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Improvement of the Material's Mechanical Characteristics using Intelligent Real Time Control Interfaces in HFC Hardening Process

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ABSTRACT

The paper presents Intelligent Control (IC) Interfaces for real time control of mechatronic systems applied to Hardening Process Control (HPC) in order to improvement of the material's mechanical characteristics. Implementation of IC laws in the intelligent real time control interfaces depends on the particular circumstances of the models characteristics used and the exact definition of optimization problem. The results led to the development of the IC interfaces in real time through Particle Swarm Optimization (PSO) and neural networks (NN) using off- line the regression methods.

Keywords: Intelligent Control, Real Time Control Systems, Hardening Process, Materials, High-Frequency Currents

1. INTRODUCTION HARDENING

Induction heating is a quick and precise technique to heat conductive materials without contact [1]. In order to obtain induction heating, equipment is necessary consisting of a source of alternative current and a solenoid to generate the electromagnetic field. The piece to be tempered is positioned inside the solenoid, with the electromagnetic field generating current inside the piece which, in turn, generates heat. Induction can heat pieces to temperatures between 100 and 300 grades Celsius. This is obtained using an electromagnetic field passing through a solenoid, which transfers energy to a working piece, which needs to be heated. When an electric field passes through a conductor, an electromagnetic field is produced around that conductor. This magnetic field produces electric current through a piece positioned in the middle of the solenoid's magnetic field, which in turn produces heat.

Eddy or Foucault currents are induced electric current loops in conductive materials by changing the magnetic field in that conductive material, due to Faraday's induction law. Eddy currents are transmitted in closed loop through the conductors, in perpendicular planes to the magnetic field. The intensity of the current in the conductor is proportional to the intensity of the magnetic field, the loop surface and the current frequency, as well as inversely proportional to the material resistance [2]. The piece to be heated and its material determine the operating frequency of the heat induction system.

It is necessary to use an induction system that ensures a larger frequency spectrum than that necessary for applications. The reason is due to the fact that when an electromagnetic field induces a current into the piece, this is largely transferred to the surface of the piece. When the operating frequency is high, the heated depth is thin. Similarly, when the operating frequency is low, the depth to which the electromagnetic field penetrates is larger. The thickness of the heated portion depends on the temperature, operating frequency and properties of the heated material.

Figure 1: HFC Hardening Process Control (HPC) During

the hardening process control (figure 1) using ***HFC*** (high-frequency currents) a metal part is placed in the electromagnetic field inside a copper tube bended to the shape of the part and the alternating high frequency currents are induced. The currents are pushed out to the part surface by the magnetic current induced inside. Since the induced currents have an extremely high density on the part surface which is being heated, the surface layer is heated quickly. The ***HFC*** induction hardening is characterized by two parameters: by the depth and hardness of the part layer being treated. Induction heaters (HFC apparatus) with the capacity ranging from 40 kVA to 160 kVA with the frequency of 20-40 kHz or 40-100 kHz are used to get thin layer in the hardened item. If deeper layers are required, the range of frequencies from 6 to 20 kHz is used. The HFC hardening has proved to be very effective [3].

Key features of induction hardening are fast heating cycles, accurate heating patterns and cores that remain relatively cold and stable. Such characteristics minimize distortion and make heating outcomes extremely repeatable, reducing post-heat processing such as grinding. This is especially true when comparing induction hardening to case carburizing. This is a cost-saving and high-productive way of metal heat treatment that provides a part with high strength and durability.

2. ARCHITECTURE OF THE HFC HARDENING SYSTEM CONTROL USING INTELLIGENT CONTROL INTERFACES

The architecture of the experimental model of the HFC (high-frequency currents) system allows the improvement of mechanical characteristics of the metallic profile by improving the performance of the control function interfaces, specific to the method of virtual projection [4,5,6], used in the real time control of the HFC hardening system. With this aim, there have been conceived and developed intelligent control interfaces using particle swarm optimisation and neural networks. The multi-functional interface (ICFM) specifies the virtual projection method, with decision making using fuzzy logic or neutrosophic logic. Through offline control, applying the methods of polynomial regression and exponential regression in estimating the frequency (FRQ) and power (POW) parameters, the parameters of the control laws for the HFC hardening system are determined. The digital – analogue conversion is done through the DAC module. The results of offline experimentation are used in implementing the versatile intelligent platform VIP, as coefficients applied to the intelligent control interfaces (ICF 1-ICF3) and in control decisions (ICMF) for the real time control of the HFC hardening system. Communication with the VIP platform is done through a software adapted to the research in the remote control communication interface (ICRM). Implementing the HFC hardening system entails applying the remote control methods through sockets with command elements through the VIP server terminals and the CIF equipment's PC system (figure 2).

The inputs of the CIF command system, considered independent variables in controlling the technological process and determined in designing the CIF experimental model, are:

Metallurgic Parameters:

TMC: Tempering temperature

PCU: Currie point

TCL: Tempering time = f(V_{Motion}, w)

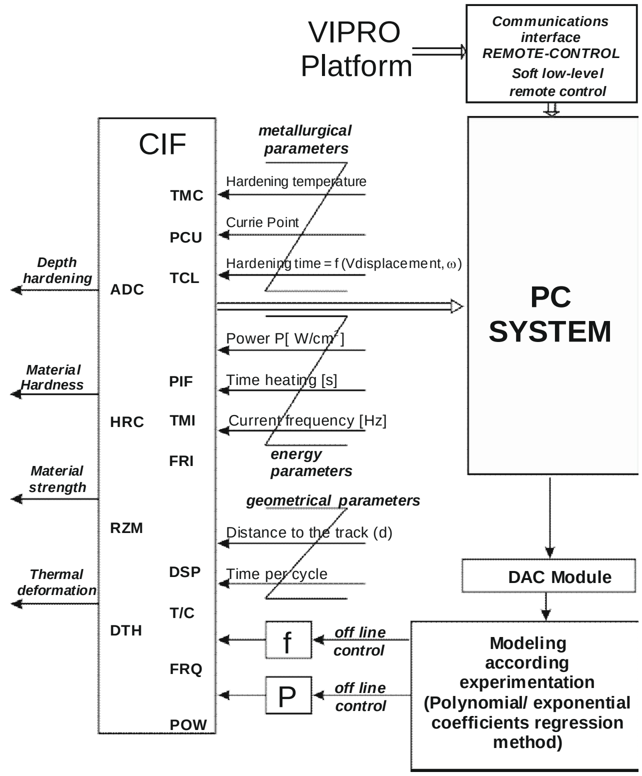


Figure 2: HFC Hardening System Architecture

Energetic Parameters:

PIF: Power P[W/cm^2]

TMI: Heating time [s]

FRI: Current frequency [Hz]

Geometric Parameters:

DSP: Distance to piece (d)

T/C: Time per cycle

The outputs of the command and control system, dependent variables upon the system inputs and the real time control laws of the speed of movement V_{Motion} and angular speed ω of the metallic profile, determined in designing the experimental model of the CIF, are:

ADC –Tempering depth

HRC – Hardness of the metallic material (Rockwell Scale)

RZM – Resistance of the metallic material

DTH – Thermic deformation

The intelligent control interfaces module uses advanced control strategies adapted to the industrial technological process of induction heating and tempering, applying IT&C techniques with fast processing and real time communication. There were designed, analysed and conceived virtual experimentations for intelligent control interfaces using ***particle swarm optimisation (PSO)*** and ***neural networks*** in decision support systems employing ***fuzzy or neutrosophic logic***, which will be shown in the following chapters.

3. INTELLIGENT CONTROL INTERFACE USING PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) is an evolutionary algorithm gaining more recent interest after being discovered by Kennedy and Eberhart [7, 8]. Instead of using genetics to modify the potential solution, the PSO algorithm has particles traverse a solution space at variable speeds, adjusted depending on their history and that of the swarm. Both of these are known for the entire population. At each instance, the speed of each particle is influenced by these two best solutions found.

The algorithm was first intended to simulate social behaviour, as a representation of swarms of flies or schools of fish. It has since been simplified to a model usable in optimisation problems. [9, 10]. It is a meta-heuristic algorithm, as there are very few assumptions, if any, about the optimisation problem, and it can search large spaces of candidate solutions. However, such algorithms cannot guarantee the optimal solution is found. PSO is not a gradient method, which means that it does not require for the optimisation problem to be differentiable, as do classical optimisation methods. It can be successfully used with partially irregular problems, including noise, time-variable, etc.

The basic version of the algorithm uses a population called swarm, made up of candidate solutions, called particles. These are moved in the search space according to a few simple calculation rules. Their movement is guided by their own best position found in the search space and by the best overall position found by the swarm. When better positions are discovered, these will be used to guide the entire swarm. The process is then repeated, which will lead in the end to a satisfactory solution.

Let $f\colon R^n \to R$ be the objective function which is to be minimised. The function takes as candidate solution a vector of real values and produces a real number which indicates the fitness of the given candidate solution. The gradient of f is unknown. The aim is to find a solution a for which $(a) \leq f(b)$ for any b in the search space, which would make it the global minimum. The maximisation can be done using$h = -f$.

Let S be the number of particles in the swarm, each with a position $x_I \in R^n$ in the search space and a speed $v_I \in R^n$. Let p_i be the best known position of the particle i and g the best known position of the entire swarm. Then, for each particle i=1,…,S, the position is initialised with a random distributed vector $x_i \sim (b_{lo}, b_{up})$, where b_{lo} and b_{up} are the upper and lower limits of the search space, the initial particle position is initialised with its best known value, $p_i \to x_i$. If $(p_i) < f(g)$ the best known position of the swarm is updated: $g \leftarrow p_i$. Then the particle speed is initialised $v_i \sim (-|b_{up} - b_{lo}|, |b_{up} - b_{lo}|)$. Until a termination criterion is met (for example the number of iterations or the solution fitness), for each particle i=1,…,S and for each dimension d=1,…,n, the particle speed is updated to:

$vi, d \leftarrow \omega\, vi, d + \varphi p\, rp\, (pi, d - xi, d) + \varphi g\, rg\, (gd - xi, d)$

and the particle position is updated to: $xi \leftarrow xi + vi$. If $f(xi) < f(pi)$, the particle best known position is updated $p_i \leftarrow x$ and, if $f(p_i) < f(g)$, the best known swarm position is also updated to $g \leftarrow p_i$. Now g contains the best known position of the swarm.

The parameters ω, φp and φg are selected by the user and control the behaviour and functionality of the POS method. The choice of PSO parameters has a significant impact on the performance of the optimisation algorithm. Therefore, the selection of PSO parameters to increase performance has been the subject of much research.

Speed initialisation may require extra inputs to the problem. A simpler alternative is accelerated particle swarm optimisation (APSO), which does not use speeds and may converge quicker in some applications.

Considering a swarm ***p*** in a n-dimensional search space, the position vector x(i,k) of each particle ***i*** is updated by:

$(i, k + 1) = x(i, k) + v(i, k + 1)$, where ***k*** is a temporal pseudo-increment.

The term $(i, k + 1)$ is the speed vector, obtained by applying the law: $v(i, k + 1) = \omega \bullet v(i, k) + v(i, k)$, in which the inertial factor ω is a real number and v(i,k) is the stochastic speed vector.

The last term is formed by summing the other two:

$$(i, k) = c1R1(p(i, k) - x(i, k)) \\ + 2R2(p(g, k) - x(i, k)), p(i, k)$$

Representing the best position vector of the particle ***i***, while p(g,k) is the best position vector of the entire swarm (up to moment *k*).

The vectors (p(i,k) – x(i,k)) and (p(g,k) – x(i,k)) use the amplitudes and directions of the vectors uniting the current particle position x(i,k) with the best particle position p(i,k) or the best swarm position p(g,k). At each iteration, the quality of each particle is evaluated through the fitness function. Each particle retains the best value of the objective function, as well as its position. The interaction between particles allows them to retain the best values of the objective function for the entire swarm over time. The particles can move in a continuous, discrete or mixed domain.

In order to design the ICF2 intelligent control interface, two possible approaches were investigated using particle swarm optimisation through virtual experimentation. The running script for particle swarm optimisation uses the following work parameters:

```
ac = randlim(100,1,0,12);      % tempering depth
tc = randlim(100,1,0,10);      % tempering time
pc = randlim(100,1,40,70);     % tempering power
```

the first being the dependent variable.

There are defined the maximum degree to which the independent variables will be combined in a polynomial, n=6, and the fitness function:

```
f=@(x) testfun(x,ac,tc,pc,n)
```

The implementation of PSO used does not require an explicit setting of simulation characteristics, being natively limited to 100 iterations and automatic listing every tenth generation. The model parameters are optimised in 5.79 s. The second version model run obtains the optimised model parameters for the variable Z in 2.2 s. A number of strategies were investigated for the optimisation of HFC Hardening. Their implementation into the intelligent real time control interfaces depends on the specific circumstances of the model characteristics used and the exact definition of the optimisation problem.

4. INTELLIGENT CONTROL INTERFACE USING NEURAL NETWORKS

Starting from the research done in the field of high frequency tempering, a number of experimentations were developed for the improvement of mechanical characteristics of the used profiles in constructing metal structure buildings through improved performance for the real time control of the HFC Hardening System using neural networks in implementing the Intelligent Real Time Control Interfaces.

To this end, with the aim of testing and simulation through neural networks [11, 12], there were considered the following inputs: - specific power, p, [kW/ cm^2], advance speed, v, [mm/min] and piece angular speed, n, [rot/min], the desired output being the piece hardness (HRC).

The dependence between inputs and outputs is based on a polynomial regression model:

$$HRC = 23 + 25\,p - 0{,}106v + 0{,}23n + 0{,}025\,pv - 0{,}125\,pn - 0{,}00126\,nv + 0{,}00075\,pvn$$

In order to train the neural network, a Levenberg-Marquardt algorithm was used, with two layers (hidden layer and output layer) and 10 neurons (figure 3). The considered samples were divided so that 70 % were used for training, 15% for validation and 15% for testing.

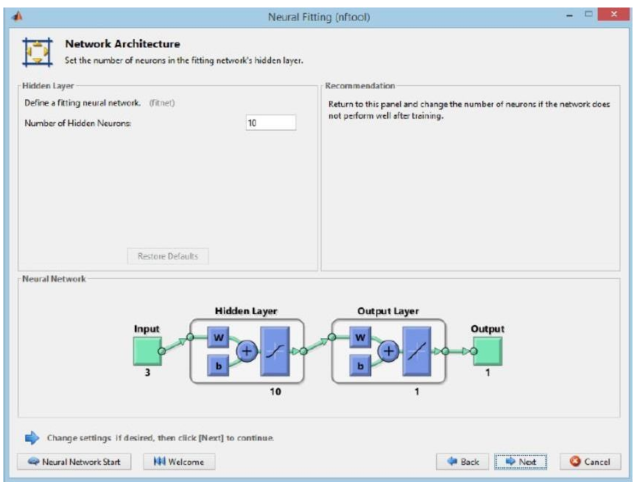


Figure 3: Neural network representation

Figure 4 shows the algorithms used in all stages of the neural network training, the progress in time and the resulting diagrams.

Training the network was done multiple times and was adjusted until the training errors were minimal.

In the case of simulation and testing in Matlab of the HFC Hardening interface, the neural network model can be used as a standalone block in Simulink.

Figure 5 shows the graphics resulting after training, validation and testing the network.

There can be observed that the errors are smaller for training and validation, but larger in testing the network.

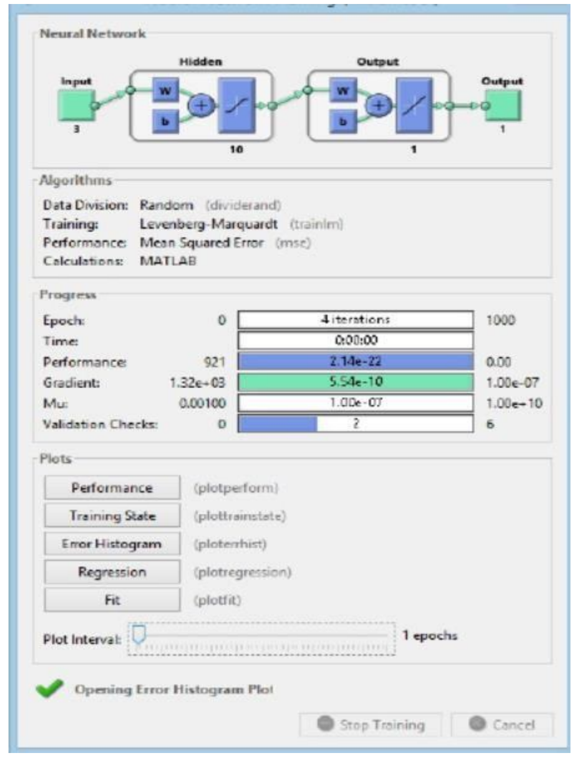


Figure 4: Neural network performance

These larger errors during testing are largely due to the restricted sample considered when training.

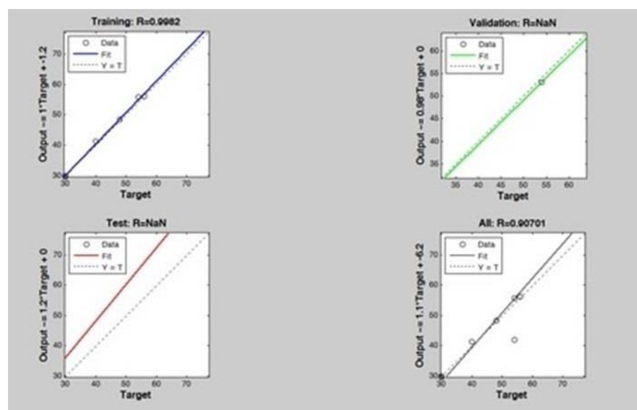


Figure 5: Training the neural networks for HFC Hardening

As the available data increases, the errors in testing will decrease to the normal level of those obtained during training and validation.

5. REGRESSION MODEL FOR SPECIFIC PARAMETERS OF THE HFC HARDENING SYSTEM

With the aim of researching the dependence functions between the CIF process parameters, specific methods of applied statistics are used, namely experiment projection and multiple regression.

If the response of a process or system is influenced by two or more factors, a factorial experiment can be programmed, meaning an experiment where each sample is a possible combination of factor levels.

The effect of a factor is evidenced by the variation of the response values, subject to modifications occurring in its level. This is called a main effect as it refers to the considered inputs (the primary factors).

There are experiments in which the variation in response values, for two different levels of a factor, are not the same at all levels of the other factors, which suggests an interaction between the factors. There are situations where the interactions are significant enough that they mask the main effects, which no longer hold a significant effect on the output value.

The program matrix (experimentation matrix) is defined as being the matrix where the levels of all factors are shown for each sample within the experiment. For ease of calculation, usually, this matrix does not contain real (natural) values of the independent variables studied, but coded (un-dimensional) values obtained from these.

The values, on various variation levels, are in arithmetic or geometric progression (in the latter case they can be brought to arithmetic progression through logarithm). The interdepence relations between the natural value and the coded value are: $\boldsymbol{z}_j$ and the coded values are:

$$x_j = 2\frac{z_j - \bar{z}_j}{z_{\max} - z_{\min}} \quad \text{and} \quad z_j = \bar{z}_j + \frac{z_{\max} - z_{\min}}{2} x_j \qquad (1)$$

where: x_j is the coded value of factor j;

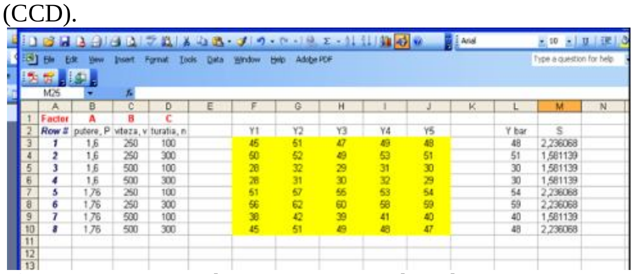
$\boldsymbol{z}_j$ - the natural value of factor j

$\bar{\boldsymbol{z}}_j$ - the mean of the natural values of factor j;

$z_{\min}$; $\boldsymbol{z}_{\max}$ - the minimum and maximum, respectively, of factor j.

Among the most frequently used types of experimental programs are ***factorial programs***, which show both the main effects of the factors, as well as their interactions. If there are *k* factors, each of these with two variation levels (minimum / maximum), then the complete factorial program (FFD) has experiences. 2^k

A flexible and efficient design for modelling the second order dependencies is the Box-Wilson or the centred composed design (CCD).



Factor	A	B	C									
Row #	putere, P	viteza, v	turatia, n		Y1	Y2	Y3	Y4	Y5		Y bar	S
1	1,6	250	100		45	51	47	49	48		48	2,236068
2	1,6	250	300		50	52	49	53	51		51	1,581139
3	1,6	500	100		28	32	29	31	30		30	1,581139
4	1,6	500	300		28	31	30	32	29		30	1,581139
5	1,76	250	100		51	57	55	53	54		54	2,236068
6	1,76	250	300		56	62	60	58	59		59	2,236068
7	1,76	500	100		38	42	39	41	40		40	1,581139
8	1,76	500	300		45	51	49	48	47		48	2,236068

Figure: 6 Experiment design – experimental results

In the case of the studied CIF process, there are considered as independent variables (the inputs), zj, the process variables:
- specific power, p, in kW/ cm2 (z1);
- advance speed, v : [mm/min] (z2);
- angular speed, n : [rot/min] (z3).

The desired dependent variable (output) is the hardness of the superficial strata, HRC. The software used for programming the experiments, data processing and obtaining the regression results is the DOE KISS (student free version).

The experimentation matrix (experiment design and experimental results, for 5 values of the replicates), is shown in Figure 6.

A multiple regression model is applied which contains more than one variable (regressor). The dependent variable, the response Y, can be correlated to k independent variables, through a linear model of multiple regressions

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \epsilon \qquad (2)$$

where: β_j , $j = 0,1,2,\ldots,k$ are called *regression coefficients*.

A second order model with interactions is considered:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 + \epsilon \qquad (3)$$

then, using the notations:

$\beta_{11} = \beta_3$; $\beta_{22} = \beta_4$; $\beta_{12} = \beta_5$

$x_1^2 = x_3$; $x_2^2 = x_4$; $x_1 x_2 = x_5$

the model becomes linear, a multiple regression, namely:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \epsilon \qquad (4)$$

In order to determine the estimators for the regression model coefficients, the *least squares method* can be used. Thus, there are the observations $(x_{i1}, x_{i2}, \ldots, x_{ik}, y_i)$, where $i = 1,2,\ldots,n$ and $n > k$, such that, for each of them is fulfilled the relation (9-1), namely:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \epsilon_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \epsilon_i \qquad (5)$$

For the studied CIF process, the results of the regression analysis, obtained with the DOE KISS software, are shown in Figure 7.

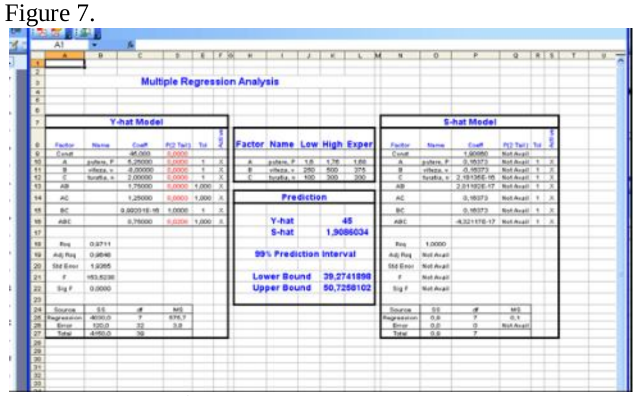


Figure: 7 Results of the regression analysis

Taking into account the value of the coefficients of the polynomial model with interactions (see Figure 2, Y-hat Model) and the dependence relations between the coded variables and the natural ones (see equation (1)), there is obtained the dependence function between the studied parameters of the CIF process, namely the second order polynomial relation with interactions:

$$HRC = 23 + 25p - 0{,}106v + 0{,}23n + 0{,}025pv - 0{,}125pn - 0{,}00126nv + 0{,}00075pvn$$

6. RESULTS AND CONCLUSIONS

Starting from the HPC were conceived, analysed by the regression method, and achieved intelligent control (IC) interfaces by virtual projection method, through Particle Swarm Optimization (PSO) and neural networks (NN) in which the control decisions (Decision making) use fuzzy logic or logic neutrosophic.

The results obtained from experiments and the multiple regression show the degree of influence on the output variable of each of the independent variables and their respective interactions.

Following the regression analysis results that the polynomial regression model with interactions is adequately adapted to the task at hand. All studied independent variables influence the output variable, the most significant influence being that of the advance speed.

There is a single interaction with insignificant influence on the hardness of the superficial tempered strata (CIF), namely the interaction between the advance speed **v** and the piece angular speed ***n.***

The results obtained outline the development of the ICI modules using advanced control strategies adapted to the induction hardening process, applying ICT techniques with fast processing and real-time communications, which led to improvement of the material's mechanical characteristics.

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