Soft Computing Methods for Practical Environment Solutions:
Techniques and Studies

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Chapter 9
A Soft Computing System for Modelling the Manufacture of Steel Components

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ABSTRACT

This chapter presents a soft computing system developed to optimize the laser milling manufacture of high value steel components, a relatively new and interesting industrial technique. This applied research presents a multidisciplinary study based on the application of unsupervised neural projection models in conjunction with identification systems, in order to find the optimal operating conditions in this industrial issue. Sensors on a laser milling centre capture the data used in this industrial case of study defined under the frame of a machine-tool that manufactures steel components for high value molds and dies. Then a detailed study of the laser milling manufacture of high value steel components is presented based mainly on the analysis of four features: angle error, depth error, surface roughness and material removal rate. The presented model is based on a two-phases application. The first phase uses an unsupervised neural projection model capable of determine if the data collected is informative enough. The second phase is focus on identifying a model for the laser-milling process based on low-order models such as Black Box ones. The whole system is capable of approximating the optimal form of the model. Finally, it is shown that the Box-Jenkins and Output Error algorithms, which calculate the function of a linear system based on its input and output variables, are the most appropriate models to control such indus-

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trial task for the case of the analysed steel tools. The model can be applied to laser milling optimization of other materials of industrial interest and also to other industrial multivariable processes like High Speed Milling or Laser Cladding.

INTRODUCTION

Soft computing represents a collection or set of computational techniques and intelligent systems principles in machine learning, computer science and some engineering disciplines, which investigate, simulate, and analyze very complex issues and phenomena in order to solve real-world problems. Laser Milling is nowadays a very interesting industrial task, which, in general, consists on the controlled evaporation of waste material due to its interaction with high-energy pulsed laser beams.

The operator of a conventional milling machine is aware at all times of the amount of waste material removed, but the same can not be said of a laser milling machine. In this case, the amount of vaporized material depends not only on laser pulse characteristics, but also on the composition of the material to be removed. Indeed, in industrial conditions, the input process variables that could be measured show a too complex relation between then to obtain a proper modelisation using analytical or empirical models.Then a soft computing model that could predict the exact amount of material that each laser pulse is able to remove would contribute to the industrial use and development of this new technology. In this case we are focus on laser milling of steel components. It is an especially interesting industrial process, due to the broad use of steel as base material for different kind of manufacture tools, like molds and dies. One of the applications of this technology to these industrial tools is the deep indelible engraving of serial numbers or barcodes for quality control and security reasons for automotive industry (Wendland et al., 2005). The soft computing model proposed in this paper is able to optimize the manufacturing process and to control laser milling to the level of accuracy that is required for the manufacture of these deep indelible engravings. It has been developed using a combination of Soft computing models and it is applied here to a data set taken from micro-manufacturing laser milling of steel components.

Unsupervised connectionist models can be used as an initial phase or step before a model is established. They are used to analyze the internal structure of the data sets in order to establish that they are sufficiently informative. In the worst case, experiments have to be carried out again.

System identification is a field that refers to the set of techniques used to provide a mathematical model M for estimating the behaviour of a signal of a process for a certain period of time prediction interval (Ljung, 1999). In this study is applied after the use of connectionist models in order to identify the exact amount of material that each laser pulse is able to remove.

The rest of the chapter is organized as follows. Following the introduction, a two-phase process is described to identify the optimal conditions for the industrial laser milling of steel components. The case study that outlines the practical application of the model is then presented. Finally, some different modelling systems are applied and compared, in order to select the optimal model, before ending with some conclusions and future work.

AN INDUSTRIAL PROCESS FOR STEEL COMPONENTS MODELLING

Analyse of the Internal Structure of the Data Set

Cooperative Maximum-Likelihood Hebbian Learning (CMLHL) (Corchado & Fyfe, 2003; Corchado et al., 2003) is used in this research in order to analyze the internal structure of a data set describing an industrial task: a laser milling manufacture of steel components, to identify whether it is "sufficiently informative" by means of the identification of clusters or groups. In the worse case, the experiments have to be performed again in order to collect a proper and informative data set.

CMLHL is a Exploratory Projection Pursuit (EPP) method (Diaconis & Freedman, 1984; Freedman & Tukey, 1974; Corchado et al., 2004). In general, EPP provides a linear projection of a data set, but it projects the data onto a set of basic vectors which help reveal the most interesting data structures; interestingness is usually defined in terms of how far removed the distribution is from the Gaussian distribution (Seung et al., 1998).

One connectionist implementation is Maximum-Likelihood Hebbian Learning (MLHL) (Corchado et al., 2004; Fyfe & Corchado, 2002). It identifies interestingness by maximising the probability of the residuals under specific probability density functions that are non-Gaussian. An extended version is the CMLHL (Corchado et al., 2003) model, which is based on MLHL (Corchado et al., 2004; Fyfe & Corchado, 2002) but adds lateral connections (Corchado & Fyfe, 2003; Corchado et al., 2003) that have been derived from the Rectified Gaussian Distribution (Corchado et al., 2004). Considering an N-dimensional input vector (x), and an M-dimensional output vector (y), with w_{ij} being the weight (linking input j to output i), then CMLHL can be expressed (Corchado & Fyfe, 2003; Corchado et al., 2003) as:

1. Feed-forward step:

$$y_i = \sum_{j=1}^{N} W_{ij} x_j, \forall i \qquad (1)$$

2. Lateral activation passing:

$$y_i\left(t+1\right) = \left[y_i(t) + \ddot{A}\left(b - Ay\right)\right]^+ \qquad (2)$$

3. Feedback step:

$$e_j = x_j - \sum_{i=1}^{M} W_{ij} y_i, \forall j \qquad (3)$$

4. Weight change:

$$\Delta W_{ij} = \eta . y_i . sign\left(e_j\right) | e_j |^{p-1} \qquad (4)$$

Where: $\eta$is the learning rate,τ is the "strength" of the lateral connections, b the bias parameter, p a parameter related to the energy function (Corchado & Fyfe, 2003; Corchado et al., 2004; Fyfe & Corchado, 2002), and A a symmetric matrix used to modify the response to the data (Corchado et al., 2004). The effect of this matrix is based on the relation between the distances separating the output neurons.

System Identification and the Knowlegde Based Systems

System identification is a well known knowledge area that refers to the set of techniques used in obtaining a mathematical model M for estimating the behaviour of a signal of a process for a certain period of time prediction interval (Ljung, 1999) For such modeling task, a dataset of representative of the process input, perturbations, and output -or controlled-signals are given. The model M establishes not only the structure or formulae but also is responsible for fitting its parameters $\hat{\theta} = \theta$. Given the characteristics of the real process, behaviour or signal to be modeled, the identification procedures establish the optimization and testing the model.

In the identification literature there has been a great deal of successful applications of system identification in different areas: control, robotics, forecasting, power systems, predictions, signal processing. Some examples are mentioned below to catch a glimpse of the wide influence of system identification. In (Jurado, 2004), SOFC energy plants and the distribution system modelling were afforded using ARX and BJ structures. In (Pacheco & Steffen, 2004), the modelling of a nonlinear mechanical system using nonlinear models and Volterra series is studied. A duffy ostrictive actuator and an electrostrictive actuator have been identified by means of the high order frequency response functions of the associated linear equations (Vazquez et al., 2004). The development of a fault detection model in Civil Engineering is detailed in (Liu et al., 2001). The identification of a delignification process (Chen & Billings, 1989), the modeling and prediction of machining errors (Fung et al., 2003), and the identification of a gas turbine power plant (Basso et al., 2002) are some examples of using nonlinear models with NARMAX structures.

The prediction of the heat transfer coefficient is analysed in (Mihir & Kishor, 2009), where a zero-order fuzzy model is compared with the prediction obtained with ANFIS. Also, several works using neural networks in practical identification applications can be found in the literature: the prediction of a machine operation conditions faults using ANFIS and pre-processing the data using nearest neighbours with the mutual information measure (Tran et al., 2009), the modelling of the termosyphon close loop cooling process (Fichera & Pagano, 2002), the prediction of the relationship between the fuel flow and the shaft speed dynamics of a gas turbine engine (Neophytos et al., 2002), the vitrations modelling in a magnetorheological damper (Xia, 2003) and the detection of the structural damage in PVC sandwich plates in the aeronautical and locomotion industry (Yam et al., 2003). In (Esen & Inalli, 2009) a vertical ground coupled heat pump system is modelled using artificial neural networks and back-propagation training method. Support vector machines have been satisfactorily applied in modelling the efficiency of a solar-air heating system (Esen et al., 2009). In (Venkatesh, 2004) some requisites for a robustness identification are analysed. Especifically, the prediction of a pulsed-laser process conditions is solved by means of neural networks hybridised with Particle Swarm Optimization in (Ciurana et al., 2009).

Nowadays there are some computer tools helping in the development of models, but they require the users´ expertise in order to obtain good results. Some computer tools are standardised in the system identification community. Mat-lab suite from The Mathworks (MathWorks) is the best known computer tool, and the greater part of the published works makes use of it. The R project (The R_project) is an equivalent, lesser used computer tool. Also, LabView is a well known commercial software tool in system identification (Labview, 2004).

The Identification Criterion

The identification criterion evaluates which of the group of candidate models is best adapted to and which best describes the data sets collected in the experiment; i.e., given a model $M(\theta_*)$ its prediction error may be defined by equation (5); and a good model (Ljung, 1999) will be that which makes the best predictions, and which produces the smallest errors when compared against the observed data. In other words, for any given data group Z^t, the ideal model will calculate the prediction error $\varepsilon(t,\theta)$, equation (5), in such a way that for any one t=N, a particular $\hat{\theta}_N$ (estimated parametrical vector) is selected so that the prediction error $\varepsilon(t,\hat{\theta}_N)$ in t=1,2,3…N, is made as small as possible.

$$\varepsilon(t,\theta_*) = y(t) - \hat{y}(t \mid \theta_*) \tag{5}$$

The estimated parametrical vector $\hat{\theta}$ that minimizes the error, equation (8), is obtained from the minimization of the error function (6). This is obtained by applying the least-squares criterion for the linear regression, i.e., by applying the quadratic norm $\ell(\varepsilon) = \frac{1}{2}\varepsilon^2$, equation (7).

Table 1. Black-box model structures

Polynomials in (10)	Polynomials used in (10)	Name of model structure
$A(q^{-1}) = 1 + a_1(q^{-1}) + a_2(q^{-2}) + \cdots + a_{n_a}(q^{-n_a})$ $B(q^{-1}) = b_1(q^{-1}) + b_2(q^{-2}) + \cdots + b_{n_b}(q^{-n_b})$ $C(q^{-1}) = 1 + c_1(q^{-1}) + c_2(q^{-2}) + \cdots + c_{n_c}(q^{-n_c})$ $D(q^{-1}) = 1 + d_1(q^{-1}) + d_2(q^{-2}) + \cdots + d_{n_d}(q^{-n_d})$ $F(q^{-1}) = 1 + f_1(q^{-1}) + f_2(q^{-2}) + \cdots + f_{n_f}(q^{-n_f})$	B AB ABC AC BF BFCD	FIR ARX ARMAX ARMA OE BJ

$$V_N(\theta, Z^N) = \frac{1}{N}\sum_{t=1}^{N} \ell(\varepsilon_F(t,\theta)) \tag{6}$$

$$V_N(\theta, Z^N) = \frac{1}{N}\sum_{t=1}^{N} \frac{1}{2}(y(t) - \hat{y}(t \mid \theta))^2 \tag{7}$$

$$\hat{\theta} = \hat{\theta}_N(Z^N) = \arg\min_{\theta \in D_M} V_N(\theta, Z^N) \tag{8}$$

The methodology of black-box structures has the advantage of only requiring very few explicit assumptions regarding the pattern to be identified, but that in turn makes it difficult to quantify the model that is obtained. The discrete linear models may be represented through the union between a deterministic and a stochastic part, equation (9); the term *e(t)* (white noise signal) includes the modelling errors and is associated with a series of random variables, of mean null value and variance λ.

$$y(t) = G(q^{-1})u(t) + H(q^{-1})e(t) \tag{9}$$

The structure of a black-box model depends on the way in which the noise is modelled $H(q^{-1})$; thus, if this value is 1, then the OE (Output Error) model is applicable; whereas, if it is different from zero a great range of models may be applicable; one of the most common being the BJ (Box Jenkins) algorithm. This structure may be represented in the form of a general model, where $B(q^{-1})$ is a polynomial of grade n_b, which can incorporate pure delay n_k in the inputs, and $A(q^{-1})$, $C(q^{-1})$, $D(q^{-1})$ and $F(q^{-1})$ are autoregressive polynomials ordered as n_a, n_c, n_d, n_f, respectively, equation (10). Likewise, it is possible to use a predictor expression, for the on-step prediction ahead of the output $\hat{y}(t \mid \theta)$, equation (11),. In Table 1, the generalized polynomial expressions are presented, as well as those that represent the polynomials used in the case of each particular model.

$$A(q^{-1})y(t) = q^{-n_k}\frac{B(q^{-1})}{F(q^{-1})}u(t) + \frac{C(q^{-1})}{D(q^{-1})}e(t) \tag{10}$$

$$\hat{y}(t \mid \theta) = \frac{D(q^{-1})B(q^{-1})}{C(q^{-1})F(q^{-1})}u(t) + \left[1 - \frac{D(q^{-1})A(q^{-1})}{C(q^{-1})}\right]y(t) \tag{11}$$

Procedure for Modelling the Laser Milling Process. The identification procedure used to arrive at a parameterized model M, which will eventually be selected as the best from among those that modelled the laser milling characteristics on the basis of the variable measurements, is carried out in accordance with two fundamental patterns: a first pre-analytical and then an analytical stage that assists with the determination of the parameters in the identification process and the model estimation. The pre-analysis test is run to establish the identification techniques (Ljung, 1999; Nögaard et al., 2000; Söderström & Stoica, 1989; Nelles, 2001; Haber & Keviczky, 1999b; Haber & Keviczky, 1999a), the selection of the model structure and its order estimation (Stoica & Söderström, 1982; He & Asada, 1993) the identification criterion and search methods that minimize it and the specific parametrical selection for each type of model structure.

A second validation stage ensures that the selected model meets the necessary conditions for estimation and prediction. Three tests were performed to validate the model: residual analysis $\varepsilon(t, \hat{\theta}(t))$, by means of a correlation test between inputs, residuals and their combinations; final prediction error (FPE) estimate, as explained by Akaike (Akaike, 1969); and the graphical comparison between desired outputs and the outcome of the models through simulation one (or k) steps before.

MODELLING STEEL COMPONENTS: AN INDUSTRIAL TASK

This research is interested on the study and identification of the optimal conditions for laser milling of deep indelible engraving of serial numbers or barcodes on steel components using a commercial Nd:YAG laser with a pulse length of 10μs. Three parameters of the laser process can be controlled: laser power (u_1), laser milling speed (u_2) and laser pulse frequency (u_3). The laser is integrated in a laser milling centre (DMG Lasertec 40).

To simplify this industrial problem a test piece was designed and used in all of the laser milling experiments. It consisted on an inverted, truncated, pyramid profile that had to be laser milled on a flat metallic piece of steel. The truncated pyramid had angles of 135º, and a depth of 1 mm, but as the optimized parameters for the laser milling of steel were not known at that point in time, both parameters showed errors, which are referred as angle error (y_1) and depth error (y_2). A third parameter to be considered was the surface roughness of the milled piece (y_3), measured on the flat surface of the truncated pyramid. A last parameter is the removal rate, that is the number of cubic millimeters of steel removed by the laser per minute (y_4). These four variables have to be optimized, because the industrial process required a precise geometrical shape, a good surface roughness of the piece and the shorter manufacturing time. We applied different modelling systems to achieve the optimal conditions of these four parameters.

The experimental design was performed on a Taguchi L25 with 3 input parameters and 5 levels, so as to include the entire range of laser milling settings that are controllable by the operator. Table 2 summarizes the input and output variables of the experiment which define the case of study. The experiment was performed on the test piece described above. After the laser milling, actual inverted pyramid depth, walls angle and surface roughness (y_3) of the bottom surface were measured using optical devices. Considering the whole time required for the manufacture of each sample and the actual volume of removed material the material removal rate (y_4) was also calculated. The measured walls angle and the pyramid depth were compared with the nominal values in the CAD model, thereby obtaining the two errors (y_1 and y_2). The test piece and the prototype were described in detail beforehand (Arias et al., 2007).

Application of the Two Phases of the Modelling System

The study has organized into two phases or steps.

- **Step 1:** Analysis of the internal structure of the data set based on the application of several unsupervised connectionist models.
- **Step 2:** Application of several identification models in order to find the one

Table 2. Variables, units and values used during the experiments. All values are common to this laser milling process. Output y(t), Input u(t)

Variable (Units)	*Range*
o Angle error of the test piece, $y_1(t)$	-1 to 1
o Depth error of the test piece, $y_2(t)$	-1 to 1
o Surface roughness of the test piece (μm), $y_3(t)$	0.8 to 15
o Material removal rate (mm^3/min), $y_4(t)$	0.32 – 4.38
o Laser power in percent of the maximum power performed by the laser (%), $u_1(t)$.	20 to 100
o Laser milling speed (mm/s), $u_2(t)$.	200 to 800
o Laser pulse frequency (kHz), $u_3(t)$.	20 to 100

that best defines the dynamic of the laser milling process.

Step 1. Figure 1 shows the results obtained by means of CMLHL projections. This model is able to identify three different clusters or groups order mainly by power. Also each group is formed by three subgroups organized by frequency and speed. After studying each cluster it can be noted a second classification based on the speed and frequency as it is shown in Figure 1. The existence of such organized internal structure indicates that the data analysed is sufficiently informative.

Step 2. Modelling the laser milling process. Figure 2, shows the results of output $y_1(t)$, angle error and $y_4(t)$, material removal rate, respectively. Figure 3, shows the results of output $y_2(t)$, depth error and $y_3(t)$, surface roughness, respectively.

They show the graphic representations of the best results, for OE y BJ models, in relation to the polynomial order and the delay in the inputs; various delays for all inputs and various polynomial orders [n_{b1} n_{b2} n_{b3} n_c n_d n_f n_{k1} n_{k2} n_{k3}] were considered to arrive at the highest degree of precision, in accordance with the structure of the models that have been used; see Table 1. In Figure 2, Figure

Figure 1. The first of two projections obtained by CMLHL

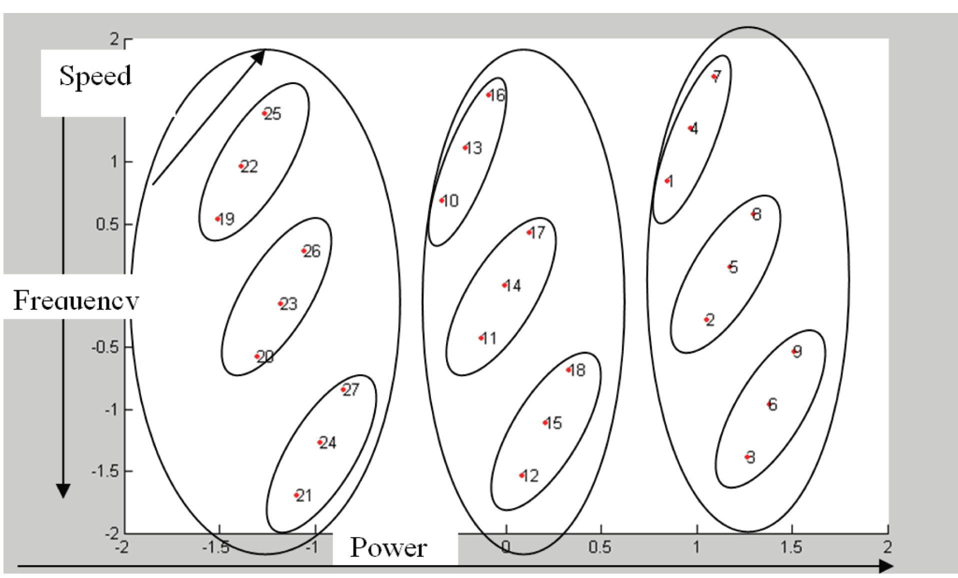
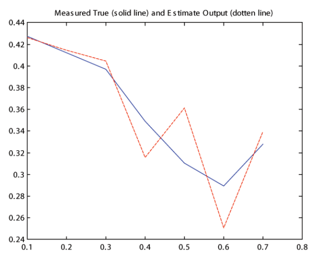
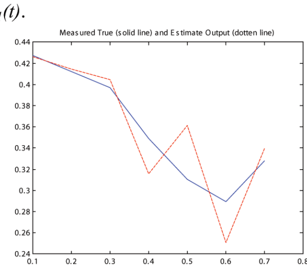


Figure 2. Representation of measured output, simulated output and one-step-ahead prediction for two–box models. The model generated by the OE and the BJ models for angle error, output $y_1(t)$, are shown in rows 1, 2, respectively. On the left, measured output vs. simulated output, on the right, measured output vs. one-step-ahead prediction. The OE and the BJ models for output $y_4(t)$, Material removal rate are shown in rows 3, 4, respectively. The validation data set was not used for the estimation of the model. The order of the structure of the model is [1 1 1 2 2 2 1 1 1] for $y_1(t)$ and [2 1 1 2 1 1 2 1 1] for $y_4(t)$. The solid line represents true measurements and the dotted line represents estimated output

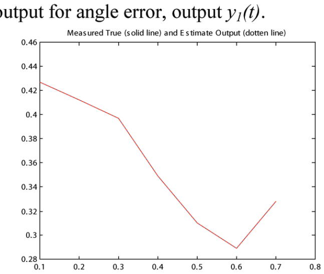
Model OE [ ]: Measured output Simulated output for angle error, output $y_1(t)$.



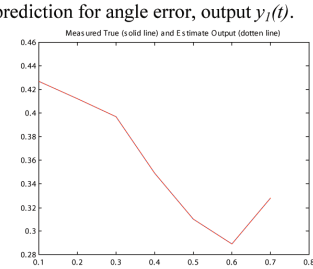
Model OE [ ]: Measured output 1 Step ahead prediction, for angle error, output $y_1(t)$.



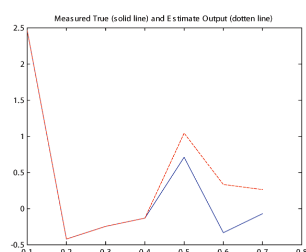
Model BJ [ ]: Measured output Simulated output for angle error, output $y_1(t)$.



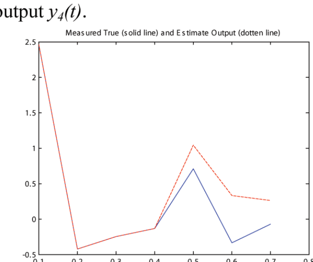
Model BJ [ ]: Measured output 1 Step ahead prediction for angle error, output $y_1(t)$.



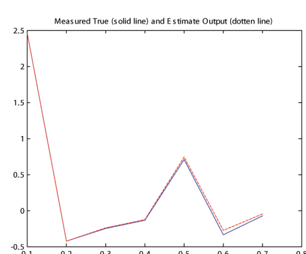
Model OE [ ]: Measured output Simulated output for material removal rate, output $y_4(t)$.



Model OE [ ]: Measured output 1 Step ahead prediction for material removal rate, output $y_4(t)$.



Model BJ [ ]: Measured output Simulated output for material removal rate, output $y_4(t)$.



Model BJ [ ]: Measured output 1 Step ahead prediction for material removal rate, output $y_4(t)$.

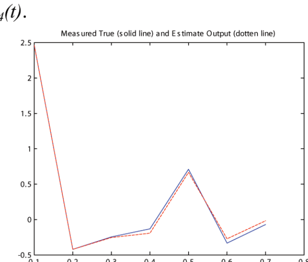
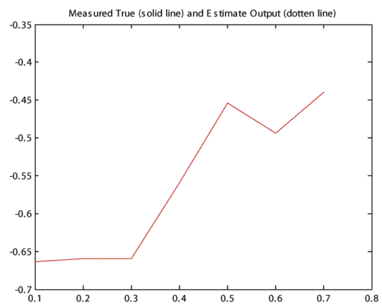
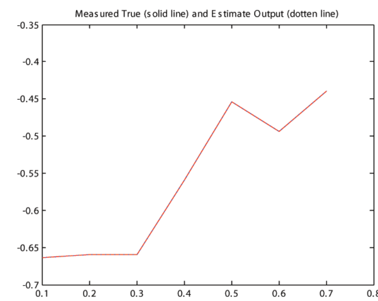


Figure 3. Representation of measured output, simulated output and one-step-ahead prediction for two–box models. The model generated by the OE model for Depth error, output $y_2(t)$, is shown in row 1. On the left, measured output vs. simulated output, on the right, measured output vs. one-step-ahead prediction. The OE and the BJ models for output $y_3(t)$, surface roughness are shown in rows 2, 3, respectively. The validation data set was not used for the estimation of the model. The order of the structure of the model is [1 2 1 2 1 2 1] for $y_2(t)$ and [3 1 1 2 1 1 2 1 1] for $y_3(t)$. The solid line represents true measurements and the dotted line represents estimated output

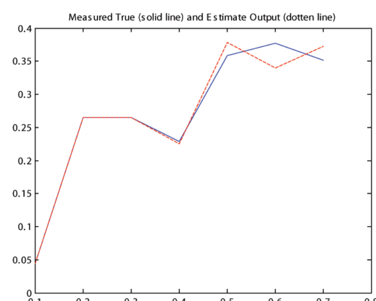
Model OE [ ]: Measured output Simulated output for depth error of the test piece, output $y_2(t)$.



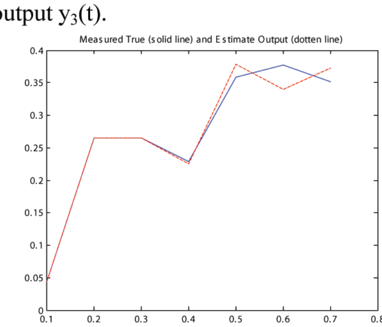
Model OE [ ]: Measured output 1 Step ahead prediction, depth error of the test piece, output $y_2(t)$.



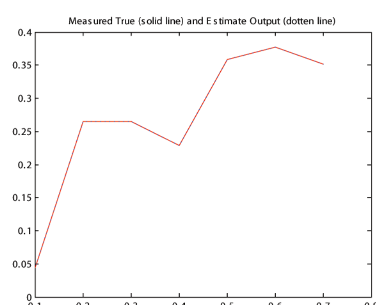
Model OE [ ]: Measured output Simulated output for surface roughness, output $y_3(t)$.



Model OE [ ]: Measured output 1 Step ahead prediction for surface roughness, output $y_3(t)$.



Model BJ [ ]: Measured output Simulated output for surface roughness, output $y_3(t)$.



Model BJ [ ]: Measured output 1 Step ahead prediction for surface roughness, output $y_3(t)$.

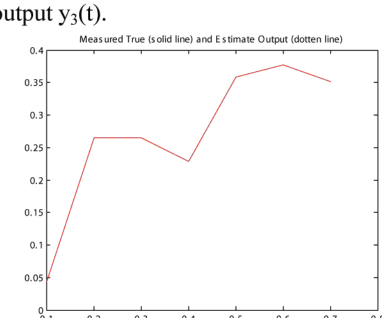


Table 3. Indicator values for several proposed models of the angle error

Model	Indexes
Black-box OE model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_f=2, n_{k1}=1, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out from the best AIC criterion (the structure that minimizes AIC).	FIT:44.04%, FIT1:44.04% FIT10:44.04%, V: 0.02 FPE:0.23, NSSE:7.71e-4
Black-box OE model n_{b1}=1, n_{b2}=1, n_{b3}=1, n_f=2, n_{k1}=1, n_{k2}=1, n_{k3}=1.The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:21.2%, FIT1: 21.2% FIT10: 21.2%, V: 0.023 FPE:0.162, NSSE:0.0015
Black-box BJ model with n_{b1}=1, n_{b2}=1, n_{b3}=1, n_c=2, n_d=2, n_f=2, n_{k1}=1, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:100%, FIT1:100% FIT10:100%, V: 0.12 FPE:0.27 NSSE:2.73e-31
Black-box BJ model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_c=2, n_d=2, n_f=2, n_{k1}=1, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:100%, FIT1:100% FIT10:100%, V: 0.97 FPE:1,75 NSSE:4.17e-30

3, the X-axis shows the number of samples used in the validation of the model, while the Y-axis represents the range of output variables.

Table 3, Table 4, Table 5 and Table 6 show a comparison of the qualities of estimation and prediction of the best models obtained, as a function of the model, the estimation method, and the indexes, which are defined as follows:

- The percentage representation of the estimated model (expressed as so many percent "%") in relation to the true system: the numeric value of the normalized mean error that is computed with one-step prediction (FIT1), with ten-step prediction (FIT10), or by means of simulation (FIT). Also shown are the graphical representations of true system output and both the one-step prediction $\hat{y}_1(t \mid m)$, the ten-step prediction $\hat{y}_{10}(t \mid m)$, and the model simulation $\hat{y}_{\infty}(t \mid m)$. The equations (12), (13) and (14) show as is calculated the percentage representation of the estimation of model from the one-step ahead prediction (FIT1), in the same form are calculated the others indexes FIT10 and FIT.

$$\hat{y}_1(t \mid m) = \hat{H}^{-1}(q)\hat{G}(q)u(t) + (1 - \hat{H}^{-1}(q))y(t) \tag{12}$$

$$J_1(m) = \frac{1}{N}\sum_{t=1}^{N} | y(t) - \hat{y}_1(t \mid m) |^2 \tag{13}$$

$$FIT1\ (\%) = \left[1 - \frac{\sqrt{J_1(m)}}{\sqrt{\frac{1}{N}\sum_{t=1}^{N} | y(t) |^2}} \right] 100 \tag{14}$$

- The loss or the error function (V): the numeric value of the mean square error that is calculated from the estimation data set, equation (13).
- The generalization error value (NSSE): the numeric value of the mean square error that is calculated from the validation data set, equation (13).
- The average generalization error value (FPE): This is the numeric value of the FPE

Table 4. Indicator values for several proposed models of the depth error

Model	Indexes
Black-box OE model with n_{b1}=1, n_{b2}=2, n_{b3}=1, n_f=2, n_{k1}=1, n_{k2}=2, n_{k3}=1.. The model is estimated using the prediction error method, the degree of the model selection is carried out from the best AIC criterion (the structure that minimizes AIC).	FIT:100%, FIT1:100% FIT10:100%, V: 0.051 FPE:0.636 NSSE:1.08e-27
Black-box BJ model with n_{b1}=1, n_{b2}=3, n_{b3}=1, n_c=2, n_d=1, n_f=1, n_{k1}=1, n_{k2}=2, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:100%, FIT1:100% FIT10:100%, V: 0.07 FPE:1.331 NSSE:1.24e-28
Black-box BJ model with n_{b1}=2, n_{b2}=2, n_{b3}=2, n_c=2, n_d=1, n_f=1, n_{k1}=2, n_{k2}=2, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:65.16%, FIT1:59.98% FIT10:63.32%, V: -0.12 FPE:0.471 NSSE:0.0014

Table 5. Indicator values for several proposed models of the surface roughness

Model	Indexes
Black-box OE model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_f=1, n_{k1}=1, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out from the best AIC criterion (the structure that minimizes AIC).	FIT:59.31%, FIT1: 59.31% FIT10: 59.31%, V: 0.005 FPE:0.0172, NSSE:0.0019
Black-box OE model with n_{b1}=3, n_{b2}=1, n_{b3}=1, n_f=1, n_{k1}=2, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:83.15%, FIT1: 83.15% FIT10: 83.15%, V: 0.055 FPE:0.031 NSSE:3.20e-4
Black-box BJ model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_c=2, n_d=1, n_f=1, n_{k1}=1, n_{k2}=1, n_{k3}=1.The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:61.68%, FIT1:60.85% FIT10:59.15%, V: 0.0024 FPE:0.045, NSSE:0.0019
Black-box BJ model with n_{b1}=3, n_{b2}=1, n_{b3}=1, n_c=2, n_d=1, n_f=1, n_{k1}=2, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:100%, FIT1:100% FIT10:100%, V: 0.0015 FPE:0.0281 NSSE:5.3e-23

Table 6. Indicator values for several proposed models of the material removal rate

Model	Indexes
Black-box OE model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_f=1, n_{k1}=1, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out from the best AIC criterion (the structure that minimizes AIC).	FIT:48.26%, FIT1: 48.26% FIT10: 48.26%, V: 0.88 FPE:3.05, NSSE:0.244
Black-box OE model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_f=1, n_{k1}=2, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:67.82%, FIT1: 67.82% FIT10: 67.82%, V: 0.34 FPE:1.29, NSSE:0.094
Black-box BJ model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_c=2, n_d=1, n_f=1, n_{k1}=1, n_{k2}=1, n_{k3}=1.The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:90.34%, FIT1:89.34% FIT10:89.5%, V: 0.3 FPE:2.11, NSSE:0.02
Black-box BJ model with n_{b1}=2, n_{b2}=1, n_{b3}=1, n_c=2, n_d=1, n_f=1, n_{k1}=2, n_{k2}=1, n_{k3}=1. The model is estimated using the prediction error method, the degree of the model selection is carried out with the best AIC criterion (the structure that minimizes AIC).	FIT:96.73%, FIT1:95.58% FIT10:95.5%, V: 0.15 FPE:1.42, NSSE:0.0018

Table 7. Function and parameters that represent the behaviour of the laser milled piece for the angle error. The degree of the BJ model polynomials are n_{b1}=1, n_{b2}=1, n_{b3}=1, n_c=2, n_d=2, n_f=2, n_{k1}=1, n_{k2}=1, n_{k3}=1. [1 1 1 2 2 2 1 1 1]

Parameters and polynomials.	
$B1(q) = 0.01269\ q^{-1}$	$D(q) = 1 + 1.208\ q^{-1} + 0.3098\ q^{-2}$
$B2(q) = 0.0004895\ q^{-1}$	$F1(q) = 1 + 0.4094\ q^{-1} - 0.16\ q^{-2}$
$B3(q) = 0.01366\ q^{-1}$	$F2(q) = 1 - 1.678\ q^{-1} + 0.7838\ q^{-2}$
$C(q) = 1 + 1.541\ q^{-1} + 1.02\ q^{-2}$	$F3(q) = 1 - 1.1\ q^{-1} + 0.7671\ q^{-2}$ e(t) is white noise signal whit variance 0.08

criterion that is calculated from the estimation data set. The equation (15) shows as is calculated the value FPE, where: d_M is the dimension of θ -estimated parametrical vector- and Z^N are the estimation data set.

$$FPE = \bar{J}_p(m) \approx J_1(m) + \frac{J_1(m)}{1-(d_M / N)} \frac{2d_M}{N} \quad (15)$$

From the graphical representation (Figure 2, Figure 3) it can be concluded that the BJ model is capable of simulating and predicting the behaviour of the laser milled piece (for angle error, for surface roughness and for material removal rate) as it meet the indicators and is capable of modelling more than 95% of the true measurements. The OE model is capable of simulating and predicting the behaviour of the other output (depth error) and it's capable of modelling 100% of the true measurements. The tests were performed using Matlab and the System Identification Toolbox. Tables 7, 9, 10 and Table 8 show the finals BJ and OE models, respectively.

The obtained models can be used not only to predict the angle error, the depth error, the surface roughness and the material removal rate, but also to determine the optimal conditions to minimize the errors. Considering that the model is a polynomial model, if all except one input variable are fixed, then the remaining variable could be calculated and fixed in order to minimize the angle error and the depth error of the flat metallic test piece of Steel.

FUTURE RESEARCH DIRECTIONS

Future work will be focus on the study and application of this model to other kinds of materials of industrial interest, such as cast single-crystal nickel superalloys for high-pressure turbine blades and also the application of this model to the optimization of other but similar industrial problems, like laser cladding, laser super-polishing and laser drilling. Also the upgrading of this model

Table 8. Function and parameters that represent the behaviour of the laser milled piece for the depth error. The degree of the OE model polynomials are n_{b1}=1, n_{b2}=2, n_{b3}=1, n_f=2, n_{k1}=1, n_{k2}=2, n_{k3}=1. [1 2 1 2 1 2 1]

Parameters and polynomials.	
$B1(q) = 0.003554\ q^{-1}$	$F1(q) = 1 - 0.4365\ q^{-1} - 0.1936\ q^{-2}$
$B2(q) = -0.00224\ q^{-2} - 0.003145\ q^{-3}$	$F2(q) = 1 - 0.5375\ q^{-1} - 0.4496\ q^{-2}$
$B3(q) = -0.02758\ q^{-1}$	$F3(q) = 1 - 1.677\ q^{-1} + 0.9613\ q^{-2}$ e(t) is white noise signal whit variance 0.34

Table 9. Function and parameters that represent the behaviour of the laser milled piece for the surface roughness. The degree of the BJ model polynomials are $n_{b1}=3$, $n_{b2}=1$, $n_{b3}=1$, $n_c=2$, $n_d=1$, $n_f=1$, $n_{k1}=2$, $n_{k2}=1$, $n_{k3}=1$. [3 1 1 2 1 1 2 1 1]

Parameters and polynomials.	
$B1(q) = -0.0110\ q^{-2} + 0.014\ q^{-3} - 0.07\ q^{-5}$	$D(q) = 1 + 0.7715\ q^{-1}$
$B2(q) = -0.0005157\ q^{-1}$	$F1(q) = 1 - 1.006\ q^{-1}$
$B3(q) = 0.003764\ q^{-1}$	$F2(q) = 1 - 0.001624\ q^{-1}$
$C(q) = 1 - 0.4865\ q^{-1} - 0.528\ q^{-2}$	$F3(q) = 1 - 0.3292\ q^{-1}$ e(t) is white noise signal whit variance 0.01

will be analysed to be improved, establishing an intermediate step allowing a feature selection process, in order to speed up the last step. Then several feature selection models will be applied and compared to identify the best one in each case/material.

CONCLUSION

We have done an investigation to study and identify the most appropriate modelling system for laser milling of steel components. Several methods were investigated to achieve the best practical solution to this interesting problem. The study shows that the BJ model is best adapted to the case of angle error, the surface roughness and the material removal rate, whereas OE model is best adapted, with lower variance of the error e(t), to the case of the depth error, in terms of identifying the best conditions and predicting future circumstances.

It is important to emphasize that a relevant aspect of this research lies in the use of a two-step model when modelling the laser milling process for steel components: a first step, which applies projection methods to establish whether the data describing the case study is "sufficiently informative". As a consequence, the first phase eliminates one of the problems associated with these identification systems, which is that of having no prior knowledge of whether the experiment that generated the data group may be considered acceptable and will present sufficient information in order to identify the overall nature of the problem. It is important to emphasize that this soft-computing based model can be applied to some other material as explained before but also to several many industrial problems related to process simulation and prediction.

Table 10. Function and parameters that represent the behaviour of the laser milled piece for the material removal rate.. The degree of the BJ model polynomials are $n_{b1}=2$, $n_{b2}=1$, $n_{b3}=1$, $n_c=2$, $n_d=1$, $n_f=1$, $n_{k1}=2$, $n_{k2}=1$, $n_{k3}=1$ [2 1 1 2 1 1 2 1 1]

Parameters and polynomials.	
$B1(q) = 0.093\ q^{-2} - 0.06508\ q^{-3}$	$D(q) = 1 + 0.647\ q^{-1}$
$B2(q) = -0.006598\ q^{-1}$	$F1(q) = 1 + 0.3556\ q^{-1}$
$B3(q) = 0.0004217\ q^{-1}$	$F2(q) = 1 + 0.9642\ q^{-1}$
$C(q) = 1 - 0.3523\ q^{-1} - 0.6638\ q^{-2}$	$F3(q) = 1 + 0.04872\ q^{-1}$ e(t) is white noise signal whit variance 0.78

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