Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Robot Digital Twin towards Industry 4.0

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Abstract: The paper presents the development of a digital twin for a high frequency hardening robot and connected hardware and software modules. The paper describes the virtual environment model, the robot emulation and optimization model, and the reference generation model, as well as their respective visual interfaces, used for controlling both the physical and digital robots. The application is integrated into the multi-purpose Virtual Intelligent Portable Robot Platform (VIPRO).

Keywords: intelligent system techniques and applications, digital enterprise, decentralized and distributed control.

1. INTRODUCTION

The high-frequency hardening process uses the heat generated by the metal when passing high-frequency currents (HFC) over the desired section. Induction heating changes the microstructure of the material. The hardening process involves heating the material until the structure reaches a state of equilibrium where is very solid and not breakable [Stich et al.]. The processes can be optimized in order to lower the costs and increase productivity and quality, as well as introducing remote operation and advanced diagnostics through the use of a digital twin, in a virtual robot environment. In order to improve this technology, the process control must be able to self-adjust the parameters in real-time, reducing the human supervision to a minimum. Such an approach will lead to a development that will be able to run the process online.
For the process to be independent and self-adjusting there are several control methods such as statistical methods (although they provide insufficient information), or intelligent methods (Neural Networks, Fuzzy, Neutrosophic Logic), the latter with the advantage of adjusting errors in real time. Given the strong nonlinear nature of such processes, artificial neural networks (ANN) have been tested for hardening process control because they manage to create an interdependence between system variables and provide a highly accurate output.
The hardening process requires several parameters: motor speed, induction coil height, distance between profile and coil (interstice), profile cooling, or profile temperature. Because some of the above parameters can only be adjusted offline, the artificial neural network algorithm takes into consideration the motor speed and profile temperature, as control variables and profile hardness as the dependent variable. The optimization of high-frequency hardening has been applied, in our case, to a metal profile made of C45 steel.

The Reference Generation Model is used for specifying the appropriate references to the high-frequency hardening process, in relation to the desired output hardening. For its training, experimental data was required from the real HFC Robot, in an attempt to learn the relation between the controlled and process variables of the control module. The module comprises a number of alternative algorithms, of which the ANFIS-based decision module is described in the paper. The overall control diagram of the application is shown in Figure 1.

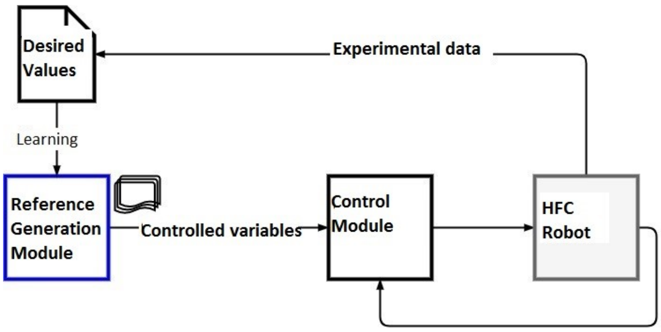


Fig. 1. Digital twin application diagram

The remainder of the paper is divided as follows: Chapter 2 explains the development of the HFC Robot digital twin in the virtual environment, Chapter 3 shows the integrated POI interface, used for estimation correction, Chapter 4 deals with reverse-engineering suitable references for the virtual and real robots, Chapter 5 discusses integration into the general purpose VIPRO platform and Chapter 6 outlines the main conclusions and directions for future research.

2. HFC ROBOT IN VIRTUAL ENVIRONMENT

The HFC Robot digital twin was created using Unity 3D v4. Using this platform, we were able to use the 3D model of the 7DOF HFC Robot to create a digital twin and use several control methods to simulate and test the way the robot works under different control configurations.

To use the HFC Robot digital twin there is a GUI (figure 2) to allow the user to input the desired hardening values and choose the control interface that will compute the speed value of the profile through the inducer to obtain the desired hardening value. This can be later used to generate a hardening pattern.

The virtual HFC robot has a top gripper to take a metal profile and pass it through the hardening inducer. The top gripper has 2DOF, one to hold the profile and the other to translate it through the inducer. The inducer has also 2DOF, one for rotation around the profile and the second adds an oscillating motion. These two motions were designed to prevent uneven heating. After the profile is passing through the inducer, the bottom gripper with 2 DOF will take it by synchronizing its speed with the top gripper. At the end of the hardening process, the bottom gripper will drop the profile into a sliding extractor with 1 DOF.

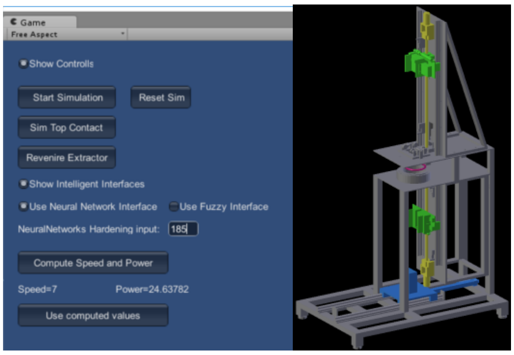


Fig. 2. Digital twin GUI and robot 3D model

All DOF of the digital twin are being controlled by separate PID controllers which are being synchronized using state machines, one for each main sections of the HFC Robot (Fig.3).

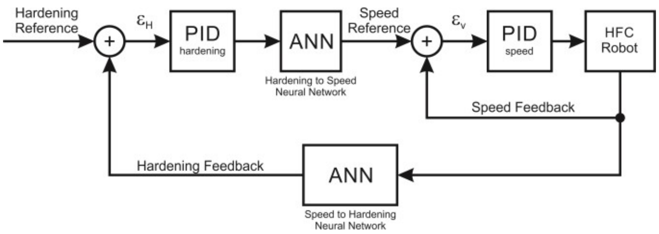


Fig. 3. Two stage hardening-speed control diagram

The PID controllers have a two stage control loops.

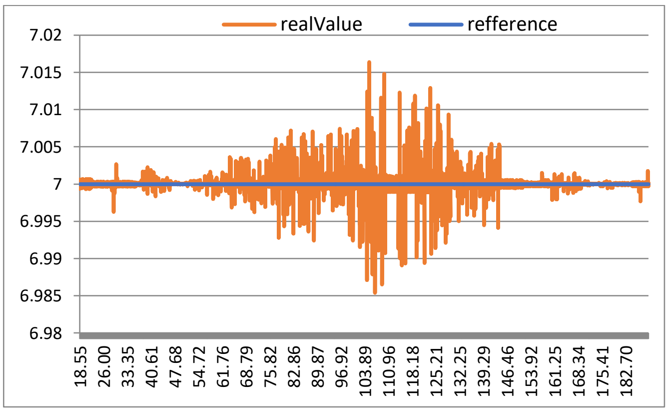


Fig. 4. Speed controlled value [mm/s] in a hardening cycle

The outer control PID loop will receive a PID controlled hardening (Brinel) value that is being used by the Process Optimization Interface to get the speed (mm/s) with witch the metal profile has to pass through the inducer in order to obtain the required hardening.

The inner PID controller will control the profile speed through the inducer. Figure 4 presents the speed of a profile during a hardening cycle, where the optimal speed value was computed at 7mm/s for a hardening of 185 (Brinel value) and an inducer power of 24,63 kW.

The speed of the profile is quite low which means that the controller is capable of reaching errors below 0,015 mm/s. The higher error values are being detected when the profile transfer between the top and bottom grippers is being conducted.

The simulation results prove that the digital twin of the HFC Robot is functional and can use different neural networks in order to achieve a hardening control loop with NN parameters. By changing the parameters of the neural networks, we can test the system in the virtual environment for behaviour differences before using the values to the real robot. This leads the Digital Twin HFC Robot towards the Industry 4.0 standard which will be a requirement for any future automated factory.

3. PROCESS OPTIMIZATION INTERFACE

The artificial neural network used for optimization is a back propagation, supervised learning network which updates weight and bias values according to Levenberg-Marquardt optimization.

The Levenberg-Marquardt method (eq.1) is a combination of two minimization methods: the gradient descent method and the Gauss-Newton method. In the gradient descent method, the sum of the squared errors is reduced by updating the parameters in the steepest-descent direction. In the Gauss-Newton method, the sum of the squared errors is reduced by assuming the least squares function is locally quadratic and finding the minimum of the quadratic [Hagan et al.].

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (1)$$

When μ is small or zero, the algorithm is Gauss-Newton method, while for a large μ this becomes gradient descent with a small step size of 1/ μ.

We first considered the independent variables, the induction coil power [kW/ cm2] and the speed of the profile [mm/s], as inputs to the ANN and the dependent variable, the hardness, as output.

The network chosen for the prediction neural network has 2 input layers, 10 hidden layers and one output. Training took place using 40 data sets and testing with 10 data sets. The speed varies between 5-7 mm/s, the power between 15-25 kW/ cm2, while the hardness is 160-200.

Figure 5 shows the regression model when training the neural network. In the first plot, the interpolation function for the training set is presented, with a regression coefficient of 0.97641, in this case. The other plots present the interpolation functions and the regression coefficients for the test and validation data sets, but also for all the data in the data set. The same as training data set, the values of the regression coefficients are close to 1, which means that the network errors are small.

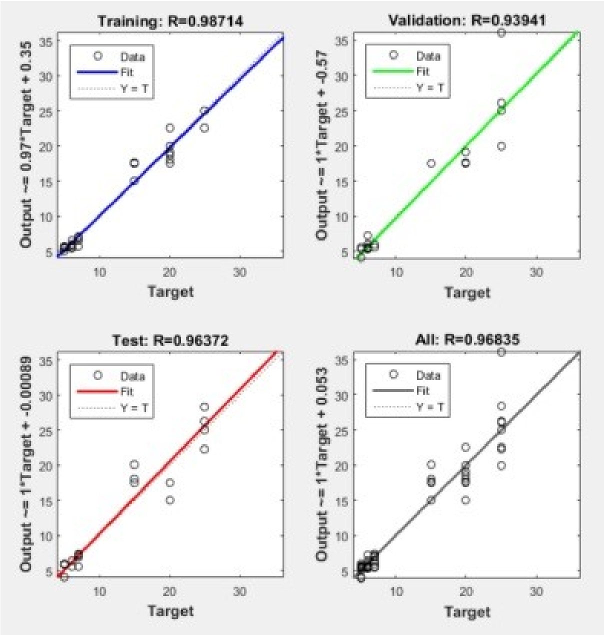


Fig. 5. Regression coefficients

The neural optimization model was developed based on the data sets and samples used previously for determining the hardness regression model. Although the calculated errors were, mainly, around 1%-2%, which is acceptable for hardening process, there were some particular errors around 20-25% (figure 6). To eliminate these errors, another neural network will be trained in the future with more datasets.

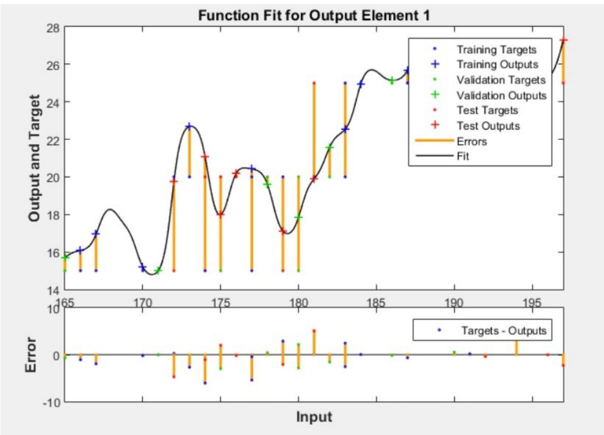


Fig. 6. Output and target values

The training of the network has been tested and adjusted for different number of neurons, hidden layers, dataset division, performance method, etc. until the error has been reduced. This optimization will depend on two parameters: the inductor power and speed of the profile through the inductor.

The training of ANN for hardening optimization is made using Matlab Neural Network Toolbox, the resulted model being converted to C# in order to run on the Process Optimization Interface (POI).

4. REFERENCE GENERATION INTERFACE

The Reference Generation Module uses an experimental ANFIS system trained on the available data. This completely automated decision system eliminates the need for human experts to be present on site. Learning is done through the ANFIS method, whereby a fuzzy inference system (FIS) is optimised using adaptive neural networks based on the experimental data collected. The obtained FIS is then used to specify the appropriate references to the lower level control system, in both the physical, as well as digital, robot. The main advantage is the possibility of generating an optimised FIS for contexts where expert analysis is either lacking or divergent. The algorithm can be re-run at any time recalibration is necessary, based on new experimental data, without the need for further oversight. The resulting module and visual interface is introduced into the VIPRO control platform.

The fuzzy inference process is used to specify the desired references for controlled variables in the high-frequency hardening process, designed as output variables for the algorithm, and dependent on the input variable. The output variables are the speed of the moving piece and the coil power. This is an inverted dependency relation to the Process Optimisation Interface (POI). This relation was previously modelled using human expertise, as a preliminary step to automating the process.

An Adaptive Neuro-Fuzzy Inference System (ANFIS) is a very useful modelling technique for systems where the mathematical equations of the governing dynamics are either very involved or outright unknown. A fuzzy inference system (FIS) is designed with the appropriate number of inputs and outputs for the given problem. An adaptive neural network is then used to optimise the parameters of this FIS in order to minimise the error with regard to the initial inputs. The position, type and shape of the fuzzy membership functions (MFs), as well as the inference rules, are the most important parameters to be optimised. Meta-parameters to be set by the operator include the number of membership functions per variable and the number of training epochs. Since ANFIS algorithms can be high dimensional problems, particular care must be taken not to overfit the available dataset, which would lead to the necessity of continuous testing, experimentation and dataset augmentation (Jang, 1991).

ANFIS is trained using a set of experimental data obtained in the practical testing of the HFC equipment. Figure 7 presents an example of inference space obtained for the speed variable, when trained using the entire dataset. One of the advantages of ANFIS is that, for points situated between the available tuples on the multidimensional space, the result is approximated using a combination of the rules supported ('fired') by the closest inputs. Once trained, the resulting FIS system may be used in any simulation or application similarly to a lookup table, with virtually instantaneous processing time, to specify the reference values for the controlled variables.

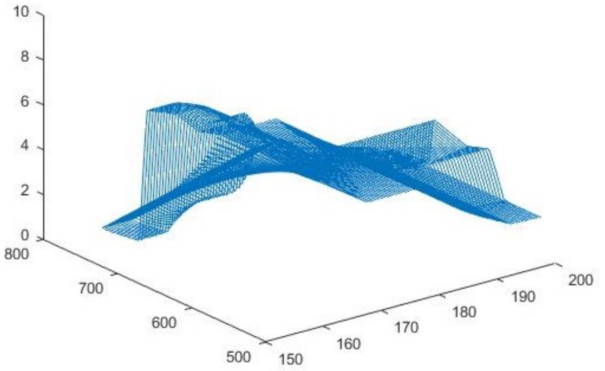


Fig. 7. ANFIS inference space

The trained fuzzy inference system is not a Mamdani type, as is common in hardcoding human expertise. Mamdani systems use regular fuzzy membership functions for the output variable, similar to those used for the inputs. This distribution is inefficient in the case of learning systems, as it is too computationally intensive (Karaboga, 2018). Instead, Sugeno fuzzy systems are used, where the membership function of the output variable is either constant (Sugeno type 0) or linear (Sugeno type 1).

In order to adapt to the learning algorithm, the decision system is not a single FIS with one input and multiple (three) outputs, as in the intermediary human expertise step, but three separate FISs, each of a single input and single output, constituted into a general system, which calls the required sub-system, depending on the required variable. This is because the learning algorithm can only learn a FIS for one output at a time.

Optimisation consists of successively improving the inference system which models the interaction between the independent (input) variable and the dependent (output) variables, in the context of the available dataset. This entails the existence of an initial inference system, which is obtained through automatic generation on the dataset. The algorithm implicitly calls a generation function, although this can be modified by the operator. The two main options are genfis1 and genfis2. Both use the training dataset to generate an initial fuzzy inference system, to be optimised through ANFIS, but they differ in two essential aspects. Firstly, genfis1 produces a partition grid of the input space, which is much more vulnerable to dimensionality issues, while genfis2 uses subtractive clustering to produce a diffuse partition. Secondly, genfis1 produces a FIS where each rule has zero coefficients in the output rule, while genfis2 uses the backslash operator to identify coefficients. Therefore, a fuzzy inference system generated with genfis1 will always require additional optimisation through ANFIS, while one generated with genfis2 may provide acceptable behaviour without optimisation, especially for lower dimensional cases (Jang, 1993). The current Reference Generation Model runs both options, as well as a number of meta-parameter tuning algorithms, and selects the best performing final model.

The learned fuzzy rules, membership function shapes and inference space are the basis for the final fuzzy decision system. A visual representation of a working learned FIS (this one using two inputs), is shown in Figure 8.

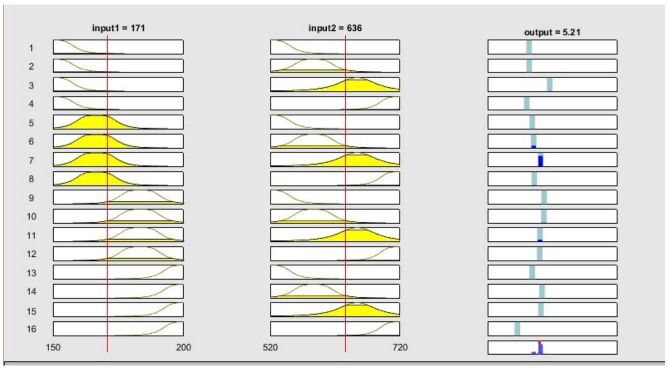


Fig. 8. Leaned Fuzzy Inference System for Speed

As can be seen in the figure, the various fuzzified inputs activate (‘fire’) a number of rules, with varying degrees of support for each rule, which depend on the membership resulting from the initial fuzzification. The fuzzy output is obtained, for each output, by the aggregation of the results of all activated rules. This is then defuzzified to obtain a crisp value, which is the actual reference to the control system for that particular variable. Aggregation is combining all resulting sets, shown in blue, into a single set. Defuzzification is choosing an output from the aggregated set, as shown in the figure with a red dash.

As seen in figure 8, the user reference is present only to provide the hardening value. This value is a static one, but can be used as a pattern to obtain a metallic profile with different values of hardening along its length.

The desired hardening value is then used to compute the speed reference using a Neural Network already trained for the job. Its values can be changed between hardening cycles if other parameters are found to be better. The NN computed reference speed value is then being used in a PID feedback regulator loop, to control the Digital Twin HFC Robot. The measured speed value of the metallic profile is then used in a different trained Neural Network that will compute the hardening value of the metallic profile from the speed with which the profile is moving through the inducer. The output of this second network is the feedback hardening value used by the outer PID controller loop.

The digital twin of the HFC Robot benefits from the speed generation of a neural network output specially trained to compute it from a hardness input value. Thereby the digital twin system provides a hardness PID reference and a speed PID reference in order for the metallic profile to achieve the user desired hardening value.

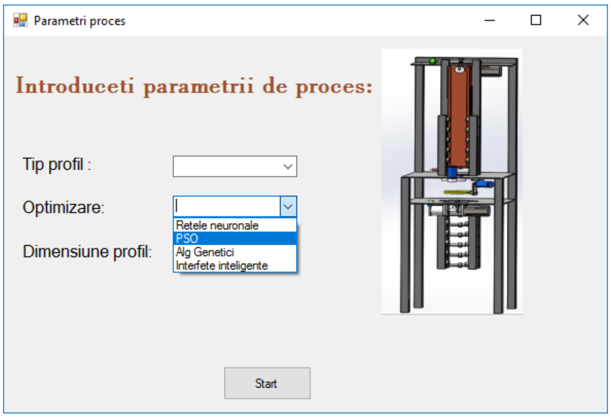
5. INTEGRATION INTO THE VIPRO PLATFORM

The Process Optimization Interface, developed in Visual Studio, is part of the VIPRO Platform, which is a modular and interdependent module, and connects the control methods module with the real or virtual hardening machine. There is a close loop control, the data received in the POI are processed and sent back to machine in real time.

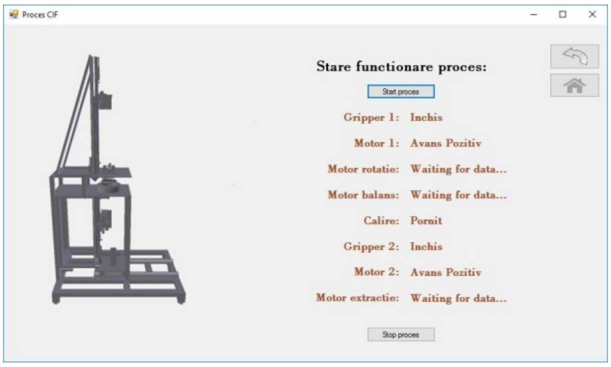
Thus the control methods module integrates process optimizations and communicates with the POI, the virtual / real machine and with the PLC system. The control methods module communicates with the virtual / real hardening machine by sending data process parameters in the process. For hardening process optimization, the target hardness is set in the POI and the desired induction power and speed are determined using the neural network model. These values are sent to the real or virtual machine and the feedback is used to close the control loop.

In figure 9 the screenshots of two POI windows are presented. The top screenshot (Fig.9a) shows the main window of the application, where the user selects the optimization and profile type, while the second image (Fig.9b) presents the window with the status of some devices used in the process. Although the hardening process depends on several parameters, we were able to improve profile hardness with 2.5% using artificial neural networks against polynomial regression.

The Reference Generation Interface contains the necessary elements for specifying the universe of discourse for each variable, both inputs and outputs, in the upper left quarter. The universe of discourse influences the decision system, due to the membership functions being appraised proportionally. The interface also contains the option of using a standard (light) dataset for testing and debugging purposes.



a.) Main window of the application



b.) Devices status used in the process

Fig. 9. VIPRO Interface screenshots

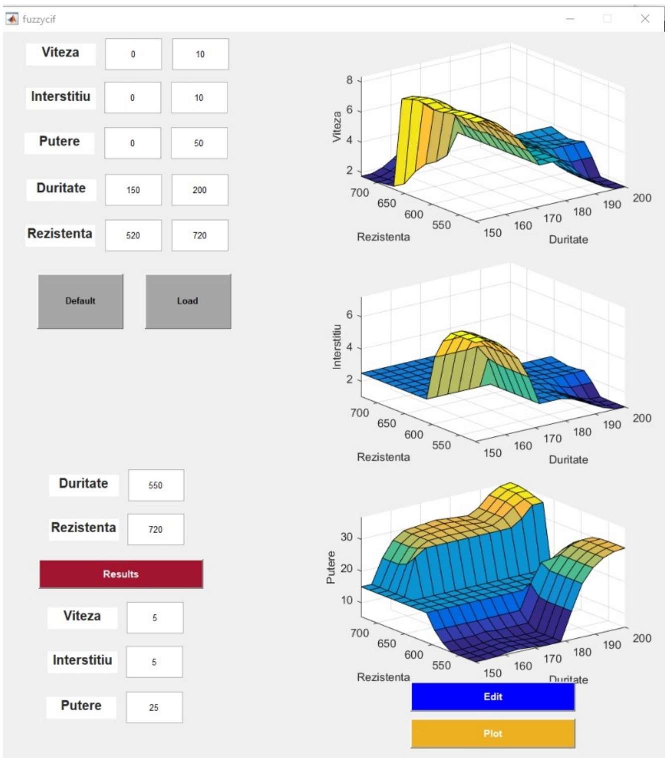


Fig. 10. The learned fuzzy inference system

The inference space can be visually represented for each of the output variables in the right half of the interface. The three-dimensional graphics can be manipulated to modify their point of view (Fig. 10). There is also the option to manually edit the learned fuzzy inference system, although recalibration and re-learning is preferred, assuming the availability of new experimental data. The interface is designed to automatically send the results of the inference to both the physical and digital twin models, but it also displays them within the GUI, for training and debugging purposes.

6. CONCLUSIONS

The paper presents the design, development and implementation of a digital twin for a high-frequency hardening robot. The digital model is integrated into a multi-purpose virtual intelligent platform, with an open software architecture, training and teaching capabilities. There are a number of add-on interfaces within the platform which relate to the digital twin, out of which, the two most important were described in the paper. The physical robot is remotely operable and synchronised with its virtual environment counterpart. The detailed results of the various platform control interfaces are saved for later analysis. These include each joint reference and position, hardening reference and real value, and the calculated speed reference and the real value.

The proposed setup also provides important operator training and debugging capabilities in order to make it easier for a new operator to use the system.

Opportunities for future research and improvement are mainly split into two broad directions: more and better experimental data, and enhanced modelling. An enlarged dataset allows for better training the neural network models and reducing the likelihood of overfitting, as well as the ability to consider more physical model parameters as controllable variables. While the current predictive performance is satisfactory, future research may well look at using different heuristic techniques, both as it relates to the optimisation (i.e. evolutionary algorithms, advanced line search, etc.), as well as the decision system itself (i.e. neutrosophic systems, Extenics, etc.).

The digital twin of the HFC Robot was built to test and help improve all intelligent interfaces, which were selected to control the hardening process of a metallic profile, through induction. The digital twin has the capability to control the virtual hardening process through two stages of a PID controller and two black boxes that implement the neural network or fuzzy intelligent interfaces. These black boxes used by the digital twin of the HFC Robot can be configured by replacing the fuzzy or neural network parameters after they were adjusted to achieve better metallic profile hardening control results.

Acknowledgment. This work was supported by a grant of the Romanian Ministry of Research and Innovation, CCCDI-UEFISCDI, MULTIMOND2 project number PN-III-P1-1.2-PCCDI2017-0637/33PCCDI/01.03.2018, within PNCDI III, and by the European Commission Marie Skłodowska-Curie SMOOTH project, Smart Robots for Fire-Fighting, H2020-MSCA-RISE-2016-734875.

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