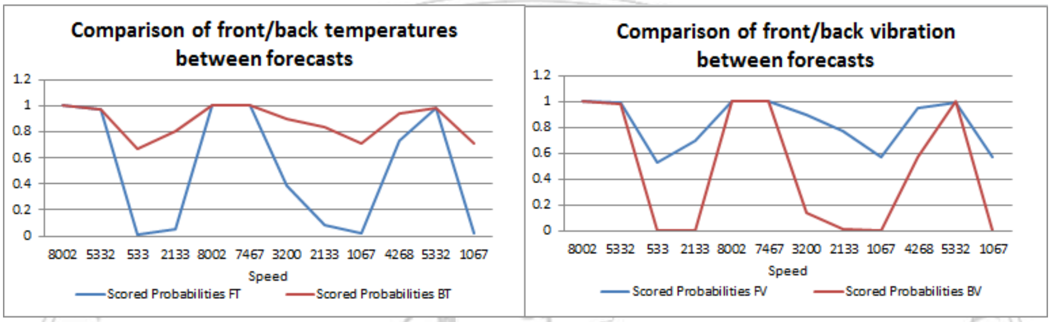

Fig. 7 Comparison of temperatures/vibrations front/back between forecasts

From the analysis of Fig. 7 is observed in the case of very large errors to front temperature and vibration back forecasts, which denotes that the division into two random classes leads to only one good approximate prognosis.

Conclusion: Two-Class Neural Network is suitable for forecasting a single set of data.

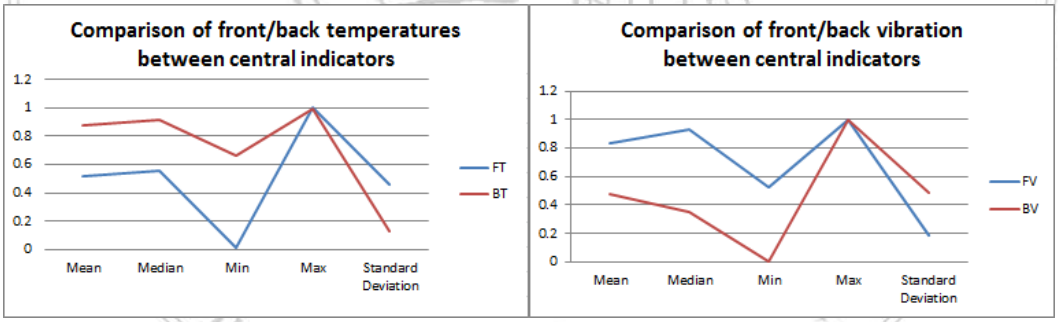

Fig. 8 Comparison temperatures/vibration front/back between central indicators

In the case of central indicators (Fig. 7) for:

- **front** temperature has a maximum of 0.9999 and a minimum of 0.0158, so a difference of 0.9841;
- **back** temperature has a maximum of 0.9982 and a minimum of 0.6667, so a difference of 0.3315;
- **front** vibration we have a maximum of 0.9995 and a minimum of 0.5289, so a difference of 0.4706;
- **back** vibration has a maximum of 1 and a minimum of 0.0005, so a difference of 0.9995;

Conclusion: the central indicators for simulations Two-Class Neural Network have a margin of dispersion of 0.9995.

2.3. Simulation with Neural Network Regression

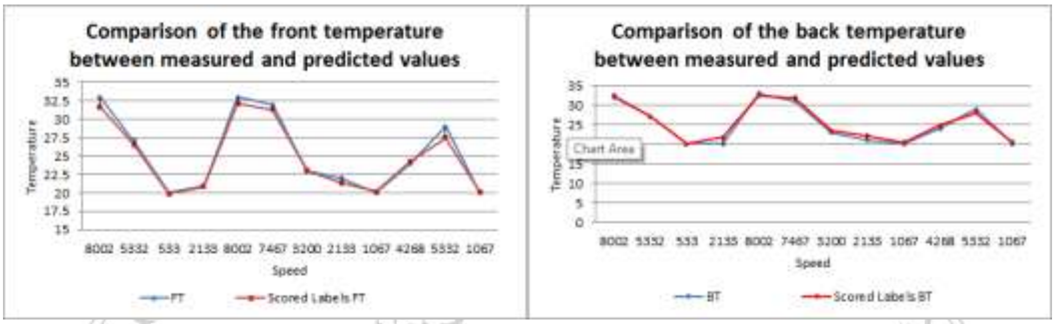

Fig. 9 Comparison of the temperature front/back between measured and predicted values

From the temperature front/back analysis (Fig. 9) between the measured and the predicted values it is observed that:

- in the case of the **front** temperature, we get a maximum overvaluation forecast from 24 [^{0}C] to 24.33 [^{0}C], so 0.33 [^{0}C] represents (1.36%) and a minimum of undervaluation forecast 33 [^{0}C] to 31.71 [^{0}C], so (-1.29) [^{0}C] represents (-3.91%).
- in the case of the **back** temperature, we get a maximum overvaluation forecast from 20 [^{0}C] to 21.69 [^{0}C], so 1.69 [^{0}C] represents (8.43%) and a minimum of undervaluation forecast 29 [^{0}C] to 28 [^{0}C], so (-1) [^{0}C] represents (-3.44%).

Conclusion: For temperature in the case of overvaluations we obtain a maximum deviation of 8.43% and for undervaluation (-3.91%).

The analysis of the vibration front/back (Figure 10) between the measured and predicted values has led to the following observations:

- in the case of the **front** vibration we get a maximum overvaluation forecast from 0.03 [mm/s] to 0.2557 [mm/s], so 0.23 [mm/s] represents (752.19%) and a minimum of undervaluation forecast 0.87 [mm/s] to 0.2975 [mm/s], so (-0.57) [mm/s] represents (-65.80%).
- in the case of the **back** vibration we get a maximum overvaluation forecast from 0.07 [mm/s] to 0.2518 [mm/s], so 0.19 [mm/s] represents (264.55%) and a minimum of undervaluation forecast 1.1 [mm/s] to 0.33486 [mm/s], so (-0.77) [mm/s] represents (-69.56%).

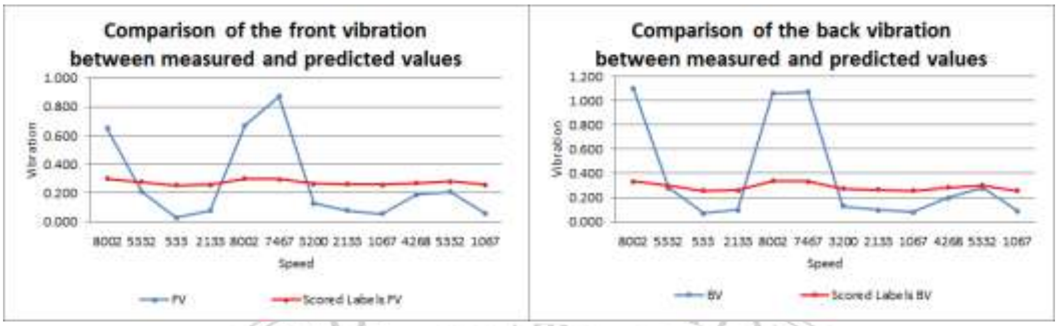

Fig. 10 Comparison of vibration front/back between measured and predicted values

Conclusion: For the over-vibration we obtain a maximum deviation of 752.19% and for underestimations (-69.56%), the NNR realizing a front/back prognosis that falls within the vibration range provided by the standard $0<x_v<2.8$ [mm/s].

NNR Conclusion: The temperature forecast is much better than the vibration, the discrepancy due to the fact that ANN attempts to achieve a satisfactory regression for the two dynamic characteristics while there are large differences between the temperature and vibration orders.

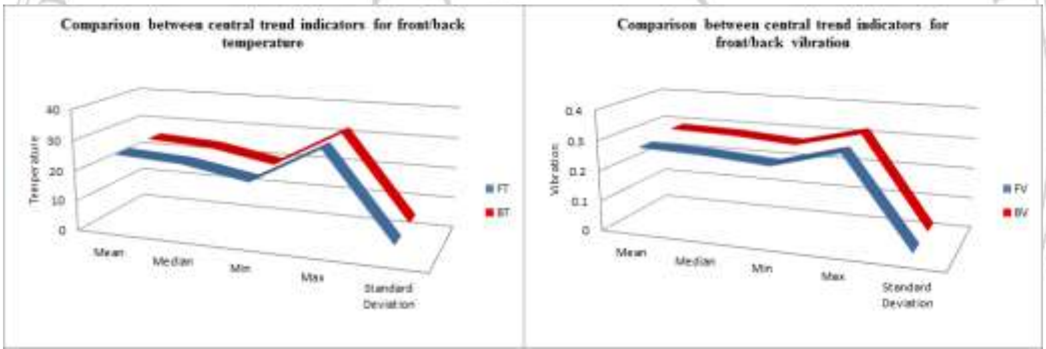

Fig. 11 Comparison between the central indicators temperature/vibration front/back

The central indicators for each pair (Fig.11), temperature front/back and vibration front/back have very close values, waveforms following each other. In the case of the temperature front/back pair we have a variation between 0.71 – 2.01%, so a margin of 1.3%, and for the vibration front/back pair the variation is between (-8.77) – 7.73%, thus a margin of 16.50%.

Conclusion: Centralized indicators retain the characteristics of forecasting indicators low temperature deviations (1.3%) and high vibrations 16.5%.

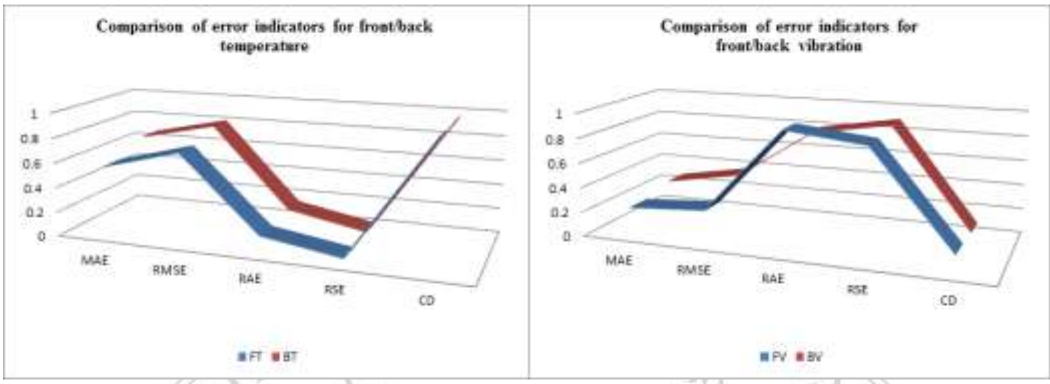

Fig. 12 Comparison of error indicators for temperature/vibration front/back

The notes for the error indicators (Figure 12) are as follows: Mean Absolute Error – MAE, Root Mean Squared Error – RMSE, Relative Absolute Error – RAE, Relative Squared Error – RSE, Coefficient of Determination – CD.

Conclusion: The charts of error indicators confirm the previous conclusions and have a mirror representation of each other vertically.

5. Conclusions

In the Multiclass Neural Network simulation, the forward propagation network is trained to manipulate sets of data with different parameters so as to obtain eligible forecasts for all parameters per sample. The forecast margin ranges between 21.34% and 153.7% (1).

For dual-class Neural Network simulation due to very large dispersion (0.9995) this type of ANN is suitable for predicting a single parameter (e.g. temperature front/back or vibration front/back) for good results (2).

Simulation with Neural Network Regression is similar to the Two-Class Neural Network simulation, which is evidenced by the forecast margins ranging from 12.34% to 821.75%, so it is indicated for the prognosis of a single parameter (3).

The analysis of the three ANN models shows that they are able to predict a single parameter with an acceptable margin of error. MNN is detached from the UCNN and NNR by the fact that for the analysis of several parameters the margin of error is much lower (4).

These very large errors between different parameters are due to their size order. It is noticeable that where orders of magnitude are concentrated and in increasing order the forecasts are very good (5).

Future studies will focus on the hybridization between ANN and fuzzy logic, so they will use adaptive neuro-fuzzy inference systems (ANFIS).

REFERENCES:

[1] Atika Qazi, H. Fayaz, A. Wadi, Ram Gopal Raj, N.A. Rahim,Waleed Ahmed Khan, The Artificial Neural Network for Solar Radiation Prediction and Designing Solar Systems: a Systematic Literature Review, Journal of Cleaner Production 104 (2015) 1-12, http://www.sciencedirect.com/science/article/pii/S0959652615004096

[2] http://www.statsoft.com/Portals/0/Support/Download/Brochures/Statistica_Data_Miner.pdf

[3] Dominika Janikova, Prediction of Production Line Performance Using Neural Networks, http://ieeexplore.ieee.org/document/7554879/?reload=true

[4] Ali Tardast, Mostafa Rahimnejad, Ghasem Najafpour, Ali Ghoreyshi, Giuliano C. Premier, Gholamreza Bakeri, Sang-Eun Oh, Use of Artificial Neural Network for the Prediction of Bioelectricity Production in a Membrane Less Microbial Fuel Cell, Fuel 117 (2014) 697–703, http://www.sciencedirect.com/science/article/pii/S0016236113008909

[5] J. J. Hopfield, Neural Networks and Physical Systems with Emergent Collective Computational Abilities, https://www.scienceopen.com/document?id=6e2e3730-61fb-4ce5-8f2e-3ed2cb581d9d

[6] Kenji Takada, Artificial Intelligence Expert Systems with Neural Network Machine Learning May Assist Decision-making for Extractions in Orthodontic Treatment Planning, http://www.sciencedirect.com/science/article/pii/S1532338216300951

[7] https://docs.microsoft.com/en-us/azure/machine-learning/