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ANN for Interpolating Instability Trends in WEDM

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Abstract: In Wire Electrical Discharge Machining (WEDM) the breakage of the cutting tool (the wire) reduces the process performance and the required accuracy. Previous works of authors showed that the behavior of the basic signals of the process (current and voltage) can be employed to detect degraded situations that can lead to wire breakage. In particular, different types of degraded behaviors in two commonly used workpiece thicknesses (50 and 100 mm) were identified. In order to achieve this objective, a set of *virtual sensors* were defined and constructed from the basic signals of the process. Although the types of degraded behaviors were common for the studied workpiece thicknesses, the thresholds achieved by the *virtual measurements* depended on these. At the sight of this conclusion, the main goal of this work is to detect the process degradation in different workpiece thicknesses using one unique empirical model. Since Artificial Neural Networks are appropriated for processes of stochastic and nonlinear nature, its use is investigated here in order to interpolate the instability trends for different workpiece thicknesses. Firstly, a comparative study performed to select the most appropriated configuration of the neural network is summarized. Secondly, the strategy applied to detect degraded situations in different workpiece thicknesses is presented. The results of this work show a satisfactory performance of the presented approach.

1. INTRODUCTION

Wire Electro-discharge Machining (WEDM) is a very important non-conventional machining process. One of the most extended WEDM applications is to machine dies aimed at producing components for many industries (for example, automobile and aeronautic industries). WEDM is based on material removing through successive electrical discharges applied between the tool -wire- and the workpiece. The only requirement for discharging is that both electrodes 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. The period of time during the ionization happens is known as ignition delay time. Between two consecutive discharges, the dielectric cools the gap and removes the erosion debris during an adjustable period of time known as off-time. The discharge rate is about few microseconds. Fig. 1 shows a schema 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 (Ho, et al., 2004). 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 (Cabanes, et al., 2006), (Lauwers, et al., 1999), (Shoda, et al., 1995), (Yan, et al., 1995). 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.

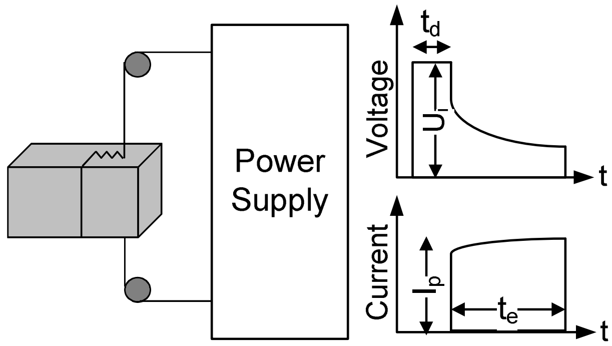

Fig. 1 Schema of WEDM process.

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 machining parameters (Fenggou, et al., 2004), (Tarng, et al., 1995), (Tsai, et al., 2001), (Wang, et al., 2004); fault diagnosis for machine maintenance and control of non-conventional machining processes (Behrens, et al., 2003), (Huang, et al., 2000), (Yan, et al., 2001), and pulse classification (Mediliyegedara, et al., 2004), (Kao, et al., 1997). 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 2 presents the main results of previous works of authors in which a heuristic approach was adopted. In Section 3, the strategy for the detection of instability trends in different workpiece thicknesses is presented. In Section 4 some industrial examples are shown. Finally, in Section 5 the conclusions are drawn.

2. HEURISTIC IDENTIFICATION OF DEGRADED BEHAVIORS

In a previous work of authors, different types of degraded behaviors were identified in two commonly used workpiece thicknesses (50 and 100 mm) (Cabanes, et al., 2008). To achieve this, different functions of the characteristic variables of the discharges were processed and monitored. In particular, the functions (the so-called *virtual measurements VM*) were related to energy (VM-E), peak current (VM-I) and ignition delay time (VM-TDH). Each virtual measurement represents a succession of percentages of discharges whose basic variables exceed (or are lower than) some pre-defined reference values. More detailed information about the nature of the virtual measurements can be found in (Portillo, et al., 2007a).

The results of the analysis of the behavior of the virtual measurements revealed three common types of degraded behavior that alert to wire breakage: 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). However, the reference values for each virtual measurement depend on the workpiece thickness. Thus, as many set of rules as workpiece thicknesses are needed.

3. ANALYSIS OF DIFFERENT NEURAL NETWORKS CONFIGURATIONS

At the sight of the previous work, the objective is to investigate the use of Artificial Neural Networks to detect the instability trends in workpiece thicknesses between 50 and 100 mm, which are very commonly used at the WEDM industry. The adopted approach is based on training neural networks with the knowledge of the WEDM process obtained in the previous works of the authors (Cabanes, et al., 2008), (Portillo, et al., 2007a). This involves applying supervised learning. Thus, following the analysis of the latter works, the inputs of the neural networks are known a priori.

To achieve this challenge, the first step has been to perform a comparative study to determine the most appropriated neural network configuration. In order to simplify this preliminary study, it has been performed on only one workpiece thickness (50 mm). In the study, the inputs of the neural networks are the outputs of the virtual measurements. The outputs consist of neurons aimed at triggering different levels of alarm that alert to the increasing risk of wire breakage. At the same time, the grade of influence of each identified trend in the process degradation is indicated. The comparative study has considered the following aspects:

1) Architecture of the neural network: both static and recurrent neural architectures are evaluated. In particular, the static architecture is the MultiLayer Perceptron (MLP), which has been applied frequently in different fields with high success. However, its use can increase significantly the size of the network. The recurrent architecture is the Elman Network (EN) (Elman, et al., 1990). Its recurrent connection provides the network with an exponential memory of past events. In this case, there is less experience in the application of this architecture to the WEDM process. However, the memory property becomes an advantage since the grade of degradation of the cutting regime depends on the accumulative effect of a set of discharges.

2) Range of the variables: in order to normalize the inputs/outputs, symmetric and asymmetric ranges have been compared during the training phase: [-1-1], [0-1].

3) Codification of the desired values (targets): during the training process of MLP networks, the targets have been codified by 1-of-(C-1). In other words, only one of the outputs is activated at the same time and all the categories C are considered minus one (Sarle, 2002). As the Elman architecture is concerned, the targets have been defined by the application of a set of algorithms explained in (Portillo, et al., 2007b).

4) Layout of the Inputs/Outputs: this criterion is related to define only one neural network that processes all the virtual measurements (unique configuration) or, on the contrary, as many neural networks as virtual former configuration has been only considered for the Elman architecture since the network size would be too large for a configuration based on the MLP architecture.

The training and simulation process has been implemented in Matlab™ 7.1. The generalization method employed during the training phase is based on early stopping. The algorithm for Bayesian Regularization available in Matlab™ 7.1 is not applied since it updates the weight and bias values according to Levenberg-Marquardt optimization, which is not recommended for Elman networks (see Matlab™ Help).

In particular, the backpropagation with adaptive learning rate and momentum has been applied. The activation functions of the hidden and output neurons are the logistic sigmoidal and the tangent sigmoidal functions. Each neural network configuration has been trained ten times due to the dependence of the error on the initial values of the weights.

The results of the comparative study have showed that the parallel Elman configuration responds better to the objectives of this work. The corresponding networks provide the lowest errors. To illustrate this, Fig. 3 shows the lowest validation errors, quantified by the Mean Squared Error, obtained for both the Elman and MLP architectures. In particular, these results refer to the parallel configurations related to the processing of the energy virtual measurement E.

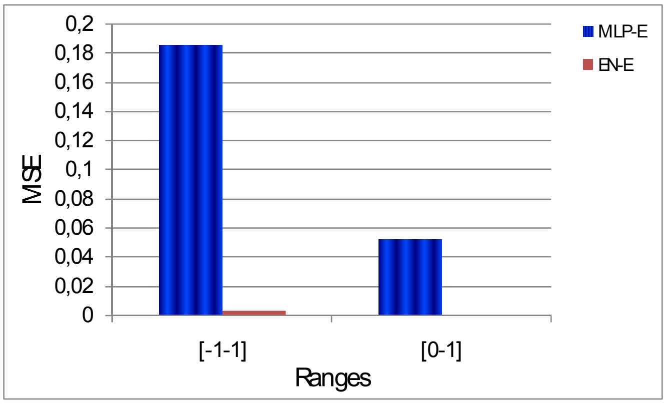

Fig. 2 Lowest validation errors in MLP-E and EN-E.

Besides this, they provide a significantly smaller size compared to the MLP networks. This means that the Elman network is less time and memory consuming compared to static neural networks. Besides, the MLP networks would require the management of an input buffer to add and remove values of the successive virtual measurements. The Elman network with unique configuration has been discarded mainly because the degraded behaviour related to the peak current and TDH (DB-C+TDH) is not properly detected.

Another aspect to stand out is that asymmetric range has provided significantly lower validation errors, independently of the network architecture.

At the sight of these conclusions, a configuration of three Elman neural networks is selected (see Fig. 3): 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). Each network is dedicated to specific virtual measurements that constitute the neural network inputs. Besides these inputs, the workpiece thickness is added to each network in order to be able to detect the process degradation in a range of workpiece thicknesses.

As mentioned above, the outputs of the recurrent neural networks represent the level of alarm whose discrete value informs about the detection of the corresponding degraded cutting regime. In the case of EN-E net, it has as outputs both types of degraded cutting regime (DB-E and DB-EO). A post-processing phase of the three networks outputs trigger different levels of alarm that alert to the increasing risk of wire breakage: A1 (low), A2 (medium) and A3 (high). In the post-processing phase the grade of influence of each type of behaviour in the degradation is also estimated.

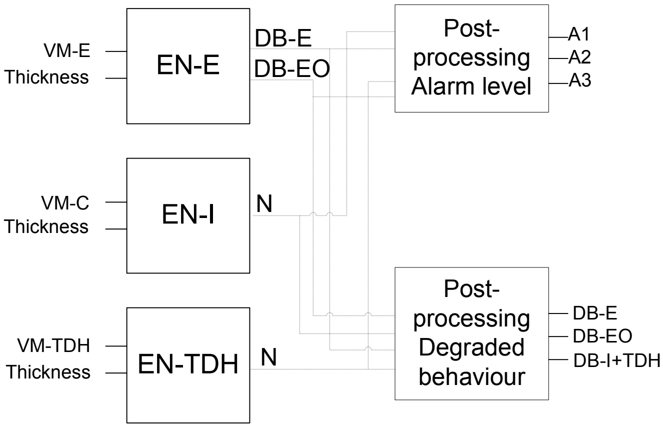

Fig. 3 Scheme of the recurrent neural network approach.

4. STRATEGY FOR INTERPOLATING INSTABILITY TRENDS

Once the appropriated neural configuration has been selected, the next objective is to obtain a unique neural structure valid for detecting the degradation of the process in different workpiece thicknesses. 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.

As the training process is concerned, in this second stage, three ranges of the inputs/outputs have been considered during the training process due to the asymptotic character of the sigmoid activation function: [0.05-0.95], [0.1-0.9] and [0.15-0.85].

On the other hand, a total of 456 sequences of 250 points each have been distributed in the three networks (70% for training and 30% for validation) during the training phase. Sarle (2002) maintained that twice as many training cases as weights may be more than enough to avoid overfitting for a noise free quantitative target variable. Some works conclude that is essential to use lots of hidden units to avoid bad local optima when using early stopping (Isasi, et al., 2004), (Sarle, et al., 1995). Considering both indications, hidden layers from 5 to 60 neurons have been evaluated, which are taken around ten by ten.

4.1 Metrics for the analysis of the results

During the analysis of the results, two main phases are distinguished:

5) Quantitative analysis: selection of the configurations that yield the lowest validation error per range. The validation error is quantified by the Mean Square Error MSE.

6) Qualitative analysis: the preselected configurations are compared by simulating their operation. In order to select the most appropriate configurations, two ratios are considered: the validation ratio and the test ratio. The

validation ratio represents a hit ratio of the validation cases employed during the training phase. The behavior of the network when processing a specific validation example is computed as correct depending on the quality of its output in tracking the output target. 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 ratio is computed over the test examples, which are not used during the training phase. In this particular case, they correspond to degradation examples occurred in workpieces 80 mm height. The detection of the degradation of the cutting regime is considered correct when the pre-established threshold, which is common for the workpiece thicknesses between 50 and 100 mm, is achieved.

If the performance of both ratios is approximately the same for different neural configurations, the smallest one is selected.

4.2 Analysis of the results

Table 1 summarizes the configurations and the performance of the selected Elman neural networks.

In order to illustrate the selection procedure, the analysis of the results of the Elman network for energy is presented. Fig. 4 shows the neural networks configurations per range that yield the lowest validation errors and the corresponding validation ratios. The numbers upon each bar represent the quantity of hidden neurons and the validation ratio respectively. It can be observed that the validation errors are quite similar in the three cases. Consequently, a qualitative analysis is performed in order to compare the characteristics of the configurations when operating. Concerning this, Fig. 4 shows that the configuration in the range [0.1-0.9] provides the highest validation ratio.

Actually, from the qualitative point of view, the performance of the target-tracking in the remaining ranges is notoriously lower. This can be observed in the examples shown in Fig. 5, Fig. 6 and Fig. 7. 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.

As the outputs are concerned, they correspond to the types of degraded behaviors related to the energy: E-E refers to a sudden increase in the energy DB-E, and E-EO refers to an oscillating behavior in the energy DB-EO.

The examples show the behavior of the three different configurations that correspond to the three evaluated ranges, respectively, when processing the same validation example. In particular, the validation example is related to the degraded behavior consisting of successive peaks of high energy DB-EO. This is the reason why the corresponding target and output E-EO present an increasing behavior, whilst E-E remains low. However, the configurations do not provide the same behavior of the output, as it can be observed in the circle areas of the figures Fig. 5, Fig. 6 and Fig. 7. While the configuration in Fig. 6 tracks satisfactorily the target by accumulating successive peaks of high energy, the configurations presented in Fig. 5 and Fig. 7 are further from the desired behavior. Consequently, the configuration obtained in the range [0.1-0.9] is selected. The test ratio of this configuration is 75%.

Table 1. Configurations of the neural network structure

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%

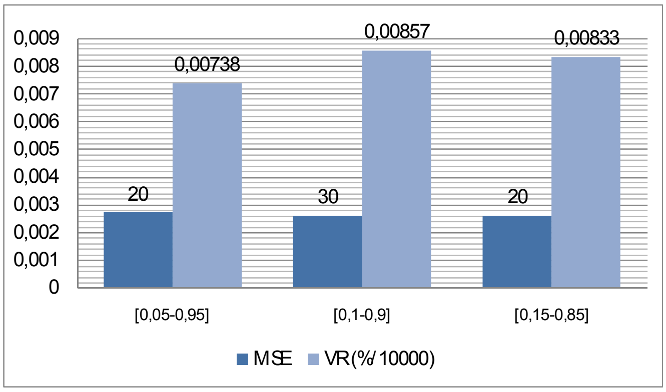

Fig. 4. Lowest validation error (MSE) and validation ratio in EN-E.

5. APPLICATION EXAMPLES IN DIFFERENT WORKPIECE THICKNESSES

This section illustrates the operation of the proposed neural structure by showing some examples related to the Elman network for energy. In the post-processing phase, a set of simple IF-THEN rules are applied in order to trigger the different levels of alarm as well as to estimate the type of degraded behaviour.

Table 2 summarizes the post-processing rules applied in the case of Elman network for energy (in particular, the rules refer to the degraded behaviour denoted as DB-EO). E-EO is the output of the network. HT_{EO}, MT_{EO} and LT_{EO} represent the high, medium and low level of alarm, respectively. $P_{DB\text{-}EO}$ divided by the sum of the contributions of all the types of degraded behavior ($P_{DB\text{-}E} + P_{DB\text{-}EO} + P_{DB\text{-}I+TDH}$) are used to infer the most probable cause of process degradation. The examples shown in Fig. 8, Fig. 9 and Fig. 10 correspond to the degraded behavior consisting of successive peaks of high energy (DB-EO) in workpieces 50, 80 and 100 mm height, respectively. As it has been established in the previous section, the thresholds of the alarms are common for all the workpiece thicknesses, independently of the differences in the thresholds achieved by the virtual measurements. Thus, the alarms are triggered by following the rules stated in Table 2, which processes concurrently. In the three examples the output E-EO of the network, which refers to the degraded behavior DB-EO, show an increasing behavior until the high level alarm is reached. As the output E-E is concerned, it remains low, except for a time lapse in the example of the Fig. 8. In this example E-E only achieves a medium level alarm, whilst the output E-EO reaches the high level. This means that the type of degraded behavior is properly estimated. The alarm levels marked on the outputs graph alert to the increasing risk of wire breakage and are computed by the post-processing phase. In the three cases, A3 is triggered approximately between 120 and 300 milliseconds before the wire breakage (marked by an arrow).

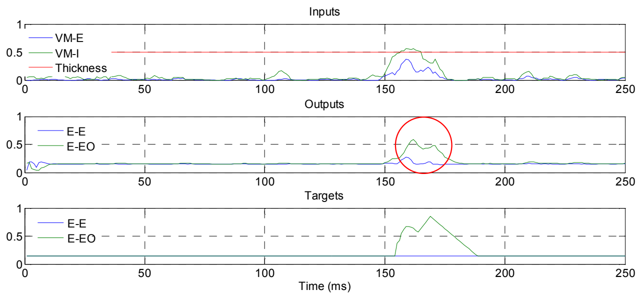

Fig. 5 Inputs, outputs and targets of EN-E generated during a DB-EO degraded cutting regime: range [0.15-0.85].

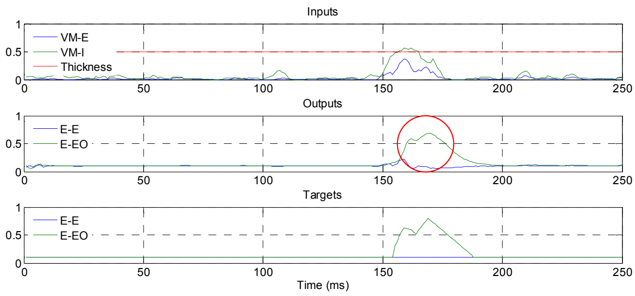

Fig. 6 Inputs, outputs and targets of EN-E generated during a DB-EO degraded cutting regime: range [0.1-0.9].

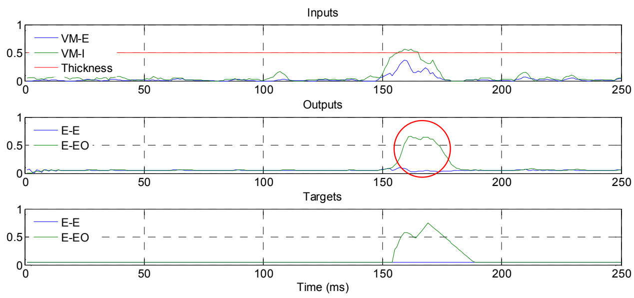

Fig. 7 Inputs, outputs and targets of EN-E generated during a DB-EO degraded cutting regime: range [0.05-0.95].

Table 2. Post-processing rules applied to the outputs of EN-E in the case of DB-E

Post-processing E-EO output
IF E-EO>HT$_{EO}$,
THEN A3=TRUE;
IF NOT, IF E-EO> MT$_{EO}$,
THEN A2=TRUE;
IF NOT, IF E-EO> LT$_{EO}$,
THEN A1=TRUE;
P$_{DB\text{-}EO}$= E-EO;

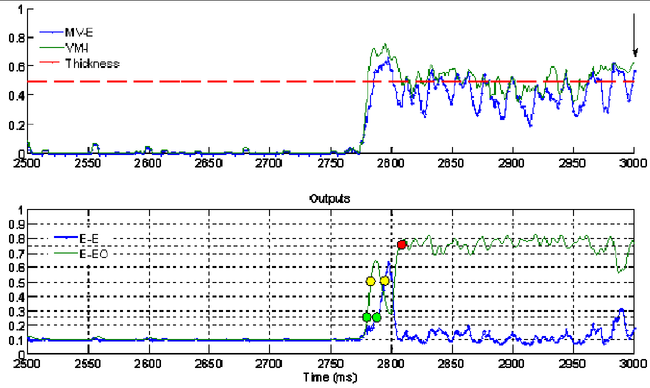

Fig. 8 Inputs and outputs of EN-E generated during a DB-EO degraded cutting regime in 50 mm

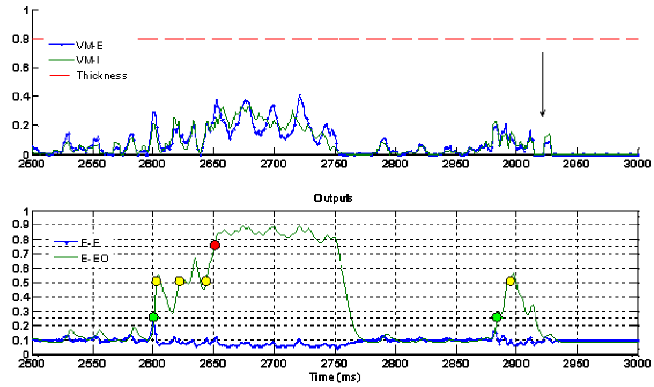

Fig. 9 Inputs and outputs of EN-E generated during a DB-EO degraded cutting regime in 80 mm

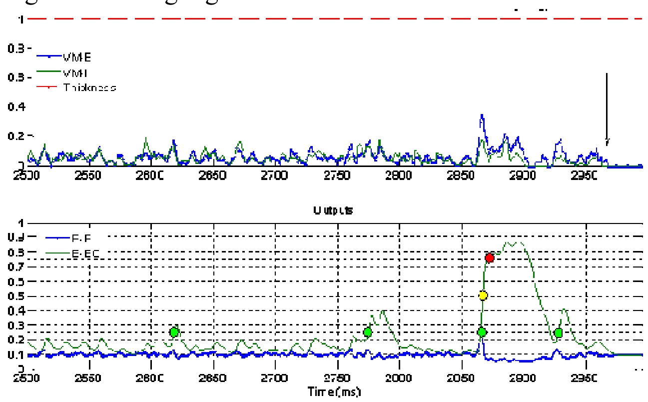

Fig. 10 Inputs and outputs of EN-E generated during a DB-EO degraded cutting regime in 100 mm

5. CONCLUSIONS

In WEDM different types of degraded behavior can lead to the breakage of the machining tool: the wire. These phenomena are characterized by a very fast dynamic (milliseconds order) that can be detected through specific trends of the so-called *virtual measurements*, whose maximum values depend on the workpiece height. Thus, the challenge of this paper is to define one unique neural structure valid for the early detection of degraded behaviors in a range of workpiece heights (50-100 mm). The achievement of this objective will allow to avoid the tool breakage by the proper control actuation. Considering the nature of the degraded phenomena, a recurrent neural network approach is implemented. It is based on three Elman networks that process three virtual measurements that constitute their inputs. The advantages of this approach are related to obtaining one unique neural structure in order to avoid having a battery of heuristic rules per workpiece height, and also to taking advantage of the learning capacity of ANN aimed at interpolating the detection of degraded behaviours in intermediate workpiece heights. The results show the viability of the presented approach. Future work will be extended to other recurrent network architectures, and to implement the diagnosis system in real-time.

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