Spectral Analysis of Ferrous Metal Based on Neural Networks

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Abstract-*This study concerns electro-magnetic signals modelling. The main proposes of the present paper consists of the specification spectral analysis of radiation emitted in heterogeneous environment. Comparative study is presented between polynomial Lagrange and neural networks modelling. We show that neural networks give best results when it is experimented to establish concentration elements of ferrous metallic elements.*

Keywords

component; formatting; spectral analysis, neural networks, algorithmic complexity, Lagrange approximation.

VII. Introduction

Our research study consists of establishing signal processing system which allows to convert data during analysis of ferrous sample using spectrophotometer using real data and using percentage of chemical elements present in the analysed sample..

As basis of our research we use standardised samples where the chemical composition is known and certified by laboratories using spectroscopy chemical analysis [2]

The purposes of the present study is the modelling of electro-magnetic signals using numerical models [1] [4], in order to establish and improve the use of spectral analysis of radiation emitted in heterogonous environment. In modelling, neural networks have emerged as powerful tool that has been applied by various researchers [5].

This study is applied to the production industry of metal and « font » which require strong competence in the field of ferrous metal analysis.

Therefore, in order to improve physical and chemical quality of the production (elasticity, hardness,…, etc.), the metallurgists need to know chemical composition of the metal to deal with. Therefore, it exist several systems of structural scruting of matters. Spectral analysis is among the more efficient methods which allows to detect the presence of different chemical elements in the analysed samples, the results of measure are done with four digits precision. For example we can speak about chemical elements the most important during metal processing like: C, Si, Mn, P, S, Al, Ni, Mo, Cr, Cu, V, Mg, Ti etc.

The principle of spectral analysis is based mainly on diffraction the light emitted by sample of production during processing, extracted from the furnace and solidified. This diffraction produces spectra with visible colours characterising each of elements present in the sample. The intensity of each of these colours is rigorously et respectively proportional to the concentration of each of these elements constituting the analysed metal.

The used equipment consists of a spectrophotometer, this equipment is based on the diffraction of the light emitted by a sample to be analysed. This sample which we transmitted an electrical arc. The white light obtained is diffracted by optical system which generates several rays with different colours. Each of these colours correspond to the frequency and the intensity of each of chemical elements present in the sample and by percentage of the concentration (%).

These rays are obtained by sensors and converted on electrical tensions using filters computed and calibrated in order that each one can react exclusively to frequency associated to its design. Consequently, each element is characterised by electrical signal with unique frequency. This signal is measurable and its amplitude is proportional to concentration of the used chemical element. At the end, these signals are recorded and converted into binary code and transmitted into numerical processing unity (PC). There fore we can visualise the concentration of the analysed sample.

The paper is presents as follows: Section 2 describes the acquisition system: spectrophotometer and PC relation. Section 3 gives the principles of neural network model used in the study. Section 4 presents the results of software based on neural network and comparison with Lagrange method.

VIII.DESCRIPTION OF THE SYSTEM

The system is constituted by two main parts:

a) Part one : the spectrophotometer : which is electronical and optical equipment which main function is the conversion of optical signal to voltage.

b) Part two : the Computer processing software which controls and commands of the spectro-photometer and the data processing ,

As example of classical methods there exits polynomial Lagrange method of N-1 degree The curve modelled by dx and dy segments**.** These classical methods have advantages and inconvenient.

Our contribution consists of establishing software processing of data obtained as voltages proportional to elements presents in the analysed sample.

During this study we show that the range of errors of classical methods which have bad effect during analysis. Specially, when we use extrapolation of results or if the analysis result value is comprised between two far points in etalonned curve.

At last, we try to prove that we can improve the result precision of the studied system using new method like neural network described in the next section.

IX. NEURAL NETWORK MODELLING

The neural network model has deterministic kind with real computed output using sigmoid function. The architecture is constituted by successive layers with input layer and output layer. The model use gradient retro-propagation algorithm. This algorithm is used through the learning of the model. We can see results obtained during learning [see annexe]

1. **Computing the output of the first hidden layer**

k=1

$$y_{kj} = \sum_{j=0}^{NS(k)-1} \sum_{m=0}^{NS(k-1)-1} w_{kjm} . X_{i,m}$$

with :

k=1 : indicate the number of the layer (in this case the first hidden layer)

J: the number of the cell of the layer k

m: the number if the cell of layer k-1

i : indice of the vector of I/O (X_i,C_i) ,

(with X_i the values of the axis of abscissa and C_i the values of the axis of ordinates)

NS (k): gives the number of cells of the layer k

2. **Computing the output of the other layer**

k≠1

with :

$$y_{kj} = \sum_{k=2}^{NC-1} \sum_{j=0}^{NS(k)-1} \sum_{m=0}^{NS(k-1)-1} w_{kjm} . y_{(k-1),m}$$

NC : Number of layers (Input layer + Output Layer + hidden layers)

X. RESULTS INTERPRETATION

Working with adequate configuration of our neural network which is specific to each of graphs which we studied. After learning of Neural Network, we obtain results in the form of modelling graphs. We compare our results with the graph generated by polynomial of Lagrange (green colour in the graphs(Annexe). This comparison shows the disadvantages of classical method which was enable to extrapolate the graph out of values of the standardised samples and also for far points.

Whereas, the graphs modelled by neural networks (blue in the graphs) follows the progression of the values of standardised samples and extrapolate perfectly the graph out of some points.

For each element, the intensities obtained by analysis versus the correspondent concentrations (%)

Table 1 : Neural Network Configuration

Element	**Epsilon**	**Input Layers**	**Hidden Layers**	**Output Layers**
Phosphore	01	1	1 60 cell	1
Carbone	0,31 E	1	3 layers 8 Cells	1
Manganese	1.2 E-04	1	5 Layers 7 cells	1

Nickel	2.3	1	5 Layers 7 cells	1
Silicium	2.3	1	4 Layers 8 cells	1

XI.CONCLUSION

The main purpose of this paper consists of presenting comparison study between polynomial Lagrange method and neural network applied to ferrous metal detection. We showed that Neural Network Model gives good performances for spectral analysis.

As future work, we think about extending the method to non – ferrous metal. In the present study we limit our selves to six elements and it seems interesting to experiment other elements and consequently produce rules for neural net-work configuration.

VI. REFERENCES

[1] N. MURATA : Network information criterion : determining the number of hidden units of an artificial network model . archives 1992

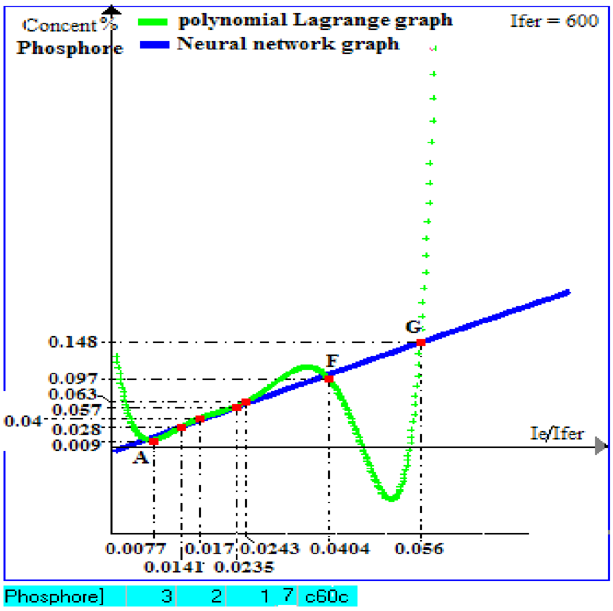
[2] M. BAGHDAD and K. GHARABI : " Modelling and simulating of polynomial La-grange method for ferrous metal using spectral analysis" Report of end of cycle Project, Univer-sity of Tiaret – June 2009.

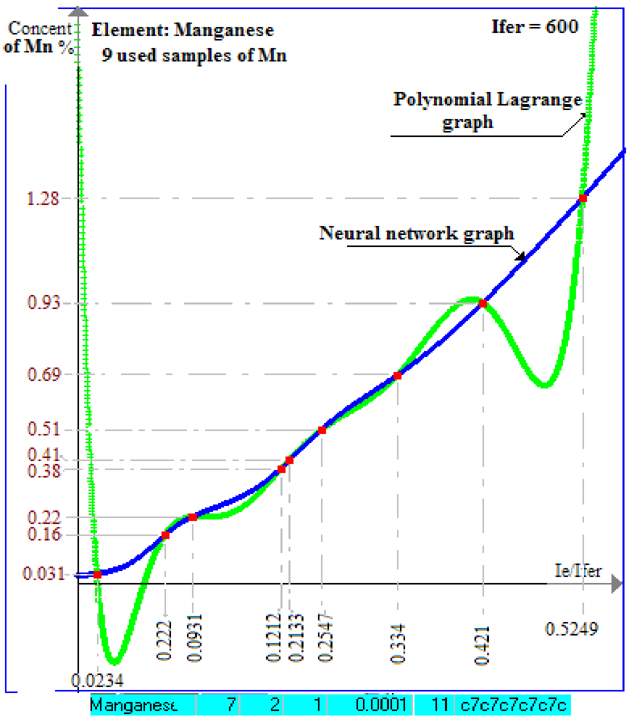
[3] H. RAR : "Detecting system and fluores-cence measure " report of end of Cycle, Universi-ty of Quebec – March 2006.

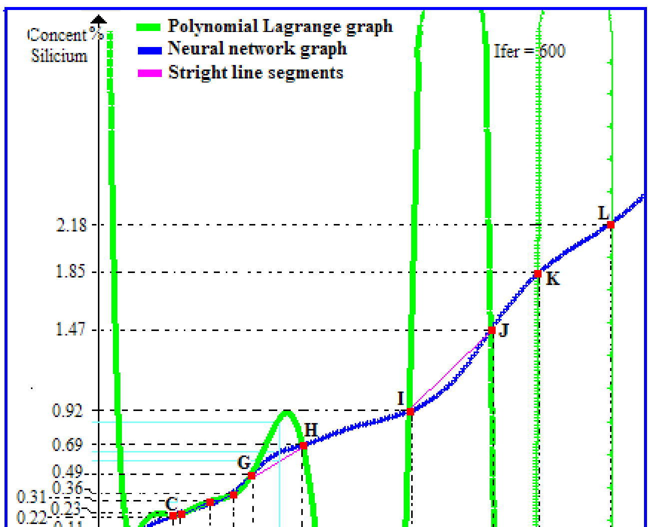
[4] F. ELIE : Design and implementation of system using neural network for identifying and characterizing transient signals of wheezing kind". Thesis dissertation, University of Orleans – France, Dec. 1997.

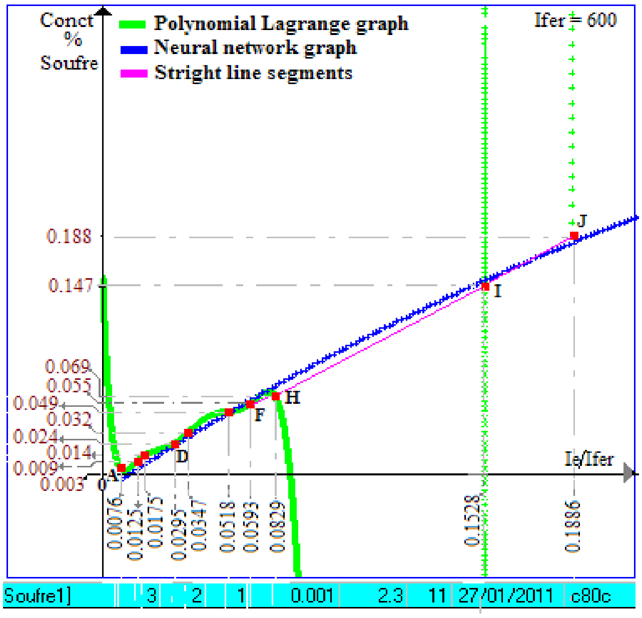
[5] B. Bhattacharyya, D. Dey, S.Munishi : " A correlation Based system identification tech-nique for a class of power converter". Applied soft computing Journal, May 2010.

ANNEXE : CURVES OF ELEMENTS








Conct
%
Soufre
Polynomial Lagrange graph
Neural network graph
Stright line segments
Ifer = 600
0.188
0.147
0.069
0.055
0.049
0.032
0.024
0.014
0.009
0.003
0
A
D
F
H
I
J
Ie/Ifer
0.0076
0.0125
0.0175
0.0295
0.0347
0.0518
0.0593
0.0829
0.1528
0.1886
Soufre1]
3
2
1
0.001
2.3
11
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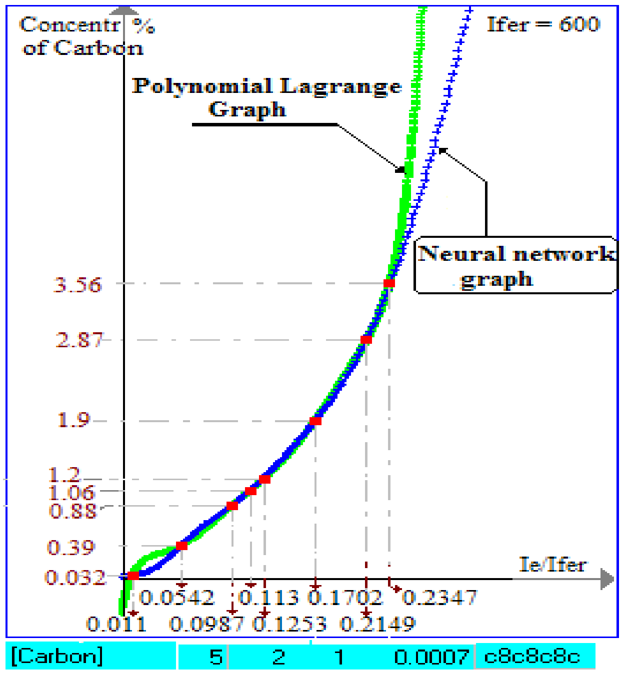
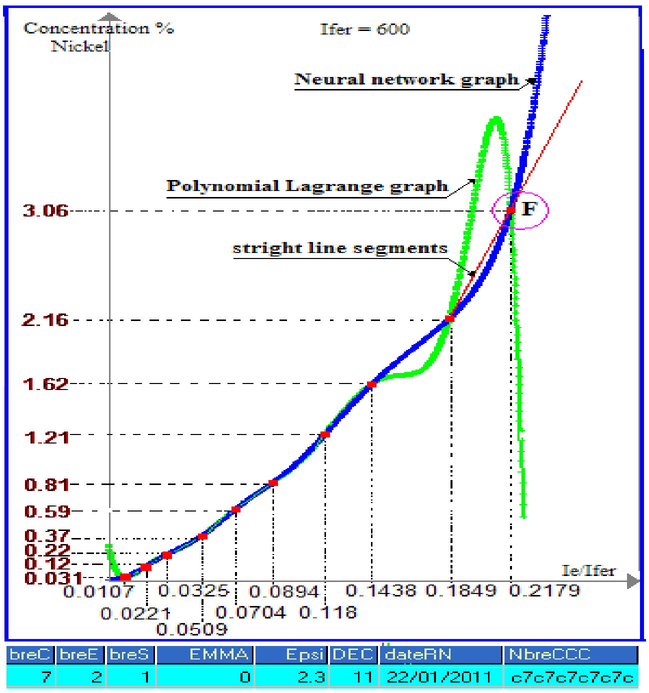

Concentr %
of Carbon
Ifer = 600
Polynomial Lagrange
Graph
Neural network
graph
3.56
2.87
1.9
1.2
1.06
0.88
0.39
0.032
Ie/Ifer
0.0542
0.113
0.1702
0.2347
0.011
0.0987
0.1253
0.2149
[Carbon]
5
2
1
0.0007
c8c8c8c


Concentration %
Nickel
Ifer = 600
Neural network graph
Polynomial Lagrange graph
stright line segments
F
3.06
2.16
1.62
1.21
0.81
0.59
0.37
0.22
0.12
0.031
Ie/Ifer
0.0107
0.0325
0.0894
0.1438
0.1849
0.2179
0.0221
0.0704
0.118
0.0509
breC
breE
breS
EMMA
Epsi
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NbreCCC
7
2
1
0
2.3
11
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c7c7c7c7c7c