Automating end-of-line quality control tests of small brushed DC motors

Francisco Rodriguez Verdugo[1], Enrico Concettoni[1], Alessandro Bastari[1], Cristina Cristalli[1],
Maurizio de Palma[2]

[1] *Loccioni Group, via Fiume 16, 60131, Angeli di Rosora (AN), Italy, c.cristalli@loccioni.com*
[2] *Global automotive components manufacturer*

Abstract - Robust end-of-line tests are important in manufacturing to monitor production quality and to guarantee that only fault-free products are delivered to customers. By automating quality control tests, subjectivity can be removed from this important process and traceability of defects can be improved. This paper describes a prototype station that automatically tests and classifies small brushed DC motors. In order to perform fault diagnosis, four different quantities are monitored: acoustic noise, mechanical vibration, voltage and current. A three-step approach consisting in a feature extraction phase, a feature space dimensional reduction through multivariate analysis and a final neural network classifier is proposed and preliminary results are in good agreement with experts' assessments.

I. Introduction

Small power permanent magnet DC motors are largely employed in automotive and home appliances industries: common applications are HVAC (Heating, Ventilation and Air Conditioning) systems, cooling fan modules, car door locks and water pumps, just to cite some. In the past 20 years, concerns about noise and vibration have grown rapidly, especially among car drivers; therefore manufacturers are constantly tightening specifications and lowering the threshold limits for homologation of single car components as for example DC motors.

Because of both high production volume and low production costs of small power DC motors, it is impossible to systematically test every manufactured motor in accordance with the international standards [1]. In fact, these tests are very time consuming and require special and expensive facilities as for example an anechoic chamber. Nowadays, end-of-line tests are performed by well-trained human operators. Repeatability is low as manual testing depends on subjective perception of the noise and vibration levels, background noise, operators' tiredness and momentary lapse in concentration.

The purpose of this paper is to define a procedure for the characterization of small power DC motors suitable to be implemented in a fully automated quality control system for assembly lines. The two main benefits from automating end-of-line tests are the possibility to remove subjectivity from quality control process and to improve reproducibility [2]. The implementation of such station is a critical issue because of the high levels of noise and vibration coming from conveyors and other moving machineries along the line and because of the short time available for the entire test in order to meet timing constraint (6-8s).

II. Description of manual end-of-line inspection

The end-of-line quality control testing of small DC motors is usually performed by human operators by following the test procedure given hereafter: take a motor from a quality inspection bin; perform visual inspection of the motor and check if all components are assembled correctly; connect power cable; check that the shaft rotates; rotate the motor in order to assess noise and vibration at different tilt angles; disconnect power cable; assign a verdict (pass or fail); transfer the motor to the corresponding bin (pass or fail).

The weight of the rotor creates an unbalance force when the rotor axis is not aligned with gravity, so it is important to test the motor in different tilt angles, paying particular attention to the angle at which the motor will be mounted in the end product. During the manual procedure only vibration and noise are monitored. It is important though to monitor the electromechanical characteristics of each motor, especially the rotational speed

(rpm): if the rpm at nominal voltage is too low, the final product would probably not satisfy requirements - air flow rate for HVAC.

III. Classification of brushed DC motor faults

Only few papers have been published on the fault classification of small brushed DC motors [3-7]. However motor manufacturers have extensive knowledge of motors faults, acquired during the periodic off-line quality control test campaigns and during regular end-of-line tests. The five most common faults of small DC motors at the end of the assembly line are:

- Faulty bearing;
- Rubbing between static and rotating parts;
- Unbalanced magnetic radial force;
- Imperfect contact between commutator and brush;
- Presence of a foreign body inside the motor.

Faulty motors have usually one or several of the following symptoms: excessive noise, excessive vibration, abnormal absorbed current, abnormal rotational speed.

IV. Test bench and test procedure

The test bench is composed of a pneumatic clamping system that secures the motor during testing, instrumented with a PCB single axis 352C33 100 mV/g IEPE accelerometer. With the adopted configuration, only radial vibration, which is usually dominant for small motors, can be measured. For the acoustic noise measurements, three GRAS 40PH ¼" 50 mV/Pa IEPE microphones are employed: the first is located on the front side of the motor, pointed toward the shaft axis; the second points toward the commutator; a third microphone measures the background noise and rejects test results if needed. Current is measured with a LEM CT10 500 mV/A transducer. Voltage is directly measured by the power supply. In order to rotate the tested DC motor around the z axis (see Figure 1), the clamping system is mounted on a rotating structure controlled by a motorized stepping motor. The angular position of the system is monitored with a 2048 tick encoder.
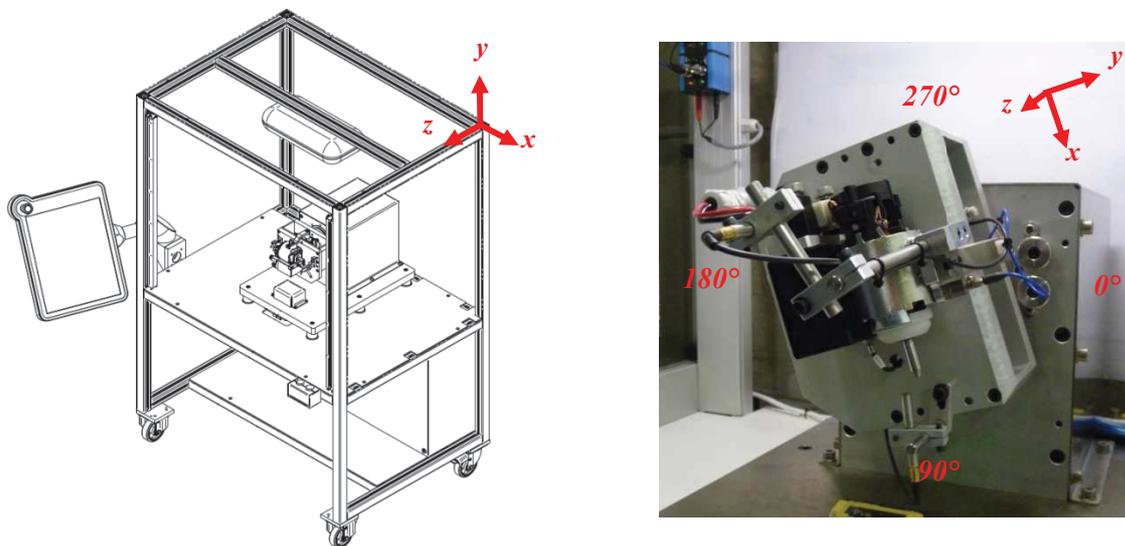

Figure 1. DC motor test bench. 3D CAD model (left) and photography during a test (right).

Signals are acquired using a 16 bit National Instruments 6251 data acquisition board and MMF M32 IEPE signal conditioners are used for the accelerometer and the microphones. The sample rate is 100 kHz and 30 kHz anti-aliasing filters are used. Furthermore, a 6 Hz high-pass filter is used to remove the rotation motion around the z axis from the acceleration signal.

The test bench is controlled with an acquisition software developed in LabVIEW. The test procedure is divided into the following steps: a ramp, a constant voltage test and a constant rotational speed test. The characteristics

of the three different tests are given in Table 1. During the ramp test, the shaft axis is kept aligned with gravity (270°). For the inspected motor, a voltage of 3 V corresponds to a rotation speed of about 1000 rpm. The test duration has been fixed to be approximately 9 seconds. Tests reported in this paper were performed inside a 3.1 m × 3.1 m × 2.5 m sound proof chamber located next to the production line. The background noise was measured at 39.5 dB(A) in the centre of the chamber.

	Voltage (V)	Tilt angle (°)
Ramp test	0-12	270
Constant voltage test	3	0-270
Constant rpm test	-	0-270

Table 1. Details of the three different tests.

V. Data Processing and Experimental Results

A preliminary test campaign was performed in order to characterize the specific DC motor of interest and to verify the feasibility of an automatic classification procedure. To the purpose, 66 sample motors were first tested and divided in three distinct classes (C_1, C_2 and C_3) by an expert operator as follows:

- Fault-free (C_1) : 27 motors ;
- Excessive noise (C_2): 29 motors;
- Excessive vibration (C_3): 10 motors.

After the manual assessment, all the motors were tested in the test bench using the procedure previously described. The different signals acquired from each motor were used as inputs for a three steps classification procedure. The first step consists in the extraction of a complete set of features from the acquired signals correlated with the common set of defects; in the second step Principal Component Analysis (PCA) [8] was used to reduce the dimensionality of the feature space, while maintaining all the information on the defects; in the final step, a neural network (NN) [9] was used to classify the motor. The three steps are described in details in the following.

A. Feature extraction

The aim of the first step is to extract different features from the acquired signals. The features shoud contain information on the defects, replicating the perceptions of a human operator. Therefore one-third octave analysis of the acoustic and of the vibration signals has been considered. Peak hold averaging is performed for features extracted from the tests in which the motor is rotated (constant voltage and constant rpm tests): by this means, the worst case scenario is retained from the different tilt angles tested. The electrical characteristics of the motor were also monitored and processed to provide important features, as for example the harmonic spectrum of current or the rotational speed of the motor estimated from the current. Table 2 summarized the different features extracted for each motor: a high dimensional feature space (262 elements) is obtained.

	Supplied Voltage	Current	Pressure	Acceleration
Ramp test	E (t=1,3,5,7s) [4]	- Mean (t=1,3,5,7s) [4] - RMS (t=1,3,5,7s) [4]	-	-
Constant voltage test	E [1]	- Mean [1] - RMS [1] - Harmonic Spectrum [25] - rpm [1]	- Overall [1]×2 - 1/3 Octave [31] ×2	- Overall [1] - 1/3 Octave [31]
Constant rpm test	E [1]	- Mean [1] - RMS [1] - Harmonic Spectrum [25] - rpm [1]	- Overall [1] ×2 - 1/3 Octave [31] ×2	- Overall [1] - 1/3 Octave [31]

Table 2. Features extracted for tested motors. The dimension of each feature is given in brackets. The two pressure signals are from the two microphones pointed toward the motor.

As mentioned before, some defects can be detected only at given angles: for the motor reported in Figure 2, acoustic bursts are clearly distinguishable from 0s to 5.5s corresponding to 0° to 150°.
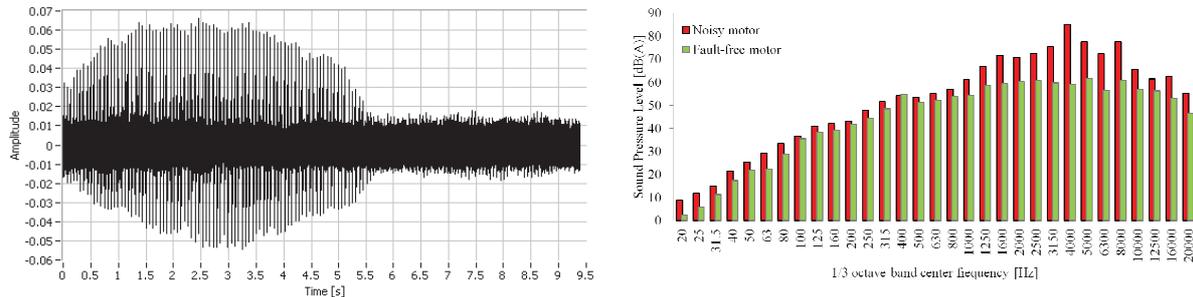

Figure 2. Right: Time history of the acoustic signal (commutator-pointed microphone) during a constant rpm test. Left: 1/3 octave of a fault-free and a noisy motor.

B. Principal Component Analysis

In order to reduce the dimensionality of the feature vector, a particular multivariate data analysis technique named Principal Component Analysis is used. In this way the number of inputs of the NN classifier can be reduced as well, along with the complexity of the network and the computational requirements during the training phase. PCA consists in building a model of the original data that contains most of the original information (data variance), by using a reduced number of variables called Principal Components (PCs). The optimal number of PCs is chosen by considering the cumulative explained variance of the first *P* PCs. PCs are selected, sorted in decreasing order of explained variance, until the cumulative explained variance does not exceed a preset threshold or until the variance added by the *(P-1)-th* PC is not worth of the increased model complexity.

The application of PCA to the 262- dimensional feature vectors originated in the first step produced a model with 9 PCs, leading to a considerable reduction of the NN classifier's input dimension. The coefficients of the feature vector in the PCs space are called *Scores*. The score plot of the first two PCs *t[1]-t[2]* is reported in Figure 3.
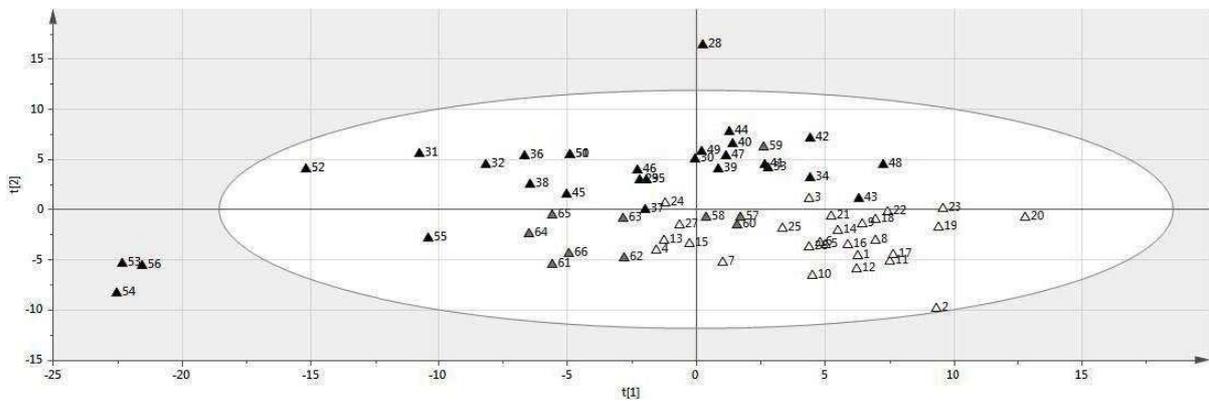

Figure 3– PC1 – PC2 score plot; colours identify the different classes provided by the operator (white = C_1, black = C_2 and grey = C_3); labels identify different motors in sequential test order (from 1 to 66).

C. Neural Network Classifier

Let x_m denote the 9-dimensional vector of scores extracted from the test on the *m-th* motor (*m = 1, …, 66*), which are the input to the NN classifier. A particular topology of NN, the Multi Layer Perceptron (MLP) [9] was chosen as structure for the classifier, with 9 (= $dim(x_m)$) inputs, a single hidden layer of 10 neurons and 3 outputs, each of which corresponds to a specific Class Ci ($i =1,2,3$). A *sigmoid function,* whose upper and lower limits are respectively 1 and 0, has been employed as activation function for both the hidden layer and the output layer neurons.

A target binary vector $T_m = [T_m^1; T_m^2; T_m^3]$ is associated to each x_m formerly classified by human operator, built as follows:

$$T_m = \begin{cases} 1 & for\ \boldsymbol{x_m}\ in\ C_n \\ 0 & otherwhise \end{cases}$$

The 66 input/output pairs $\{\boldsymbol{x_m} \quad \boldsymbol{T_m}\}$ are then employed to train the MLP, by using the cross validation procedure with the back-propagation learning rule:

1. *Input pre-processing*: the 9 components of input vectors are normalized to zero mean and unit variance in the whole training set;
2. *I/O random partitioning*: the complete I/O observation set is randomly partitioned in three disjoint sets, that are the training set (70% of observations, corresponding to 46 motors), the test set (15%, 10 motors) and the validation set (15%, 10 motors);
3. *MLP training*: following the cross-validation procedure, training on the first subset is stopped when the mean-squared error on the test set stops decreasing; validation set is used, after the end of the training, to verify the performances of the trained neural network in terms of generalization.

Decision Rule: Denoting with $F_n(\boldsymbol{x_m}), n = 1,2,3$ the *n-th* output of the MLP, when it is fed with the input $\boldsymbol{x_m}$, an appropriate decision rule for classifying the MLP output is the approximate Bayes rule generated by the a posteriori probability estimates:

$$\boldsymbol{x_m} \in C_n \leftrightarrow F_n(\boldsymbol{x_m}) > F_q(\boldsymbol{x_m})\ \forall n \neq m, where\ n, q \in \{1,2,3\}.$$

D. Results

The performances of the previously described procedure and decision rule can be evaluated by looking at the data in Figure 4, which reports the Confusion Matrices of the Training Set, the Validation Set, the Test Set and the Complete Data Set. Each column C_i of a matrix contains the original class of the pattern (class attributed by the operator), while each row C_i' contains the output of the NN classifier. The gray cells report the number (or percentage) of patterns classified in the same way by the operator and by the NN classifier. These cells should be ideally the only ones containing non-zero values (perfect matching).
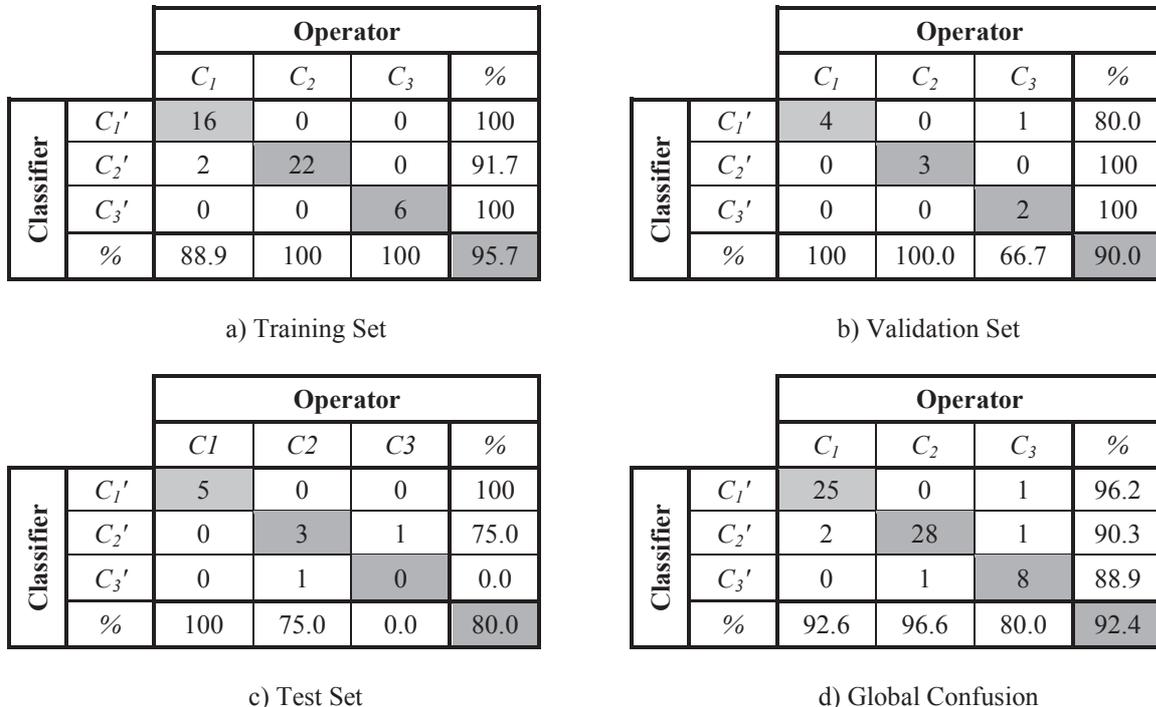
		Operator			
		C_1	C_2	C_3	%
Classifier	C_1'	16	0	0	100
	C_2'	2	22	0	91.7
	C_3'	0	0	6	100
	%	88.9	100	100	95.7

a) Training Set

		Operator			
		C_1	C_2	C_3	%
Classifier	C_1'	4	0	1	80.0
	C_2'	0	3	0	100
	C_3'	0	0	2	100
	%	100	100.0	66.7	90.0

b) Validation Set

		Operator			
		C1	C2	C3	%
Classifier	C_1'	5	0	0	100
	C_2'	0	3	1	75.0
	C_3'	0	1	0	0.0
	%	100	75.0	0.0	80.0

c) Test Set

		Operator			
		C_1	C_2	C_3	%
Classifier	C_1'	25	0	1	96.2
	C_2'	2	28	1	90.3
	C_3'	0	1	8	88.9
	%	92.6	96.6	80.0	92.4

d) Global Confusion

Figure 4. Confusion Matrices. Each table shows the number of motors classified in each class by the operator (columns C_i) and by the classifier (rows C_i'), and the percentage of motors correctly classified in each row and columns .

From the analysis of the data in the Figure 4, it is possible to deduce the good performance of the classifier, as the 92.4 % of all the tested motors are correctly classified. The following observations can be made by analyzing the tables in further detail:

- Only one motor classified in C_3 by the operator (*motor #57*, used in the Validation Set), is judged as fault-free and, therefore, associated to class C_1' by the NN classifier; this situation must be avoided in a industrial application, otherwise faulty motors could passed end-of-line quality control tests;
- Two motors considered as fault-free (C_1) by the operator, *motor #19* and *motor #24* - both used in the Training Set – are classified as faulty (C_2) by the NN classifier; the score plot in Figure 3 shows that *motor #24* is indeed a limit case, as it is actually closer to class C_2 than to class C_1; *motor #24*, on the contrary, does not show anomalies in the score plot but, as previously mentioned, this plot only reports a partial view of the PCA model, as it shows 2 out of the 9 PCs of the complete model (even though the two most important ones); in conclusion it can be said that the implemented classification procedure is *conservative*, since it classifies limit cases as faults; this is a good characteristics for an end-of-line implementation, as motors discarded by the automatic procedure can be tested again out of line.
- *Motor #59*, classified in C_3 by the operator and used in the Test Set, is associated to class C_2' by the NN classifier, while, on the contrary, *motor #55*, classified in C_2 and used in the Test Set as well, is associated to class C_3'; both of the results are in good accordance with the score plot, where the two motors are actually closer to the class associated by the NN classifier than the original class; these probably represent two other limit cases that the operator could assign to either the first or the second defect class; the most important thing is, however, that both of the faulty motors are identified as faults.

The good agreement between the operators' classification and the automatic classification suggests that the proposed procedure could be successfully implemented in quality control station. However, it is important to highlight that the model has been developed with a small number of motors; therefore it is recommended to validate the procedure with a higher number of motors, an issue that will addressed in a forthcoming study.

VI. Conclusions

A prototype of a semi-automatic test bench has been designed to monitor voltage, current, noise and vibration of small permanent magnets DC motors. The first results are encouraging and improvement of the fault characteristic extraction method presented is ongoing. The system will be further trained with healthy and faulty motors in order to better replicate the classification made by human experts. Finally, the three step approach will be implemented in a fully automatic quality control station to be placed in production line to perform 100% inspection.

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