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Artificial Neural Networks for Detecting Instability Trends in Different Workpiece Thicknesses in a Machining Process

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***Abstract*— This paper presents the use of Artificial Neural Networks to diagnose degraded behaviours in Wire Electrical Discharge Machining (WEDM). The detection in advance of the degradation of the cutting process is crucial since this can lead to the breakage of the cutting tool (the wire), reducing the process productivity and the required accuracy. Concerning this, previous investigations have identified different types of degraded behaviors in two commonly used workpiece thicknesses (50 and 100 mm). This goal was achieved by monitoring different functions of the characteristic variables of the discharges. However, the thresholds achieved by these functions depended on the workpiece thickness. Consequently, the main objective of this work is to detect the process degradation in different workpiece thicknesses using one unique empirical model. Since Neural network techniques are appropriate for stochastic and nonlinear nature processes, its use is investigated here to cope with different workpiece thicknesses. The results of this work show a satisfactory performance of the presented approach.**

I. Introduction

Wire Electro-discharge Machining (WEDM) is one of the most extended non-conventional machining processes. WEDM is widely used to machine dies aimed at producing components for many industries. Among them, automobile and aeronautic industries stand out. WEDM is based on material removing through a series of electrical discharges applied between the electrodes (the tool -wire- and the workpiece). The only requirement for discharging is that both the tool and the workpiece are electrically conductive. During the cutting process, dielectric fluid is injected into the gap, which is the space between the electrodes. In order to provoke a discharge, the machine power supply applies a voltage between the electrodes. Then, the discharge is produced after the dielectric ionization achieving a peak value I_p and with duration of t_e. The period of time during the ionization happens is known as ignition delay time (t_d). Between two consecutive discharges, the dielectric cools the gap and removes the erosion debris during an adjustable period of time known as off-time (t_{off}). The discharge rate is about few microseconds. Fig. 1 shows the shape of the theoretical discharges of the WEDM process.

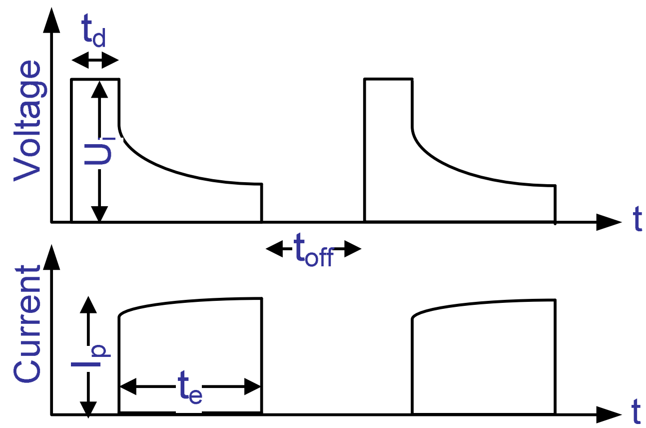

Fig. 1 Theoretical discharges of the WEDM process.

The main advantage of WEDM is its capability for the production of complex geometries with a high degree of accuracy, independently of the mechanical properties of the material, such as hardness, brittleness and resistance.

One of the main research fields in WEDM is related to the improvement of the process productivity by avoiding wire breakage that derives from degraded cutting regimes [1]. However, the difficulty in the study and optimization of WEDM is due to the stochastic and non-linear nature of the process as well as the multiple machining parameters that condition the process performance. Given the nature of the process, the application of intelligent control techniques becomes appropriated to deal with the early diagnostic of degraded cutting regimes in WEDM. Among these techniques both, heuristic and neural network techniques, stand out in WEDM and in other non-conventional machining processes (such as Sinking Electrical Discharge Machining SEDM and Electro Chemical Machining ECM). The former has been traditionally applied to wire breakage diagnosing [2]-[5]. However, developing ad-hoc rules is an arduous work when generic rules that cover a wide variety of degradation behaviors are established. Moreover, these works are focused on one unique workpiece thickness, often around 50 mm.

Neural network techniques have been also applied to WEDM and other non-conventional machining processes with different aims. In particular, three main application areas have been identified: establishment of optimum

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machining parameters [6]-[8]; fault diagnosis for machine maintenance and control of non-conventional machining processes [9]-[12] and pulse classification [13]-[14]. It is remarkable that in all these works static neural network architectures (especially Multilayer Perceptron MLP) have been employed. However, neural network techniques have not been previously employed for wire breakage forecasting.

The layout of the paper is as follows. Section II presents the main results of previous works of authors in which a heuristic approach was adopted. In Section III, the strategy for the detection of instability trends in different workpiece thicknesses is presented. In Section IV some industrial examples are shown. Finally, in Section V the conclusions are drawn.

II. Previous work: heuristic approach for the detection of degraded cutting regimes

The main objective of a previous work was related to the classification of different types of degraded behaviors in 50 and 100 mm steel workpiece thicknesses in the WEDM process [5]. To achieve this, firstly, a battery of experiments that reproduce common process disturbances were defined and performed in [5]. Secondly, different functions designated as *virtual measurements VM* were obtained by processing the current and voltage signals of the discharges. Each virtual measurement refers to a succession of percentages of discharges whose basic variables (for example, the energy) exceed (or are lower than) some pre-defined reference values. In particular, a preliminary analysis revealed that the functions that better discriminate the degraded behaviours were related to energy (VM-E), peak current (VM-I) and ignition delay time (VM-TDH). More detailed information about the nature of the virtual measurements can be found in [15].

By the analysis of the behavior of the virtual measurements three types of degraded behavior that alert to wire breakage were identified: a sudden increase in the energy (Degraded Behavior of Energy, DB-E); an oscillating behavior in the energy (Degraded Behavior of Energy Oscillation, DB-EO); and a sudden increase in the peak current combined with high values of ignition delay time (Degraded Behavior of Current plus Time Delay High, DB-C+TDH). These behaviors indicate that the tool (the wire) will probably brake imminently. The results were successful showing an average system efficiency higher than 80%. However, the thresholds achieved by the virtual measurements depended on the workpiece thickness. Thus, following the heuristic approach would involve the analysis and the definition of a set of rules per workpiece thickness in the worst case.

III. Strategy for the detection of instability trends in different workpiece thicknesses

Taking into account the results of the previous work, the next challenge is to analyze the viability of using Artificial Neural Networks to detect the degraded behaviours in a range of workpiece thicknesses commonly used at the WEDM industry (between 50 and 100 mm). Specifically, the proposed strategy consists of obtaining a neural network structure by performing a training process that takes advantage of the knowledge gathered about the degradation of the WEDM process from the previous works of the authors [5], [15]. Since these latter are considered during the training process, supervised learning is applied, and the inputs of the neural structure are inferred.

The proposed configuration of the neural structure consists of three Elman neural networks in parallel (see Fig. 2): Elman Network for Energy (EN-E), Elman Network for Current (EN-I) and Elman Network for high values of ignition delay time TDH (EN-TDH). The reason why the Elman architecture has been chosen is its memorization capability and its dynamic character [16]. As the latter is concerned, it allows to introduce into the network one after one the values of the sequential patterns of the inputs. In other words, unlike the static neural architectures, in the case of the Elman network the values of the required historical data of one specific input are not introduced concurrently. This reduces drastically the neural network size.

Referring to the inputs, each network input is one of the virtual measurements, and the corresponding workpiece thickness.

As the outputs are concerned, on one hand, three levels of alarm are triggered in a postprocessing phase depending on the values achieved by the outputs: A1 (low), A2 (medium) and A3 (high). These alarms are used to alert to the increasing risk of wire breakage. It is remarkable that in the particular case of the network EN-E, it has as outputs both types of degraded cutting regime (DB-E and DB-EO).

On the other hand, in the post-processing phase the grade of influence in the degradation of the cutting process of each type of behaviour is also estimated.

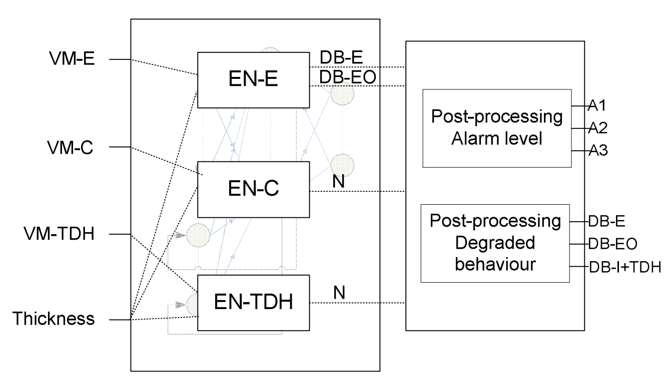

Fig. 2 Scheme of the recurrent neural network approach.

The advantages of the presented approach are the following:

1) Unique neural structure in order to avoid having a battery of heuristic rules per workpiece thickness. This objective involves as well having common post-

processing rules for a range of thicknesses. To achieve this, the proposed approach is to train the networks with examples of 50 and 100 mm to give outputs of the same high level independently of the workpiece thickness. Fig. 3 illustrates the proposed strategy. In Fig. 3, N_A represents the same high level alarm.

2) Learning capacity to interpolate the detection of degraded behaviours in intermediate workpiece thicknesses (between 50 and 100 mm). To achieve this, experiments of workpiece thickness between 50 and 100 mm are used. These cases constitute the *test examples*, which are not used during the training phase. In this manner, training the neural networks with examples of degradation in each workpiece thickness could be avoided.

A. Training process

In order to perform the training and simulation process Matlab™ 7.1 has been employed. As the generalization method is concerned, the early stopping alternative has been chosen. To make this decision has been considered that the algorithm for Bayesian Regularization available in Matlab™ 7.1 is not recommended for Elman networks since it updates the weight and bias values according to Levenberg-Marquardt optimization [17].

To be more specific, the backpropagation with adaptive learning rate and momentum has been applied. The activation function of the hidden and outputs neurons is the logistic sigmoidal function. Taking into account the dependence of the error on the initial values of the weights, each neural network configuration has been trained ten times. A preliminary analysis revealed that asymmetric ranges of the inputs/outputs yielded lower validation errors. Thus, three ranges have been considered due to the asymptotic character of the sigmoid activation function: [0.05-0.95], [0.1-0.9] and [0.15-0.85]. In the training phase, a total of 456 sequences of 250 points each are distributed in the three networks (70% for training and 30% for validation). In order to define the dimension of the evaluated configurations, the specifications of different works have been considered. Related to this, in [18] is maintained that twice as many training cases as weights may be more than enough to avoid overfitting for a noise free quantitative target variable. Other works such as [19] and [20] conclude that is essential to use lots of hidden units to avoid bad local optima when using early stopping. Considering both indications, hidden layers from 5 to 60 neurons have been evaluated, which are taken around ten by ten.

B. Analysis of the results

In order to analyze the results, two main types of analysis are performed sequentially:

1) Quantitative analysis: in this phase the configurations that provide the lowest validation error per range are pre-selected. The validation error, which refers to the error corresponding to the validation examples, is quantified by the Mean Square Error MSE.
2) Qualitative analysis: in order to compare the behavior of the pre-selected configurations, their operation is simulated during this phase. In order to select the most appropriated, the *validation ratio* and the *test ratio* have been defined. The validation ratio is applied to the validation cases, which basically are used during the training phase to decide when this phase concludes. The test ratio is computed over the test cases, which are not used during the training phase.

   The validation ratio represents a hit ratio. Depending on the quality of the output of a validation case in tracking the output target, it is computed as correct or not.

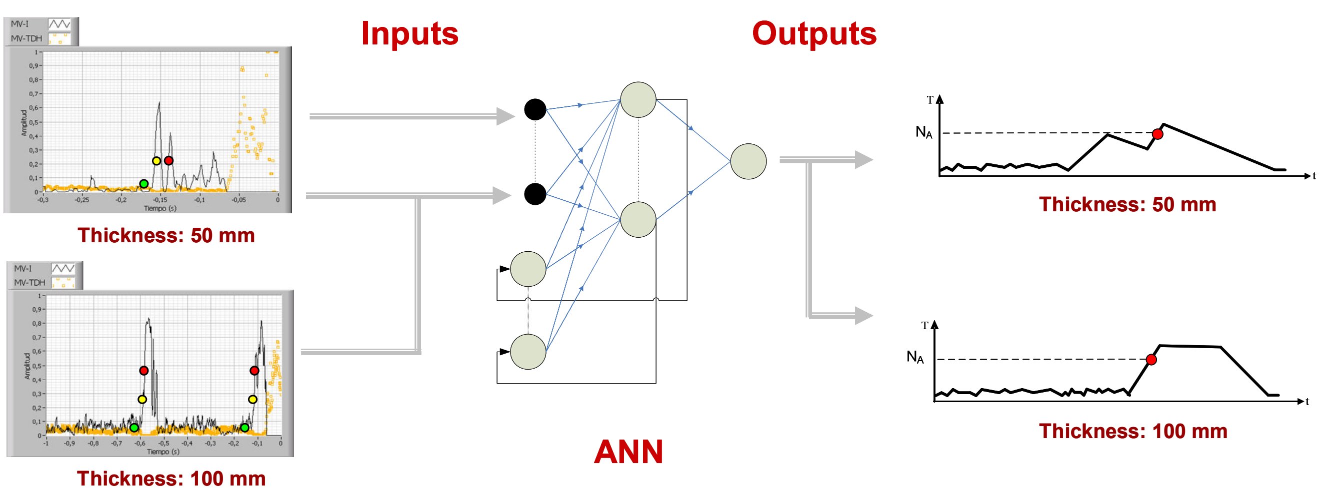

Fig. 3 Strategy for obtaining the unique neural structure

The concept of quality involves aspects such as the output achieves a minimum threshold that allows to discriminate a high level alarm, and the correct estimation of the type of degraded behavior.

The test cases correspond to degradation examples occurred in workpieces 80 mm height. The behavior of the case is considered correct when the pre-established threshold, which is common for the workpiece thicknesses between 50 and 100 mm, is achieved.

Provided the difference in the value of both ratios is insignificant for different neural configurations, the configuration that yields the smallest value is selected.

With the aim of illustrating the application of the quantitative and qualitative analysis, the process of selection of the Elman network for energy is presented. In Fig. 4 the lowest validation errors of the neural networks configurations per evaluated range is shown. The quantity of hidden neurons is specified by the numbers upon each bar of the graph. Also, in the graph can be appreciated that the validation errors are quite similar for the evaluated ranges. In order to select the most appropriated configuration, a qualitative analysis is performed. Through the qualitative analysis, the behaviors of the configurations during their operation are compared and the validation ratio is computed (see the results in Fig. 5). The results show that the configuration in the range [0.1-0.9] yields the highest validation ratio.

The better performance of the selected configuration can be appreciated in some examples shown in Fig. 6, Fig. 7 and Fig. 8. Each example shows the inputs, outputs and targets of the evaluated network. The inputs of this network are the energy and peak current virtual measurements (VM-E and VM-I) and the thickness.

The outputs correspond to the types of degraded behaviors associated to the energy virtual measurement: E-E corresponds to a sudden increase in the energy DB-E, and E-EO corresponds to an oscillating behavior in the energy DB-EO.

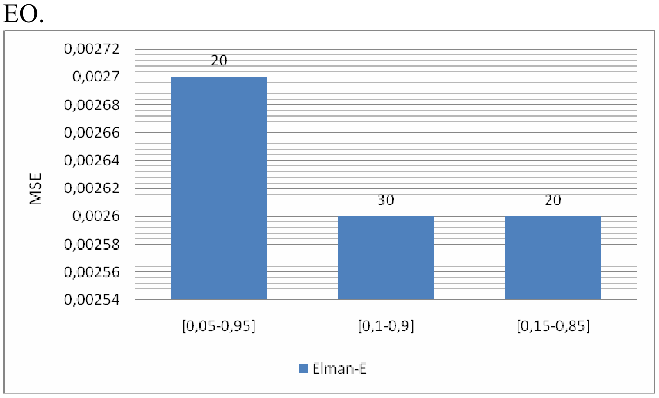

Fig. 4. Lowest validation errors in EN-E.

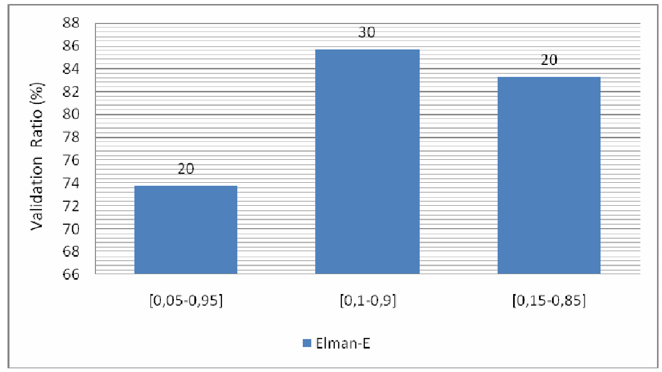

Fig. 5 Validation ratio in EN-E.

In order to define the targets, a set of algorithms explained in [21] have been defined.

In the examples, the responses of three configurations when processing a particular validation example are depicted. The difference between the three neural network configurations are the range of the inputs/outputs, and the number of the hidden neurons. As the validation example is concerned, it corresponds to the degraded behavior characterized by successive peaks of high energy DB-EO. Thus, it makes sense that the corresponding target and output E-EO show an increasing behavior, while both the target and output of E-E remain low. As it can be observed, the output responses have different characteristics that are remarked by the circle areas in the figures Fig. 6, Fig. 7 and Fig. 8. While the network whose behavior is depicted in Fig. 7 is correct (since successive peaks of high energy are accumulated), the Fig. 6 and Fig. 8 show that the behavior of the corresponding networks do not follow the desired behavior. Thus, the network that operates in the range [0.1-0.9] is chosen.

Table 1 presents the characteristics of the performance of the selected Elman neural networks.

TABLE 1 CHARACTERISTICS OF THE SELECTED NEURAL NETWORKS EN-E, EN-I AND EN-TDH

Network	Energy (EN-E)	Peak Current (EN-I)	High ignition delay time (EN-TDH)
Hidden neurons	30	10	10
Range	[0.1-0.9]	[0.05-0.95]	[0.1-0.9]
Validation error (MSE)	0.0026	0.0063	0.0065
Validation ratio	85.7%	85.7%	100%
Test ratio	75%	91%	100%

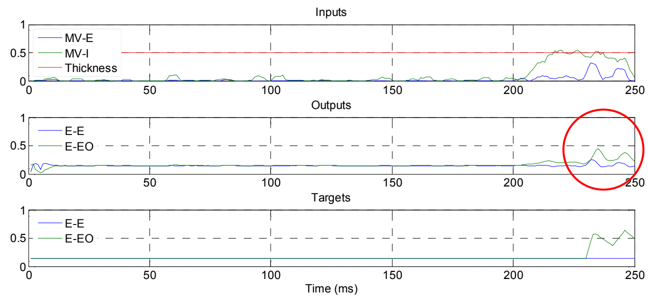

Fig. 6 Inputs, outputs and targets of EN-E generated during a DB-EO degraded cutting regime: range [0.15-0.85].

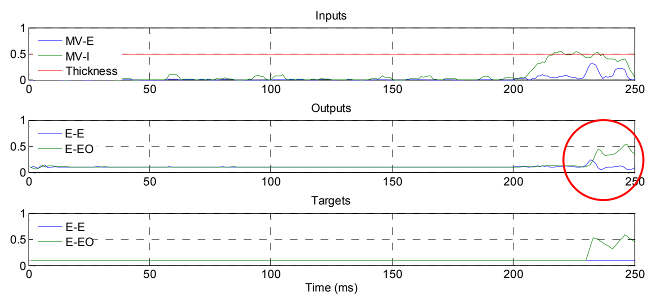

Fig. 7 Inputs, outputs and targets of EN-E generated during a DB-EO degraded cutting regime: range [0.1-0.9].

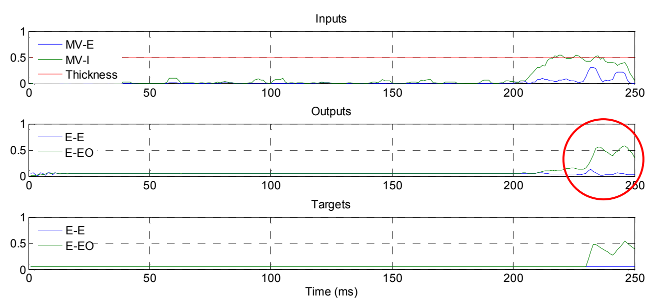

Fig. 8 Inputs, outputs and targets of EN-E generated during a DB-EO degraded cutting regime: range [0.05-0.95].

IV. Examples of Detection of Instability Trends in Different Workpiece Thicknesses

This section show some examples that correspond to the Elman network for energy aimed at illustrating the operation of the proposed neural structure. In particular, the examples are related to the degraded cutting regime characterized by a sudden increase in the energy virtual measurement DB-E.

During the post-processing phase, some simple IF-THEN rules are processed so as the decision of triggering the different levels of alarm can be performed, and the type of degraded behavior can be also estimated. The rules applied in the case of the degraded cutting regime DB-E are summarized in Table 2.

E-E represents the outputs of the network. HT_E, MT_E and LT_E represent the high, medium and low level of alarm, respectively. $P_{DB\text{-}E}$ divided by the sum of the contributions of all the types of degraded behaviors ($P_{DB\text{-}E} + P_{DB\text{-}EO} + P_{DB\text{-}I+TDH}$) are used to compute the most probable cause of process degradation.

TABLE 2 POST-PROCESSING RULES APPLIED TO THE OUTPUTS OF EN-E WHEN DB-E

Post-processing E-E output
IF E-E> HT_E,
THEN A3=TRUE;
IF NOT, IF E-E> MT_E,
THEN A2=TRUE;
IF NOT, IF E-E> LT_E,
THEN A1=TRUE;
$P_{DB\text{-}E}$= E-E;

Fig. 9, Fig. 10 and Fig. 11 represent the neural network behavior when the degraded cutting regime DB-E is the predominant one. The three circles in each figure illustrate the subsequent triggering of the low, medium and high level alarms, respectively. In these cases, when the high level alarm triggers, the output E-EO maintains at low level, while the corresponding output E-E reaches the high level alarm. In the post-processing phase, the high level alarm has been triggered approximately between 20 and 250 milliseconds before the wire breakage.

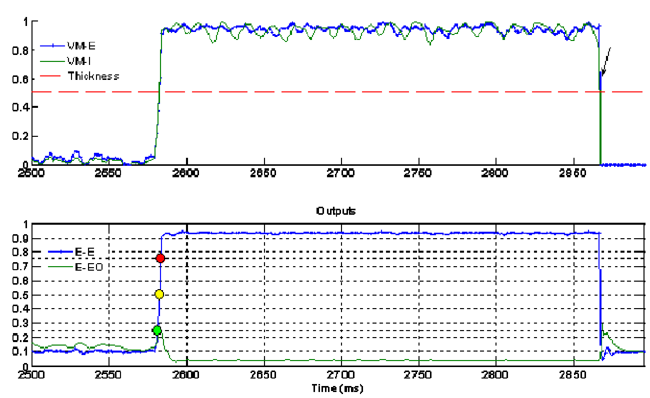

Fig. 9 Inputs and outputs of EN-E during DB-E in 50 mm

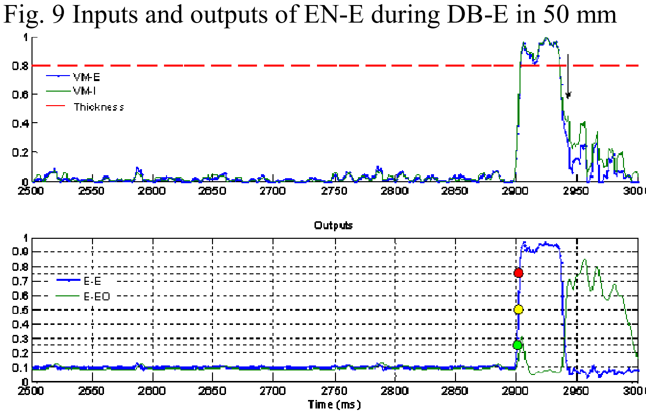

Fig. 10 Inputs and outputs of EN-E during DB-E in 80 mm

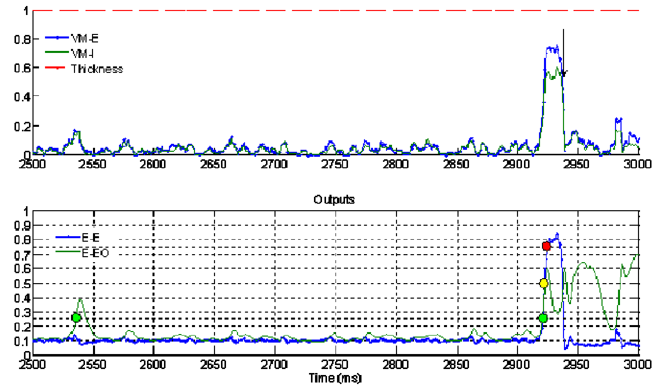

Fig. 11 Inputs and outputs of EN-E during DB-E in 100 mm

V. CONCLUSIONS

This paper demonstrates the viability of the application of Recurrent Artificial Neural Networks to detect the degradation of the Wire Electrical Discharge Machining process in a range of steel workpiece thicknesses. The goal is to define a neural structure capable of performing the early detection of degraded behaviours in a range of workpiece thicknesses (50-100 mm). The final purpose is to avoid the tool breakage (the wire) by applying the proper control actuation, depending on the most probable cause of degradation.

The presented approach is based on three Elman neural networks that process three virtual measurements which are the inputs of the networks. In particular, the success of the presented approach has been quantified through both the validation ratio and the test ratio. Both ratios have been computed for each parallel Elman network. In particular, the validation ratio ranges between 85 and 100%, and the test ratio between 75 and 100%.

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