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ANALYSIS DATA SETS USING HYBRID TECHNIQUES APPLIED ARTIFICIAL INTELLIGENCE BASED PRODUCTION SYSTEMS INTEGRATED DESIGN

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Rezumat. *Lucrarea propune un model de previziune a comportării arborelui principal din punct de vedere al deformațiilor termice și a nivelului vibrațiilor prin evidențierea și prelucrarea ecuațiilor caracteristice. Acesta reprezintă un model de analiză pentru arbore cu caracteristici electro-mecanice asemănătoare se poate realiza utilizând o analiză hibridă bazată pe inteligență artificială (algoritmi genetici – rețele neuronale artificiale – fuzzy logic). Lucrarea prezintă modul de obținere a predicției unui domeniu de valori valabil pentru arbori principali cu caracteristici apropiate pe baza unor seturi de date măsurate la câțiva arbori principali de test fără a fi necesare efectuarea de măsurători suplimentare. Extragerea funcțiilor polinomiale din graficele rezultate din măsurători și prognozarea simultană a dinamicii celor două caracteristici cu ajutorul criteriului multiobiectiv constituie principalul avantaj al acestei metode.*

Abstract. *The paper proposes a prediction model of behavior spindle from the point of view of the thermal deformations and the level of the vibrations by highlighting and processing the characteristic equations. This is a model analysis for the shaft with similar electro-mechanical characteristics can be achieved using a hybrid analysis based on artificial intelligence (genetic algorithms - artificial neural networks - fuzzy logic). The paper presents a prediction mode obtaining valid range of values for spindles with similar characteristics based on measured data sets from a few spindles test without additional measures being required. Extracting polynomial functions of graphs resulting from simultaneous measurements and predict the dynamics of the two features with multi-objective criterion is the main advantage of this method.*

Keywords: *fuzzy logic, artificial neural network, genetic algorithms, Matlab R2011b, VGD 1.7*

1. Introduction

The machining process stills the most widely used process in making metal parts. Optimizing cutting parameters in increased productivity and improved quality requires the use of artificial intelligence.

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Under these conditions, the occurrence of vibrations and the reduction of the life span of different components are inevitable.

For this purpose the reliability of the machine-tools spindle requires the application of methods based on genetic algorithms in order to optimize dynamic and thermal characteristics.

Currently research forecasting the evolution of different phenomena and their parameters are based on equations that describe the theoretical point of view. This prediction is made with components of artificial intelligence (Fuzzy Logic - FL, logic neutrosophic - LN, artificial neural networks - ANN, genetic algorithms - GA) or by hybridization with different chaining (FL-ANN-GA, ANN-GA-FL, FL-ANN, ANN-GA, FL-GA, etc.). This research seeks to predict evolution by optimizing mathematical functions based on theory, so that the resulting graphs closely follow the shape and amplitude of the wave resulting from the measurements.

The use of the theoretic mathematical functions is used to optimize the process and planning stages of the elementary work units facing the fluctuations in time represented by the flexibility of the operations, the total number of machines allocated and the maximum number of operations per elementary work unit as well as the flexibility of the process [1].

To achieve that, a GA-ANFIS hybridization is performed, so in the first step the genetic algorithm (GA) is applied to the equation and the result is processed with an adaptive neuro-fuzzy inference system (ANFIS).

Mathematical equations are also used in the economy to predict cash flow [2]. The forecast is made by hybridization using fuzzy logic, genetic algorithms and a combination of two types of neural networks, namely traditional (single hidden layer) and higher order (more hidden layers).

The genetic algorithm is applied to the upper-order neural network and it operates on the traditional neural network that is inserted into the fuzzy engine by the ANFIS method.

In contrast to the given examples, this paper presents a different approach, in that the prognosis is based on the polynomial equation extracted from the graph obtained on the basis of the experimental measurements.

The modeling of the prognosis by extracting the polynomial function from the graph is characterized by a more accurate function interpolation than interpolation with a theoretical function, as all the non-determinant elements that can be described by the neutrosophic logic [3] are contained in the graph resulting from the measurements, a indeterminacy comprising, the known part and the unknown side [4].

2. Research methodology

The methodology introduces genetic algorithms (GA) to Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict temperature/vibration front/back as a continuation and development of the methodology presented in [5].

Research objectives:

1. Defining the polynomials characteristic of the temperature/vibration front/back (12) for the three main spindles based on the data set obtained by measurements;
2. Formation of the General System of Polynomial Functions (GSPF). It is achieved by calculating the arithmetic meaning for each individual characteristic (FT, BT, BV FV) of the three spindles, resulting in four polynomial function.
3. General System of Polynomial Functions (GSPF) analysis with classical genetic algorithms (GA) and multi-objective optimization using genetic algorithms (MOGA);
4. Comparative analysis for the three modes;
5. Hybrid analysis MOAG-ANN;
6. Hybrid analysis MOAG-ANFIS;
7. Determine the optimal path for getting a low error.

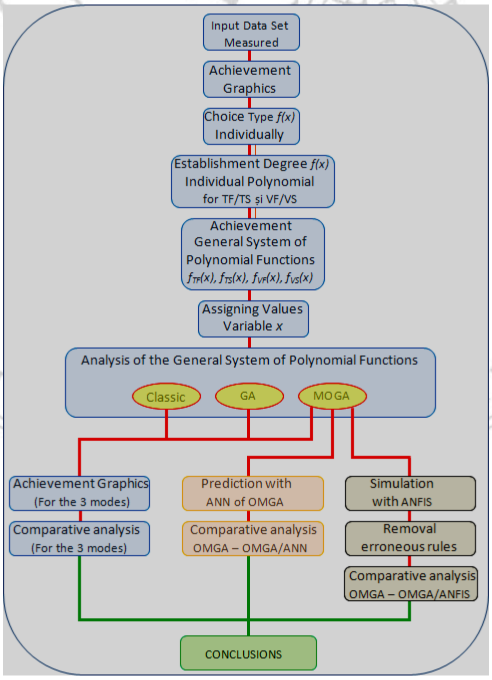


Fig. 1. Scheme of the algorithm.

The test stand, the configuration of the three spindles, the equipment used and the measured data set are presented in [5].

Based on measured values for temperatures/vibrations front/back, there are 12 graphs for the three spindles, with the following notations:

- temperature in front – FT; temperature in back – BT;
- vibration in front – FV; vibration in back – BV;

The degree of polynomial function is chosen in such a way that the graph describing it is as accurate as possible to the chart made on the basis of the measurements.

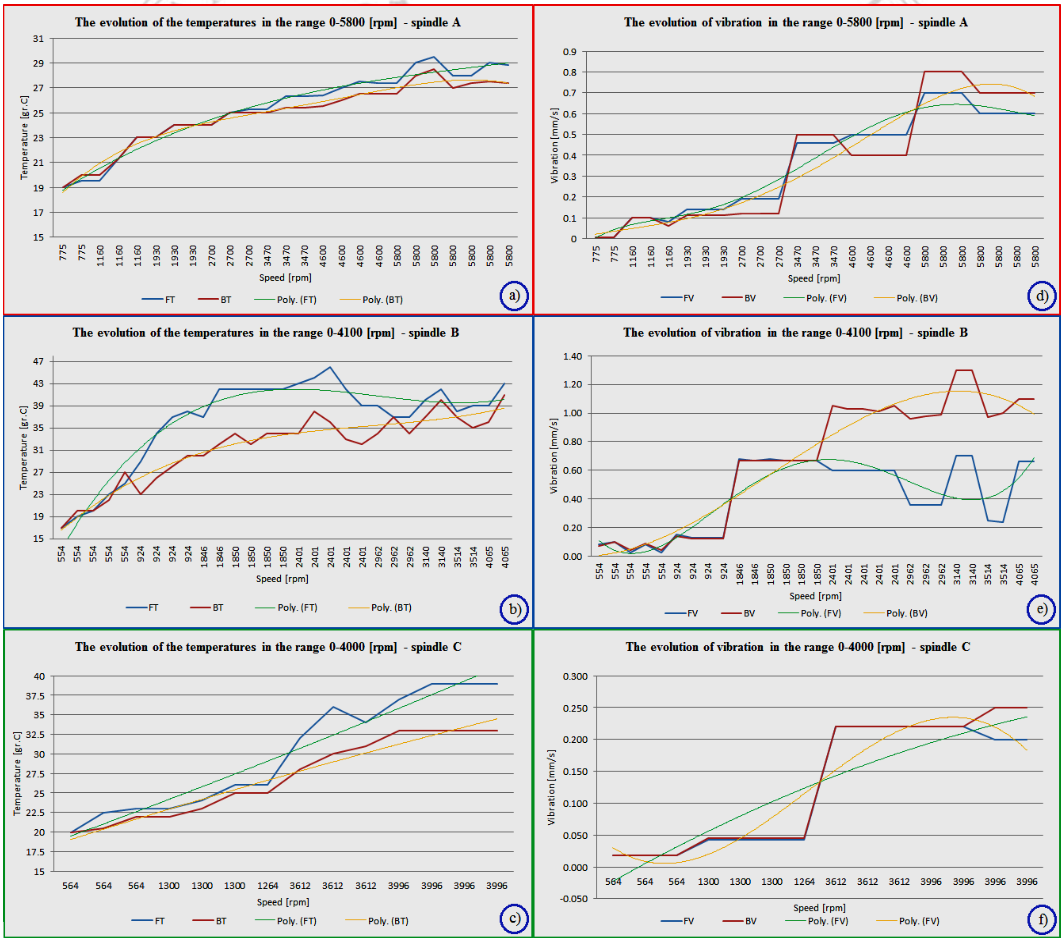


Fig. 2. Diagrams of three spindles for the measured values and those described in the extraction of the equations.

Following the operations, we obtain the general polynomial function system (Table 1) describing the temperature/vibration front/back characteristics.

Table 1. The general system of polynomial functions for temperatures/vibrations front/back

$$y_{FT} = 0{,}0024x^3 - 0{,}09967x^2 + 2{,}642733x + 14{,}55863 \quad (1)$$

$$y_{BT} = -0{,}0001x^4 + 0{,}00475x^3 - 0{,}09587x^2 + 1{,}904267x + 16{,}223 \quad (2)$$

$$y_{FV} = 0{,}000001x^5 - 0{,}000043x^4 + 0{,}0005x^3 - 0{,}00087x^2 + 0{,}00923x + 0{,}0105 \quad (3)$$

$$y_{BV} = 0{,}0000001x^5 + 0{,}000008x^4 - 0{,}0003x^3 + 0{,}0065x^2 - 0{,}01447x + 0{,}0269 \quad (4)$$

2.1. Classic analysis

In Matlab R2011b, functions are written in the Editor and in Command Window we assign values to x in the range $1 \le x \le 33$. Keep study results for $6 \le x \le 24$. For other values of not satisfied one of the conditions of operation of the main shaft or temperature: $25\,[^0\mathrm{C}] < t < 55\,[^0\mathrm{C}]$, or range of vibrations $0 < \underset{cod\_galben}{2{,}8\ [\mathrm{mm/s}]} < \underset{cod\_rosu}{4{,}5\ [\mathrm{mm/s}]}$.

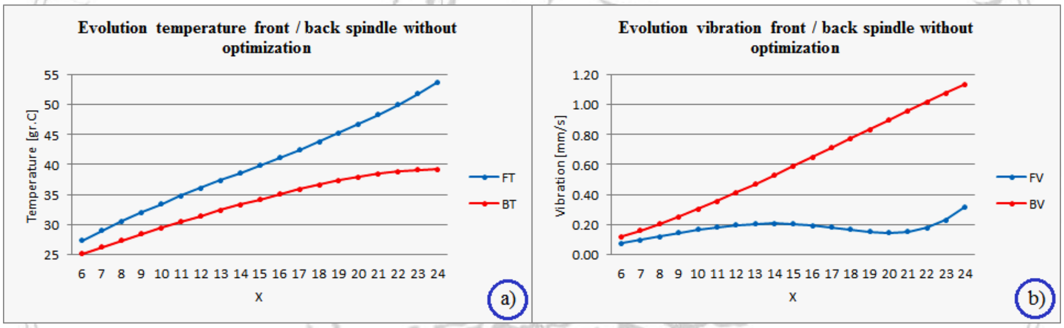


Fig. 3. Evolution temperature/vibration front/back spindle generally without optimization solutions.

The graph in Fig. 3 a) / b) shows a processing by approximating the average per portion of the equations describing the graphs shown in Fig. 2 (a), b), c)) / (d), e), f)), synthesizing a possible evolution of temperatures/vibrations.

2.2. Analysis using genetic algorithms

For this mode of analysis, polynomial functions (Table 1) are used as a function system.

Command Window launches the *Optimtool* command to access the *Solver* type. From the Solver bar choose ga - *Genetic Algorithm.*

The settings are as follows:

```
Solver: ga - Genetic Algorithm;
Problem
   Fitness function: @fitnesstf
   Number of variables: 1
Constraints
   Bounds: Lower:  6 ≤ x ≤ 24
```

```
                  Upper: 25
           Population
              Population type: Double vector
              Population size: Specify: 4
              Creation function: Feasible population
              Initial Population: Specify: 4
           Fitness scaling
              Scaling function: Rank
           Selection
              Selection function: Tournament
           Mutation
              Mutation function: Adaptive feasible
           Crossover
Crossover function: Single point
```

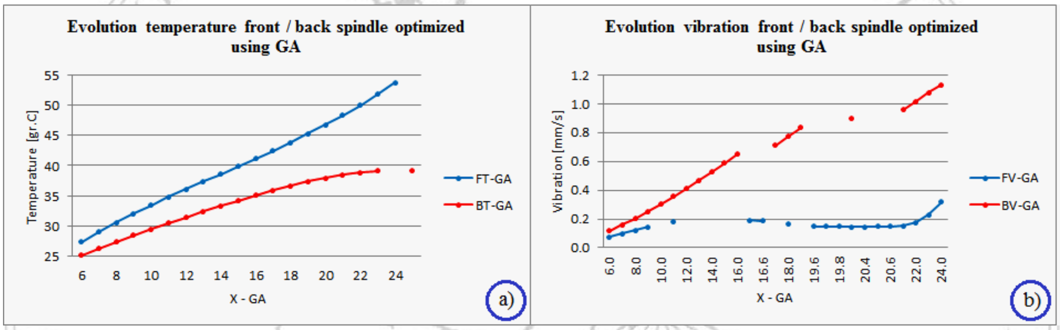


Fig. 4 Evolution of temperatures/vibrations front/back to the general spindle with solution optimization using genetic algorithms

For x, integer values were assigned in the range [1, 25]. For x values in intervals [1, 5] and [10, 19] it is noted that the genetic algorithm begins to perform a wide area scan to find optimal solutions. For example, for x = 1, the algorithm finds solutions for values x-GA = 4 for all 4 functions (FT, BT, FV and BV), so search from 3 orders of superior to 7-8. The rest of the values obtained are the same as those obtained without optimization.

It is noted that in the graph of Fig. 4 a) is almost identical to the graph in Fig. 3 a) for the front temperature and for the back temperature the difference lies in the approximate temperature for x = 24 and x = 24.8. In this case, there is an intention of the genetic algorithm for solution zonal solution.

On the graph in Fig. 4b) for both the search vibrations tend solutions zone. The trend of the back vibrations is characterized by the appearance of 3 levels, from which the algorithm scans a larger area, so the linear trend shown in the graph Fig. 3 b). The trend of the front vibrations in Fig. 4 b) has a similar character represented by 4 levels but with slight deviations from the trend in the graph in Fig. 3 b). In conclusion, the graph trend in Fig. 4 b) attempts to emulate the trend graph Fig. 3 b).

Table 2. Simulation results using genetic algorithms

Characteristic GA	**Temperature** *(for x=6 and x=24)*	**Vibration** *(for x=6 and x=24)*
Best fitness	The optimum value is obtained in 3 generations	
Distance	The average distance between individuals is 0, and is maintained constant throughout the analysis;	The average distance between individuals in which the optimum value is reached decreases from 1 for x = 6 to 0 for x = 24;
Range	The optimum value is obtained in 3 generations	
	The search of the optimal solutions decreases to 10 [^{0}C] (zonal search range) for x = 6, at 0.085 [^{0}C] (minimum zonal search) for x = 24, so the search time decreases 111.48;	The search of the optimal solutions decreases to 0.098 [mm/s] (search zone range) for x = 6, at 0.052 [mm/s] (search zone minimum) for x = 24, so the search area decreases by 53%;
Selection	The number of individuals (parents) contributing to the children is the same for both situations. The contribution of the first parent is maximum (5 children - 83.33%), the second parent has a minimum contribution (1 child - 16.67% each). Parents 3 and 4 do not contribute to optimizing the solution;	The number of individuals (parents) contributing to the children are: ➢ For x = 6, the contribution of the first parent is maximum (4 children - 66.67%), the second parent has a minimal contribution (2 children - 33.33%) and parents 3 and 4 do not contribute to optimizing the solution; ➢ For x = 24, the contribution of the first two parents is equal (3 children each) and parents 3 and 4 do not contribute to optimizing the solution;

2.3.Analysis with multi-objective optimization using genetic algorithms

The settings are as follows:

```
Solver: gamultiobj - Multiobjective optimization using
                     Genetic Algorithm
Problem
   Fitness function: @ANSMOTV
   Number of variables: 1
Constraints
   Bounds: Lower: x
Population
   Population type: Double vector
   Population size: Specify: 15
   Creation function: Feasible population
   Initial Population: Specify: 4
Selection
   Selection function: Tournament
Mutation
   Mutation function: Adaptive feasible
Crossover
   Crossover function: Single point
```

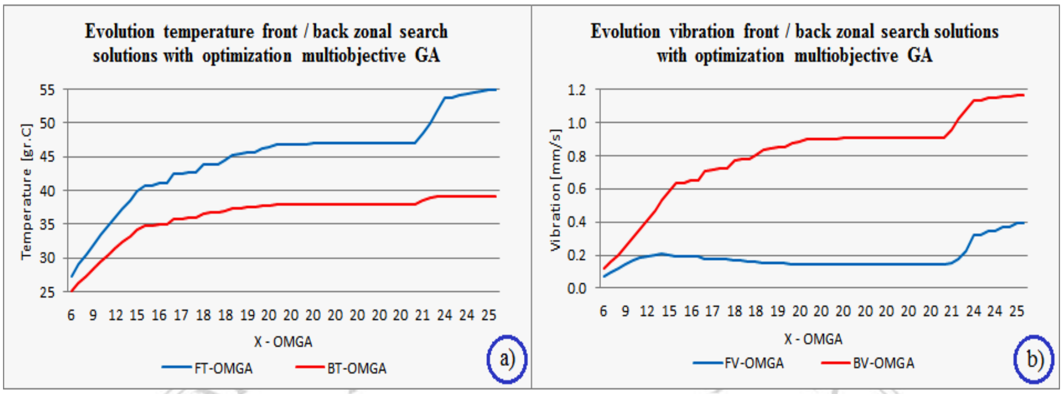


Fig. 5. Evolution temperatures/vibrations front/back to the general spindle using multi-objective optimization with genetic algorithms.

Applying the general system of polynomial functions (equations (1)–(4)), describing the general spindle, multi-objective optimization using genetic algorithms, the graphs in Fig. 5.

In the case of the graph characteristic temperatures of Fig. 5 a) is the generation of more precise solutions on local areas, that is to say, on the portions of the graphs of the main spindle studied. The graph in Fig. 5 a) better characterizes the starting area of Fig. 2 a), the middle area of Fig. 2 b) and the end region of Fig. 2 c). We see a very good improvement of the results from the approximations presented in Fig. 3 a) and Fig. 4 a).

In the case of multi-objective optimized vibrations using genetic algorithms (Fig. 5b)) the trends of the front / back vibrations approach the evolution of the real trends presented in Fig. 2 d), e) and f). This graph is the result of 59 solutions found for the same number of values of x, respectively 19.

From the point of view of evolution on the characteristic domain of each spindle, it is observed that the trend of the graph Fig. 5 b) the back vibrations (red line) approach the most from the real evolutions shown in Fig. 2 d), e) and f).

The front vibrations (blue line) have a less accurate trend due to the large discrepancies in the individual vibrations of the spindle.

2.4. Predicting the results of equations modeled with genetic algorithms using artificial neural networks

The prediction of main spindle behavior when we have partial results obtained through multi-objective optimization using genetic algorithms is achieved with the Visual Gene Developer 1.7 - VGD (Build 763 - 11 Aug 2016) developed by the Department of Chemical Engineering and Materials Science - University of California-Davis, which is based on a standardized learning algorithm with backward propagation [6].

We construct the artificial neural network with VGD having its input variable as its values $x \in [6,24]$ and as the output temperature/vibrations front/back, so we will have 1 input variable and 4 output variables.

Visual Gene Developer works with series of closed-ended numbers [-1, 1], therefore the values of each parameter of the dataset need to be scaled down so as to obtain subunit series and the results will be multiplied corresponding to the demultiplication factor for each parameter of the data set.

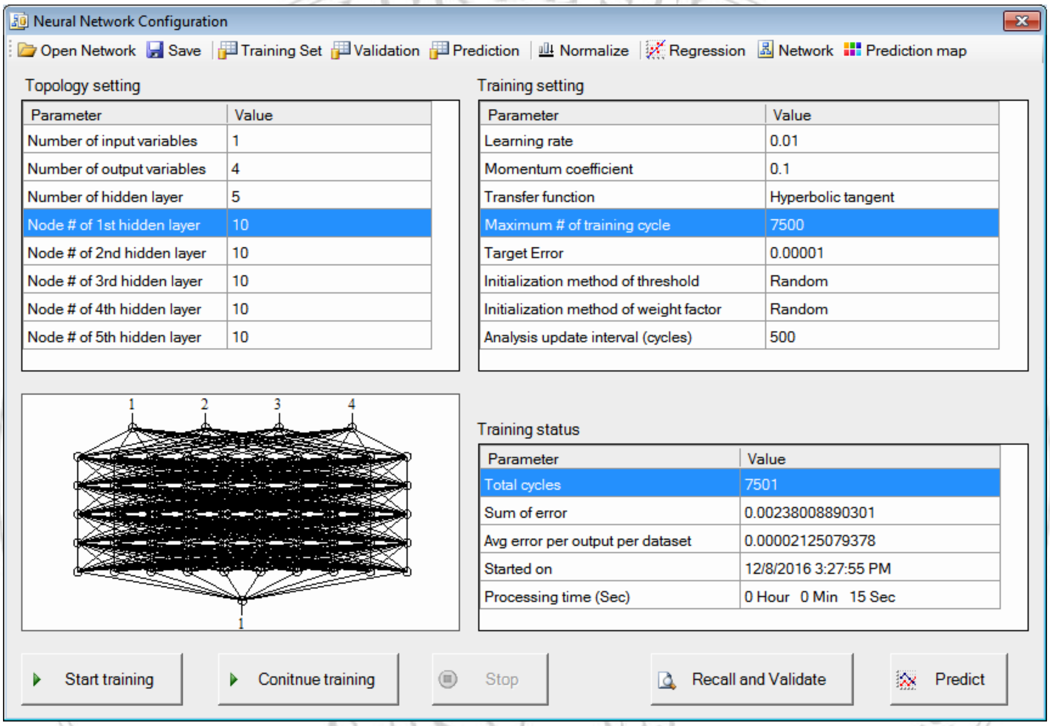


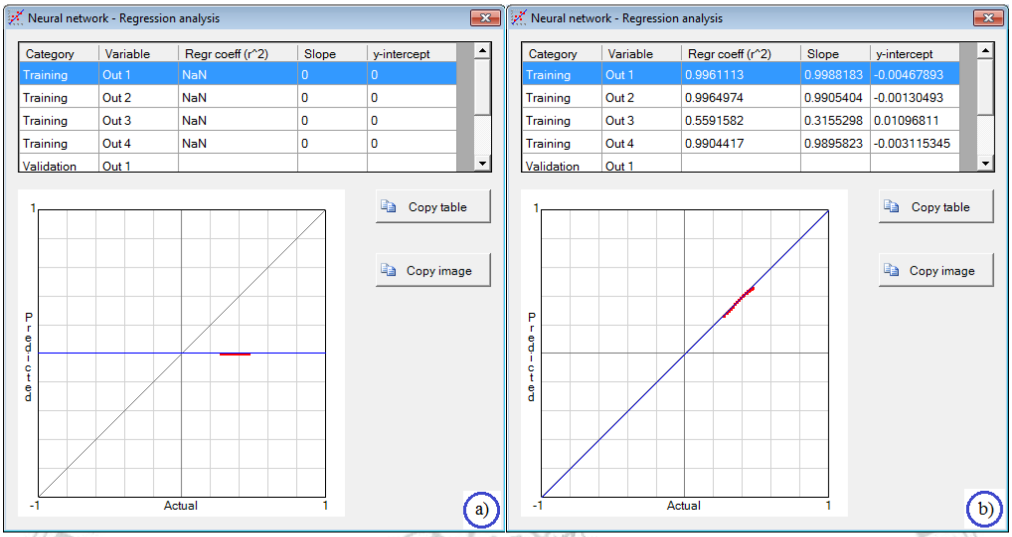
Fig. 6. Configuring artificial neural network using Visual Gene Developer 1.7 software.

Regression coefficient (R) is optimally valued at: $R_{gen\_optim} = 0.93$.

The settings for which the best results are obtained are:

```
Number of input variables - 1;
Number of output variables - 4;
Number of hidden layers - 5
Number of nodes (neurons) per hidden layer - 10;
Learning rate - 0.01;
Transfer function - hyperbolic tangent;
Maximum number of training cycles - 7500;
```

In Fig. 7 there is a uniform distribution on the field of the data series, which provides good results. Very good results are obtained by grouping the set of data to extreme fields of the domain [5, 7].



a) $t = 0$ b) $t = 15$ [sec]

Fig. 7. Representation of the regression coefficient *R*.

In Fig. 7 (top table of the image) contains information about regression slope coefficient for the four output variables (FT, BT, FV and BV). From his analysis we note that for FT, BT and BV, $R_{gen\_optim} = 0.93 < 0.99$, *good* coefficients are obtained so the series of data obtained is close to reality. If FV has $R_{gen\_optim} = 0.93 > 0.56$, satisfactory data are obtained.

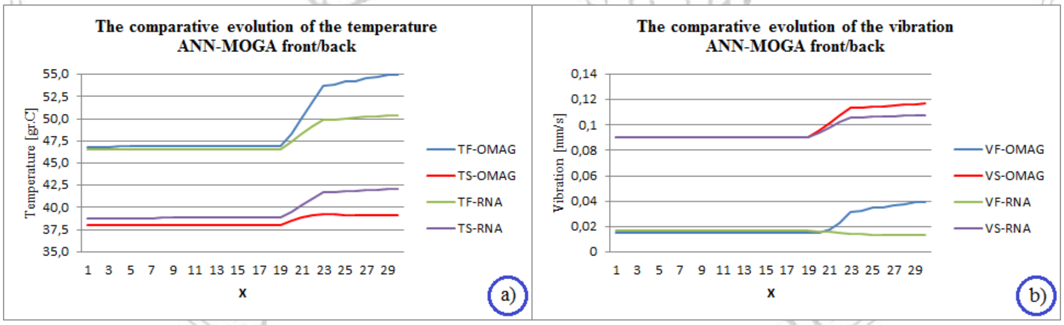


Fig. 8. MOGA-ANN comparative evolution of front/back temperatures /vibrations.

In the case of front temperatures (Fig.8a), it is observed that the prediction with ANN is achieved by sub-evaluation (2.94%) and over temperature back temperatures (3.5%) than those obtained with MOGA, but following the trend. Rear vibrations (Figure 8b)) are achieved by sub-evaluation (2.32%) with ANN following the trend. Front vibrations are overvalued with ANN for $1 \le x \le 20$ with tracking the MOGA trend and for $20 < x \le 29$ are sub-estimated with a strong tendency to increase the distance between the trends, the average of this pair being 9.04%. On the whole, we have an overvaluation of 0.8%, for vibrations an sub-valuation of 5.68% and for the whole main spindle we have an sub-estimation of 5.4%.

2.5. Predicting the results of equations modeled with genetic algorithms using neuro-fuzzy hybrid techniques (ANFIS)

ANFIS prediction is a hybrid system consisting of artificial neural networks (ANN) and fuzzy logic (FL) [8], which leads to genetic algorithms with the prediction optimization [9].

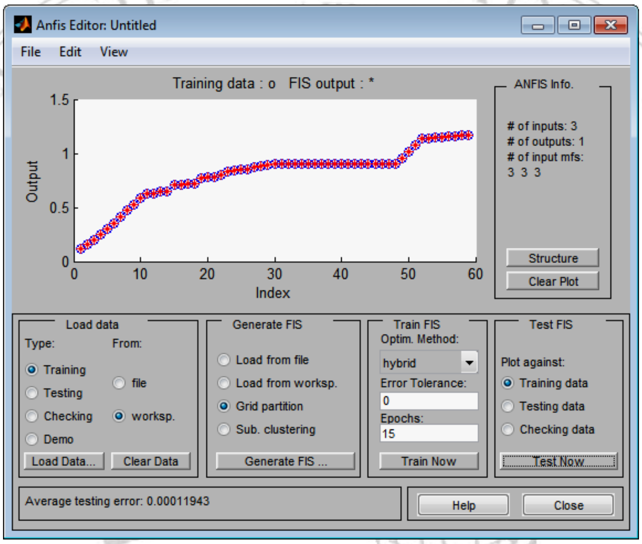


Fig. 9. Degree of coincidence between input and error data set.

It is observed (Fig.9) that the initial data and the error coincide.

The artificial neural system looks for the lesser learning error. Thus, three situations can occur (Figure 10): overlap (maximum precision - low error) in the neighborhood (near the values underlying the analysis, medium accuracy – mean error) and outside (mimic precision - large error).

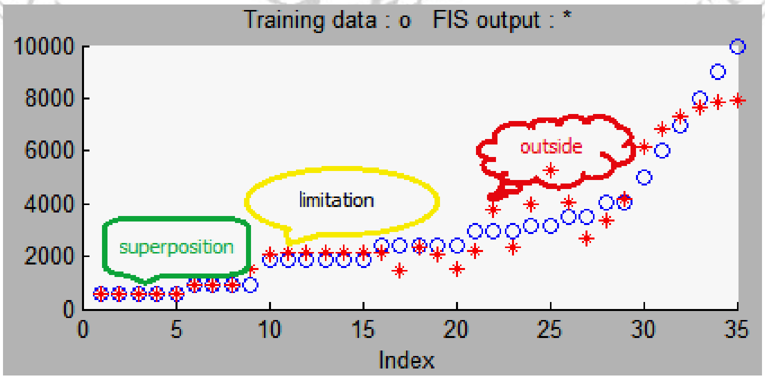


Fig. 10. Possible types of errors that occur during training.

ANFIS based on the [59x3] matrix, which represents the input variables, has produced a set of 19 rules that underlie the results forecast for BV. A number of 8 rules were eliminated because the physical significance of the result was impossible (back vibrations 0 or negative).

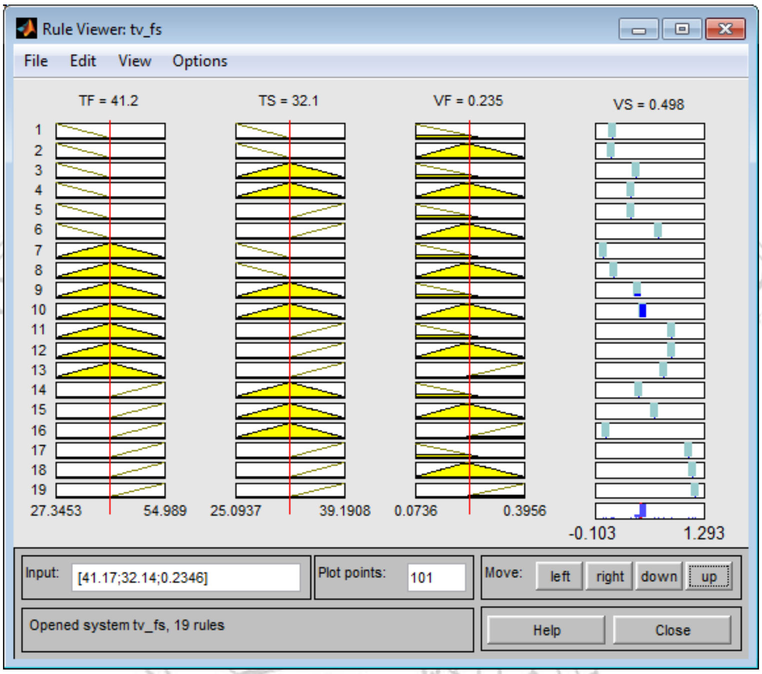


Fig. 11. Predicting values for BV.

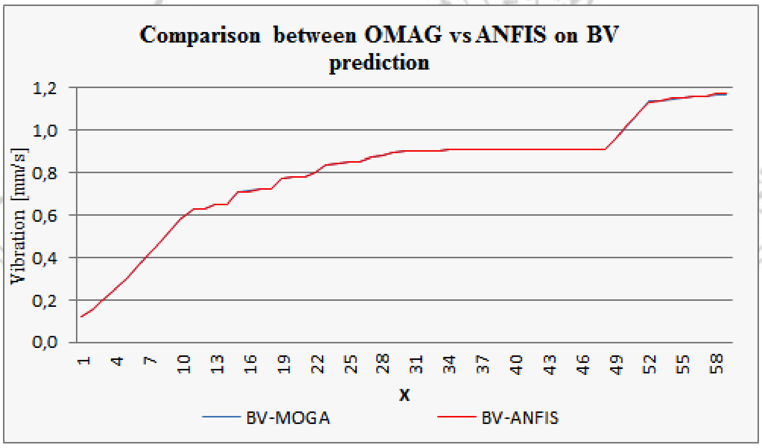


Fig. 12. Comparison between OMAG and ANFIS on BV prediction.

The results obtained with ANFIS are for a number of:

- 7 values (11.86%) lower with 0.001-0.004 [mm/s];
- 11 values (18.64%) higher by 0.001-0.005 [mm/s];

Then those obtained with MOGA, overall being an overvaluation of 0.025%.

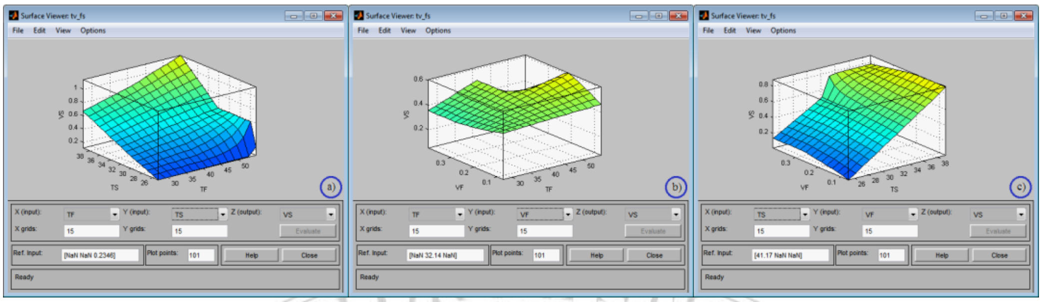


Fig. 13. The 3D shape of the input variable surface variable of the input variables.

Analysis Fig. 13 is made in conjunction with Fig. 14. The variation dynamics of the FT-BT pair (Fig. 14 a)) tends to focus on the admissible maximum of FT (55 [^{0}C]) for a BV vibration of no more than 1.15 [mm/s]) (Fig. 13 a)).

In the case of the variation dynamics of the FV - FT pair (Figure 14b) it has a homogeneous distribution for FT across the field and approximately parallel to FV for a variation of BV in the domain $0.38-0.6[mm/s]$ (Fig. 13 b)) with focus on two peaks, the first of 0.5 [mm/s] for $FT=40^0[C], FV=0.4[mm/s]$ and second by 0.6 [mm/s] for $FT=55^0[C], FV=0.2[mm/s]$.

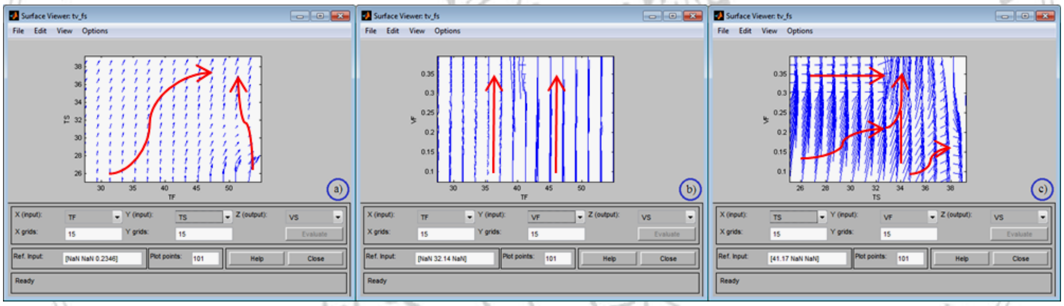


Fig. 14. Dynamics quiver between input variables.

The variation dynamics of the FV - BT pair (Figure 14c) is composed of 4 directions of the FV to two BT peaks (Fig. 13c)), respectively 33 and 39.5 [^{0}C]. The FV concentration is observed to temperature scale scales with a tendency to form a parallelism.

Conclusions

Due to the scarcity of genetic algorithms (AG) types, it is difficult to determine which performs the best optimizations. The analogy of AG building based on the biological reproductive system of individuals leads to 80% eligible results if one single phenomenon/process is analyzed. In the case of the analysis of an ensemble of interdependence characteristics of correlated systems, the eligible results decrease, due to the limitation of these AG because of their inability to optimize the crosses of individuals of different species but which are in correlation (1).

One such example is that discussed in this article, namely vibration-temperature. It is normal for the increase in temperature to result in the expansion of the bearings and the increase of the vibrations, but the bearing characteristics are removed from the chain, which is why errors occur (2).

An attempt to increase the number of eligible results (increase accuracy/precision) by introducing artificial neural networks (ANN) and fuzzy logic (FL) into the modeling chain can lead to improved results (3).

A very important factor is the type of data underlying the processing. The AG is the type of equation. In the present report, the equations were extracted based on the temperature/vibration graphs according to the speed. The type of these equations is greatly influenced by the human factor that can interpret them differently from the researcher to the researcher, which is why there are already errors that are multiplied in cascade if the modeling is of the *polynomial function type-GA-ANN-FL* (4).

The size of those errors is reduced if a short chain of GA-ANFIS or ANFIS is used. The error rate is reduced when the data series is modeled directly with ANN or FL, as there are no intermediate analysis and optimization models (5).

Considering that often only an overall picture of evolution is desired by the prediction of the analyzed phenomenon characterized by the critical area sizes, the use of such modeling techniques leads to good results to very good depending on the length of the modeling type (6).

3. Acknowledgment

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