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IDENTIFICATION OF THE OPTIMAL CONDITIONS OF A PNEUMATIC DRILL

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Abstract

This paper presents a multidisciplinary study that identifies and applies unsupervised connectionist models in conjunction with modelling systems, in order to determine optimal conditions to perform automated drilling tasks. This industrial problem is defined by a data set relayed through sensors situated on a robotic drill that is used to build industrial warehouses. The results of the study and the application of the connectionist architectures allow the identification, in a second phase, of a model for a drilling robot based on low-order models such as Black Box, which are capable of approximating the optimal form of the model. Finally, it is shown that the most appropriate model to control these industrial tasks is the Box-Jenkins algorithm, which calculates the function of a linear system from its input and output samples.

1. Introduction

The storage of goods under optimal conditions represents an important industrial need that often calls for the modernisation or replacement of existing facilities. Large warehouses often need to be built, for example, for auto-carrier storage. The drilling of reinforced concrete slabs, needed to install shelves in such warehouses, is generally a manual task performed by the workforce. This process may be automatised however, thereby reducing overall construction costs and shortening assembly times. Automatisation requires the design of a drilling robot that can carry out the aforementioned operation and make more economic use of the drilling tool. The robot must be capable of calibrating the position of the bits and their diameters, determining operations to suck in, to filter and to recirculate the water for drilling, and testing the tool conditions during automatic changing when required. Performing these tasks regularly improves assembly quality, decreases drilling time and wear, all of which adds to the duration of the drill bit and reduces corrective actions, saving both time and money. These very real types of industrial problems may be analysed by a combination of conventional and AI models.

Unsupervised learning can be used initially, as a preliminary phase before the model is established that will analyse the internal structure of the data sets. Consequentially, we need to know whether the data sets are “informative enough”, i.e., to know whether the data allows discrimination between any two different models in the set. Exploratory Projection Pursuit (EPP) [1] is a statistical method aimed at solving the difficult problem of identifying structure in high dimensional data.

From the latter analysis, of the data, i.e., whether the experiment and the data are “informative enough”, and from the nature of their dynamics, they will be used to obtain a model, which represents the real system sufficiently well. To do so, different techniques for the identification of the systems will be used; these consist in obtaining the mathematical models of the dynamic systems from measurements of the process: inputs u(t), outputs y(t) and perturbations e(t)

Then, this research presents a two-phase process in order to identify the optimal conditions of a pneumatic drill. The paper is organised as follows. Section 2 introduces the first step of the modelling process, based on an internal structural analysis of a data set in order to know whether the data is “informative enough. Section 3 present the identification of the modelling system, after which section 4, provides details on the problem, data description and an analysis and comparison of the best models and results, before moving on to a brief conclusion in the final section.

2. Analysis of the Internal Structure of the data set

2. 1.a Principal Component Analysis

Principal Component Analysis (PCA) originated in work by Pearson [2], and independently by Hotelling [3] describing multivariate data set variations in terms of uncorrelated variables, each of which is a linear combination of the original variables. Its main goal is to derive new variables, in decreasing order of importance, which are linear combinations of the original variables and are uncorrelated with each other. It is a well-known technique that can be implemented by a number of connectionist models [4], [5].

2. 1.b A Neural Implementation of Exploratory Projection Pursuit

The standard statistical method of EPP [6], [7] provides a linear projection of a data set, but it projects the data onto a set of basic vectors which best reveal the interesting structure in data; interestingness is usually defined in terms of how far the distribution is from the Gaussian distribution [8].

One neural implementation of EPP is Maximum Likelihood Hebbian Learning (MLHL) [7], [9]. It identifies interestingness by maximising the probability of the residuals under specific probability density functions that are non-Gaussian.

An extended version of this model is the Cooperative Maximum Likelihood Hebbian Learning (CMLHL) [10] model. CMLHL is based on MLHL [7], [9] adding lateral connections [11], [10] which have been derived from the Rectified Gaussian Distribution [8]. The resultant net can find the independent factors of a data set but does so in a way that captures some type of global ordering in the data set.

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 [12], [13] as:

1. Feed-forward step:

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

2. Lateral activation passing:

$$y_i(t+1) = [y_i(t) + \tau(b - Ay)]^+ \quad . \qquad (2)$$

3. Feedback step:

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

4. Weight change:

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

Where: t is the temperature, $[\ ]^+$ is the rectification necessary to ensure that the **y**-values keep to the positive quadrant, η is the learning rate, τ is the "strength" of the lateral connections, b the bias parameter, p a parameter related to the energy function [10], [7], [9] and A a symmetric matrix used to modify the response to the data [10]. The effect of this matrix is based on the relation between the distances separating the output neurons.

3. Classical Modelling System: Identification algorithms.

3.1 The identification criterion

The identification criterion consists in evaluating which of the group of candidate models is best adapted and best described the group of data collected in the experiment; i.e., given a certain model $M(\theta_*)$ its prediction error may be defined by equation (5); what wish to obtain is a model that complies with the following premise [12]: a good model is one that makes good predictions, and which produces tiny errors when the observed data is applied, i.e., on any one data group Z^t it 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.

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

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).

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

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

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

3.2 Black-box models

The methodology of black-box structures has the advantage of only requiring very few explicit assumptions on 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 are applicable; one of the most common is the BJ (Box Jenkins) . 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 $A(q^{-1})$, $C(q^{-1})$, $D(q^{-1})$ y $F(q^{-1})$ are autroregressive polynomials ordered as n_a, n_c, n_d, n_f, respectively (10). In the same way, it is possible to use a predictor expression, for the on-step prediction ahead of the output $\hat{y}(t \mid \theta)$ (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.

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

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

Table 1. Black-box models structures

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

3.3 Procedure for modelling the drilling robot

The identification procedure followed to obtain a parametrized model *M*, selected as the best of those that model the drilling characteristics based on 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 establishes the identification techniques [12], [13], [14], [15], [16], [17], the selection of the model structure and its order estimation [18], [19], 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. In order to validate the model, three tests were performed: 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 [20] and the graphical comparison between desired outputs and the outcome of the models through simulation one (or k) steps before.

4. Description of the Robotic Drill Industrial Problem

The purpose of the multidisciplinary work presented in this paper is the study of the best conditions for drilling reinforced concrete slabs, using a pneumatic drill with diamond bits, allocated in a robot.

We have applied different modelling systems to arrive at the optimal conditions; which cause least wear of the bits and provide the best result in the shortest time, thereby saving time and money. The experiments are based on a data set [21] obtained from a test on steel-bar reinforced concrete. The data set has been collected under different conditions, both on the tool and on the drilling material, in order to identify the optimal conditions in each case related to aspects such as:

- A bit that only engages a concrete slab.
- A bit that engages a concrete slab and a small portion of a steel bar.
- A bit that engages a steel bar and a concrete slab.

Several variables and their responses were studied across a discrete range of values, as shown in Table 2.

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

Variable (Units)	Range
Wear on the tool, y1(t)	
Applied strength (N), u1(t).	65, 80.5, 96, 11.5
The speed of turn (r.p.m). u2(t).	1000, 2000, 3000,4000
Refrigerating volume water of the tool (l/min), which avoids its overheating and evacuates the waste, u3(t).	2, 3, 4, 5
The drilling time (s), u4(t).	80 different times.

The data set was obtained from the drilling of reinforced concrete test tubes with steel bars. Eighty samples were taken, a relatively small number due to the high cost of the diamond bits.

4.1 Application of the 2 phases of the modelling system

The experiments have been organized into two phases.

- Phase 1. Initial identification of the internal structure of the data set. Application of several unsupervised neural models.
- Phase 2. Final identification of the model that best defines the dynamic of the robotic drilling process.

4. 1.a Phase 1

Figure 1 shows the results obtained using Principal Component Analysis (PCA) Cooperative Maximum Likelihood Hebbian Learning (CMLHL). We can see that both methods have identified four different clusters.

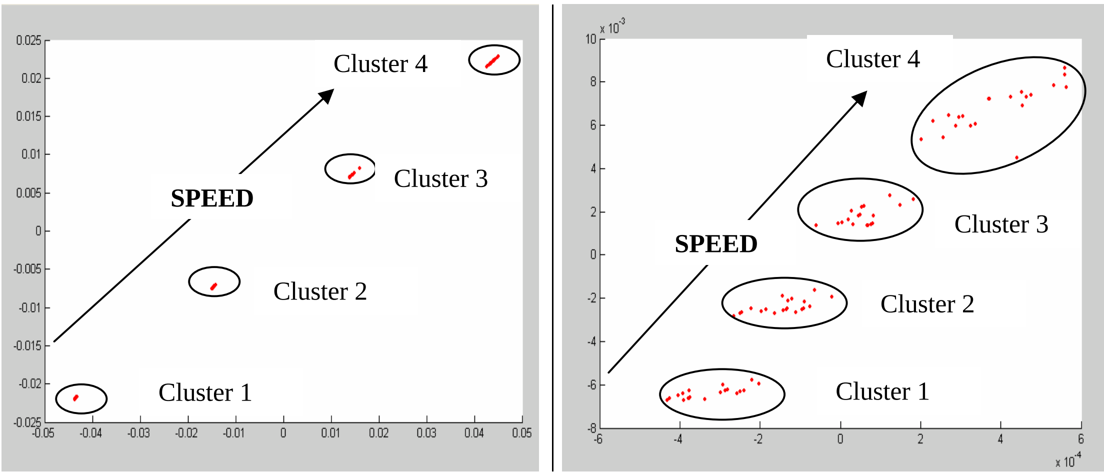


Fig. 1. Principal Component Analysis (left figure) and Cooperative Maximum Likelihood Hebbian Learning (right figure). The CMLHL projection shows a wider data spread than the PCA projection.

Both methods have identified a clear internal structure based on an initial classification relating to the speed factor. It may be easily be affirmed that CMLHL (Fig.1.- right figure) provides a sparser representation than PCA (Fig.1.- left figure).

Having analysed the overall global results an interesting internal structure was noted which led to the application of the second phase of the process, which accurately and efficiently optimizes the model of the robotic drilling system, before the application of several classical modelling systems.

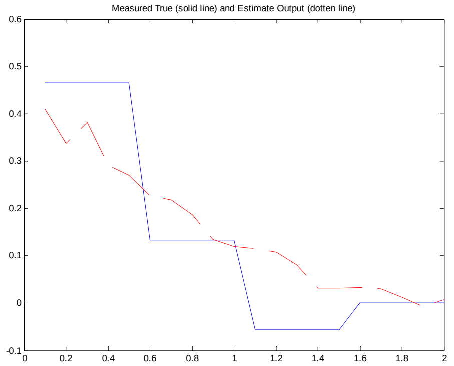
4. 1.b Phase 2. Modelling robotic drilling by means of classical models

Figure 2 shows the graphic representations of the results, for different models, in relation to the polynomial order and the delay in the inputs; for ease of presentation, we have considered the same delay for all inputs and the same polynomial order, which is [na, nb, nc, nd, nf, nk], in accordance with the structure of the models that have been used; see Table 1. In figure 2, the X-axis shows the number of samples used in the validation of the model, whereas the Y-axis represents the range of output variable.

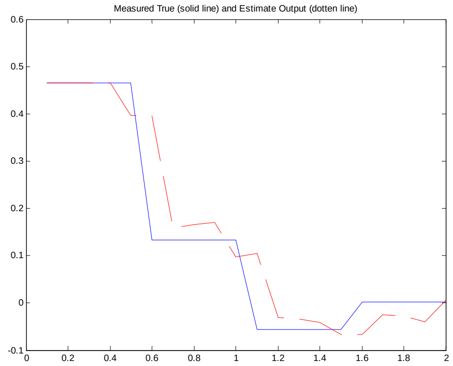
Table 3 shows a comparison of the qualities of estimation and prediction of the models obtained, as a function of the model, the estimation method, and the indicators, which are defined as follows:

- The percentage representation of the estimated model (expressed in so many percent "%") in relation to the true system. This is 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, the graphical representation of true system output and the one-step prediction $\hat{y}_1(t \mid m)$, the ten-step prediction $\hat{y}_{10}(t \mid m)$, or the model simulation $\hat{y}_\infty(t \mid m)$.
- The loss function or error function (V). This is the numeric value of the mean square error that is computed with the estimation data set.
- The generalization error value (NSSE). This is the numeric value of the mean square error that is computed with the validation data set.
- The average generalization error value (FPE). This is the numeric value of the criterion FPE that is computed with the estimation data set.

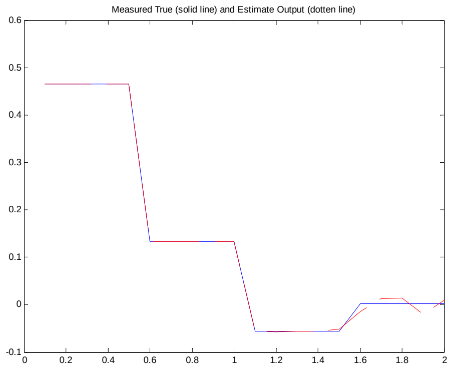
Model ARX [ ]: Measured output Simulated output



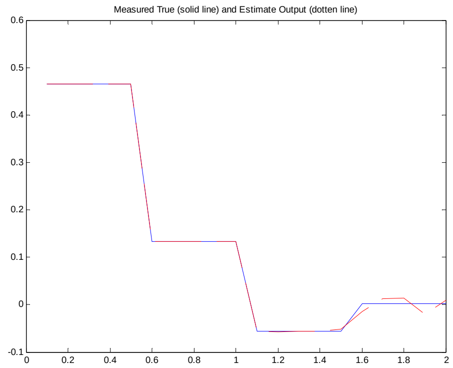
Model ARX [ ]: Measured output 1 Step ahead predition



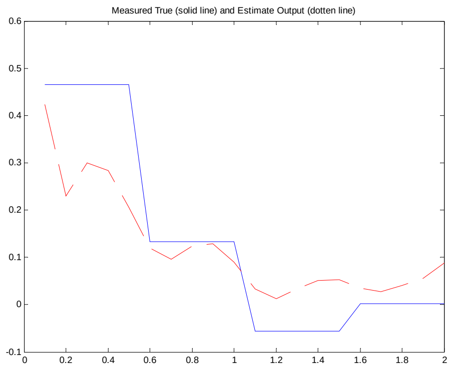
Model OE [ ]: Measured output Simulated output



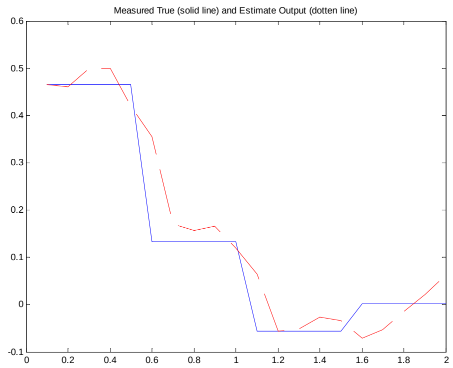
Model OE [ ]: Measured output 1 Step ahead predition



Model ARMAX [ ]: Measured output Simulated output



Model ARMAX [ ]: Measured output 1 Step ahead predition



Model BJ [ ]: Measured output Simulated output

Model BJ [ ]: Measured output 1 Step ahead predition

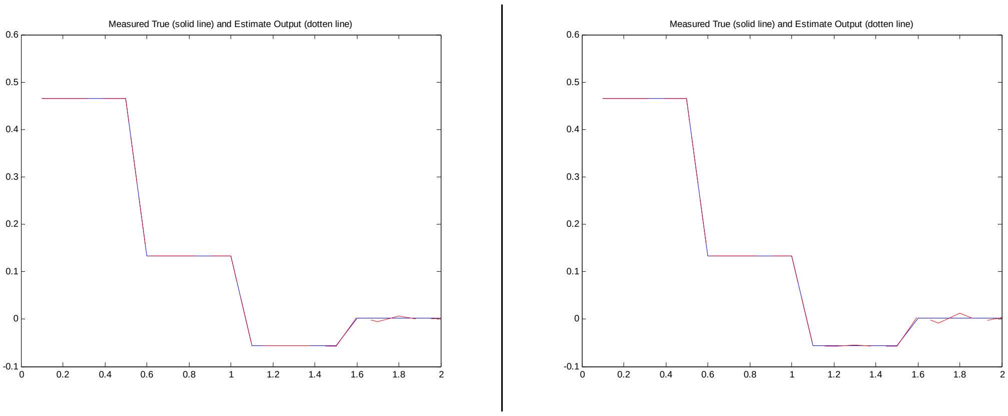


Fig.2. Representation of measured output, simulated output and one-step-ahead prediction for four black–box models. The model generated by the OE model is shown in the upper row. On the left, measured ouput vs. simulated output, on the right, measured output vs. one-step-ahead prediction. In row 2, the results obtained with the BJ model. The validation data set was not used for the estimation of the model. The order of the structure of the model is [4, 2, 3, 2, 4, 3] according to the model type. The solid line represents true measurements and the dotted line represents estimated output.

It may be seen from Fig.2 that the OE and the BJ models are capable of simulating and predicting the behaviour of the drilling robot as they meet the indicators and are capable of modelling 96.33% and 97.70% of the true measurements, respectively. This is also evident from Table 3. Table 4 shows the function and the parameters that define the drilling robot, on the basis of the BJ model. The tests were performed using Matlab and the System Identification Toolbox.

Table 3: Indicator values for several proposed models.

Model	***Indicators and order [na, nb, nc, nd, nf, nk]***					
	[1 1 3 2 1 1]	[1 2 3 2 1 2]	[2 2 3 2 2 2]	[3 2 3 2 3 2]	[4 2 3 2 4 2]	[4 2 3 2 4 3]
Black-box model, ARX model is estimated using the least squares method, QR factorization.	FIT:43.7% FIT1:59.7% FIT10:31.0% V: 0.003 FPE:0.004 NSSE:0.006	FIT:61.86% FIT1:63.23% FIT10:61.3% V: 0.0032 FPE:0.004 NSSE:0.005	FIT:56.65% FIT1:62.02% FIT10:50.7% V: 0.005 FPE:0.004 NSSE:0.005	FIT:55.59% FIT1:61.59% FIT10:41.5% V: 0.005 FPE:0.004 NSSE:0.006	FIT:57.15% FIT1:62.6% FIT10:48.8% V: 0.003 FPE:0.004 NSSE:0.005	FIT:49.73% FIT1:62.95% FIT10:33.1% V: 0.003 FPE:0.004 NSSE:0.005
Black-box model, OE model is estimated using the prediction error method	FIT:56.53% FIT1:56.53% FIT10:56.5% V: 0.006 FPE:0.01 NSSE:0.007	FIT:71.09% FIT1:71.09% FIT10:71.0% V: 0.002 FPE:0.004 NSSE:0.003	FIT:76.19% FIT1:76.19% FIT10:76.1% V: 0.002 FPE:0.006 NSSE:0.002	FIT:77.81% FIT1:77.81% FIT10:77.8% V: 0.001 FPE:0.003 NSSE:0.002	FIT:91.56% FIT1:91.56% FIT10:91.5% V: 0.04 FPE:0.02 NSSE:0.0003	FIT:**96.33%** FIT1:**96.33%** FIT10:96.3% V: 0.05 FPE:0.025 NSSE:**0.00005**

Black-box model, ARMAX model is estimated using the prediction error method.	FIT:23.39% FIT1:58.93% FIT10:314.9% V: 0.0036 FPE:0.004 NSSE:0.006	FIT:33.15% FIT1:57.51% FIT10:-30% V: 0.003 FPE:0.0055 NSSE:0.007	FIT:57.03% FIT1:61.84% FIT10:51.9% V: 0.003 FPE:0.0055 NSSE:0.007	FIT:54.36% FIT1:62.4% FIT10:45.1% V: 0.003 FPE:0.0055 NSSE:0.005	FIT:63.45% FIT1:64.35% FIT10:66.2% V: 0.002 FPE:0.005 NSSE:0.005	FIT:45.11% FIT1:67.68% FIT10:-12% V: 0.001 FPE:0.004 NSSE:0.004
Black-box model, BJ model is estimated using the prediction error method.	FIT:71.5% FIT1:77.5% FIT10:69.8% V: 0.0078 FPE:0.015 NSSE:0.002	FIT:73.84% FIT1:65.25% FIT10:70.5% V: 0.002 FPE:0.005 NSSE:0.002	FIT:82.71% FIT1:76.11% FIT10:82.5% V: 0.002 FPE:0.005 NSSE:0.002	FIT:89.36% FIT1:92.39% FIT10:88.1% V: 0.001 FPE:0.01 NSSE:0.0002	FIT:94.56% FIT1:94.69% FIT10:94.1% V: 0.005 FPE:0.009 NSSE:0.0001	FIT:**97.7%** FIT1:**98.98%** FIT10:98.98% V: 0.02 FPE:0.02 NSSE:**0.00001**

Table 4. Function and parameters that represent the behaviour of the drilling robot.

Model BJ [*0, 2, 3, 2, 4, 3*].

$$y(t) = q^{-n_k}\frac{B_1(q^{-1})}{F_1(q^{-1})}u_1(t) + q^{-n_k}\frac{B_2(q^{-1})}{F_2(q^{-1})}u_2(t) + q^{-n_k}\frac{B_3(q^{-1})}{F_3(q^{-1})}u_3(t) + q^{-n_k}\frac{B_4(q^{-1})}{F_4(q^{-1})}u_4(t) + \frac{C(q^{-1})}{D(q^{-1})}e(t)$$

Parameters and polynomials.

$B_1(q) = -0.04883\ q^{-3} - 0.01538\ q^{-4}$	$D(q) = 1 - 0.4843\ q^{-1} - 0.3384\ q^{-2}$
$B_2(q) = -0.000169\ q^{-3} + 9.223e\text{-}005\ q^{-4}$	$F_1(q) = 1 - 0.4102\ q^{-1} - 0.1256\ q^{-2} - 0.03927\ q^{-3} + 0.04401\ q^{-4}$
$B_3(q) = -0.145\ q^{-3} + 0.1575\ q^{-4}$	$F_2(q) = 1 - 1.158\ q^{-1} + 0.3967\ q^{-2} + 0.01603\ q^{-3} - 0.1476\ q^{-4}$
$B_4(q) = -0.0001203\ q^{-3} + 0.0001846\ q^{-4}$	$F_3(q) = 1 - 1.241\ q^{-1} + 0.412\ q^{-2} - 0.006801$ *q-3* $- 0.1674\ q^{-4}$
$C(q) = 1 + 0.6335\ q^{-1} + 0.5132\ q^{-2} + 0.3435\ q^{-3}$	$F_4(q) = 1 - 1.556\ q^{-1} + 0.6325\ q^{-2} - 0.3091\ q^{-3} + 0.3692\ q^{-4}$ *e(t) is white noise signal whit variance 0.11*

5. Conclusions and Future Work

This paper has presented an investigation to identify the most appropriate modelling system to solve a real-life industrial problem: the drilling robot. Several methods were investigated to achieve the best practical solution to this interesting problem. The paper shows why, from among the classical models, the BJ model is the one that is best adapted to this case in terms of identifying the best conditions and predicting future circumstances.

The novelty of the article lies in the use of a two-phase model: a first phase, which applies unsupervised connectionist processes to establish whether the data sets are "informative enough", i.e., to know whether the data allows discrimination between any two different models in the set, following which a group of models is applied to identify the most appropriate one. As a consequence, the first phase eliminates one of the problems that these identification systems have, which is that of not knowing beforehand if the experiment that generates the data group can be considered acceptable and will present sufficient information in order to indentify the overall nature of the problem.

Future work will be focus on the study and application of other modelling systems and also this modelling system will be applied in order to automate similar industrial problems that are of interest.

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