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Using the Total Multiple Linear Regression and Artificial Neurons Network-Multi Layer Perceptron for Modelling the Normal System, at Variable Point of Functioning of a Continuous Distillation Column Methylcyclohexane

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Abstract: ***This paper describes the modeling methods of normal functioning of a system of continuous distillation with variable working point of methylcyclohexane from a binary mixture (toluene / methylcyclohexane) using techniques of artificial Intelligence. Initially, the learning basis of the neural network was composed of 577 samples. In a second step, the weights and biases are determined by using the Levenberg Marquardt algorithm. Once the architecture, weights and biases of the neural network were established, it was necessary to know if the neural model is likely to be widespread. The validation of the neural architecture [7-14-1] is therefore to assess its ability to predict the temperature at the column head using the weights and biases calculated during learning, and apply them to another database "tests basis" composed of 384 data samples. The model of artificial neural network MLP-type [7-14-1] gave a factor of success for the testing and validation phase of 81.9%. A comparative study was established between the neural model MLP type and classical statistical models, i.e. the total multiple linear regression.***

Keywords: Modeling, Total multiple linear regression (TMLR), Neural Networks MLP, continuous distillation column

1. Introduction

The need to model a normal functioning allows the operator to detect any damage which will modify the normal operating of the system and lead to a disturbance in its functioning, which causes lack of production safety, and a loss of quality. Modeling is to gather knowledge that we have the dynamic behavior of a physical process by analysis of the phenomena involved, and analysis of experimental data. These analyzes lead to the definition of the quantities characterizing the process, that is to say, its inputs, its status variables, its outputs, and also disturbances, measurable or not, which it is subjected. The modeling of process is to find a parameterized model whose dynamic behaviour approaches that of the process. This model will be used to make predictions of the process output, or for a corrective learning, or to simulate the process in a control system.

Reliable modeling of normal functioning of a system is essential to ensure the safety of the installation and maintenance of product quality. We find in literature several modeling methods, among which we mention:

[1] Describe a new approach using WPA (Wavelet Analysis Packer) for extracting characteristics from the vibration signals generated by rotating machines in the time-frequency domain and hybrid SVM for classification of models. The extracted characteristics are applied to hybrid SVM for estimating defect type; the effectiveness of the hybrid SVM method is demonstrated in the success of failure diagnostic. The test results of hybrid SVM demonstrate that the application of the criterion of energy vibration signals after WPA is a very powerful and reliable method and therefore estimating fault type on rotating machinery is carried out with accuracy and rapidity.

[2] Present a new method based on improved empirical mode decomposition energy entropy (Empirical Mode Decomposition energy entropy) and MSVM (Multi-class Support Vector Machine) to diagnose the defects of high voltage machines CB (Circuit Breakage) using vibration analysis without load. SVM with cross-validation technique and the gradient method to sort the optimal parameters are used and compared to determine fault types. The test results show that the proposed MSVM with OAOT (One Against Others) algorithm can diagnose correctly and efficiently, defects in multi class machines for high voltage CB (High Voltage Circuit Breakage). Compared with several other algorithms, it is faster compared with a greater precision.

[3] Propose an intelligent diagnosis of piston compressor based on multi-agent systems. This system improves the diagnostic capability and reduces the complexity of the structure. At the same time, it enhances the effectiveness of monitoring the condition of the compressor piston the rapidity of failure diagnostic and scalability of multi-agent system.

[4] Describe an approach to detection and fault diagnosis applied to an industrial facility which employs neural

networks RBF (Radial Basis Function) combined with the backpropagation algorithm for separating the two operating modes "normal and abnormal" in a continuous distillation system, methylcyclohexane from a binary mixture toluene \ methylcyclohexane to a fixed point of functioning.

The main objective of this study is to develop a neural model of MLP type and compared to a linear model based on the total multiple linear regression, which allow to model the normal system variable operating point of an industrial continuous distillation system automated, of methylcyclohexane from a binary mixture toluene \ methylcyclohexane to ensure the safety of the installation and maintenance of product quality.

2. Model Generation

2.1. Development of multiple linear regression model

Multiple regressions is a linear statistical model that aims to explain the variability existing in a random variable (Y) when the behaviour of this variable is conditioned by some values that can take other variables, controlled or not by the experimenter.
The general form of the multiple linear regression model can be written as following:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p \qquad (1)$$

Y is the dependent or explained randomness variable;
X_1, X_2 ... X_p are independent or explanatory variables measured without error or set at arbitrary levels (not random).
β_0, β_1, β_2... β_p are the model parameters (we estimate using the square method); β_0 is the average of Yi when the value of each explanatory variable is equal to 0. And $\beta_{j\,=\,1,\,2,\,\ldots,\,p}$ represents the change undergone by E (Yi) corresponding to a unit change in the value of the j^{th} explanatory variable when other variables remain unchanged.

2.2. Development of the model based on artificial neural networks type Multilayer Perceptron

An artificial neural network is a computational model whose original inspiration was a biological model. [5] Computing and mathematical representation of a biological neuron in the artificial neural networks is called formal neuron; we have shown schematically the structure of an artificial neuron in Figure1.

It is then possible to characterize a formal neuron by:

- A combine function or a summing which performs the weighted sum A_j. The weighted sum is equal to:

$$A_j = \sum_{i=1}^{n} W_{ij} X_i \qquad (2)$$

Where W_{ij} is the synaptic weight and Xi is the input value related to the variable i. This is the weighted sum of activation which converges to the neuron j;

- An activation function (or transfer) f, which drives the neuron by determining its activation;
- An activation function Yj, equivalent to the output of neuron. It is equal to:

$$Yj = f\left(\sum_{i=1}^{n} W_{ij} X_i + \theta_j\right) \qquad (3)$$

Where θ_j is the bias of neuron j.
There are several activation functions (hyperbolic tangent, Gaussian, sigmoid ...), but the most used is the sigmoid function;[6], [7], [8], It is written in the following form:

$$f(x) = 1/(1+\exp(-x)) \qquad (4)$$

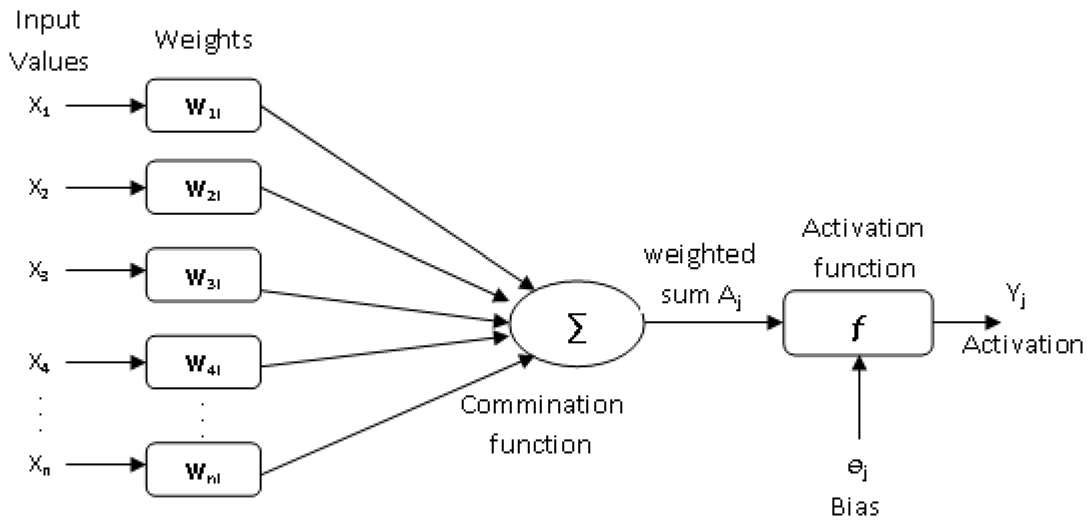

Figure 1: Structure of an artificial neuron.

3. Installation Overview

The installation studied is a distillation system methylcyclohexane from a toluene / methylcyclohexane mixture which was defined mass composition of 23% methylcyclohexane. The main parts that forms the continuous distillation installation, are packing column, the reboiler, the column overhead condenser and the metering pump (Figure 2).

Figure 2: Installation of continuous distillation

3.1. Description the functioning of the continuous distillation column

The mixture (toluene / methylcyclohexane) is introduced through the feeding tray of the column; a part of this mixture is volatilized while the other part goes down into the boiler with the reflux from the column heading.

The quality of the product obtained at the top of the column depends on the flow rate of the reflux which is varied by using an electromagnetic valve controlled by the temperature at the column head, when the latter is reached, the valve opens, in the opposite case, it remains closed. The condenser with exchange surface area of 0.08 m2 is placed at the column to completely condense the vapour and associated heat exchangers are integrated to provide cooling of either the distillate or residue.

The preheating system is constituted of three sub-assembly heating resistors of a power of 250 W each one, with more, a level sensor preventing starting if the level in the glass body is too low in the boiler.

The dosing pump is constituted by a membrane ensuring the aspiration of mixture to be distilled and to discharge the preheating tank.

The packing of the continuous distillation column facilitates the transfer of the material between the liquid and vapour phase. The type of packing selected for this role is Multiknit 316 L stainless steel; in addition, to be closer to adiabatic conditions, insulation consisting of glass wool is used.

For the monitoring system, it consists of ETP200 software and it has several features, it allows you to change the input and output parameters of the system, monitor their progress and ensure the tendency for group. The tendency group can follow the evolution of the measures of each apparatus connected to the control unit. This evolution can be displayed in real time or historical.

3.2. Determination of normal mode of the continuous distillation installation

To determine the range of work, we have defined the objective of obtaining a rich mixture, in methylcyclohexane, for that and from the isobaric vapour-liquid diagram of toluene / methylcyclohexane; we determined the temperature range which is [101.1° C; 103.4°C] equal to an interval of concentrations [0.48; 0.84] defining the normal functioning and this by using the Wilson model for modeling the mixture (Figure 3). The explanation of this temperature range derives from the fact that the purification of this binary mixture in industry occurs in this range.

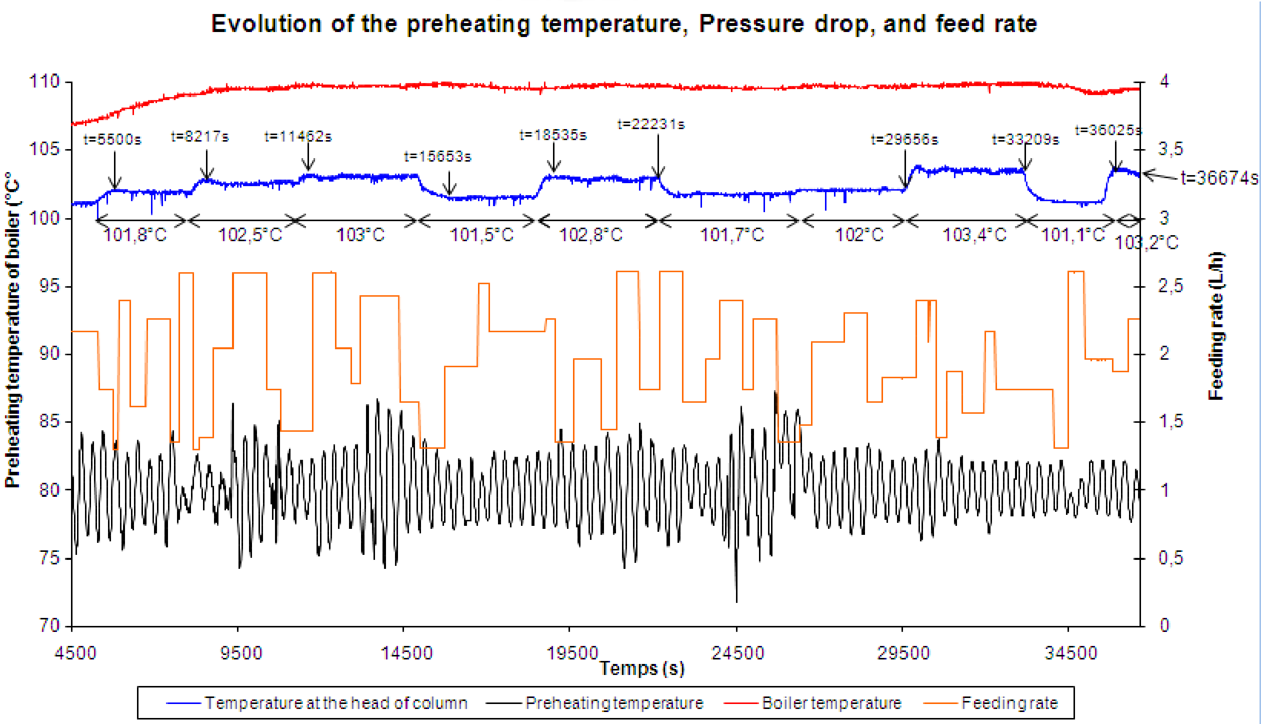

Figure 3: Normal behaviour of the continuous distillation column

This selection has to assign a range for each input (figure 4) of the system to have a constant outlet temperature.

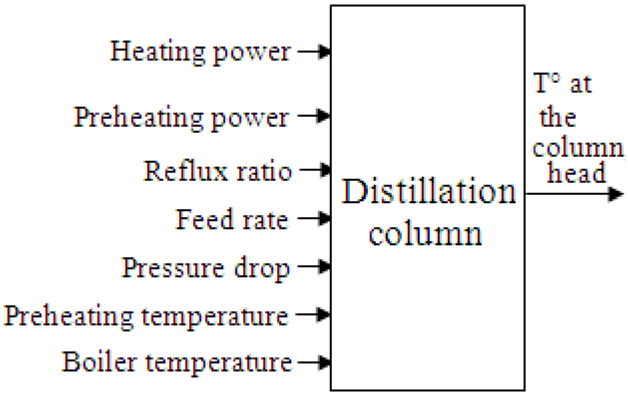

Figure 4: Determination of inputs/output of the distillation column

4. Results and Discussion

The temperature at the head of distillation column (Td), is modeled as a function of input variables of the process such as the heating power (x_1), the preheating power (x_2), the reflux ratio (x_3), the feed rate (x_4), the pressure drop (x_5), the preheating temperature (x_6) and the temperature of the boiler (x_7).

In general, the databases require a pre-treatment in order to be adapted to the inputs and outputs of stochastic mathematical models. A common pre-processing is to conduct a proper normalization, which takes into account the amplitude of the values accepted by the models. A standardized data between 0.1 and 0.9 is obtained.

The normalization of each input xi is given by the formula:

$$x_{i\ new}^{k} = 0,8 * \frac{x_{i\ old}^{k} - \min(x_i)}{\max(x_i) - \min(x_i)} + 0,1 \quad (5)$$

4.1. Results of the model developed by the Total Multiple Linear Regression

This method has been implemented and tested in C + + and the program was run on a machine I3 3 GB of RAM. By performing the analysis by multiple linear regression with all variables we got the following:

*) Equation of TMLR:

$$Y_n = -1,3538 - 8,8659 * 10^{-2} * x_{1n} + 1,15225 * x_{2n} + 2,4619 * x_{3n} - 0,1103 * x_{4n} - 0,0701 * x_{5n} + 1,3084 * x_{6n} + 0,60135 * x_{7n} \quad (6)$$

*) Correlation coefficient: $R^2 = 0,369$

*) Probability: $p < 0, 0001$

The linear model is significant because it represents a low probability but has a correlation coefficient less important.

4.2. Results of the model developed by Artificial Neural Network – Multi Layer Perceptron

The analysis was limited to networks that contain a single hidden layer since this architecture is able to predict all outputs. The independent variables inputs X = (x_1, x_2 ... x_7) are normalized between 0.1 and 0.9 and then presented to the input layer of the network. They, initially, are multiplied by the weight IW, and then added to the bias IB existing between the input layer and the hidden layer. The neurons of the hidden layer receive the weighted signals. After addition, they transform them by employing a nonlinear Sigmoid function F1 (.).

The following mathematical model F1 (IW * X + IB) is presented to the input of the output layer. This model will be multiplied by the weight WL and then added to bias LB that exist between the hidden layer and the output layer and then transformed by a nonlinear sigmoid function F2 (.)

Finally we obtain the mathematical model of artificial neural network as follows:
F2 {LW* F1 (IW*X+IB) +LB}.

The Levenberg Marquardt algorithm was used to determine the weights and biases of the artificial neural network in a quick and robust way.

To choose the "best" architecture of neural network, two statistical tests were used; RMSE Root Mean Square Error, and the linear correlation coefficient R^2. Figures (5-6-7 and 8)

RMSE and R^2 (Learning and Test) after 1500 iterations for different numbers of neurons in the hidden layer, give the ability to choose 14 neurons in the hidden layer. We then obtain the architecture [7-14-1] as "best" configuration of the neural network Due to its good predictive capacity.

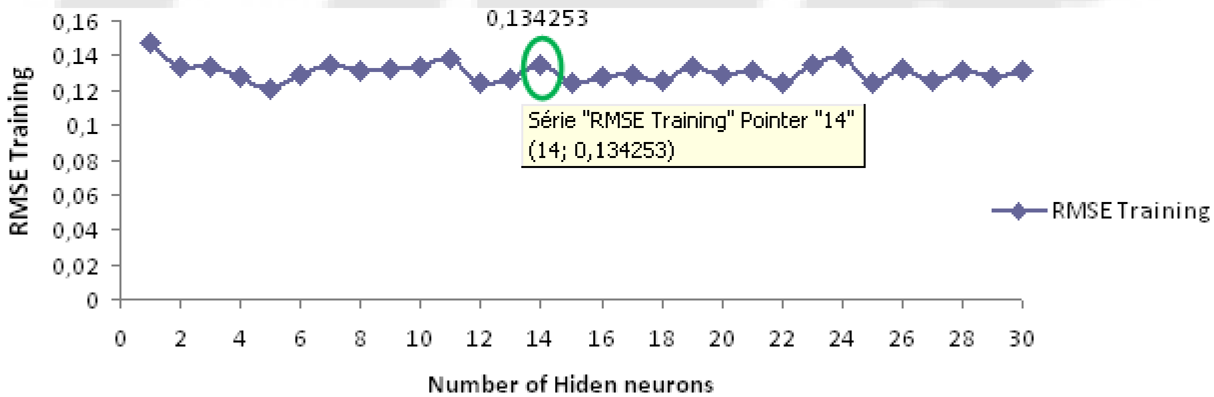

Figure 5: Root Mean Square Error Training

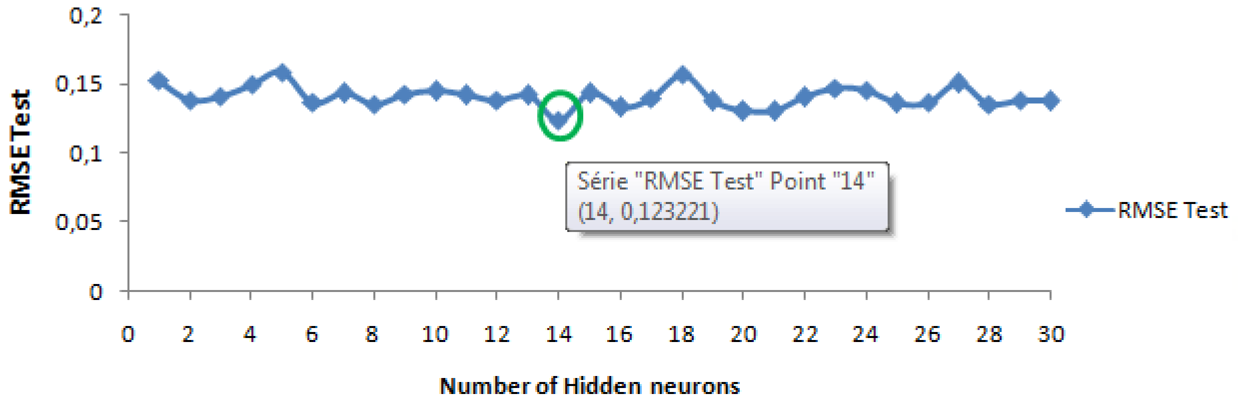

Figure 6: Root Mean Square Error Test

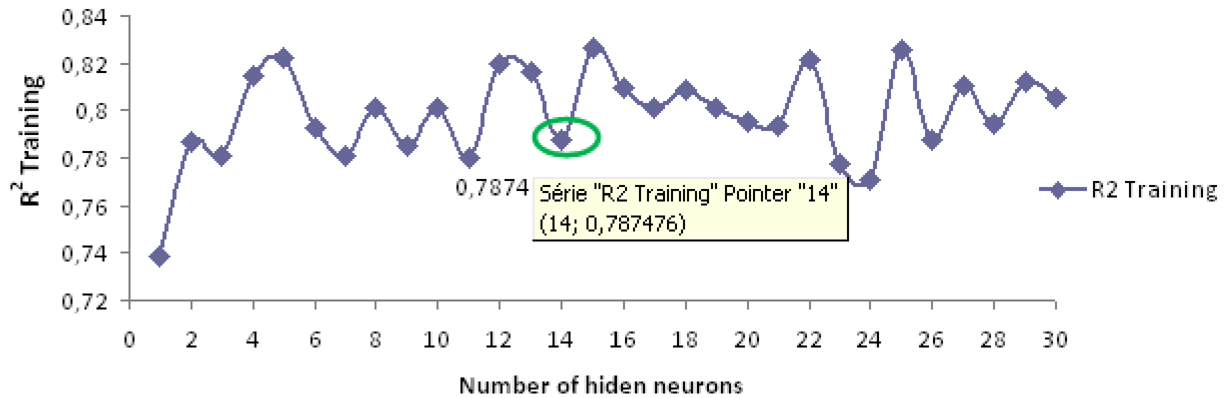

Figure 7: Correlation coefficient R2 Training

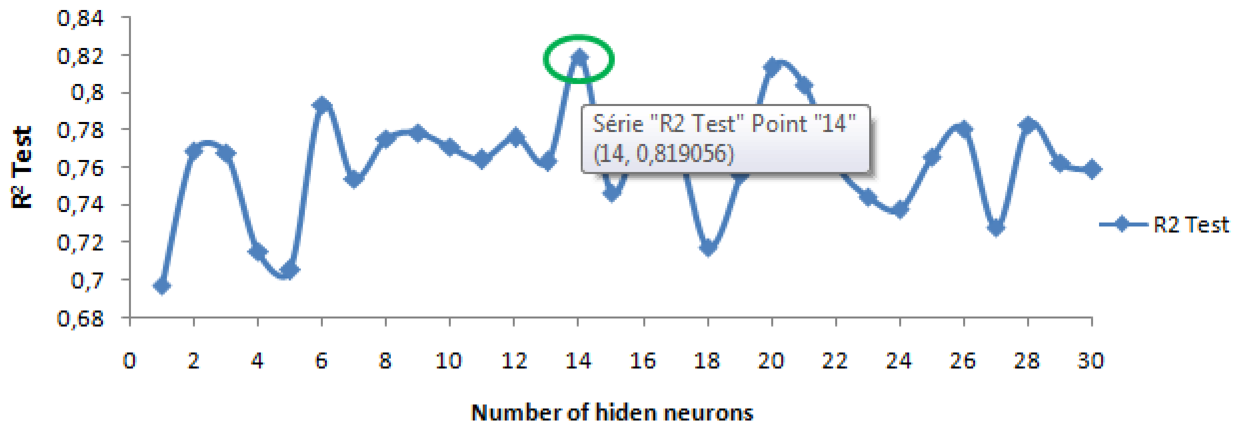

Figure 8: Correlation coefficient R2 Test

Learning and validation

The artificial neural network MLP "Multilayer Perceptron" consists of an input layer containing seven neurons, a hidden layer containing fourteen neurons and an output layer containing a single neuron (Figure 9).

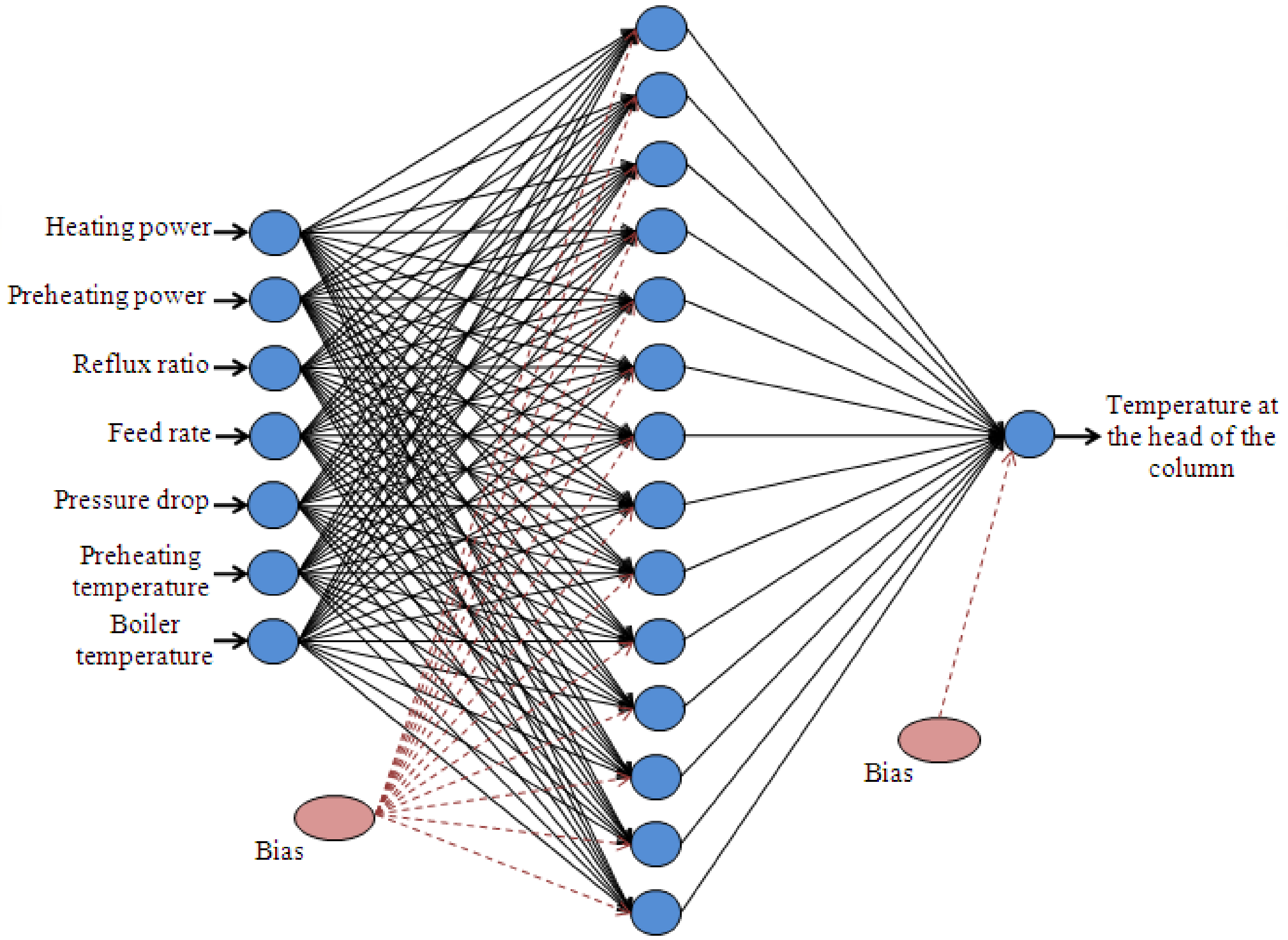

Figure 9: Neurons network - architecture [7-14-1]

The basis of learning, of the neural network consists of 577 samples i.e. 60% of the entire data. Weights and biases of the network were adjusted using the Levenberg Marquardt algorithm. Once the architecture, weights and biases of the neural network have been fixed we must know if this neural model is likely to be widespread.

The validation of the neural architecture [7-14-1] is therefore to assess its ability to predict the temperature at the top of the column, using the weights and biases calculated during learning, and apply them to another basis of test, compounds of 384 samples, i.e. 40% of the entire data (Figure 10).

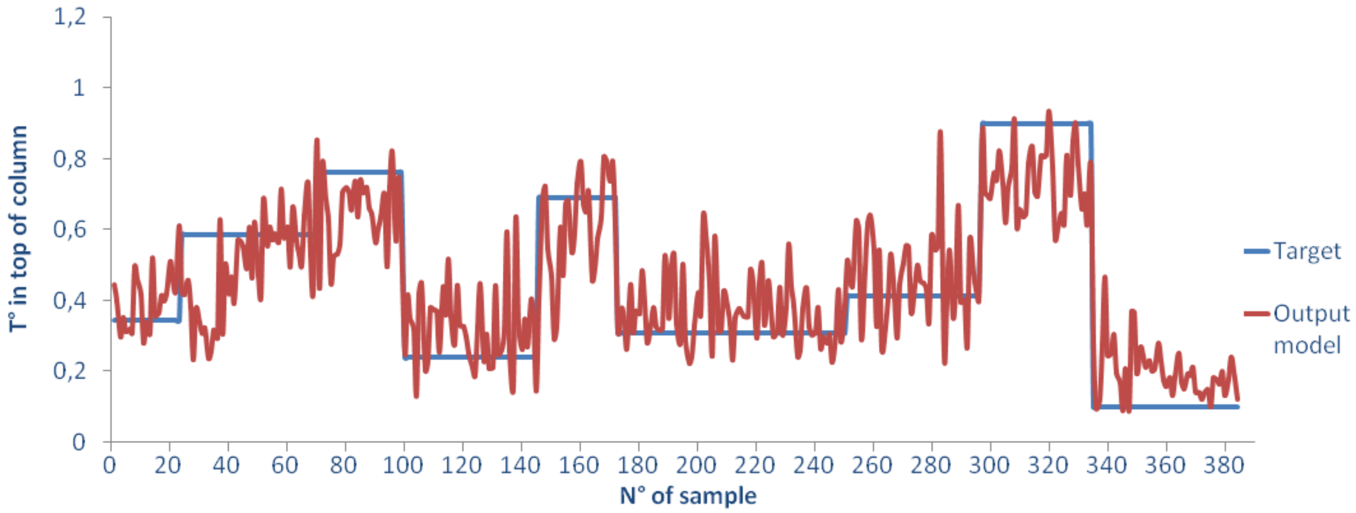

Figure 10: Results of temperature prediction in the head of column ANN-MLP [7-14-1]

The ANN model [7-14-1] gave a correlation coefficient for the test phase and validation of 0.819056 and a mean square error of 0.123221. The average of the absolute values of the residues (Residue = Target - output) is about 0.1 (Figure 11).

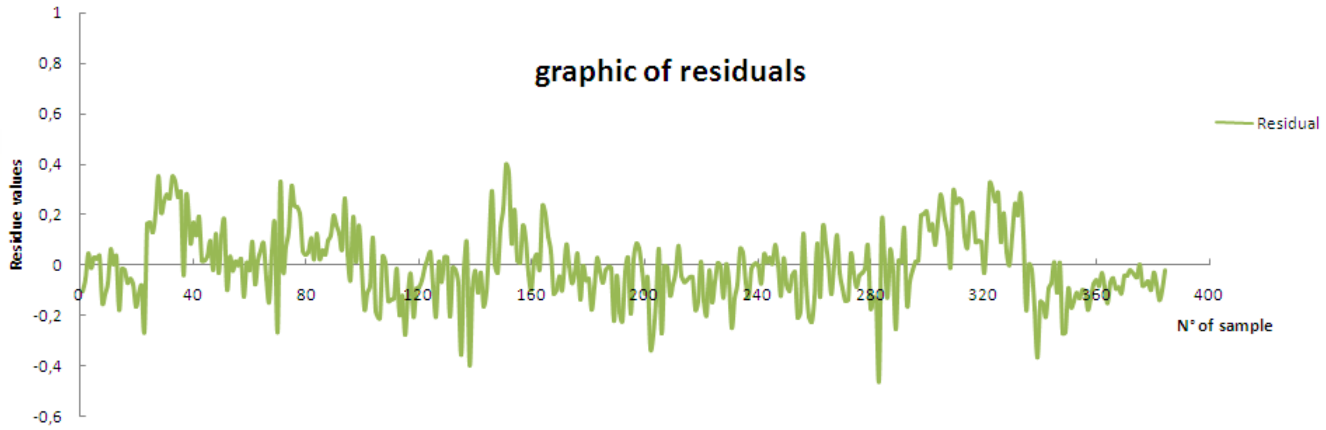

Figure 11: Residuals graphic

5. Conclusion

In this study, the pattern made on the basis of the artificial neural network of MLP type gave the best result the architecture chosen of the model [7-14-1] has achieved a coefficient of success for test and validation phase of 81.9% and a mean square error of 0.12.

The learning of the developed neural model was accomplished by determining the weights and biases using the Levenberg Marquardt algorithm. To build the learning base, we relied on data under normal conditions of our system of distillation. To assess the performance of the ANN-MLP [7-14-1] method, we compared this method with the method of total multiple linear regression TMLR. The correlation coefficient calculated with ANN-MLP [7-14-1] is significantly higher (81.9056%) than the correlation coefficient calculated with the TMLR (36.9%).

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