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Cognitive decision-making systems for scraps control in aerospace turbine blade casting

Davide Matarazzo[a,]*, Doriana M. D'Addona[a], Ciro Caramiello[b], Michele Di Foggia[b], Roberto Teti[a]

[a] *Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT Naples)*
Dept. of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, Piazzale Tecchio 80, Naples 80125, Italy
[b] *Europea Microfusioni Aerospaziali SpA (EMA), Morra de Sanctis (AV), Italy*

* Corresponding author. Tel.: +39 320 7173783. *E-mail address:* davide.matarazzo@unina.it

Abstract

The competitiveness of a casting system in modern lost wax production of superalloy turbine blades strongly depends on the reduction of scraps, which commonly affect superalloy cast parts. In order to achieve a focused goal of competitiveness, some key and vital parameters (Key Process Variables) have to be continuously taken under control to make very accurate predictions of Target Variables, which represent, as mapped KPVs domain, the ultimate performance of the entire production link.
Such an approach is based on the development of robust control monitoring of the ceramic shell manufacture, which is specifically conceived to foster a possible reduction of scraps in the production if superalloy components. The concerned control will take into consideration data coming from both sensors and measured values in laboratory. The sensor data, which is originated from both new adopted inline and offline equipments at Europea Microfusioni Aerospaziali S.p.A. (EMA) and data measured in the EMA laboratories, will be merged into a sensor pattern vector which represents the basis to develop the EMA demonstrator within the Intelligent Fault Correction and self Optimizing manufacturing systems EU project funded in FP7. The sensor pattern vector will be used to feed an automatic system for the prediction of the process vital parameters. An automated system, based on artificial intelligence paradigms, in particular neural networks, will be fed with the data coming from the sensor pattern vector in order to produce an optimal multi-object output.

Keywords: Artificial Neural Networks; Casting; Decision-making

1. Introduction

The extraction and selection of relevant features from sensor signals along with their concurrent fusion, in order to get an improved perception of monitoring processes, have been already studied in previous works [1]. In the present study some of the outcomes of the previous studies are used as inputs for the development of Decision Making Support Systems (DMSS). DMSS are represented by computer-based systems that support individual or organizational decision-making processes usually designed as interactive software-based systems. They are specifically designed to help decision makers to compile useful information from raw data, documents, personal knowledge and/or business models in order to ultimately identify and solve decision problems.

In this research work, DMSS have been designed to be applied on manufacturing processes with the aid of on Artificial Intelligence (AI) methodologies for the analysis of sensor data and the solution of complex problems by suggesting possible choices/ corrections for the current process to the end user. Depending on the type of application, different AI methods can be applied. Amongst them, neural networks have been chosen then applied on pre-casting processes data at EMA.

The study focuses mainly the application of cognitive paradigms to the EMA case. During the Intelligent Fault Correction and self Optimizing Manufacturing systems project (IFaCOM), different sensors have been installed at EMA, in order to monitor the ceramic shell manufacturing, in particular the so called *primary layer* which is represented by

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a complex rheological slurry consisting of a colloidal suspension of ceramic nanoparticles.

The final aim of the EMA demo is controlling the variations of some measured parameters which could influence the amount of defects as scrap pieces. In order to fulfill this task, it is necessary to find and suitably characterize a possible correlation law between sensor inputs and final quality outputs. This is exactly what was done in this study by resorting to Cognitive Paradigms in terms of Artificial Neural Networks (ANN). It was observed that the adopted ANNs were specifically optimized in order to provide a better performance and establish a robust correlation between process inputs and outputs.

The optimization process starts from data collection and continues with the selection of the optimal network configuration. Preliminary results, with the selected network configuration, are shown in the paper not only to predict the final output quality based on the process data but also to implement an inverse procedure. This procedure allows for the prediction of optimal process parameters based on the desired output (zero-defects manufactured parts). Furthermore, since the accuracy of the network are affected presently by a very reduced dataset coming from the first measurements, in order to validate their performance, the first test have been performed resorting to historical data. These tests have fully confirmed the validity of the chosen approach [2 - 4].

2. Overview of the EMA application case

The final goal of the research associated to EMA-Demonstrator is to optimize the process of ceramic shell manufacturing by monitoring and controlling the primary slurry parameters along with the quality characteristics of the shell, in order to reach a feasible reduction of the scrap rate.

The EMA-demonstrator activities have been planned as measurement campaigns performed on the production line called *iterations*. The investigations done during the first iteration have resorted to cognitive systems, such as ANN data analysis, with the aim to find possible correlations between the measured Key Process Variables (KPV) and previously identified Target Variable (TV, i.e. output quality parameters). In the first iteration it was assumed that TV has only one dimension represented by the scrap rate.

The examined components and the corresponding quality controls, both for standard production cycles and dedicated IFaCOM tests, have been performed during a period of more than four months. During this time, the surveyed components have been consisting in 124 multivane blades of the demo products, and 42 dummies (20x15x1 cm^3, 21 assembly parts of 1x2 cm, Figure 1), that is one assembly for each day in pair with a production assembly (built for performing destructive testing on the shell) in order to check the mechanical properties of the shell in two different conditions (*pre-fire* and *pre-heat*).

Incidentally, the quality of the primary ceramic slurry and the resulting shells has been monitored using both traditional methods and advanced investigation techniques based on the recently installed IFaCOM equipment.

Fig. 1. Assembly (1 x 2) of ceramic dummies and corresponding samples for adhesion and hardness measurements.

The final effects on the casting have been monitored using both statistical techniques and algebraic data analysis. The statistical data analysis consisted in both standard and advanced classification of the dataset. In particular, advanced statistics was performed using the Karhunen-Loève Transform (Principal Component Analysis, PCA) in order to lower the effective dimension of the input phase space (KPV domain). Algebraic analysis had been done via a subspace analysis with effective (numerical) rank evaluation by means of SVD (Singular Value Decomposition). These last have been utilized in a synergic way to make a preliminary filtering of unnecessary (i.e. noisy and/or redundant) degrees of freedom before ANN analysis. Canonical (standard) statistical data analysis has been also carried out with a multivariate regressive analysis performed over the complete dataset (input vs. output matrices).

2.1. Analyzed parameters

The activities of this study are targeted to validate the developed feature vectors in a significant environment [1], by paying attention to the identification of defective products, i.e., scrap components due to ceramic inclusions. This assessment process is performed in terms of success rate and in terms of Euclidean norm for the identification of scraps. Cognitive systems, such as ANN, are used to find possible relations between input features (vital characteristics of the primary slurry, mechanical properties of the developed ceramic shells) and vital quality characteristics (scraps in the manufactured superalloy components [5]).

The sensor fusion feature vectors represent the input while the output is the end-user given quality parameters which evaluate the final product quality in terms of number of scrap components. The monitored parameters are summarized in Table 1. These parameters are acquired using different methods. Some of them were acquired in an in-line fashion, while others required some off-line testing/measurements carried out in EMA laboratory.

After the *data retrieval* phase, all the data were stored in EMA database (DB). Since these data are commonly acquired on the production line, while real products are being manufactured, it is not always possible to perform all the planned measurements due to many unpredictable events. Moreover, since EMA planned measurements include Non-Destructive Tests (NDT), during the first iteration some data were acquired on one dummy sample per day.

Table 1. Monitored Key Process Variables (KPV).

KPV	unit	Characteristic Type
Density	g/cm^3	primary slurry
Temperature	°C	primary slurry
Viscosity	s	primary slurry
Plate Weight	g/cm^3	primary slurry
Silica Content	wt%	primary slurry
pH		primary slurry
Hardness (HRB)	HRC	Shell
Adhesion	MPa	Shell

The relevant matrix, extracted from EMA database and representative of the first iteration, showed some lack of information. This is what is commonly known as a *missing data block*(s) and is due to the impossibility to fill up in short times sampled rows with each single entry (columns or Degree of Freedom values, DoF).

That matrix structure was studied, possibly rebuilt then adjusted in order to make the data usable for the implementation of cognitive paradigms for the decision making. All the acquired data were formatted for both Excel and MATLAB handling.

In the first Excel sheet, all the acquired input data (viscosity, plate weight, hardness, etc.) and the amount (percentage) of scraps after all NDT controls were loaded. Each row shows measurements and results.

3. Cognitive System for decision-making

Cognitive paradigms can be used for the optimization of the ceramic shell manufacturing in lost-wax process by finding and assessing possible correlations between the Key Process Variable domain (KPV) and the Target Variable domain (TV) (the measured parameters and the quality of the final product. Please refer to [7]).

In order to find a possible functional relation among the parameters, an analysis of the trend of the KPVs was performed. The ANNs suggest possible corrections applicable on the slurry composition before reaching the final product optimum [8]. The optimization consists in finding such correlations, over a large set of experimental data affected by acquisition noise and incomplete sampling, possibly leading to multi-block arrays [6].

In recent years, several researchers have, explored such routes by resorting to ANN for prediction of mechanical properties of materials as well. The ANN can learn from examples, and have powerful capabilities to classify and recognize the trend of specific and selected properties. They can establish functional relationships from experimental data even when the correlations are difficult to be found or be clearly described from a scientific point of view. As above explained, several parameters are influencing the whole process and the mechanical properties of the operations at EMA [9].

An important aspect for ANN utilisation is the extreme care needed in collecting the data since it affects the accuracy of subsequent predictions. An ANN requires to adjust the output by iterations during the training period until the error is minimized. Hence, the selection of appropriate training algorithms and the number of neurons in the hidden layer can be critical for modelling an ANN for a given purpose [10].

In order to predict the best output from any given input, it was agreed to work from the beginning with Back Propagation Neural Networks (BP NN) [1] as they are able to catch functional relationships between given inputs and outputs in a very efficient way [11 - 13].

The *cascadeforwardnet* (CFN) function, specifically in the MATLAB implementation, is a BP NN, which creates a weighted connection from the input and every previous layer to the following layers. Here the three-layer network also has connections from the input to all three layers. The CFN was trained with the Training-Validation-Testing (T-V-T) approach [14], by setting the Training as the 70% of the input data, Validation as the 15% and Test as the remaining 15%. The best number of hidden nodes was chosen by studying the response of the systems in terms of L_1, L_2 and L_∞ norms.

To achieve the best ANN performances [1], the ANNs have been also trained by using the *"new cascade forward net"* (N_CF) function, which is a BP NN. They were run in MATLAB R2014b as a three-layer cascade-forward BP network. As concerns the ANN settings, it was chosen the tangent sigmoid transfer function (between input and hidden layer), while for the output a linear function was chosen. The optimal number of nodes in hidden layer, *I*, was determined by making a phase space exploration for different *I* trials.

3.1. Artificial Neural Network training set

For each Serial Number (SN), a 12-elements sensor fusion pattern vector has been assembled using the following data:

- Coded Serial Number (ANN SN)
- Worked blades per ANN SN
- Silica Content (%)
- Density (g/cm^3)
- Temperature (°C)
- Viscosity measured by the IFaCOM equipment and Viscosity manually measured (Ford Cup)
- pH
- Plate Weight (PW) measured by the IFaCOM equipment and PW manually measured
- Hardness
- Adhesion

These vectors were used as input to cognitive decision making systems that provided, as output, two quality parameters (Table 2): *'#inclus'*, which represents the number of blade with inclusions, and *'inclus%'*, which represents the percentage of blades with inclusions on the total number of worked blades in a dummy [1].

In the manufacturing process, the control performed at the final step is the most relevant in order to take a decision. Considering the first inspection means understanding if the blade presents scraps and, at the same time, if it requires suitable additional corrections.

A feasible reduction of the number of scraps at the first inspection will imply for EMA a possible reduction of costs as a consequence of a conceivable process improvement and an augmented knowledge base (in terms of relevant correlations amongst KPVs).

Table 2. Output of the ANN training vector.

	Inspection	
Blade	#inclus	inclus%
1	*n*	%
…	*n*	%
i	*0*	

Upon summarizing, the number of scraps in every blade represents the target to study and optimize as a function of relevant ceramic process KPVs for possible reductions in terms of costs and time.

Moreover, it should be kept in mind that a reduction of the number of blades that present inclusions will avoid loops in the process link. This means that the blades will not need further operations before leaving the plant site. Due to the above considerations, in the implementation of a cognitive decision making system, the sensor fusion pattern vector could also be considered only with the column concerning the first inspection.

Furthermore, it should be also beneficial to perform a pre-analysis (*data refinement*) on the database array in order to avoid possible redundancies that would only confuse the cognitive system during the decision-making phase.

3.2. *Artificial Neural Networks implementation*

Many tests have been performed on the ANNs in order to define which type of ANN was most effective in correlating inputs and outputs in the EMA case. In particular:

- which is the optimal MATLAB function for implementing a cascade-forward backpropagation network configuration, CFN or N_CF and which are the optimal settings for both (number of nodes, training epochs, training set dimension, etc);
- which influence have inputs on the network performances (evaluation of network stability);
- investigation on cascade-forward ANN with a Bayesian training function for including statistical information into the learning process and comparison with a standard backpropagation approach;
- application and performance evaluation of the cascade-forward backpropagation ANN using EMA's pre-IFaCOM data.

The results and the considerations deriving from these studies are shown below.

3.3. Investigation on the newcf function

The first tests consisted on a general exploration in the phase space by utilizing the N_CF MATLAB function. The first set of trials tested the sensitivity of the network with respect to nodes number and epoch, respectively. Here the relative percent error as the quantity [13]:

$$\varepsilon = |Y\text{-}B|/Y \tag{1}$$

The formula in (1) represents the deviation of the ANN predicted (Y) set with respect to original sampled data (B) in the same fashion of *Mean Absolute Error* (MAE) and *Mean Square Error* (MSE) [15].

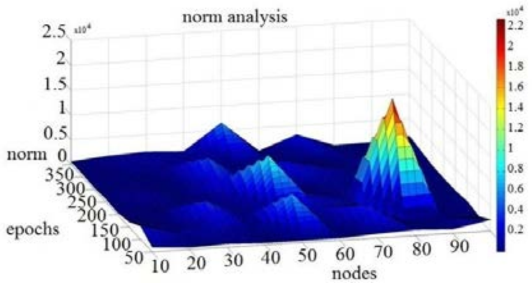

Fig. 2. ANN dependency on nodes number and epochs.

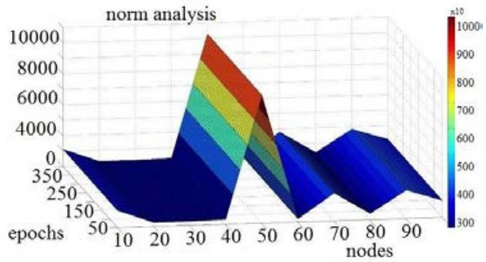

Fig. 3. ANN dependency on nodes number and epochs, same seed.

Of course, in order to obtain a unique value for each experiment in the phase space L_1, L_2 and L_∞ norms have been adopted for each point in the phase space.

A second attempt has been carried out extending the dimension of the inspection domain. Here two DoFs have been chosen i.e. nodes number and epochs as depicted in Figs 2 - 3, respectively. In the first case it is evident that there are some regions in which the ANN should not be used due to a particular combination of the values of the two variables which lets L-norms grow too much (Z axis is in log scale) [1].

On the other hand, if one freezes MATLAB *rng* (*random number generator*) in order to force determinism on ANN generation, it turns out that there is practically no dependence on epoch even though nodes influence is still strong. In particular, it is possible to see that the best performances of the net are obtained in the vicinity of $n = 20 \div 40$ where reductions of one/two order of magnitude for L_x (x=1, 2, ∞) are reached with respect to other nodes number.

Of course, if same MATLAB seeds are not considered, the average values need to be taken into account over a (possibly) large set of trials.

3.4. Investigation on the cascadeforwardnet function

Here the error and the performance still depend, of course, on the *rng* seed. Apart from the improved algorithm, the procedure used in this case is quite different in terms of training as well. While the leave-k-out method has been adopted as in the other analyses presented in this study, the criterion that was resorted to relies on a different variable training set. Typical values adopted for these experiments are [14]:

- net2b.divideParam.trainRatio = 70/100
- net2b.divideParam.valRatio = 15/100
- net2b.divideParam.testRatio = 15/100.

This means that the training phase does not use only (*n-1*) sampled as in the previous cases (N_CF), but a well-defined dimension for both train ratio and evaluate ratio. In spite of a good performance of the net with such values, it is evident that input parameters are mostly empirical. For this reason, it is necessary to set up a suitable inspection in the phase space in order to find the optima for all the possible process datasets. It can be observed that a well-defined region for optimal performance is achievable in correspondence of the plane subset:

$$[\text{training ratio}]\text{x}[\text{node number}]=[10,20]\text{x}[70,80] \qquad (2)$$

where all norms, in particular L_1, are strongly damped. Therefore, in this area the least drift to the ANN predicted values with respect to observed experimental data can be given. me stability considerations for the *cascadeforwardnet* performance were issued. In Figs 4 -5, the output vector (B) has been randomly perturbed (amount: ~3 % in terms of L_2 norm). The final outcome seems not to be affected by this perturbation at all. Of course, major perturbations can affect stability performance in dependence of specific norm drifts (in an averaged sense) but also with respect to single components (i.e. DoFs). Any stability threshold has been roughly observed up to 5% approx.

3.5. Cascadeforwardnet with Bayesian training function

In order to optimize the performances of the ANNs, another training function for the cascade-forward function was considered. The new training function is the Bayesian regulation backpropagation (*'trainbr'*), instead of the network training function, which updates the weight and bias values according to Levenberg-Marquardt (*'trainlm'*) optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is called *Bayesian regularization.* To understand which was the number of nodes and the ANN parameters for the training, evaluation and testing phases, it was implemented a deep analysis based on the MATLAB code generated by EMA for the ANN implementation. The *'trainbr'* function was utilized for the optimization of the *cascadeforward* ANN: Figure 6 shows the optimal region in terms of number of nodes and training set dimension. This first inspection returned a value of 55% for the training set dimension, while the optimal number of nodes was 65. These values return an optimized ANN in terms of norms L_1, L_2 and L_∞, and in terms of ANN performance. Table 3 summarizes the results of the several trials performed with the implementation of the Bayesian ANN.

As shown in Figure 6 the best trend obtained with the Bayesian training function returns good results, even if they are not comparable to the Levenberg-Marquardt backpropagation function.

Anyway, it is important to note that this is a preliminary step of the analysis because the Bayesian function is strongly influenced by the sample size. In fact, a small sample size could be not sufficient for recognizing a specific data trend.

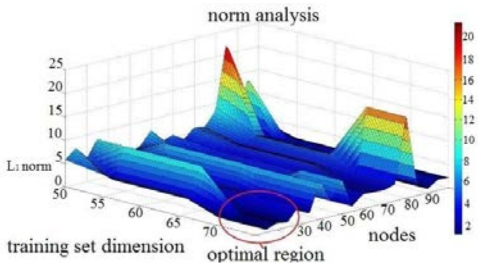

Fig. 4. Phase space inspection as a function of node# and TS dimension.

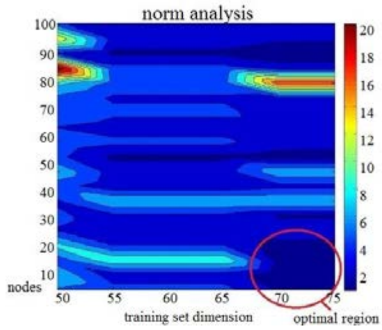

Fig. 5. Phase space inspection as a function of node# and TS dimension.

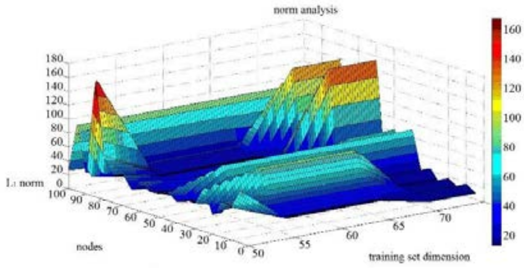

Fig. 6. Phase space inspection as a function of node# and TS dimension.

Table 3. Comparison of the Bayesian NNs.

		Train Parameters				Performances			
	Function	Nodes	Train	Val.	Test	L_1	L_2	L_∞	Perf.
1	*trainlm*	15	70	15	15	7,1	4,2	3,1	6,3
2	*trainbr*	5	70	15	15	19,0	6,3	4,0	3,0
3	*trainbr*	15	70	15	15	19,4	6,2	4,1	2,8
4	*trainbr*	20	70	15	15	21,2	6,6	4,1	3,0
5	*trainbr*	25	70	15	15	20,3	6,5	4,0	3,2
6	*trainbr*	30	70	15	15	21,2	6,5	4,0	3,1
7	*trainbr*	50	70	15	15	21,0	6,6	4,1	3,1
9	*trainbr*	65	55	22,5	22,5	15,7	6,9	5,7	3,2
8	*trainbr*	80	60	20	20	20,3	6,4	4,1	3,0

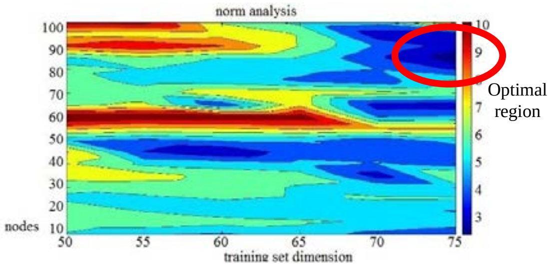

Fig. 7. Norm analysis on historical data with *'trainlm'*.

Table 4. *'trainlm'* vs. *'trainbr'* results for historical input dataset.

			Train Parameters			Performances		
	Function	Nodes	Train	Val.	Test	L_1	L_2	L_∞
1	*trainlm*	85	75	12,5	12,5	2,4	0,6	0,3
2	*trainbr*	85	75	12,5	12,5	5,5	0,9	0,4
3	*trainbr*	95	60	20	20	5,3	0,9	0,4

3.6. Historical data investigation

In order to definitely validate the ANN, several tests on the historical data have been performed (Figure 7). These tests are fundamental to understand if the ANNs can be used for a larger dataset, as the ones which will be provided during the 2nd and 3rd IFaCOM iterations (the following data acquisitions planned for the EMA Demonstrator). In Table 4, the comparison between *'trainlm'* and *'trainbr'* in terms of ANN results for historical input dataset are reported.

From t, it can be concluded that:

- a larger dataset, that is directly comparable to the full dataset, would allow to train a more precise ANN
- by using a larger dataset, a Bayesian training function can substantially improve its performances
- however, the '*trainlm*' function obtains the best performances, with the lowest L_1 norm and the highest performance indicator.

4. Concluding Remarks

The operative application of ANN was tested to ceramic slurry optimization, according to the IFaCOM demo plan. The highlighted results represent a general test for the right choose of the optimal configuration of the ANN parameters.

The experimental data were processed through 3-layers back-propagation ANNs with the aim to find possible correlations between the process parameters and the number of scraps for each blade. However, it is important to observe that all the considerations and results achieved in this research work were based on a sample of a very reduced cardinality consisting in not more than fifteen items.

The work done on EMA's pre-IFaCOM data has taken into account the indications given by the first ANN training and testing phases. With a larger data set (historical data) the prediction phase reduced the gap between the measured output and the predicted one so when applied on a relevant amount of data, the selected approach shows good results in terms of L_1, L_2 and $L\infty$ norms. Therefore, the implementation of ANNs on a larger dataset, such as expected in the 2nd and 3rd IFaCOM iterations, would produce feasible results in terms of optimization of the parameters of the primary slurry scraps prediction.

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