Proc. of the International Conference on Electrical, Computer and Energy Technologies (ICECET)
9-10 December 2021, Cape Town-South Africa

Machine Learning Methods for Quality Prediction in Thermoplastics Injection Molding

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***Abstract*—Nowadays, competitiveness is a reality in all industrial fields and the plastic injection industry is not an exception. Due to the complex intrinsic changes that the parameters undergo during the injection process, it is essential to monitor the parameters that influence the quality of the final part to guarantee a superior quality of service provided to customers. Quality requirements impose the development of intelligent systems capable to detect defects in the produced parts. This article presents a first step towards building an intelligent system for classifying the quality of produced parts. The basic approach of this work is machine learning methods (Artificial Neural Networks and Support Vector Machines) and techniques that combine the two previous approaches (ensemble method). These are trained as classifiers to detect conformity or even defect types in parts. The data analyzed were collected at a plastic injection company in Portugal. The results show that these techniques are capable of incorporating the non-linear relationships between the process variables, which allows for a good accuracy (≈99%) in the identification of defects. Although these techniques present good accuracy, we show that taking into account the history of the last cycles and the use of combined techniques improves even further the performance. The approach presented in this article has a number of potential advantages for online predicting of parts quality in injection molding processes.**

***Index Terms*—Artificial Neural Network, Support Vector Machines, Injection Molding and Machine Learning.**

I. Introduction

The world is in constant evolution and today to remain competitive in the market, quality standards must be higher to offer the customer a product that leaves a process with the least possible failures. By increasing the quality of processes, it is possible to reduce production costs, reaction time, and company downtime, which allows them to be more productive with the same number of equipment and thus survive. Therefore, there must be constant innovation and investment in this area.

The size of the global plastics market was valued at $579.7 billion in 2020 and is expected to expand at a compound annual growth rate of 3.4% from 2021 to 2028 [1]. Increased plastic consumption in the construction, automotive and electrical, and electronics industries are expected to support market growth over the forecast period.

To obtain an injected part with high quality, it is necessary to use the best machine and process parameters [2] [3] which are not always easy to define and most of the time are obtained through trial and error method by injection technicians based on their field experience [4]. Injection molding is the most common process in the production of plastic parts and this process is very dynamic in regard to variations in its parameters. Therefore, it is difficult to understand and predict the quality of the final parts by varying the process parameters.

The production of defective parts must always be avoided, but the delivery of defective parts to the customer must never take place because it generates unpredictable costs. To mitigate this, it is very useful to build an online monitoring and classification system that is capable of detecting all defective parts. To do this analysis it is necessary to access the data in real-time. If the equipment is not capable of making the data available, it is necessary an adaption process [5] [6]. Some of the most frequently occurring defects during injection molding are unfilled, burr, burn marks, short shot, warpage, and flow line [7] [8].

In the literature, there are several approaches to defect classification. Although the use of these techniques individually has good accuracy (≈99%), in industrial terms, we are still talking about significant monetary losses. The automatic classification of parts will change the way the plastic industry works, in the sense that it will move from a reactive action to preventive action. That is, in the past, we expected that a problem would occur for it to be identified and corrected, which implied the production of non-conforming parts that only serve to material and production time-wasting, and then the machine was stopped and the problem was solved upon. With this new approach, the objective is to detect the problem even before it occurs so that the process can be intervened before non-conforming parts are produced [9]. It is an important step because often machine operators do not immediately detect the

This work was partially supported by the Spanish State Research Agency through the project CHLOE-GRAPH (PID2020-118649RB-l00) and by FCT—Portuguese Foundation for Science and Technology under project grant UIDB/00308/2020.

problem of non-compliance, because they may be on another machine, or defects may not be easily seen with the naked eye until the process is very degraded. This causes problems and losses not only in terms of production of conforming parts, but also in terms of logistics, quality, and human resources allocation (full inspection until finding the first defective part), among others. This leads to the reduction of the environmental footprint in this type of industry because only a percentage of the material can be changed and reused, but much of the remaining are still not recyclable, so by reducing these non-conforming produced parts we are moving in a direction of increased sustainability.

Our motivation is to design an automatic procedure to rapidly identify defective parts based on some machine parameters' evolution and to classify the type of defect. This may avoid the need for human inspection in real-time, leading to considerably reducing the wasting material, the downtime and even mitigating the risk of compromising the company's image in a scenario with increasingly demanding customers.

In this paper, models to classify the quality of the produced parts are proposed by using Artificial Neural Networks (ANN) and Support Vector Machines (SVM) algorithms. The proposed approaches are able to distinguish good parts (OK) and defective parts (NOK), either parts with burr problems or parts with filling problems. By observing the temporal nature of the data, we propose and evaluate a windowed approach that obtains improved classification results. Additionally, we further propose the combination of two different techniques to obtain an improved performance. Problems related to the classification in transition zones between conforming and non-conforming parts were also identified and a first approach was made to the interpretation of these problems. Regarding the process data, this was collected in a real environment in a plastic injection company in Portugal, the Vipex company.

The paper is organized as follows. In Section II are presented some of the works done in the area and how they can relate to our work. Section III resumes the methodology followed to carry out the work presented. Section IV is concerned with the results obtained from the tests and with their explanation. To conclude, the last section presents some conclusions and future work to be developed.

II. Related Work

The quality of injection molded parts depends on a lot of factors and they are related both to plastic material properties and the process parameters [10]. Related to the identification of the variables to be monitored, Tripathi *et al.* [11] state that the temperature, the maximum pressure, and the cushion are variables that must be taken into account. Bernardete [8] states that cycle time, plastification time, injection time, barrel temperature before the nozzle, cushion must be monitored. Saleh *et al.* [12] identify that the variables that have the most impact on the injection process are melt temperature, plastification time, maximum pressure, mold wall temperature, and injection time. Jung [9] concluded that temperature, injection time, and cycle time are important variables commonly selected by machine learning techniques. As we can see in these and other research works, there are variables that are transversal in the researcher's opinion to be monitored. In this work, and since it was not possible to access the temperature value in each cycle, the cycle time, injection time, plastification time, cushion, and maximum injection pressure were considered for analysis. These process parameters are also typically used on a daily basis on the factory floor by injection technicians to diagnose the process.

It is possible to find in the literature works related to the use of injection process parameters to classify the quality of parts [3], [8], [13]. These works compare different methods and their respective performances. There are also works that include not only the use of parameters but parameters in conjunction with other methods such as computer vision images [14]. This means that other types of approaches may have been considered to complement the analysis. Lately, studies are not restricted only to the use of separate machine learning methods but have started to integrate the use of combinations of methods (ensemble methods [15]) and also the use of deep learning techniques such as, for example, autoencoders, to improve the efficiency of classification/regression [9], [16]. Thus, in this work, we compare different classifiers, the use of ensemble methods, and a first approach to the use of a deep learning technique to solve classification problems directly related to the injection process.

In [17] the data is used to build a model based on support vector machine (SVM) regression algorithm and Schreiber [18] proved the efficiency when using an injection molding process model based on artificial neural networks. As mentioned in [19] several methods have been developed for online diagnosis and fault detection, such as expert systems and systems based on mathematical models. Both require that the system must be well known [20], [21], which is not always the case in this type of process, especially when we are talking about the start of a new product in production. Artificial Neural Networks (ANN) and Support Vector Machine (SVM) require little or no prior knowledge [22], [23] of the system. These were some of the points that made us try these two types of classifiers, but there are still other studies in this area that use these machine learning techniques [8], [19].

Regarding the accuracy values obtained, there are studies that obtain identical values [3], [19], and despite these values being high ($\approx$99%), they do not go any further in improving these percentages. This is because, as will be shown later in the results, 1% failure in a classifier, for example, in 100 000 pieces means a bad classification out of 100. Taking into account, a 20-second injection cycle, we are talking about a production of approx 1 600 000 pieces in a year which means 16 000 are poorly classified. This in terms of monetary losses is significant for a company. So in the study presented in this article, we go further and tried to identify and improve these performances in order to understand where the biggest failure in the classification was and the results showed that it is in the transition zones between conforming and non-conforming parts.

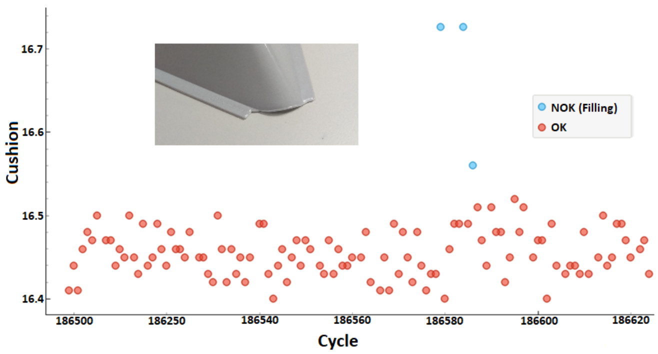

Fig. 1. Production cycle with NOK parts associated with filling problems (blue).

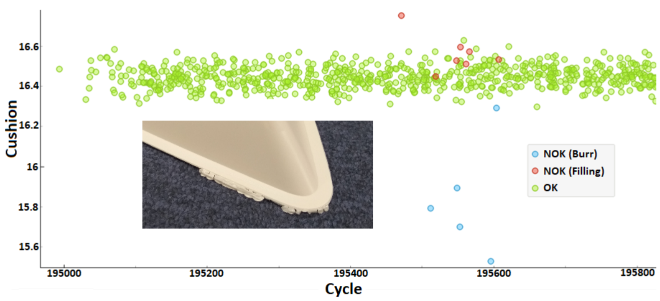

Fig. 2. Production cycle with NOK parts associated with burr problems (blue).

III. Data Collection

A typically stable injection process was chosen and dominated at Vipex, operating on a 220 Tonne Negri Bossi machine working with LLDPE (Linear Low-Density Polyethylene) material, working for 5 days, and being made a quality control piece by piece by the machine operator and a weight and cycle control by the quality operator every 15 minutes to create the dataset. The variables to be monitored (features used in the analysis) were injection time, plasticization time, cycle time, cushion, and maximum injection pressure.

During this process, two types of parts in non-compliance with burr and filling defects were identified and labeled, as shown in Fig. 1 and Fig. 2.

Moreover, we offer some intuition about the two non-compliance labels. In Fig. 1 it is possible to observe that in case the cushion value increases, which means that there was more material in the spindle after the machine was injected a part, the part was left with a lack of material, as shown in the real example in the graphic.

Alternatively, in Fig. 2 it is possible to observe the opposite effect, when the cushion value decreases, it means that more material was placed in the mold than expected, hence the amount of material in the piece that is also possible to observe. In this case, it is worth highlighting the fact that the difference between the pieces with filling and burr problems in terms of cushion value, the drop is more significant in the case of burr (the NOK(Filling) pieces in this chart scale on the yy's axis

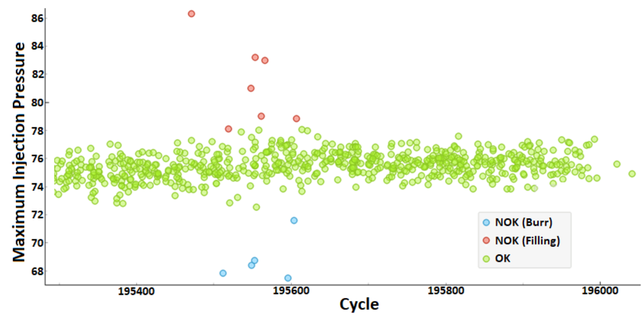

Fig. 3. Maximum injection pressure parameter representation.

appear mixed with OK). That suggests that cushion is not the only parameter that plays a role.

Fig. 3 shows the maximum injection pressure for the same cycles as Fig. 2. It is possible to observe a lag of the average values in the two types of failures, and suggests that by analyzing this combination of parameters (cushion and maximum injection pressure) it is possible to understand what type of failure we are dealing with.

The dataset contains 39827 injection cycles, with 892 non-conforming parts (499 NOK Filling and 393 NOK Burr). Since this is a dataset of a real process taken from the normal shop floor operation of an injection process, the dataset will be made available to the academic community (through a request to the authors) in order to be useful in further research work so allows other groups to replicate, draw other conclusions or apply other data analysis techniques.

In Fig. 4 it is possible to observe a representation of the dataset in four dimensions, namely cushion, injection time, and plastification time (graphic axes) and the maximum injection pressure (represented by color, the darker the greater the value of the parameter). The variables were normalized between the values 0 and 1.

By observing the graph and by way of explanation of the injection process, it is possible to observe that the higher the cushion value (which means that more material remains in the spindle after the injection of the part), the plasticization time is shorter, because there is less material to solidify and thus the injection time is shorter. Regarding the maximum injection pressure for this case, it is also lower, because the machine did not have to apply as much force to put all the material in the mold cavity.

That said, it is possible to observe three zones where there is a larger cluster of points, but they are not totally isolated which shows that there is no clear threshold between the different behaviors of the process parameters during a production, this can make it difficult to classify the different cycles.

Thus, classifiers such as artificial neural networks (ANN) and support vector machines (SVM) were used as is often applied in similar studies [9] [3] [8]. In order to observe the improvement in the performance of the classifiers, ensemble methods and the use of the deep-learning technique Gaussian Process Latent Variable Model were tested.

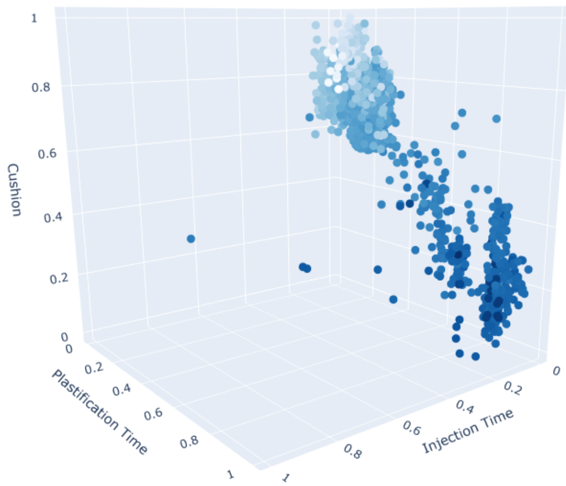

Fig. 4. Dataset 4D representation.

IV. Methods and Data Analysis

The main goal of this study was to create classification models capable of distinguishing between OK, NOK (Filling) and NOK (Burr) parts based on process parameters. After training the model, it is capable of notifying a machine operator that the parameters need to be adjusted not to produce defective parts.

As mentioned, the classifiers were created using ANN and SVM. These were programmed in python language through the scikit-learn library. In the ANN case, several tests were carried out with different numbers of neurons in the hidden layers, and with different numbers of hidden layers. Several solvers were also tested (lbgfs, sgd and adam) and several activation functions (logistic, relu and tanh), and the architecture for which the best performance was obtained was the use of a hidden layer with 200 neurons with the logistic activation function and lbfgs solver.

In the case of SVM, the grid search was drawn using the GridSearchCV from the scikit-learn library to define the most suitable parameters. The parameters that resulted from the grid search were a cost function value of 1000, a gamma of 0.01, and the linear kernel. Fig. 5 represents the referred architectures (can be identified at the top of each table) and the confusion matrices related to the classification of the different labels. 80% of the data were used for training and 20% for testing (the values presented in the confusion matrices are related to this latter percentage).

The performance is below the expected values as the classifiers fail to classify many of the parts (as can be observed in the confusion matrices in Fig. 5).

We observed that for some errors there was a temporal component, so we proposed a method that includes a moving window technique, that is, including in the input vector information about the previous and subsequent cycles. The cycles taken into account were the five previous ones [t-5]

ANN - Artificial Neural Network

Average values of 10 tests.

A: HL – 1, N – 200, ACT – Logistic, V - 20% , S: Lbfgs

Confusion Matrix	NOK(Burr)	NOK(Filling)	OK
NOK (Burr)	41	5,5	42,5
NOK (Filling)	3	12	91
OK	33,5	14,5	7720

SVM – Support Vector Machine

A:- C - 1000, Gamma - 0.01 and Kernel - linear

Confusion Matrix	NOK (Burr)	NOK (Filling)	OK
NOK (Burr)	42	1	46
NOK (Filling)	3	2	101
OK	32	8	7728

Fig. 5. ANN and SVM confusion matrices.

ANN - [Moving Window Solution]

[t-3, t-2, t-1, t]			
	Precision	Recall	F1-Score
NOK (Burr)	0,94	0,93	0,93
NOK (Filling)	0,87	0,57	0,69
OK	0,99	1	1
Accuracy			0,99
Macro Average	0,93	0,83	0,87
Weighted Average	0,99	0,99	0,99

Confusion Matrix	NOK(Burr)	NOK(Filling)	OK
NOK (Burr)	82,67	0,33	6
NOK (Filling)	1	60,33	44,67
OK	4,33	9	7754,67

Fig. 6. ANN accuracy and confusion matrix regarding windows solution.

and the three following ones [t+3] and for both cases, the best performance was for the three previous ones [t-3, t-2 and t-1]. Fig. 6 and Fig. 7 show the results and the accuracy of ANN and SVM classifiers.

Analyzing the classification performances with the window solution technique, it is possible to observe that they have improved significantly, although the accuracy of both being 99%, in the case of classification of parts in non-conformity with filling problems, there is still a significant error in their classification. 99% is not an unreasonable value since in identical works these results were also obtained [3] [19], but for the industry, this 1% still represents a high number of failures.

SVM - [Moving Window Solution]

[t-3, t-2, t-1, t]			
	Precision	Recall	F1-Score
NOK (Burr)	0,97	0,98	0,97
NOK (Filling)	0,83	0,81	0,82
OK	1	1	1
Accuracy			0,99
Macro Average	0,93	0,93	0,93
Weighted Average	0,99	0,99	0,99

Confusion Matrix	NOK(Burr)	NOK(Filling)	OK
NOK (Burr)	86	0	3
NOK (Filling)	0	86	20
OK	3	17	7748

Fig. 7. SVM accuracy and confusion matrix regarding windows solution.

Ensemble Method			
	Precision	Recall	F1-Score
NOK (Burr)	0,94	0,99	0,96
NOK (Filling)	0,88	0,79	0,84
OK	1	1	1
Accuracy			1
Macro Average	0,95	0,94	0,94
Weighted Average	1	1	1

Confusion Matrix	NOK(Burr)	NOK(Filling)	OK
NOK (Burr)	87	1	1
NOK (Filling)	3	94	9
OK	5	11,25	7751,75

Fig. 8. Ensemble method confusion matrix regarding windows solution [t-3].

To go even further and with the observation that each method classifies correctly one type of NOK but not the other one, we designed a voting-based ensemble method technique [24] (with window solution). Our proposal is to create a classifier with both the contribution of ANN and SVM previous approaches. As can be seen in Fig. 8, the performance of this method is better than the performance of previous methods. The values correspond to the average value of 10 ANN trains.

Although with the use of this technique there is an improvement in the classifier performance compared to the isolated use of ANN and SVM, we experimented with other approaches to go even further. Taking into account that there was still a failure in the classification of the part in non-conformity related to a burr problem, and some related to the classification of the pieces NOK (Filling) and OK, an analysis of the weights of the classifications of the different labels (Fig. 9) was

			NOK (Burr)	NOK (Fill)	OK
2038	NOK (Burr)	2038	0.99977	3.91806e-17	0.000230076
2039	NOK (Burr)	2039	0.99977	3.9061e-17	0.000230163
2040	NOK (Burr)	2040	0.999768	5.41326e-17	0.000231873
2041	NOK (Burr)	2041	0.999769	3.92049e-17	0.000230808
2042	NOK (Burr)	2042	0.0560626	0.943937	8.0859e-08
2043	NOK (Burr)	2043	1.89829e-05	2.1726e-11	0.999981
2044	OK	2044	1.79365e-05	1.8774e-11	0.999982

Fig. 9. Probabilistic weights of the different classification labels.

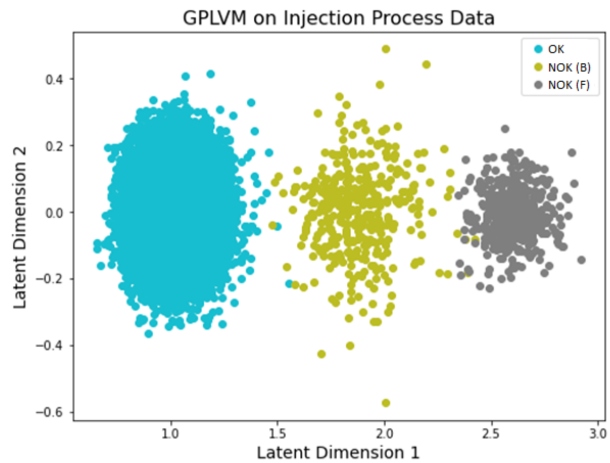

Fig. 10. Two-dimension representation of the process data.

carried out to understand if this failure was at a classification threshold between two different labels. It should be noted that as previously mentioned (Fig. 2), the distinction between NOK (Burr) parts is easy to identify, for example, in the case of the cushion parameter and is not mixed with the values related to the parts OK and this is highlighted in the performance of the classifier.

Analyzing the weights of the different classifications, it is possible to conclude that the misclassifications occur in transition zones between labels (as shown in Fig. 9). The two penultimate lines are misclassified and are in the transition between conforming and non-conforming parts.

In order to verify whether it is possible to improve performance and despite our dimensional space only having five dimensions, the use of the dimensionality reduction technique Gaussian Process Latent Variable Model was tested to try to reduce the representation space to only two dimensions and thus understand whether it is easier to identify the different classification groups. The Gaussian Process Latent Variable Model (GPLVM) is a dimensionality reduction method that uses a Gaussian process to learn a low-dimensional representation from (potentially) high-dimensional data.

Fig. 10 shows the result of the application of this tool where we can see that reducing the total dimension to two, although there are still some values on the transition border (less than in the case of the ensemble) it is possible to observe that the labels are grouped by distinct clusters. This means that this tool can be an asset in analyzing data related to injection processes and it will be a good tool to explore in the future and with other datasets to see if these types of issues are common for different materials and different types of parts.

V. Conclusions and Future Work

In this study, experimental data has been collected from a 220 Tonne Negri Bossi molding machine working with LLDPE (Linear Low-Density Polyethylene) material. The data includes 5 process parameters (features) from 39827 parts produced and labels indicating OK or 2 different NOK values.

We present several approaches for the classification of the data. We started using two different quality prediction models based on ANN and SVM methods. Although these models present accuracy of around 99%, there were still some flaws in the classification of non-conforming parts, so the best accuracy was obtained when it introduced a combination of these models through the Voting Based Ensemble Method and taking into account a windowed approach using the last three injection cycles history.

Even so, and despite the few wrong classified parts, the classification weights of the different parts produced were analyzed and it was possible to identify that the failures occurred in-between transition phases between conforming and non-conforming parts.

For this purpose, the Gaussian Process Latent Variable Model (GPLVM) technique was used to reduce the dimension of the dataset and thus see if this facilitates the analysis of the difficult cases. Although not conclusive, this technique has shown to be promising and so this may be a work to be developed in the future to test whether it applies to more injection processes and thus help to improve the performance of the classifiers.

In the future, we aim to use classification methods using windowed approaches to alert of the existence of problems in the process that are often only detected hours later, reducing the production of non-conforming parts. This leads to the reduction of the environmental footprint in this type of industry because only a percentage of the material can be changed and reused, but much of the remaining are still not recyclable, so by reducing these non-conforming produced parts we are moving in a direction of increased sustainability.

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