Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 93 (2020) 1236–1240

www.elsevier.com/locate/procedia

53rd CIRP Conference on Manufacturing Systems

Experimental Investigation of rubber extrusion process through vibrational testing

Alexios Papacharalampopoulos[a], Demitris Petridis[a] and Panos Stavropoulos[a]*

[a]*Laboratory for Manufacturing Systems and Automation, Department of Mechanical Engineering and Aeronautics, University of Patras, Patras 265 04, Greece*

* Corresponding author. Tel.: +30-2610-910160; fax: +30-2610-997314. *E-mail address:* pstavr@lms.mech.upatras.gr

Abstract

This paper presents an experimental investigation of rubber material quality during extrusion phase utilizing vibrational testing. An attempt to classify rubber profile samples including two kinds of defects (material based and geometrical), based on the response acquired from vibration test is presented. An experimental apparatus has been built for the purposes of this work. Vibrational signals were captured through a series of experiments and signal processing methods have been used for analysing the captured signals. The investigation revealed that the samples could be classified according to their quality characteristics.

Keywords:
Signal Processing, Defect Detection, Vibration test, Non-destructive methods

1. Introduction

Through the emergence of the new industrial era, the so-called Industry 4.0, there has been a great discussion related to the concept of Zero-Defect Manufacturing (hereafter ZDM). In the context of Industry 4.0, the high level of digitization of the production chain, led the industries to the opportunity to gather a vast amount of data from the lines, through a number on line-installed sensors [1]. These data in combination to state-of-the-art ICT technologies now existing in the lines, can now be processed in real-time, providing, amongst other, a prediction related to the final product. Real-time defect detection has received the interest of several researchers and industries, while Industry 4.0 gets more and more mature by the year. It is arguably a major issue for manufacturing industries, since the reduction of the defective products will result to lower production costs, and better quality, amongst other benefits. To achieve ZDM innovative quality monitoring and measurement systems are required. In general, reducing the variability in the process consists the basic principle of ZDM. For this to be possible, continuous data gathering from the line is required. Data processing techniques, simulation tools and decision-making algorithms are then responsible for reducing this variability and maintain the produced parts under specified tolerances. The timely defect detection and the corrective feedback to the machines are crucial for the product quality improvement and the economic impact reduction caused by discarding defective products [2]. The development of fast and reliable non-destructive methods, suitable for inline implementation, considers as a great challenge for the industry.

To this end, within the scope of Industry 4.0 and its aim for zero defect manufacturing [3], it is of great importance to develop fast and reliable solutions for defect detection. Towards this purpose, several studies have been made; in [4] a methodology for achieving ZDM has been proposed, based on intelligent monitoring of vital process parameters in an attempt to predict possible undesired situations. Similarly, in [5] an

10.1016/j.procir.2020.04.160

overview of possible actions towards zero defect manufacturing is presented.

Simulation tools and physics-based models combined to the gathered data, can provide a detailed knowledge of the process itself and the whole line in general and therefore helping towards both process planning and process control [6][7]. Additionally, in the context of zero defect manufacturing, signal processing and decision-making solutions has been studied in [8].

For this work, a paradigm from the automotive rubber manufacturing is considered and specifically the production of a rubber weather strip. Rubber materials are widely used by the automotive industry in a considerable number of applications. More specifically, weather strips are used for preventing from water and dust influx, as well as noise. The durability of the rubber products, along with the dimensional accuracy are of high importance for the life cycle of the weather strip [9]. Currently, destructive methods are being used for determining the mechanical properties of the rubber weather strips. The major drawback of this method, is that the product quality is evaluated off line. As a result, the manufacturing process parameters cannot be reconfigured in fast pace and the scrap rate gets increased. The correct characterization of the rubber material upon its processing is of major importance for the production and therefore studies have been performed to this purpose. In a simulation model of the extrusion process [10] of a weather strip product was made in an attempt to establish a correlation between the input parameters and the output characteristics of the extrude. The results from the simulations were compared to the ideal profile of the product and then using image processing techniques the defective products were identified, presenting in that way a solution for real-time defect detection. The thermal flow characteristics of the extrusion process have been numerically investigated in [11]. A methodology for validating constitutive models for the simulation of rubber compounds in extrusion process was presented in [12]. In [13] the authors developed hyper elastic and viscoelastic models of the weather-strip seal for prediction of the dynamic performance of the door and its effect on the vehicle dynamics. Furthermore, for the estimation of rubber material properties, vibration tests have been considered on several studies [14–16]. The authors in [17] developed a methodology to characterize the viscoelastic coefficients of a weather-strip seal using experimental methods and curve fitting techniques.

Vibrational analysis has been used in several studies related to defect detection using non-destructive methods [18–21]. These methods are related to the vibrations of a system, from which the interpretation of the signals could lead to meaningful results and conclusions.

The goal of this study is to establish an accurate relationship between the received signals and the quality of the final product. To this purpose, an experimental device was designed and manufactured, in which the specimens were mounted. The device received an excitation from an impact hammer and the received signals were logged. The signals were processed leading to their interpretation and the classification of the samples based on the results. This signal processing approach provided the base for a data platform that could be implemented in line as a solution for non-destructive test of the weather strips and the reconfiguration of the manufacturing process parameters.

2. Method

This work was based on two separate signal processing methods as shown in Fig.1. The twofold framework presented here, combines several signal processing methods and algorithms in an attempt to extract meaningful metrics from the acquired signal.

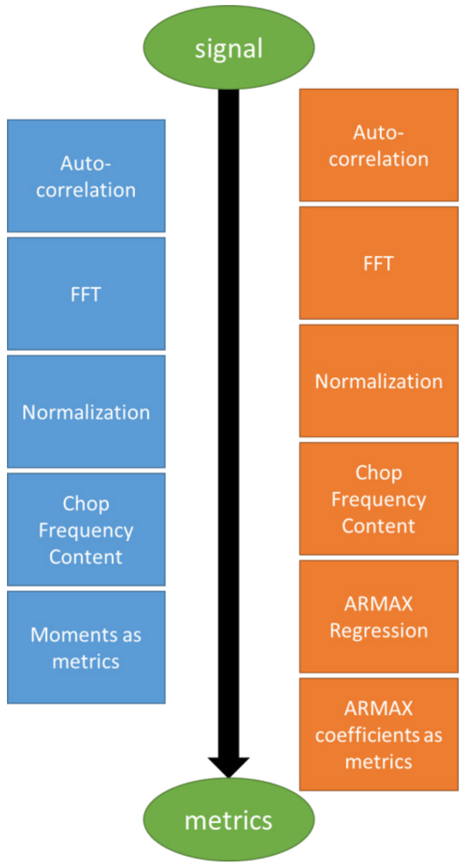

Figure 1 - Framework of methodology

The performed methods have as a result the data dimensionality reduction of the acquired signal for reducing the amount of data to be considered. The proposed framework uses two methods for identifying meaningful results from the signal. The first method uses the Moment of the signal and the second is based on the ARMA model. They have different efficiency in detecting different types of defects. The pre-processing, however, of the signal is similar for both methods. To begin with, autocorrelation techniques are used. A Fast-Fourier-Transform algorithm is then used to convert the signal into the corresponding frequency domain. This can be characterized by the abusive term "denoising", which is used herein to imply statistical processing. In stochastic signals processing, these two methods, help in retrieving the so-called spectral density [22] of a stochastic signal, which is equivalent to the spectrum of a deterministic signal. It has noted here that the signals appeared to have a partially stochastic behaviour (Fig. 2) either due to excitation or due to clamping (shown below). To eliminate of this stochastic behaviour, after assuming that the signals have been ergodic and stationary, their spectral density has been retrieved.

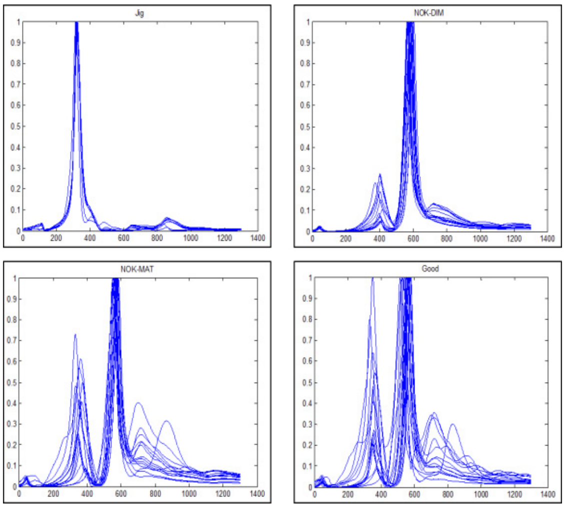

Figure 2 - Examples of stochastic behaviour of the received signals

Next, normalization techniques are used to adjust the signal values into manageable range for further processing. This is a rather optional step, which in the case of an online quality assessment system could be omitted. Herein, however, it is used, as it facilitates the normalization of the dynamic range of data. Additionally, for the pre-processing, chopping frequency content is used to remove unnecessary very high or very low frequencies. This is performed due to physical limitations of both the excitation and signal acquisition systems. The criterion used to chop these frequencies is that the variation within the signals ensemble retrieved is less than *1/10* of the maximum variation. Absolute variation has been used in the normalized signals.

For the processing phase, two approaches have been experimentally validated to work. A model taking into account Moments of lower order of the processed signal. This can be used for identifying the dimensional defect of the rubber profile. Additionally, the coefficients of an ARMA (Autoregressive-moving average) model (a differences equation) [23] has been utilized for the detection of the material defects. Moments have to do with encountering the signal as geometrical object and calculating moments in terms of integrals [24]. For instance, the first order moment has to do with mass center and the central moment of second order has to do with dispersion (size). ARMA(X) method focuses on regression [25], using an input signal (Moving Average-MA), previous samples of the output (Auto-Regressive AR) and eXogenous noise.

3. Experimental setup

3.1. Experimental design – Device

The device presented in Fig. 3, has been developed and built for the purposes of this experiment. The rubber part is being hold on a fixed point using clamps.

A PC-based data acquisition system has been used, consisting of an eight-channel dynamic signal acquisition module and a dedicated ID Heidi IDSA meaning one to eight analogue-to-digital converter per channel. The acceleration sensor was a triaxle accelerometer with an effective frequency range, up to 6kHz, and a sensitivity of 100 mV/g. Additionally, the software used for data acquisition was LabVIEW from National Instruments [26] and the impulse force hammer used for the excitation was a Kistler Model 9724A5000 [27].

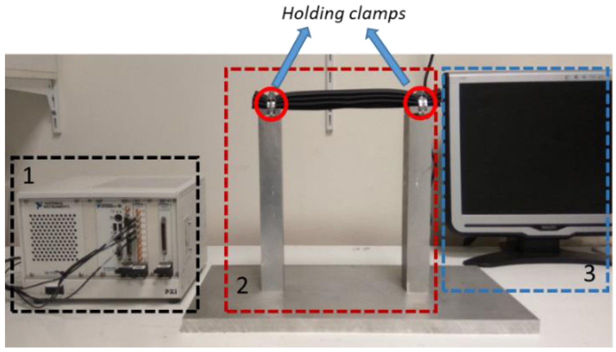

Figure 3 - Experimental Device (1. National Instruments DAQ, 2. Experimental Device, 3. Monitor)

3.2. Experimental Procedure

For the experiments, a specific procedure has been designed and followed throughout the experiment.

1. A control test has been made in order to determine the self-frequency of the device. During this control test, no sample was attached on the device.
2. Using an impact hammer connected to the DAQ, an excitation was given on two defined points of the device
3. The vibration signal was captured through the accelerometer sensor and stored for further processing
4. A total of 300 experiments was performed.
5. The signals received from OK samples consists 1/3 of the total signals, while the signals from NOK (material defect) consists another 1/3. The last 1/3 involves signals describing the NOK samples with dimensional defects (Table 1: Experiments Breakdown)

Table 1 - Experiments Breakdown

Sample	Experiment repetitions		Total
	Point 1	Point 2	
OK	50	50	100
NOK (material defect)	50	50	100
NOK (dimensional defect)	50	50	100
			300
Sample rate	20kHz		
Samples to read	40000		

4. Results and Discussion

The experiments made, provided a significant amount of data to be processed. Through the processing of those data, several results have occurred. As presented below, a classification of the NOK rubber samples according to their defect characterization was possible. Samples related to dimensional defects were possible to be detected using a MOMENTs model. Respectively, samples related to material defects were detected using an ARMAX model.

Table 2 - List of Symbols

Symbol	Explanation
+ (cross) – Green	OK samples
Δ (triangle) – Red	NOK samples – Dimensional Defect
x (cross) – Red	NOK samples – Material Defect
o (circle) – Blue	Jig

The following figures present the results from the analysis and the classification of each sample. The analysis from the MOMENTs method resulted on a clear classification of the samples related to dimensional defects (red triangles). Those samples were concentrated on the same area (right bottom corner), with the rest of the samples being scattered (Figure 4).

Similarly, the second method (ARMAX method) resulted to the concentration of the samples related to material defect (red 'x' cross), at their majority, into the same area (left bottom corner). The results are presented in the figure below (Fig 5).

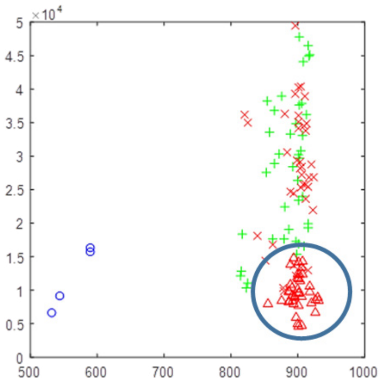

Figure 4 – MOMENTs Model – NOK (dimension defects) concentration

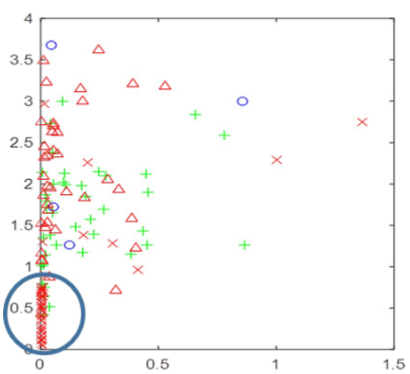

Figure 5 – ARMAX Model– NOK (material defects) concentration

The results occurred from the analysis provided some interesting and promising insights. A classification of the samples according to their defect has been achieved.

The fact that two different types of processing are utilized to detect different types of defects is rather counter-intuitive, but the complexity of the rubber profile could justify it. It is a multi-material structure, of complex geometry, and different defects would affect the vibration signals in either the phase or the amplitude of different frequencies [28]. What is really interesting, is that the authors have attempted to train also Artificial Neural Networks (ANNs) consisting of a small number of neurons. What they came up with, is that the efficiency of the classification was larger in the case where different ANNs were utilized to detect the two kinds of defects. Furthermore, the "simplest" ANN that would predict quite successfully the dimensional defects, was found to be consisting of 2 layers, each one of 2 neurons. The response of the ANN in all the ensemble of measurements (training + test) is shown below in Figure 6. In the case of the material defects, a quite bigger ANN was utilized. It should be noted that a Principal Components Analysis (PCA) was performed as a data dimensionality reduction technique in an attempt to extract the most important features of the dataset, prior running the ANN.

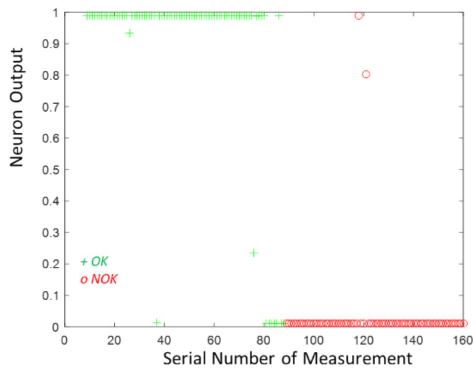

Figure 6 – Response of the ANN for all measurements – Dimensional Defects Case

The proposed solution is fast and does not require any high computational power to be performed. Additionally, in contrast to the ANN's, it is physically intuitive since the defects are detected in the distribution of vibration along spectrum.

It is a fact that, in the case of dimensional defects, the false positive error (is_NOK) is approximately equal to 2.5%, given that a Radial Basis Function is used to classify good parts from defective. In the case of an artificial neural network this value is equal to 8%. Also, no false negative error (is_OK) is observed in the case of moments, where in the case of neural network it is approximately equal to 2.5%. of the case of the material defect, the false negative error is found to be around 4%, while the false positive error marginally exceeds 10% for ARMAX and is around 8% for ANNs. Unfortunately, there has been found no similar experimental configuration in literature to compare the results. However, it can be directly concluded that further elaboration is required to meet the requirements for zero defect manufacturing, as for now the method can achieve only $\pm 2\sigma$ policy (around 5% rejection rate). Finally, it is noted that in order to estimate the total error, as this occurs from both types of defects, it is required to know each defect occurrence probability as well the monetary costs of rejection and warranty. However, this exceeds the purposes of the current study.

5. Conclusion and Future Outlook

This study investigated the correlation between the signals acquired from the excitation of the rubber profiles and their defect character. The experiments were made on a device designed and manufactured for this purpose. Each rubber sample was attached on the device and using an impulse force hammer an excitation was given to the device. Through an accelerometer sensor, the signal created from the excitation was captured. Following, the signals have been processed on an attempt to extract meaningful results.

The classification of selected rubber profile into NOK with dimensional inaccuracies and NOK with material defects was possible via the proposed experimental procedure and the signal processing. There was a clear trend of classification for each defect category (material and dimensional). This offers a great extent of intuition to an engineer desiring to design an online quality assessment system of high technological readiness level. Also, the methods can be considered to be complementary; if ARMAX or moments are regarded as feature extraction, PCA can be enriched towards a non-linear extension. This could be verified in a future work.

The online verification of the two-fold method is expected to be evaluated using real vibrational data from the line, utilizing the motion of the rubber profile itself as excitation. Further to that, it is planned to check the efficiency of other sensors, such as Acoustic Emissions.

Acknowledgments

This work is under the framework of EU Project STREAM-0d. This project has received funding from the European Union’s Horizon 2020 research and innovation program under grant agreement No 723082. The dissemination of results herein reflects only the authors’ view and the Commission is not responsible for any use that may be made of the information it contains.

References

[1] EFFRA. Factories 4.0 and Beyond v30 Dec. 2016.
[2] Chryssolouris G. Manufacturing Systems: Theory and Practice, 2nd ed. New York: Springer-Verlag 2006.
[3] Smit J, Kreutzer S, Moeller V, Carlberg M. Policy Department A: Economic and Scientific Policy - Industry 4.0 2016. Available: http://www.europarl.europa.eu/RegData/etudes/STUD/2016/570007/IPOL_STU(2016)570007_EN.pdf. Accessed: 31-May-2018.
[4] Eleftheriadis MSRJ, Myklebust O. A guideline of quality steps towards Zero Defect Manufacturing in Industry. International Conference on Industrial Engineering and Operations Management 2016.
[5] Ferretti S, Caputo D, Penza M, D’Addona DM. Monitoring Systems for Zero Defect Manufacturing. Procedia CIRP 2013;12:258–263.
[6] Fysikopoulos A, Stavropoulos P, Papacharalampopoulos A, Calefati P, Chryssolouris G. A process planning system for energy efficiency. Proceedings of the 14th International Conference on Modern Information Technology in the Innovation Processes of the Industrial Enterprises 2012:24-26.
[7] Papacharalampopoulos A, Stavridis J, Stavropoulos P, Chryssolouris G. Cloud-based Control of Thermal Based Manufacturing Processes/ Procedia CIRP 2016;55:254–259.
[8] Teti R. Advanced IT Methods of Signal Processing and Decision Making for Zero Defect Manufacturing in Machining. Procedia CIRP 2015;28:3–15.
[9] Ha YS, Cho JR, Kim TH, Kim JH. Finite element analysis of rubber extrusion forming process for automobile weather strip. J. Mater. Process. Technol. 2008;201(1):168–173.
[10] Stavropoulos P, Alexopoulos H, Papacharalampopoulos A, Mourtzis D. Automotive weather strip manufacturing: Process modeling and extrudate dimensional accuracy evaluation. Procedia CIRP 2018;72:375-380.
[11] Cho JR, Choi JH. Numerical investigation of weather strip extrusion forming process by thermal flow analysis. Int. J. Adv. Manuf. Technol., 2016;87(9–12):2841–2851.
[12] Urraca R, Pernía-Espinoza A, Díaz I, Sanz-Garcia A. Practical methodology for validating constitutive models for the simulation of rubber compounds in extrusion processes. Int. J. Adv. Manuf. Technol. 2017; 90(5–8):2377–2387.
[13] Dikmen E, Basdogan I. Material characteristics of a vehicle door seal and its effect on vehicle vibrations. Veh. Syst. Dyn. 2008;46(11):975–990.
[14] Rahim IMA, Mat F, Yaacob S, Siregar RA. The classification of material mechanical properties using non-destructive vibration technique. IEEE 7th International Colloquium on Signal Processing and its Applications 2011: 202–206.
[15] Davis A, Bouman KL, Chen JG, Rubinstein M, Durand F, Freeman W T. Visual Vibrometry: Estimating Material Properties from Small Motions in Video. IEEE Trans. Pattern Anal. Mach. Intell., 2017;39(4):732–745.
[16] Lin TR, Farag NH, Pan J. Evaluation of frequency dependent rubber mount stiffness and damping by impact test. Appl. Acoust. 2005;66(7):829–844.
[17] Basdogan I, Dikmen E. Modeling viscoelastic response of vehicle door seal. Experimental Techniques 2011;35(3):29-35.
[18] Ammari H, Kang H, Lee H. Layer Potential Techniques in Spectral Analysis. American Mathematical Society 2009;153.
[19] Mantena PR. Frequency Domain Vibration Analysis for Characterizing The Dynamic Mechanical Properties Of Materials. Annu. Conf. 1996:1.222.1-1.222.7.
[20] Altıntas G. Effect of Material Properties on Vibrations of Nonsymmetrical Axially Loaded Thin-Walled Euler-Bernoulli Beams. Math. Comput. Appl. 2010;15(1):96–107.
[21] Papacharalampopoulos A, Stavropoulos P, Doukas C, Foteinopoulos P, Chryssolouris G. Acoustic Emission Signal Through Turning Tools: A Computational Study. Procedia CIRP 2013;8:426–431.
[22] Girod B, Rabenstein R, Stenger A. Signals and Systems, 1 edition. Chichester; New York: Wiley 2001.
[23] Aghdam BH, Vahdati M, Sadeghi MH. Vibration-based estimation of tool major flank wear in a turning process using ARMA models. Int. J. Adv. Manuf. Technol. 2015;76(9–12):1631–1642.
[24] Papacharalampopoulos A, Polyzos D. Wave propagation of Rayleigh waves in bones: A gradient viscoelastic approach. IEEE 10th International Workshop on Biomedical Engineering 2011:1-4).
[25] Stavropoulos P, Papacharalampopoulos A, Souflas T. Indirect online tool wear monitoring and model-based identification of process-related signal. Accepted in Advances in Mechanical Engineering 2020.
[26] LabVIEW 2017 - National Instruments. [Online] Available: http://www.ni.com/en-us/shop/select/labview. Accessed: 31-May-2018.
[27] Measuring Systems and Sensors | Kistler. [Online] Available: https://www.kistler.com/en/. Accessed: 31-May-2018.
[28] Polyzos D, Papacharalampopoulos A, Shiotani T, Aggelis D. Dependence of AE parameters on the propagation distance. J. Acoust. Emiss. 2011;29:57–67