Fuzzy Model of the Heat Treatment Process in an Automotive Production Application

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Abstract: Historically, the most fundamental approach of the safety management has focused on human capital failures, uncertainties and the resulting changes in performance. As the complexity of these processes has evolved and become more complex, their unpredictability and uncertainty has increased as economic and technological aspects have been taken into account. Thus, starting from the theme induced by the previous ones, and focusing on the idea of Industry 4.0 and Industry 5.0, my research aims to optimise the technical parameters of production machines using fuzzy models by exploiting the potential of human capital. Fuzzy model can be one of the best solution if mathematical modelling is not possible involving all of data in order to achieve truly efficient and effective development. At the end of this study the proper parameter-window of this technical production process is defined.

Keywords: automotive industry; fuzzy model; production application; industry 5.0

1 Introduction

Organizations must adapt to change, whether driven by internal or external forces, as ongoing evolution and increasing complexity demand transformation. Technological advancements, particularly those exemplified by Industry 4.0, have not only reconfigured operational processes but also engendered a decline in transparency, thereby contributing to an increase in errors that often remain concealed until a confluence of factors surfaces their existence, often originating from systemic or human failures. While not all errors result in failure, when they do, they expose the visible tip of a much deeper issue. In order to maintain consistent quality in repetitive tasks, automation – when properly parameterized – offers a solution; however, real value emerges only when data is consciously processed and abstracted, enhancing both company efficiency and employee recognition. This synergy plays a vital role in fostering a strong safety climate. The ensuing sections will offer an exhaustive review of the extant literature on related topics, to be followed by a thorough exposition of the research methodology and a presentation of the key conclusions.

It is imperative to underscore that the core of the study does not lie in the materials science and engineering approach, but rather in the optimization of the parameters of the EMA production machine in the automotive mass production during the induction hardening manufacturing process. This optimization is conducted with respect to the variables under study, while simultaneously accounting for quality aspects that can result in the satisfaction of business economics aspects.

1.1 Motivation and Antecedents

Guided by personal experience, an investigation was initiated into methods to enhance the efficiency of the process in practice by maintaining a healthy balance in the human-machine relationship. In accordance with the principles of Industry 5.0, it is posited that a heightened degree of collaboration between machines and humans can engender substantial added value for companies. This assertion is predicated on the premise that automation and robotics are accorded a prominent role in Industry 4.0. [1]

In the context of automation manufacturing activities that are designed in accordance with the principles of Industry 4.0, a substantial amount of data is accumulated pertaining to the parameters of the manufacturing activity. A notable deficiency lies in the company's inability to rationalize the processing of stored data and the examination of its relationship with the potential for deriving additional value. The central theme of this paper is to underscore, in accordance with the tenets of Industry 5.0, the manner in which the tacit knowledge of human resources can be leveraged to enhance the value of a company. This assertion is exemplified by an automotive heat treatment process that employs a fuzzy model.

At the end of this paper this analysis will provide the optimal parameter-window for the variables (voltage, current, frequency, quench level) involved in a given manufacturing process.

1.2 Paper Structure and Aims

The main objective of the study is to optimize the parameters of the heat treatment process in mass production, to increase efficiency and to reduce scrap by using the fuzzy model. The absence of a mathematical model to describe this production process necessitates the implementation of a fuzzy model as a novel approach to address this gap in modeling.

In Chapter 2, the reader is introduced to a variety of non-linear systems that have been used in previous studies. The text expounds on the fundamental principles of the heat-treatment process in mass production, presents the extant production results, and delineates the hypotheses for the present study. Subsequently, Chapter 3 delves into the implementation of a fuzzy model, emphasizing its application in the context of historical data. This model is employed to quantify and adjust parameters that are measured by the production machine. Conclusively, the paper is brought to a close by demonstrating the approach's effectiveness and discussing potential future optimization opportunities.

To date, the sole aspect that has been subject to tolerance interval in the context of mass production is the energy level. However, given the multifaceted nature of the resultant effects of heat treatment, a more comprehensive understanding can be achieved by examining the extreme values and tolerances of the other parameters necessary to ensure the successful production of the intended product. To this end, the fuzzy model is required, as the mathematical model is not known to describe the combination of these parameters to describe the resulting process.

The objective is to ascertain, through the utilization of the fuzzy model, which parameter windows (comprising all variable parameters) are interdependently feasible to modify, in the event that a parameter becomes distorted due to a malfunction, while still yielding a correct product within prescribed limits. This could potentially enhance production efficiency. In the event of a malfunction that is so extensive that it cannot be rectified through parameter modification, the production process will halt, accompanied by the transmission of an error message. Consequently, the generation of scrap material will be impeded. Further direct essences is in chapter 2.3. where hypotheses are as well.

The machine manual and the production description are devoid of any mathematical model that would elucidate the production process in question. This is why this study could be a novel concept in terms of its implementation.

2 Literature Review

2.1 Already Applied Non-Linear Systems in another Studies

Several related opportunities of practical application of the non-linear systems and their modeling:

- Fuzzy models are particularly useful when dealing with uncertainty and nonlinear behavior, which are common in viscosity-related phenomena. Traditional viscosity models rely on precise equations, but real-world applications often involve unpredictable variations due to temperature fluctuations, shear rate changes, and material inconsistencies. A fuzzy model can incorporate linguistic variables (e.g., high viscosity, moderate shear rate) and rule-based reasoning to make more adaptable predictions. [2]
- New Opportunities Model for Monitoring, Analyzing, and Forecasting the Official Statistics on the Coronavirus Disease Pandemic study introduces a new opportunitiy model designed to monitor, analyze, and forecast government-reported statistics on the COVID-19 pandemic. The authors highlight that official statistics often differ from the actual pandemic dynamics due to various objective and subjective factors. Instead of modeling the pandemic itself, the study focuses on predicting the behavior of official statistics using data-driven modeling techniques, including parabolic regression and optimization methods. The model is applied to data from Russia, Romania, Moldova, and the Campania region in Italy, demonstrating its effectiveness compared to traditional epidemiological models like the Susceptible-Infected (SI) model2. [3]
- Another study focuses potential applications in robotics, vehicle suspension systems, and industrial automation. The study contributes to the development of more reliable pneumatic control systems, expanding their usability beyond simple end-to-end motions. [4]
- A further article presents a novel pose estimation algorithm designed to enhance robotic navigation accuracy. The authors focus on improving localization and mapping by integrating advanced filtering techniques. The algorithm leverages Bayesian filtering methods, including Kalman filters and particle filters, to refine pose estimation in dynamic environments. The research is particularly relevant for autonomous mobile robots, where precise pose estimation is critical for obstacle avoidance and path planning. [5] In a separate study, the non-linear version of the Kalman filter – that is, the extended Kalman filter (EKF) – has garnered significant attention in conjunction with fuzzy modeling. [6]

2.2 Induction Heat-Treatment Process (in a Mass Production)

2.2.1 General Approach of the Induction Heat-Treatment Procedure

The following is a list of camshaft materials and their respective purposes [7].

Camshaft material and purposes: in the context of four-stroke engines, camshafts are typically composed of chrome alloy cold forming tool steel, a material that is highly regarded for its hardness, wear resistance, and capacity to withstand mechanical stress. This steel is particularly well-suited for components that experience high pressure and friction, such as bearings. The alloying elements introduced into the steel matrix serve to modify its structural properties, thereby ensuring a prolonged service life when subjected to appropriate heat treatment processes. [8]

Design and Manufacturing Process: the cams are subjected to a process of hardening, which is carried out separately from their subsequent mounting onto shafts. This results in the formation of a camshaft assembly that is both modular and durable. The integration of high precision and modularity within the design of internal combustion engines serves to enhance their versatility and longevity. EMA, a machine manufacturer, employs optimized heat cycles and system maintenance to ensure mass-production quality.

Induction hardening technology: the apparatus uses electromagnetic fields to apply heat to steel components without the need for direct contact: The camshaft undergoes heating due to eddy currents and hysteresis losses, which are induced by a magnetic field: the magnitude of heating is determined by the frequency of the applied electric current: it has been demonstrated that lower frequencies, ranging from 1 to 20 kHz, are associated with more profound hardening effects. It has been established that higher frequencies result in shallower surface heating (<400 kHz), a phenomenon known as the skin effect. The system operates at a frequency of approximately 20 kHz, as determined through empirical testing.

Cooling and Energy Optimization: subsequent to the heating process, cooling water (frequently shared with the inductor's own cooling system) rapidly cools the camshaft, thereby ensuring the consolidation of its hardness. The parameters of voltage, frequency, and cooling volume are meticulously calibrated to regulate energy consumption and the extent of hardening.

Equipment and electrical demands: The generation of magnetic fields by induction systems necessitates the utilization of high-power current converters and induction coils (spindles). The coils are composed of hollow brass, a material selected for its capacity to facilitate internal cooling in response to the substantial thermal, electrical, and mechanical stresses to which it is subjected. It is important to note that this process is not exclusive to steel; it is also applicable to other metals, including aluminum and copper alloys. [9]

Induction hardening parameters:

P in kW, according to which the results are obtained from the formula:

$$P = U \cdot I \cdot \cos\varphi \tag{1}$$

it is also possible to modify the voltage and current separately, in which case the electrical power (of induction hardening) varies according to the theoretical law (formula referred to above).

In case of "E" (energy) parameter, there is no (known) formula describing the relationship between the parameters, but it can be determined by performing successive tests on the same machine at the same time: the increase of the energy level (which has adjusted tolerance in the current manufacturing process) will lead to an increase in both the current and voltage (of course, the P value will also increase), in varying proportions; Energy also varies to an undefined extent - but empirical evidence suggests that it varies less than if both power factors (U; I) varied in the same direction; The smallest change for the interval under consideration is the value of the frequency, whose role is to show the speed at which a signal or an electric wave decays. This is usually important for AC systems. AC signals can take different forms, such as sinusoidal, square or triangular waveforms, and frequency measures how quickly these waveforms repeat. [10]

2.2.2 Results so far

2.2.2.1 Regression Analysis

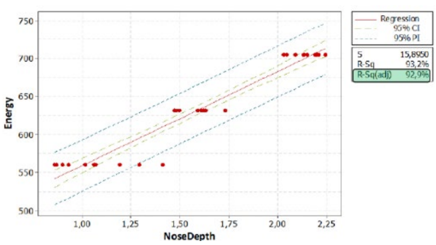
The form and type of heat treatment becomes determined by the size, type and quantity of the piece to be hardened (custom or mass production) and, of course, the question of economic efficiency and return on investment, which is increasingly becoming a pillar of corporate culture in our globalised world. [11]

The aim was to define a result that would help to ensure stability in mass production in the light of quality requirements for each type of component in the future. As a result, of the correlation test of Hugyi [10], the desired results can be ensured and maintained, but the basic structure and properties of the raw material can change, which makes it necessary to test the result of the heat treatment of the hardened part on a daily basis using the control plan approach. If anything else (e.g. criteria, customer expectations, production machine) changes, it is necessary to repeat the correlation test described. During this process, it is not sufficient to find a suitable value, but it is also necessary to sample and analyse overstressed and understressed parts to draw the appropriate conclusions.

The formula for calculating the hardness depth - nose side - is as follows to determine the desired energy level:

$$435{,}6 + 123{,}9 \cdot ND \qquad (2)$$

where ND is the hardness depth.



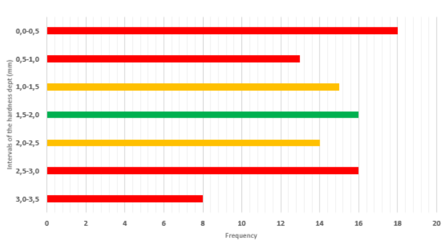


Figure 1 (left): Fitted line plot of the nose side [11]

Figure 2 (right): Development of hardness depth intervals in the reflection of the frequencies of the given depths (mm) in the observation series consisting of 100 experiments, marked OK-NOK [12]

2.2.2.2 Monte-Carlo Approach

The essence of the Monte-Carlo approach is to randomly select a value for each uncertain excited parameter based on the probability distribution (Figure 2). The advantage of the approach is that by simply solving the random numbers quickly and easily, the questions can be answered. [12] [13] [14]

It has been demonstrated that, given these settings, the production rate is 66% rejected, which is not acceptable. This is due to the inefficiencies and economic disadvantages that result. Thus, the energy level needs to be optimised during the production process. [12]

Based on the relationship in the previous subsection: 2.2.2.1 (hardness depth, nose), by fitting the hardness depth (mm) value (lower bound: 1.3 mm and upper bound: 2.3 mm) it has been demonstrated that, given these settings, the production rate is 66% rejected, which is not acceptable. This is due to the inefficiencies and economic disadvantages that result. In the present case, these energy levels (lower and upper) are 597 and 720. [12]

2.3 Empirical Basis of Mathematical Model

In order to define the fuzzy model, it was necessary to analyze the empirical basis of related data of the heat-treatment production process. A preliminary investigation of the available parameters reveals that main parameters of the requested parameters for this process are obtainable, including current (primary input), voltage (primary input), energy level (mid-output), and hardness depth (final output) values. The rationale behind the exclusion of further data from visualization, including quench value, frequency, and power, is predicated on the observation that the data range of these variables is characterized by narrower intervals.

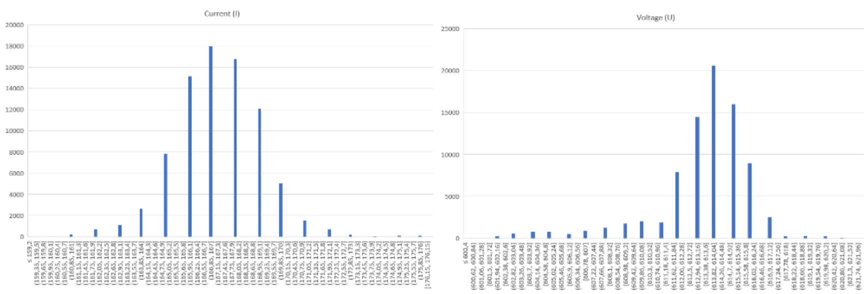


Figure 3

Empirical basis of the current- (left) and voltage-values (right) [edited by authors]

A review of the empirical data on voltage values reveals a relatively narrow range, approximately from <600 to 620. In the absence of a comprehensive analysis that accounts for all the aforementioned parameters, the parameter window remains uncertain. In addition, most of the data attains between 611 and 615 V. Historically, process engineers lacked the requisite knowledge of the proper interval of the given parameter, leaving them unable to determine the appropriate setting for the other parameters in the event of a parameter change. This limitation impeded the realization of the intended hardness depth value restricting effectiveness of the production as well.

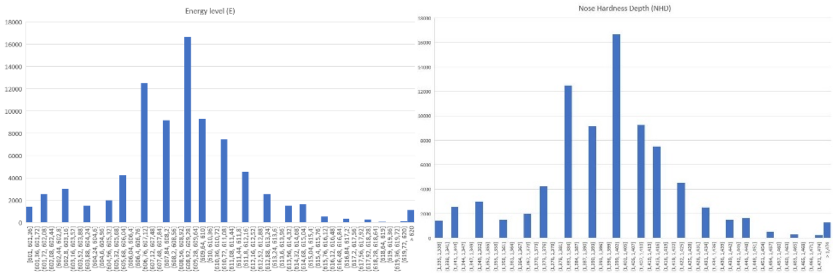


Figure 4

Empirical basis of the 'energy level' (left) and 'nose hardness depth'-values (right) [edited by authors]

Based on the data-frequency of histograms it is stated that almost 100 000 data-line meant empirical bases of this analysis. Subsequently, few additional trials were necessitated to obtain further data from their marginal interval to extend the knowledge of operation of edge-parameters.

Our aim is to find the ideal interval of the lifting cam (NHD) machine parameter for this material, with which, in addition to the Energy parameter, whose relationship has already been defined by Hugyi [11], sub-parameters such as current and voltage can be outlined, so that the desired intervention can be more effective, thus knowing the basic independent variables.

Further, it should be mentioned here that the hardness depth for the lifting cam section will be a few tenths of a millimeter less than the hardness depth of the zero cam section. This is also confirmed in Hugyi's study. [11]

Hypotheses:

H1: The effect of the voltage (U) is greater since its (its) elevation(s) - compared to the current (I) - results in a greater depth of hardness.

H2: The importance of more intense cooling (with a higher flow rate in litres/min) is decisive since without reaching its minimum level the desired hardness depth cannot be achieved without an adequate intensity of re-cooling.

H3: Reducing the frequency may increase the hardness depth (mm) in a limited extent (within a given range), but this may depend on the composition (possibly geometry and size) of the material structure to be hardened.

3 Application of the Fuzzy Model for more Effective Contolled Heat-Treatment Process in the Production

The Fuzzy Logic Toolbox was used, and it functions by specifying membership functions, parameter ranges, and the rule base. Subsequently, the system provides the inference interface. The Mamdani inference system is employed in conjunction with the conventional aggregation method and the centroid defuzzification rule. [15] [16] [17] [18] [19] As it is emphasized above why fuzzy approach is needed because there were not determined mathematics formulas.

In our case, the FIS tree model can be described as follows [20] [21] [22] [23], in accordance with the operating principle of the EMA machine mentioned above.

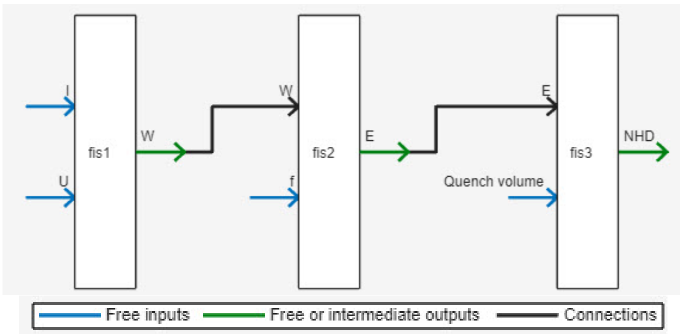


Figure 5

FIS tree model of operation of the investigated production machine [edited by authors]

On the basis of empirical data, the following set of rules was established for the three FIS (fuzzy inference system) in the tree models. As illustrated in Figure 5, the model accurately represents the actual process, as the two main inputs essential for induction heat treatment, namely current and voltage, are found in FIS1. The resultant outcome is associated with frequency (FIS2), which is in turn linked to penetration capacity. The known outcome of this process was the energy level itself, which could be parameterized during production with the specified tolerance. Consequently, this resulted in the generation of more scraps, and without the requisite knowledge of the combined parameter window related to these parameters (current, voltage, power, frequency, energy level, and quench-volume). According to the iron-carbon phase diagram, the role of recooling is also very critical in terms of the heat treatment process and hardness depth data. For this reason, this parameter also play a prominent role in the defined process (FIS3).

FIS1 – rules: if I is low and U is high then kW is ok; if I is high and U is low then kW is ok; if I is high and U is high then kW is high; if I is low and U is low then kW is low; if I is ok U is ok then kW is ok; if I is ok and U high kW is high; If I is low and U is ok then kW is low; If I is ok and U is low then kW is low; If I is high and U is ok then kW is high; defuzzication approach: Centroid.

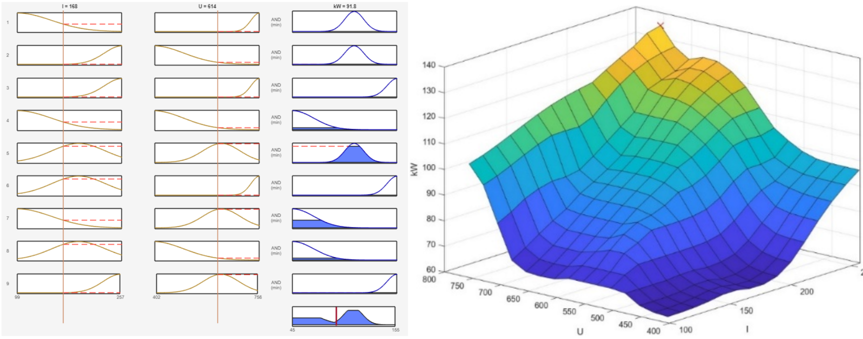


Figure 6
Rule inference and control surface of the FIS1 [edited by authors]

Subsequent to the parameter analysis, the objective is to refine and optimize the production process through the intervention points that have been revealed. This will be based on the following rule conclusions in case of FIS1: for example, if I=168 and U=614, kW will be 91,8.

Figure 6 shows the relationship between the two inputs (current and voltage) and one output (power) associated with FIS1. It can be seen that for currents above 180 A some power rise is already possible below 500 V, but cca. Above 550 V, a closer interaction of the two inputs is observed, and even with a slight increase in current, higher power (kW) levels can be achieved in the present production process.

FIS2 – rules: if kW is low and f is low then E is low; if kW is ok and f is then E is low; if kW is high and f is low then E is low; if kW is low and f is ok then E is ok; if kW is ok and f is ok then E is ok; if kW is high and f is ok then E is high; if kW is low and f is high then E is low; if kW is ok and f is high then E is low; if kW is high and f is high then E is high; defuzzication approach: Centroid.

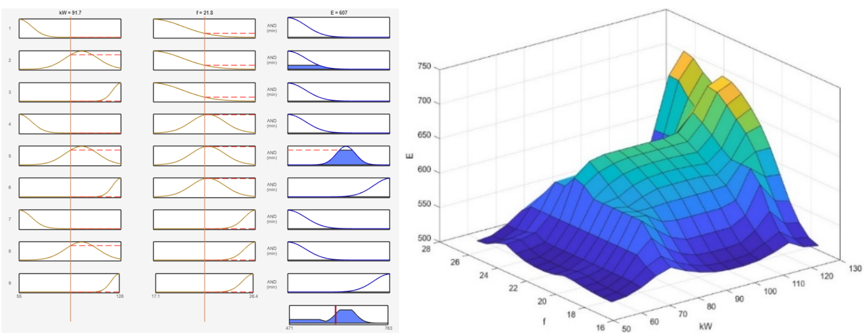


Figure 7
Rule inference and control surface of the FIS2 [edited by authors]

For example, if kW=91,7 and f= 21.8 kHz, E will be 607. Figure 7 shows that for power levels above 81 kW, the skin effect, i.e. the lower the frequency value, the higher the energy level. This is most noticeable at the frequency level of about 23.7 kHz. Above this frequency level the energy level decreases by nearly 60 units per kHz. This is not observed over the whole range of the process under investigation.

FIS3 – rules: if E is low and Quench volume (QV) is ok then Nose Hardness Depth (NHD) is low; if E is high and QV is ok then NHD is high; if E is low or QV is low then NHD is low; if E is high and QV is high then NHD is high; if E is high and QV is low then NHD is low; if E is low and QV is high then NHD is low; if E is ok and QV is low then NHD is not ok; if E is ok and QV is high then NHD is ok; defuzzication approach: Centroid.

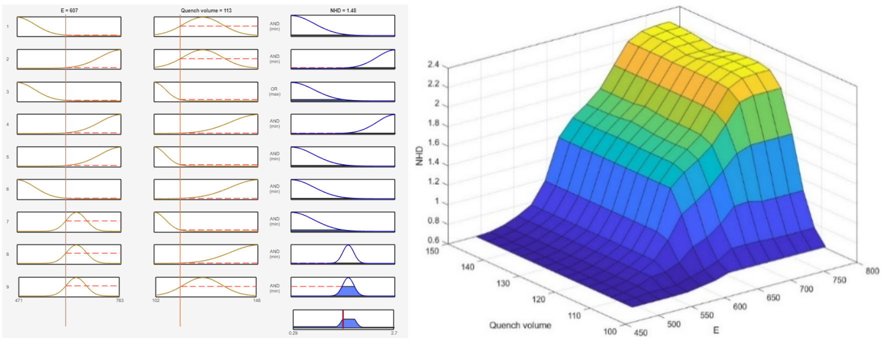


Figure 8

Rule inference and control surface of the FIS3 [edited by authors]

For example, if E=607. and QV= 113 l/min, NHD will be 1,48 mm. As an energy gradient, it is clear that, in some cases, faster cooling (at least 115 litres/minute) can result in an increase of one-two tenths of a millimetre in the hardness depth data (520 HV). The evidence and validation of this hardened fabric structure has been previously reported by Hugyi [10]. Furthermore, it is also well illustrated in Figure 8 in general that higher energy levels result in greater hardness depth (at the nose section).

Conclusions

Earlier studies [11] [24] have been complemented and, with the inclusion of newer mathematical approaches, its knowledge have been developed. Until now, only the level of energy tolerance has been the parameter requirement to achieve the desired hardness depth - leaving the input data of the energy unexamined and unprescribed.

In the knowledge of the above, result of nose part of the cam can be controlled on the basis of the two main inputs (I; U) as shown in Figure 9.

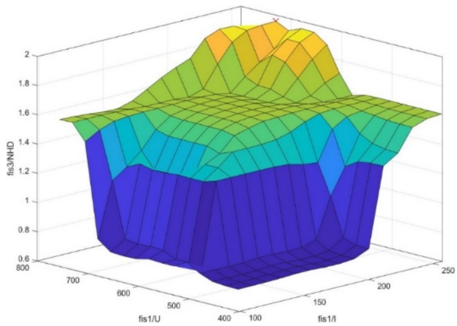


Figure 9
Control surface of connections of FIS tree model (U-I-NHD) [edited by authors]

To achieve the minimum depth of hardening mentioned by Hugyi [24], in the case of the present nose part of the cams with the fabric structure, geometry and size, the following parameters are required to achieve the desired depth of 520 HV1 by induction hardening with the above-mentioned machine in mass production: I - 120 A; U - 500 V. Of course, the other factors considered cannot be ignored in order to achieve the desired result.

Confirmation of the hypotheses:

H1: Verified, since the effect of voltage (U) is greater since it increases the depth of hardness in the desired range compared to the current (I). It can be seen in Figure 10 that voltage plays a dominant role in achieving hardness depths deeper than 1.6 mm.

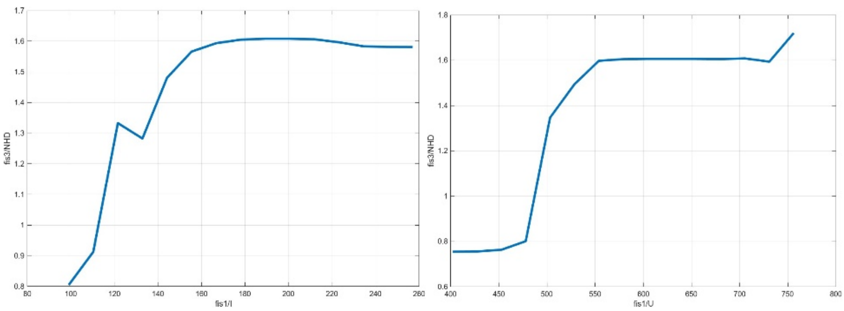
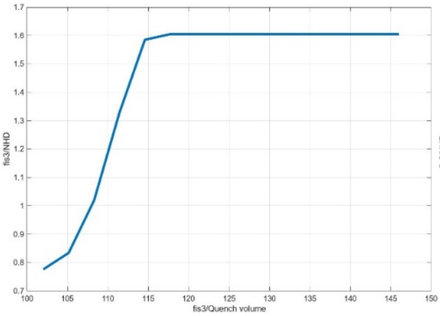


Figure 10
Comparison of the effects of I and U [edited by authors]

H2: Verified, since the importance of more intense cooling (with higher litre/min flow) is crucial because without reaching the minimum level, the desired hardness depth cannot be achieved without the intensity of the cooling back. This minimum level is 110-115 litres/min.



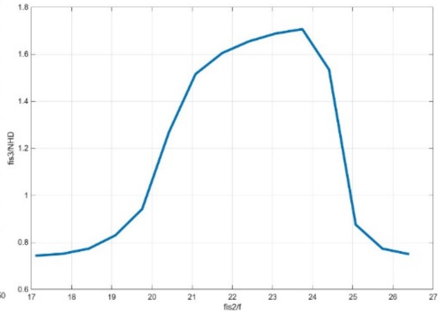


Figure 11 and Figure 12
Effects of the Quench volume (litre/min) and Effects of the frequency (kHz) [edited by authors]

H3: Verified, since by decreasing frequency (up to about 23.7 kHz, if there is talking about a range above this value), the depth of hardness depth (mm) can be increased to a limited extent (within a given range), but this may depend on the composition (possibly geometry and size) of the material structure to be hardened. Below this value, with frequency decrease(s), a decrease in hardness depth is predicted.

The hypotheses are confirmed through Figures 10-12. In addition to the verification of the hypotheses, an evidence was obtained by objectifying the parameters required to achieve the desired level of sub-parameters (inputs) with exact numbers, i.e. for the minimum acceptable hardness depth (1.3 mm) of nose of the lobe (I: 130-200 A; U: 500-650, which are interdependent). If, during this process, the desired minimum but necessary and sufficient value is reached on the nose part of the nose, so that the null-section of the piece is approx. 0,2 mm more (deeper hardness depth) is obtained. Although Hugyi [24] mentions a higher tolerance for the parameter E in his study, the reason is that it includes the whole part without distinguishing between the two parts of the lobe, and the aim is to use the minimum and sufficient resources to achieve cost-effective and profitable mass production, in order to reduce and optimise the use of resources.

In the case of missing data from data streams, there are online semi-supervised ensemble systems that aim to improve the handling of missing data in a real-time environment by applying learning techniques and fuzzy logic. [25] This approach can be also developed that it is also conceivable to conceptualize a scenario in which a robot is incorporated into a cognitive system to evaluate theoretical approaches. [26]

Knowing the input data that can be measured and parameterized so far (for example, in the context of capacitor coefficient or other variables, these are regarded as constants), a set of rules can be developed that, recognizing a change in a given parameter, can correct the input data even automatically in the case of a development related to this study, in order to achieve the desired goal. Also, a self-improving production system can be developed if additional determinant events can be incorporated into this control system. It is also our intention to conduct additional research in this area in the future. In addition, the objective is to identify opportunities for enhancing energy efficiency while maintaining the established quality standards.

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