Tool Delivery Prediction through Adaptive Neuro-Fuzzy Inferencing

Doriana D'Addona

Roberto Teti

University of Naples Federico II, Dept. of Materials and Production Engineering, Naples, Italy

The development of a tool management system for reliable tool delivery prediction in a supply network for optimum tool inventory sizing based on reliable delivery forecasting of Cubic Boron Nitride (CBN) grinding wheels for nickel base alloy turbine blade fabrication is illustrated in this work. The basis for the development of the system is represented by the historical data on tool management including the chronological series of CBN grinding wheel shipment and delivery dates between one manufacturing company (client) and several tool manufacturers (suppliers) in a supply network. If historical data are highly variable, stochastic management methods, such as time series analysis, are either inapplicable or responsible for excessive inventory sizing. Alternative approaches are given by special analysis and modelling methodologies, such as those based on fuzzy logic, which deal with deterministic events but are also capable to take into account unpredictable factors for better results in prediction and forecast. In this paper, supplier-dependent dressing cycle time predictions for each external tool manufacturer in the supply network are obtained through a neuro-fuzzy approach whose structure is a 1st order Sugeno fuzzy model known as Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANFIS predictions can be utilized by the customer to evaluate the supplier reliability in the delivery of CBN grinding wheels, which represents a critical decision parameter in the dressing order allocation procedure and a key reference factor for the implementation of flexible tool management strategies.

Keywords: Tool management, Grinding wheels, Neuro-fuzzy system

1 INTRODUCTION

In highly complex manufacturing systems, it is very difficult to precisely define not only the performance of operation and the quality of service but also the lead-times characterizing the customer-supplier relationship in a supply network [1]. The latter aspect marks the main focus of this work, where the development of a multiple supplier tool management system for optimum tool inventory sizing based on reliable delivery forecasting of CBN grinding wheels for Ni base alloy turbine blade fabrication is confronted.

The basis for the development of the system is given by the historical data on tool management consisting of the chronological series of CBN grinding wheel shipment and delivery dates between one manufacturing company (customer) and four external tool manufacturers (suppliers) in a supply network for CBN grinding wheel dressing and fabrication [2]. If historical data are highly variable, as in the present case, stochastic management methods, such as time series analysis [3], are either inapplicable or responsible for excessive inventory sizing. Classical times series analysis only deals with the randomness of the historical data but does not consider the fuzziness (uncertainty) in the underlying model of a practical system and cannot measure the imprecision that derives from human intervention which is neither stochastic nor casual (e.g. changes in business policy, unpredicted competition, etc.) [4]. Being stochastic by nature, classical time series theory only deals with the randomness of the historical data but does not consider the fuzziness (uncertainty) in the underlying system model and cannot measure the imprecision that derives from human intervention which is neither stochastic nor casual. This calls for special analysis and modelling methodologies, such as those based on fuzzy logic [5], which deal with deterministic events but are also capable to take into account unpredictable factors for better results in prediction and forecast [6].

In this paper, the supplier-dependent prediction of CBN grinding wheel dressing cycle time is carried out for each external tool manufacturer in the supply network through a set of multiple-input-single-output (MISO) adaptive neuro-fuzzy inference systems (ANFIS).

The ANFIS predictions can be utilized by the customer to evaluate the supplier reliability in the delivery of CBN grinding wheels. The reliability of delivery represents, together with price and delivery time, a critical decision parameter in the dressing order allocation procedure carried out by the turbine blade producer [7] and a key reference factor for the implementation of a flexible tool management strategy [6].

2 TURBINE BLADE MANUFACTURING

Turbine blade manufacturing is carried out along several production lines. One production line corresponds to a specific aircraft engine model and requires a set of CBN grinding wheel types. Each CBN grinding wheel type, identified by a part-number, is planned by the technology function of the turbine blade producer to work a maximum number of pieces. Once a CBN grinding wheel wears out, it is sent out for dressing to an external tool manufacturer belonging to a supply network and remains unavailable for a time defined as dressing cycle time. For each part-number, a sufficient number of CBN grinding wheels (serial-numbers) must be available at all times (part-number on-hand inventory) to prevent production interruptions due to tool run out. The part-number on-hand inventory size, I, depends on: (a) # of pieces to be produced per month, P; (b) # of pieces machinable by one CBN grinding wheel, G; (c) # of months required without new or dressed CBN grinding wheel supply (coverage period), C. The grinding wheel demand, D, for each part-number is D = (P/G) * C – I, where P/G is the demand rate and the coverage period C is heuristically selected by the logistics function of the turbine blade producer based on past experience.

3 TRADITIONAL TOOL MANAGEMENT PROCEDURES

The approach currently utilized by the logistics function of the turbine blade producer for the strategic planning of CBN grinding wheel inventory size is based on the selection of an appropriate coverage on-hand inventory for each CBN grinding wheel part-number depending on the specific production line. The coverage on-hand inventory is given by the number of CBN grinding wheels (serial-numbers) for each part-number sufficient to cover production needs for a time period (coverage period, C) variable between 3 and 6 months according to the characteristics of the production line (higher values for new production lines, lower values for consolidated production lines). The coverage period is heuristically selected by the logistics function purely on the basis of past experience. This degree of decisional freedom of the logistics function is applied at the beginning of the planning stage. However, it does not always prove satisfactorily reliable in assuring a correct CBN grinding wheel management. Besides cases where the actual trend of CBN grinding wheel availability corresponds somewhat faithfully to the expected one, there are cases where the expected trend is highly underestimated or largely overestimated, with risk of stock breakage or excessive capital investment [2, 6, 7].

4 TOOL MANAGEMENT BASED ON NEURO-FUZZY DELIVERY FORECASTING

4.1 Neuro-fuzzy system

Fuzzy systems are considered to be a natural link between symbolic and subsymbolic approaches in artificial intelligence. On the one hand they can work in real time circumstances and handle uncertainties as NN, on the other hand they can manage both symbolic and numerical information. However, fuzzy systems usually do not incorporate automatic learning abilities and adaptive features. It seems that a very high performance can prospectively be obtained by combining NN and FL approaches and integrating their benefits. Neural network learning provides a good way to adjust the expert's knowledge and automatically generate additional fuzzy rules and membership functions, to meet certain specifications and reduce design time and costs. On the other hand, fuzzy logic enhances the generalization capability of a neural network system by providing more reliable output when extrapolation is needed beyond the limits of the training data. The resulting neuro-system is a hybrid system where the architecture remains fuzzy but, using neural learning techniques, it can be trained automatically. Thus, the Neuro-Fuzzy System (NFS) hybrid approach can comply with requirements such as real-time nature, uncertainty handling and learning ability, but moreover expert knowledge can be easily incorporated in the system and the transparency of rule-based expert systems is preserved [8, 9]. NFS are trained by a learning algorithm derived from NN theory and their architecture can be viewed as a 3-layer FF NN (Figure 1): the first layer contains the membership functions of the input variables, the middle (hidden) layer the fuzzy rules, and the third layer the membership functions of the output variables.

Figure 2 shows a 1st order Sugeno fuzzy inference system [10, 11] with n inputs, n*r input membership functions, r rules, r output membership functions, and p = 1 outputs. Each node on layer 1 includes a membership function for one of the inputs. The membership functions are defined using a set of parameters referred to as premise parameters. The outputs of layer 1 are the membership grades of the inputs in a fuzzy set. On layer 2, each node represents one fuzzy inference rule performing a fuzzy AND operation on the membership grades defined in the rule premises. The outputs are the rule firing strengths. Layer 3 includes the output member-

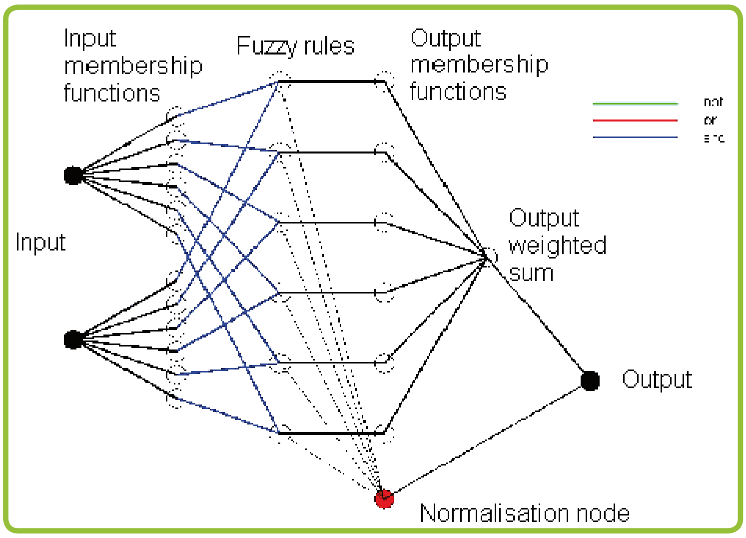

Figure 1.

Neuro-fuzzy system architecture.

ship functions that in the Sugeno case are linear [9]:

$$O_j = w_j \left(\sum_{k=1}^{n} a_{jk}\, t_k + b_j\right) \qquad (1)$$

where O_j is the output from layer 3, w_j the firing strength of rule j (input from layer 2), a_{jk} and b_j are consequent parameters, and t_k is the k^{th} input value. Layer 4 includes just summations of rule outputs and firing strengths (normalisation node), the former sum being divided by the latter on layer 5 to yield the overall system output(s).

4.2 Adaptive Neuro-Fuzzy Inference System

A set of NFS was utilized to provide for supplier-dependent CBN grinding wheel dressing time forecasting for order allocation and optimum tool inventory sizing. The structure of each NFS was a 1st order Sugeno fuzzy model, known as Adaptive Neuro- Fuzzy Inference System (ANFIS) [12, 13], similar to the Multiple-Input-Single-Output (MISO) ANFIS developed in a previous work [6].

Every MISO ANFIS was formulated as a feed-forward NN and utilized as a basis for constructing a set of fuzzy IF-THEN rules with appropriate membership functions to generate the input-output vector pairs (Fig. 3). For further details on ANFIS generation, optimisation and learning, reference can be made to the ANFIS model described in [6], the differences being in the possibility to select a variable number of inputs, n, a variable number of outputs, p, and two different methods for multiple dressing cycle time prediction (single iterated prediction and multiple direct prediction).

4.3 MISO ANFIS for dressing cycle time prediction

The set of MISO ANFIS for supplier-dependent dressing cycle time prediction was developed on the basis of the historical data on CBN grinding wheel dressing comprising a total of 5433 dressing cases, chronologically recorded in a 5 years time span by the logistics function of the turbine blade producer with reference to a supply network of 4 external tool manufacturers.

The ANFIS input is given by a series of n consecutive dressing cycle times (see Figures 2 and 3, where n = 4) and the output consists of one or more predicted times, as close as possible to actual dressing cycle times following the input series. Index (i) in Figures 2 and 3 indicates the last dressed CBN grinding wheel and t(i) is the corresponding input dressing cycle time.

Each dressing case record reports the CBN grinding wheel shipment and delivery dates for the tool manufacturer that carried out the dressing operation. This population includes historical data on all existing CBN grinding wheels and all 4 tool manufacturers in the supply network. In a previous work [6], ANFIS dressing cycle time prediction was carried out on a supplier-independent basis. In that case, all tool manufacturers were considered equivalent in terms of dressing cycle times that they could provide. This supplier-independent prediction turns out useful when the turbine blade producer has to decide at what date a worn out CBN grinding wheel with a specific part-number should be sent out for dressing: whether right away or at a later date (e.g. when the part-number inventory size decreases below a threshold level). This decision is taken before supplier selection for dressing performance, in fact even before knowing whether the dressing operation needs to be carried out at all. Thus, this type of resolution can only be taken on the basis of a "generic" dressing cycle time prediction, i.e. independently of which supplier will carry out the dressing operation. The generic or supplier-independent prediction, however, is not helpful in a procedure for the selection of the supplier that will perform the dressing [7]. Such procedure envisages that the customer contacts the suppliers in the network with the aim to place a dressing order. This customer/supplier interaction is called negotiation and its contents are the prices and the delivery dates

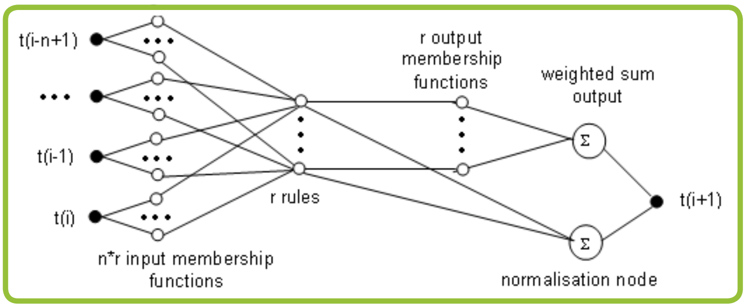

Figure 2.

Neuro-fuzzy system with n inputs, n * r input membership functions

and p = 1 outputs

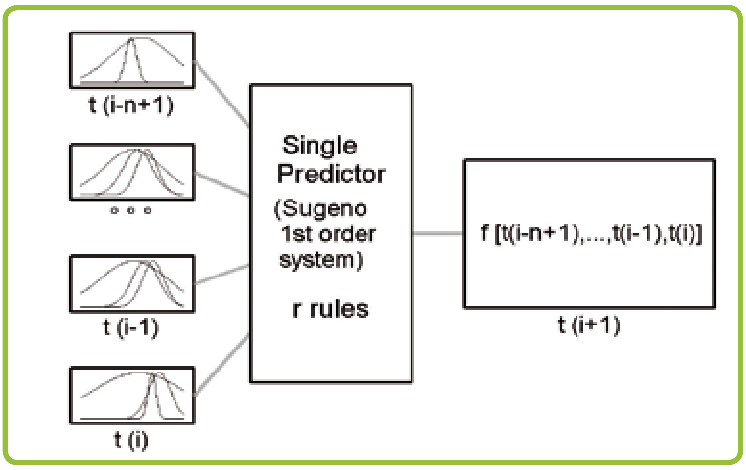

Figure 3.

Multiple-Input-Single-Outputs (MISO) Adaptive Neuro-Fuzzy Inference System (ANFIS): n inputs, r fuzzy rules, p = 1 outputs (quotations). Once the supplier quotations are received, the customer selects the most convenient one. A supplier selection is generally carried out according to the following criteria [14]: delivery time, price, quality, reliability of delivery. Quality as a selection factor can be neglected if all suppliers in the network are certified; under these circumstances, the fulfilment of the required supply quality is presumed. In the case of dressing order allocation, quality is not considered (all suppliers are certified), dressing time and price are those declared by the suppliers during negotiation, but the reliability of delivery must be evaluated. Dressing time reliability can be estimated by comparing the dressing time declared by the supplier and the dressing time predicted for that supplier. To this purpose, a supplier-dependent dressing cycle time prediction is required for each of the external tool manufacturers in the supply network. To obtain a supplier-dependent dressing cycle time prediction through the developed set of MISO ANFIS, it is necessary to build a distinct ANFIS training data set for each external supplier in the network. Thus, the total historical data set was divided into 4 historical data sub-sets, one for each of the 4 external tool manufacturers, containing information on dressing operations carried out only by a single supplier. Each historical data subset was partitioned into a learning set, comprising the first 60% dressing cases in the supplier's series, and a testing set, comprising the remaining 40% dressing cases. In Tab. 1, information on the number of dressing cases for each supplier are reported together with the statistical analysis of the testing data set.

It is worth noting that the 4 suppliers belong to two levels of technological capability. Supplier_1 and Supplier_2 (high level) can perform dressing operations on both simple and complex geometry CBN grinding wheels, whereas Supplier_3 and Supplier_4 (low level) can do dressing operations only on simple geometry CBN grinding wheels. As a consequence, Supplier_1 and Supplier_2 carried out a larger number of dressing operations (> 2000) whereas Supplier_3 and Supplier_4 performed a smaller number of dressing operations (< 500) (Tab. 1). The trained ANFIS for supplier-dependent dressing cycle time prediction were identified as ANFIS_S, with S = 1, …, 4 according to the supplier ID: Supplier_1, …, Supplier_4.

ANFIS_S inputs are given by a series of n consecutive dressing cycle times from the relevant historical data sub-set (see Figs. 1 and 2) and the outputs are p predicted times, as close as possible to actual dressing cycle times following the input series (Figs. 1 and 2, where index (i) indicates the last CBN grinding wheel dressed by a given supplier and t(i) is the corresponding input dressing cycle time).

Single CBN grinding wheels are rarely sent out for dressing but are generally assembled into groups of up to p = 10 before shipping. The developed ANFIS_S can perform p-step-ahead forecasting for any CBN grinding wheel group size, p, in 2 ways: by single iterated predictions (method A) or by multiple direct predictions (method B).

Single iterated predictions are carried out by iterating p times the one-step-ahead ANFIS prediction. One input vector with the last n dressing times for a given supplier [t(i-n+1), …, t(i)] is inputted into the ANFIS and the predicted dressing time (i+1) is obtained. The predicted (i+1) value is substituted for the most recent dressing time t(i), t(i) is substituted for t(i-1) and so on, until the whole n-component input vector is modified by shifting the input values one step backward. Then, a subsequent predicted dressing cycle time (i+2) is obtained. This procedure is repeated until the p required predictions [(i+1), …, (i+p)] are achieved, as illustrated in relationships (2):

$$\begin{aligned}
&[t(i-n+1),\dots,t(i)] \Rightarrow \hat{t}(i+1)\\
&[t(i-n+2),\dots,\hat{t}(i+1)] \Rightarrow \hat{t}(i+2)\\
&\dots\\
&[\hat{t}(i-n+p),\dots,\hat{t}(i+p-1)] \Rightarrow \hat{t}(i+p)
\end{aligned} \qquad (2)$$

where p is taken to be > n, implying that in the last input pattern all features are predicted values. Relationships (2) show that, when p > n, the initial prediction is obtained from historical data alone, the following predictions are obtained from a combination

Table 1.
Dressing cycle cases in the training set for each supplier.
Dispersion parameter = St. dev./Mean.

Supplier ID	Technology level	Total	Learning	Testing			
		# of cases	# of cases	# of cases	Mean (weeks)	St. dev. (weeks)	Dispersion parameter
Supplier_1	High	2428	1457	971	6.82	1.78	0.26
Supplier_2	High	2123	1274	849	6.08	2.11	0.35
Supplier_3	Low	485	291	194	2.72	2.68	0.98
Supplier_4	Low	397	238	159	4.68	1.01	0.22

ANFIS predictor	# of inputs	# of outputs	Prediction method	Prediction error (RMSE)			
				S = 1	S = 2	S = 3	S = 4
ANFIS_S/5/1/*	5	1	A ≡ B	1.23	1.30	1.71	1.14
ANFIS_S/5/5/A	5	5	A	1.28	1.42	1.73	1.15
ANFIS_S/5/5/B	5	5	B	1.27	1.39	1.78	1.25
ANFIS_S/5/10/A	5	10	A	1.30	1.50	1.74	1.20
ANFIS_S/5/10/B	5	10	B	1.29	1.46	2.23	1.28

Table 2.
ANFIS predictors utilized for supplier-dependent p-step-ahead forecasting.

of historical data and predicted values, and the final (p – n) predictions are obtained solely from predicted values. Thus, higher p values are expected to reduce the prediction accuracy because of accumulation of error due to iterations [15].

Multiple direct predictions (method B) are carried out by developing p parallel one-step ahead ANFIS_S, each performing a single forecast as indicated by relationships (3):

$$
\begin{aligned}
&[t(i-n+1),\dots,t(i)] \Rightarrow \hat{t}(i+1)\\
&[t(i-n+1),\dots,t(i)] \Rightarrow \hat{t}(i+2)\\
&\dots\\
&[t(i-n+p),\dots,t(i+p-1)] \Rightarrow \hat{t}(i+p)
\end{aligned}
\tag{3}
$$

From relationships (3), it can be observed that the same input vector, containing the n most recent historical dressing cycle times, is fed into each of p parallel ANFIS_S to perform a direct prediction of the p-th forecast. In this case, each single prediction is always achieved uniquely by means of historical data. The procedure accuracy, however, decreases as p grows as this requires increasingly distant forecasts.

5 SUPPLIER-DEPENDENT DRESSING CYCLE TIME FORECASTING

A set of ANFIS predictors were subjected to learning and testing with the following data processing conditions: historical data training sub-set: S = 1, ..., 4; # of inputs: n = 5; # of outputs: p = 1, 5 or 10; prediction method: A or B. The notation ANFIS_S/n/p/A (or B) is used to indicate the ANFIS predictor for supplier S, with n inputs and p outputs, utilizing method A (or B) for p-step-ahead forecasting. When p = 1, the two prediction methods coincide and the notation becomes: ANFIS_S/n/1/*. In Tab. 2, the supplier-dependent ANFIS predictor data processing conditions and the obtained prediction errors (RMSE) are summarised. From Tab. 2, it can be noted that for all suppliers the lowest prediction error is obtained with the ANFIS_S/5/1/* predictor that is the simplest predictor in terms of computational complexity.

By comparing ANFIS_S performance using the same prediction method A or B, prediction error increases with increasing p due to the lengthening of prediction span. By comparing prediction methods A and B using the same number of inputs and outputs, method A has a higher prediction error for S = 1 and S = 2, whereas method B has a higher prediction error for S = 3 and S = 4. This could be due to the much higher number of learning cases for high technology level suppliers, generating better learned ANFIS_S that can make good use of the higher computational complexity of method B. The contrary happens for low technology level suppliers.

Examining Tabs. 1 and 2 allows to assess supplier reliability in terms of dressing cycle time prediction carried out through the learned ANFIS_S. By comparing suppliers with the same technology level for all ANFIS_S predictors, from Tab. 2 it can be noted that, for high technology level suppliers, lower prediction errors are observed for Supplier_1 than for Supplier_2. For low technology level suppliers, lower prediction errors are observed for Supplier_4 than for Supplier_3. This can be explained by the statistical properties of the testing data sub-sets (Tab. 1): the dressing cases used for testing the ANFIS predictors of Supplier_1 and Supplier_4 have lower standard deviations and dispersion parameters than the dressing cases used for testing the ANFIS predictors of Supplier_2 and Supplier_3, respectively. By comparing suppliers independently from their technology level, for all ANFIS predictors the best performance is obtained for Supplier_4 and the worst is verified for Supplier_3. Also this can be justified by the fact that the testing cases of Supplier_4 have the lowest standard deviation and dispersion parameter, whereas the testing cases of Supplier 3 present the highest standard deviation and dispersion parameter (Tab. 1).

As an example, in Fig. 3 the typical response of the different ANFIS_1 predictors is presented for the first 100 testing cases of Supplier_1 historical data sub-set. From the figure, it can be noted that the predictions of the ANFIS_1/5/1/* (Fig. 5a) display the lowest prediction error of all the ANFIS_1 predictors. Moreover, prediction method A shows a sensitivity to CBN grinding wheel group size p = 5 or 10 by generating typical patterns of 5 or 10 predicted values (Figs. 5b and d), whereas prediction method B yields unrelated predicted values, independently of CBN grinding wheel group size.

6 CONCLUSIONS

Dressing cycle time prediction of CBN grinding wheels for Ni base alloy turbine blade fabrication was carried out for each external tool manufacturer (supplier) in a supply network through a set of multiple-input-single-output Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The ANFIS predictions can be utilised by the turbine blade producer (customer) to evaluate the supplier reliability in CBN grinding wheel delivery, which is a critical parameter in the dressing order allocation procedure. The lowest prediction error was provided, for all suppliers, by the simplest supplier-dependent ANFIS predictor that, however, allows only for one-step-ahead dressing time forecast for single CBN grinding wheel delivery. This prediction is hardly useful because CBN grinding wheels are typically assembled into groups of up to p = 10 before shipping.

ANFIS predictors for p-step-ahead dressing time forecasting for any

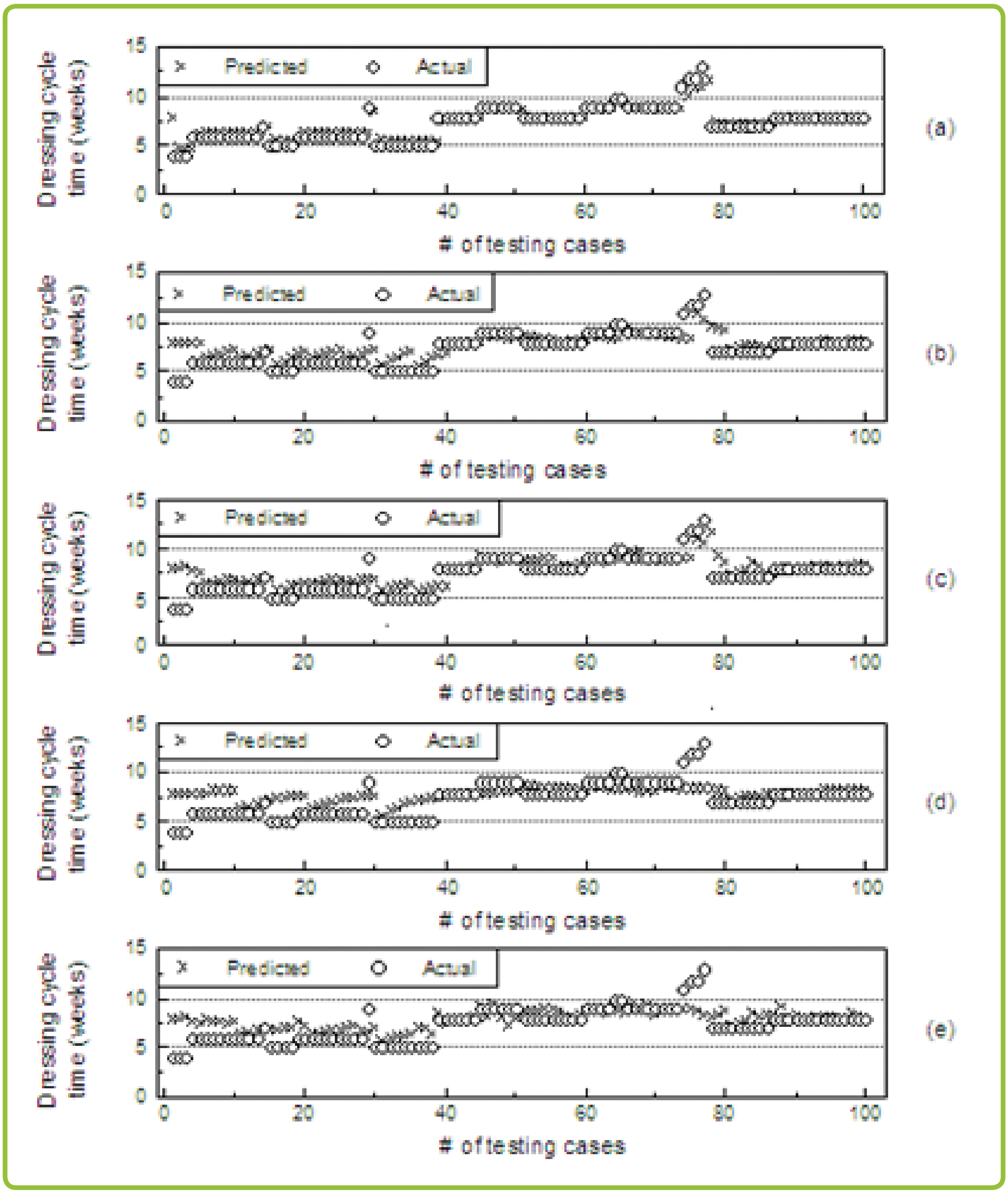

Figure 4.
Predicted and actual dressing cycle times for the first 100 testing cases of Supplier_1:
(a) ANFIS_1/5/1/*;
(b) ANFIS_1/5/5/A;
(c) ANFIS_1/5/5/B;
(d) ANFIS_1/5/10/A;
(e) ANFIS_1/5/10/B

CBN grinding wheel group size, p, were developed according to two methods: single iterated forecasting (method A) or multiple direct forecasting (method B). By comparing ANFIS performance using the same prediction method, prediction error increases with increasing p due to the lengthening of prediction span. By comparing ANFIS performance using the same number of inputs and outputs, method A is better for low technology level suppliers and method B is better for high technology level suppliers; this could be due to the much higher number of learning cases for high technology level suppliers, providing for better learned ANFIS_S that can make good use of the higher computational complexity of method B. By comparing ANFIS performance for all tool manufacturers in the supply network, suppliers with testing data sets displaying lower data dispersion are characterised by lower ANFIS prediction error. The basis of the system development is given by the historical data on tool management. If these data are highly variable, classical stochastic management methods are inapplicable or responsible for excessive inventory sizing. As an alternative, adaptive neuro-fuzzy inference systems (ANFIS) were used for data analysis. ANFIS predictors for dependable tool delivery forecasting were developed in a multiple supplier/single customer transaction scheme. The performance of the ANFIS predictors was higher than the one obtained through a purely stochastic approach, even under the worst operative conditions. Thus, a flexible tool management strategy based on dressing cycle time ANFIS forecasting was proposed.

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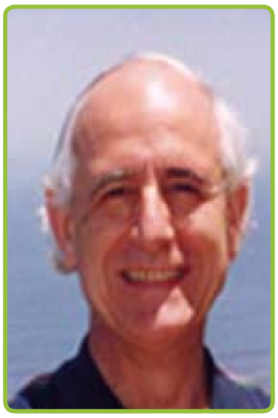
Dr. Doriana D'Addona

daddona@unina.it

Dr. Doriana D'Addona received her MSc in Electronics Eng. at the Univ. of Naples Federico II. After obtaining her PhD title, she received a Post-Doc Fellow contract to work on Intelligent Computation for Production Systems. At present, she works as a Doctoral Research Assistant at the Univ. of Naples.

She has taken part in international research projects and is member of international scientific associations for production engineering. Her research activity is focused on cognitive manufacturing technology and systems.



Prof. Roberto Teti

tetiro@unina.it

Prof. Roberto Teti is a Full Professor of Manufacturing Technology and Systems at the Dept. of Materials and Production Eng., University of Naples Federico II. His research activity is focused on advanced sensor systems for process monitoring; 3D metrology and reverse engineering; cognitive manufacturing technology and systems; NDE techniques. He authored over 200 publications, chaired several international conferences and is a member of international scientific associations for production engineering.