Relevant Parameters Identification in Traditional & Stretch and Blow Thermoplastics Injection Molding

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***Abstract*—Prediction of the quality of plastic molded parts based on process parameters is gaining a lot of attention. The complexity of the injection molding process lies in the high number of parameters that intervene throughout the process. From the large set of process parameters, the key issue is to find the relevant ones that should be used to correctly classify the produced parts. In this work we compared algorithms from the three main families of feature selection methods: filter, wrapper, and embedded. Additionally, a hybrid approach was also evaluated that takes into account not only the supervised contribution but also an unsupervised method in an effort to evaluate each feature without the influence of the target label. Validation involves three different machines from three different brands working with three different processes and materials. A novelty in this paper is the inclusion of two injection molding processes: traditional injection molding and stretch blow injection molding. All datasets were provided by a plastic injection company in Portugal. The results show that despite the variability in materials and machines, there is a group of variables that should be monitored in all of these processes (including the two types of molding techniques). In addition to the process parameters, adding the ambiance temperature around the machine improves the representation of the process through the data.**

***Index Terms*—Feature Selection, Hybrid Method, Injection Molding, and Stretch Blow Injection.**

I. Introduction

With the arrival of the new era of massive information through access to real-time data from various processes [1], information sets are increasingly complex. Data processing has become a fundamental procedure for the monitoring of any event. With the evolution of data collection technologies, there is also an increase in the number of features, which is consecutively directly proportional to the gain in the entropy of the dataset [2].

The presence of high levels of entropy in the framework degrades the performance of machine learning models. To ensure the reliability of machine learning models, feature selection methods are applied. These methods reduce the size of the dataset resulting in a reduction of most of the entropy, ensuring the integrity of the associated values. The datasets of an injection process are not an exception. As it is a dynamic process, there are several parameters associated with the quality of the process and it is essential to identify which have the greatest effect on the outcome of the process [3]. Most of the time, these parameters are identified by trial and error, which consumes time, company resources, and waste material [4].

The application of Machine Learning (ML) methods to determine the most relevant process parameters, as well as process monitoring and control, has been shown to be useful [5]. So, the motivation is to primarily analyze feature selection algorithms in the three main groups (filter, wrapper, and embedded) to understand whether or not different methods present identical results. By observing the results obtained from feature selection methods and how well it performs in predicting the quality of the part with Artificial Neural Networks (ANN), Support Vector Machines (SVM), and a recent Ensemble Method classifier [6], the first features will be extracted.

In the literature, there are works that combine the use of feature selection methods with unsupervised and supervised learning (hybrid methods) to exclude the bias that the "target label" of the supervised method could have on the selection of the most important variables [7]. This type of approach was used in the study presented in this article to understand if there are variables suggested by this hybrid method that increases the classifier's accuracy.

In the case of data collected, three different datasets were obtained in a real scenario at Vipex, a plastic injection molding company in Portugal with multiple production processes. Two traditional injection processes and a stretch and blow injection process were chosen to understand if there are correlations in the variables to be monitored. There are works in the literature relative to stretch and blow injection [8] [9] but they do not focus on either feature selection or on comparing the two injection processes and their most relevant features. Thus, the additional value of this data collection consists in the study of the "stretch-blow" injection molding process, which is different from the usual injection molding process.

With the focus on adding diversity to the datasets, three

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different machines developed by three distinct brands and (as mentioned) working on different processes were used. To understand whether external conditions have any influence on the outcome of the process, weather measuring stations were also integrated to record temperature and humidity variations. The variables were appended as features in the main datasets already formed by features directly collected from the machines. To the best of our knowledge, this is the first time that weather variables have been included in this type of dataset.

To summarize, the contributions of this paper are:

- Identification of the relevant variables to be monitored in thermoplastic injection molding, taking into account different processes, materials, and machines;
- Validation in two different types of injection molding (traditional and stretch and blow);
- Study and validation of the importance of ambiance temperature in quality prediction.

II. Feature Selection Stage

The plastic injection process is a mass-production method that involves a large number of parameters. It is a sensitive process that can be affected by various external events.

Feature selection has been used to select the smallest number of features with the most relevant information about the process. Three main classes of supervised feature selection methods were approached: filter, wrapper, and embedded. After using them individually, the methods were used together with an unsupervised learning algorithm to understand whether a contribution of this kind would improve the performance in predicting the quality of the parts.

Several methods were used to understand if the outputs were identical and if they could contribute in different ways to a better selection of the features that best represent the process. Several works in the literature were taken into account and focused on plastic injection to select the methods to be used. The algorithms were implemented using the Scikit-Learn library (open-source Python programming language for ML methods).

A. Filter

Filter-type methods select variables regardless of the model, they are based only on general features like the correlation with the variable to predict. Filter methods suppress the least interesting variables. In filter methods, Info Gain [10] [11] and Chi-Squared [12] were chosen based on the work carried out on feature selection in this area.

Info Gain is used for measuring how much useful information a parameter has about the dataset. In this specific framework, it allows to figure out how much information is being shared from a random feature of the injection process to the target label. In addition, Chi-Squared is a statistically based method that tries to capture the independence of variables based on another variable. In other words, Chi-Squared measures how the expected count X is derived from the observed count Z.

B. Wrapper

Wrapper methods evaluate subsets of variables which allows, unlike filter approaches, to detect the possible interactions amongst variables. Struchtrup *et al.* [13] identified that in the case of comparison of feature selection methods for supervised machine learning models the feature forward selection provides the best results, so it was chosen to represent the wrapper models.

This method starts with an ”empty set of attributes”. In each subsequent step adds attributes that add value to the final label. It is also considered a greedy feature selection method because it works in a pair with the cross-validation algorithm.

C. Embedded

Embedded methods combine the advantages of both previous methods. A learning algorithm takes advantage of its own variable selection process and performs feature selection and classification simultaneously, such as the Random Forest Importance algorithm [14]. This method adjusts the subset of information using data from the classifier and has deeper insights than the filter method [15]. It becomes a useful method to give a clear view of all features, how significant they are, and a second validation of the filter method. The Random Forest method creates several sub-trees which can produce an evaluation of each feature. Each result is then averaged to get the final rating of each feature.

D. Hybrid Approach

The purpose of using the Hybrid Method lies in the unsupervised and supervised learning combination. Through the addition of the unsupervised method, it becomes possible to analyze the feature selection without the influence of the ”target label” [7]. For the application of this hybrid method, Principal Components Analysis has been added in the unsupervised condition. The PCA appears to reinforce the weights of each feature. This method was selected because of its specialty of maintaining the most effective subspace using an optimal linear transformation [16].

III. Case Study Description

The basis of the work presented in this article was planned to allow us to answer the following questions:

- Can the quality of different injection processes (parts of different materials produced on machines of different brands) be represented through the same monitored variables?
- Do different feature selection algorithms present identical results for the same dataset?
- The features to be monitored are the same in traditional injection processes and in stretch and blow injection processes?
- Does meteorological variables have an impact on improving the quality prediction performance?

For this purpose, three different injection processes were selected (two normal injection and one stretch and blow injection) typically common at Vipex. One of the processes

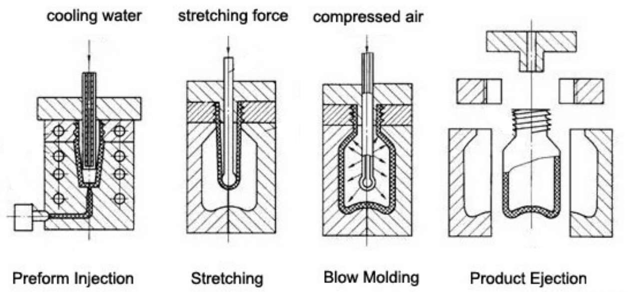

Fig. 1. Injection stretch blow molding process step by step.

was operating on a 400 ton Negri Bossi machine (NB400), producing PP (Polypropylene) parts. The second selected process was performed on an 850-ton machine of the Tederic brand (TD850) producing ABS (Acrylonitrile butadiene styrene) material parts. Finally, the third process associated with stretch and blow injection was operating on a Nissei ASB machine producing bottles from Tritan material.

The thermoplastic injection molding process includes four main stages: plasticization, injection, cooling, and ejection [17]. At first, plastic pellets are melted with the help of a reciprocating screw, afterwards the plastic melt is injected into a mold with a cavity in the form of a produced part with the help of injection pressure, and finally, the plastic melt cools down and solidifies.

The stretch and blow injection process is composed of four phases, two phases identical to the normal injection (injection and ejection) mentioned above and another two where the part is stretched and blown. As shown in Fig. 1[1] in the first phase the preforms of the bottles are injected, in the second phase the preforms are stretched and in the third it is blown to give the final shape. After, the part is extracted. Between the first and the second phase, there is an intermediate phase (not represented in the figure but existing on the machine) where the preforms are left in pots at a specific temperature in order to guarantee the correct consistency of the material to be stretched and blown.

In order to relate the parameters to the quality of the parts, the same tests were carried out on all machines. These tests covered the typical problems that occur during a process and that can interfere with the quality of the parts. These problems are water cooling, failure of spindle heating elements, and failure of mold heating systems. The tests were carried out in the same order in the different processes and the quality of the parts was monitored in order to create the dataset. Regarding the blowing part in the third process, the temperatures of the pots were also changed to maintain the correct consistency of the material to see if this interfered with the quality of the final product.

A. Available Features

The number of variables available on the different machines is different. On both injection machines, the TD850 provides real-time data via OPC-DA and the NB400 and Nissei ASB provide data via OPC-UA. On the TD850 we were able to access 29 features and on the NB400 22 features. Regarding the stretch and blow injection machine, we have access to 29 features.

As a novelty, we also gathered the ambient temperature and humidity using a DHT22 sensor in each machine connected to a Raspberry Pi where an OPC-UA server was created to make the data available and synchronized. We are not aware of other datasets that include this type of information.

IV. Results and Discussion

Once we knew the quality of each injected part and which parameters originated them, supervised learning feature selection methods were used (filter, wrapper and embedded).

The strategy implemented to test the different datasets was composed of five steps (see Fig. 2). These steps were performed consistently in the same order on the different datasets.

The results of performing the combination of methods (InfoGain (IG), Chi-Squared (Chi^2), Forward Selection (FS), and Random Forest Importance (RFI)) and datasets are reported in Fig. 3 where "*" indicates that the variable has a residual impact on the process and "-" indicates that the variable has very low impact. There is also a list of variables that appeared as a result of the different tests, this number being less than the total number of features. The pots temperature are only relative to the blow injection machine (Dataset 3).

Regarding the classification, since the different methods have different convergence metrics, numbers were used to represent the magnitude in ascending order that each feature obtained in a given algorithm. For example, the Maximum Injection Pressure (MIP) obtained the first rank in the IG and the second in the Chi^2, this being the first rank for the temperature of the nozzle.

The next subsections present the results for each of the datasets as well as the combination of features that presents a

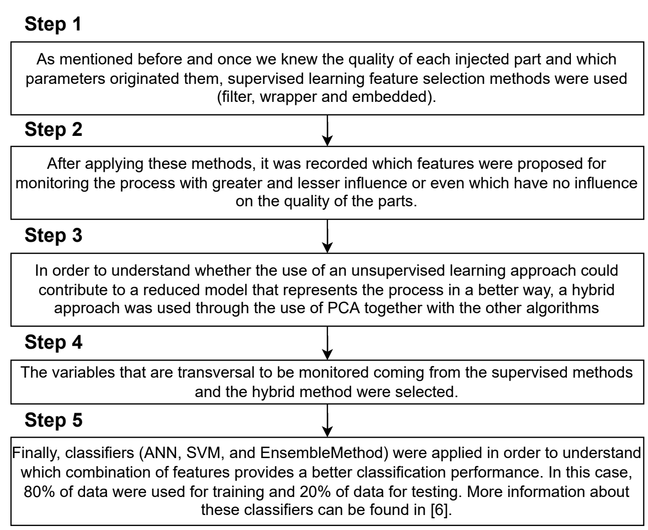

Fig. 2. Implemented strategy to test the different datasets.

[1] https://alleycho.com/plastic-injection-stretch-blow-moulding-process/

		Dataset 1					Dataset 2					Dataset 3				
		Supervised				Unsupervised	Supervised				Unsupervised	Supervised				Unsupervised
		IG	Chi²	FS	RFI	PCA	IG	Chi²	FS	RFI	PCA	IG	Chi²	FS	RFI	PCA
Injection Unit	MIP	1	2	*	1	5	3	1	1	1	5	*	4	*	3	8
	Nozzle Temp.	2	1	2	2	1	5	5	2	2	1	5	1	7	*	*
	Z1 Temp.	3	3	3	3	2	4	3	4	*	2	4	5	*	1	5
	Z2 Temp.	*	*	5	*	4	*	*	*	*	3	3	*	*	6	4
	Z4 Temp.	4	5	4	*	*	-	-	-	-	-	2	2	*	7	3
	Cushion	6	4	1	-	*	*	6	*	5	6	*	*	*	4	*
	Ambience Temp.	5	6	*	*	6	1	*	5	4	5	*	8	8	5	*
	Injection Velocity	*	*	*	5	3	-	*	*	*	7	-	-	*	2	-
	Injection Time	*	*	6	*	-	6	-	-	*	-	-	-	*	-	-
	Backpressure	-	-	-	4	-	-	-	-	-	-	-	-	-	-	-
	Switching Pressure	-	-	-	-	-	2	2	6	3	4	-	-	-	-	-
	Air Humidity	-	-	*	-	-	*	-	*	6	*	-	-	-	*	*
	Closing Force	-	-	-	-	-	-	4	3	*	*	-	-	-	-	-
	M2	-	-	-	-	-	-	-	-	-	-	1	-	2	-	*
	Plastification Time	-	-	-	-	-	-	-	-	-	-	6	3	1	*	*
	Block HR1	-	-	-	-	-	-	-	-	-	-	7	*	6	*	*
Stretch and Blow Unit	Pot 1 Temp.											-	*	4	*	7
	Pot 4 Temp.											-	6	*	*	1
	Pot 5 Temp.											*	*	5	*	6
	Pot 8 Temp.											-	7	3	*	2

Fig. 3. Evaluation from the different feature selection algorithms: InfoGain (IG), Chi-Squared (Chi^2), .

better classification performance. The classifiers were created using ANN, SVM and an Ensemble Method that takes both classifiers into account. In the ANN case, the architecture with the best performance uses 200 neurons with the logistic activation function and lbfgs solver. In the case of SVM, a cost function of 10000, a gamma of 0.01, and the linear kernel was the best performing architecture.

A. Dataset 1

Figure 3 shows the results for the different methods evaluated. Taking into account the average output of all supervised learning algorithms, we can conclude that the variables to select are: Maximum Injection Pressure (MIP), Nozzle Temperature, Zone 1 Temperature, Zone 4 Temperature, and the Cushion.

Taking into account the hybrid method (supervised + unsupervised) we also took into account, due to the reinforcement, the Ambience Temperature, the Injection Velocity, and the Zone 2 Temperature.

Table I presents the results of the different ANN, SVM, and Ensemble Method classifiers for each of the scenarios. The first scenario is to apply these classifiers to predict the quality of the parts using all the collected features (22 features), the second applying the features resulting from the supervised learning methods (5 features), and finally using the classifiers on the features resulting from the hybrid method (8 features).

We can see that there was a performance improvement when using the five features from the supervised methods instead of all the collected features. But the use of the hybrid method was the one with the best performance.

	ANN	SVM	EM
All Features	94%	91%	95%
FS (SL)	96%	96%	97%
FS (Hybrid)	97%	98%	98%

TABLE I
CLASSIFICATION PERFORMANCE RESULTS FOR DATASET 1.

	ANN	SVM	EM
All Features	80%	85%	88%
FS (SL)	87%	92%	91%
FS (Hybrid)	89%	92%	93%

TABLE II
CLASSIFICATION PERFORMANCE RESULTS FOR DATASET 2.

B. Dataset 2

Analyzing the Fig. 3 it is possible to conclude that the variables to select are: Maximum Injection Pressure (MIP), Nozzle Temperature, Zone 1 Temperature, Switching Pressure, Closing Force, and Ambience Temperature.

Taking into account the hybrid method (supervised + unsupervised) we also took into account, due to the reinforcement, the Cushion, and Zone 2 Temperature.

Table II presents the results of the different ANN, SVM, and Ensemble Method classifiers for each of the scenarios. The first scenario is to apply these classifiers to predict the quality of the parts using all the collected features (29 features), the second applying the features resulting from the supervised learning methods (6 features), and finally using the classifiers on the features resulting from the hybrid method (8 features).

C. Dataset 3

In this case, we also have to take into account the variables related to the stretch and blow part. So, analyzing the results of the supervised algorithms, we can observe that the variables to use are: Maximum Injection Pressure, Nozzle Temperature, Spindle Temperatures (Z1, Z2, and Z3), Plastification Time, M2, and Ambience Temperature.

Taking into account the hybrid method (supervised + unsupervised) we also took into account, due to the reinforcement, the Pot 4 and Pot 8 Temperatures and Cushion. The final result of the feature selection was from 29 features to 9.

It is worth noting here the impact that the PCA gives on the temperatures of the Pots, an impact that the supervised methods do not represent. Looking at the Table III and compared to the others, we can see that the increase here between not using feature selection or using the variables proposed by the hybrid method is what allows to increase the performance. Questioning the technicians and through their practical knowledge, they validate these results in the sense that they say that one of the ways to guarantee the quality of the final piece is to keep the temperature of the pots stable at the defined temperature. Each of the two pots has 4 resistors, resistors 4 and 8 being the resistors at the bottom of the pot, this resistor is the one that suffers the most variations in case of problems because it is where the highest temperature is. Thus, with the reinforcement that the PCA gave in order to verify this variable, we had the clear contribution of the use of the hybrid methodology.

D. Selected Features

It is important to note that there are variables that are transversal to the three datasets that work with different machines (including the injection part related to the Nissei ASB machine) and materials, namely: Maximum Injection Pressure, Nozzle Temp, Z1 Temperature, Z2 Temperature, Z4 Temperature (Z3 in Nissei ASB case because it only has three resistors on the spindle), Cushion and Ambience Temperature. In the case of the stretch and blow injection machine, we have the temperature variables of the pots and M2. The M2 represents the difference between the configured injection time (expected value) and the actual injection time.

Of these variables, there are some that appear in some of the processes and that can be advantageous to take into account, such as Injection Velocity, Switching Pressure, Closing Force, and Plastification Time.

After showing and discussing the outputs of the algorithms with the injection technicians and process engineers, they said that among the identified variables, we can also, in certain specific cases, monitor the Cycle Time and the Injection Time, as these can help not so much in directly observing the quality of the parts, but in solving some specific problems.

	ANN	SVM	EM
All Features	72%	72%	88%
FS (SL)	72%	72%	92%
FS (Hybrid)	78%	75%	95%

TABLE III
CLASSIFICATION PERFORMANCE RESULTS FOR DATASET 3.

E. Meteorological Variables

The test with meteorological variables was introduced to observe if the variation of temperature and humidity had an impact on the prediction of the quality of the pieces. It had already been reported by process engineers that the ambience temperature could influence the quality of the parts because between summer and winter the parameters often had to be adjusted and the material dampened before entering the machine.

To this end, a sensor was placed on each machine, as they are distributed in different places in the pavilion and we also wanted to analyze this situation. The NB400 is in the middle of a row of six machines and next to a gate that is opened several times a day for logistical tasks. The TD850 is at the top of a row and the Nissei ASB is in a different pavilion from the previous ones and in a more isolated area.

Observing Table IV the ambience temperature has a greater impact in the case of the TD850 machine since it is at the top of one of the rows and is more susceptible to temperature variations. Despite the NB400 being next to the gate that is opened several times a day, it is in the middle of other machines and so the variation ends up being mitigated. But even so, the impact is still relevant in terms of feature selection and process representation. The Nissei ASB is in a more controlled environment so the impact, despite existing, turns out not to be as pronounced in terms of ranking as the others.

Table IV only serves to validate the impact of the introduction of temperature measurement (external variable to those provided by the machine) on the performance of the dataset when used to predict the quality of the parts.

From table we can see that the temperature contributes to the improvement of the predict performance and that it goes against the weight/rank that the variables have in the different datasets. TD850 (Dataset 2) with greater impact as it also has a greater influence on the dataset. NB400 (Dataset 1) with still some impact, and Nissei ASB (Dataset 3) with a more residual impact. The data, in this case, were indicated with more decimal places to get an idea of the impact variation.

Figure 4 shows a time window of 150 cycles recorded between 9am and 12pm in each of the processes during the tests. It is possible to observe in a more intuitive way the temperature variations based on the position of the machines in the pavillion and the importance that these have in the classification performance (the smaller the variation, the smaller the impact on the performance of the classifiers).

Regarding humidity, according to empirical knowledge, this usually affects the material's stoving time before entering the

	Dataset with Temperature	Dataset without Temperature
Dataset 1	97.872%	96.923%
Dataset 2	93.317%	91.463%
Dataset 3	95.302%	95.041%

TABLE IV
CLASSIFICATION PERFORMANCE RESULTS WITH AND WITHOUT AMBIANCE TEMPERATURE.

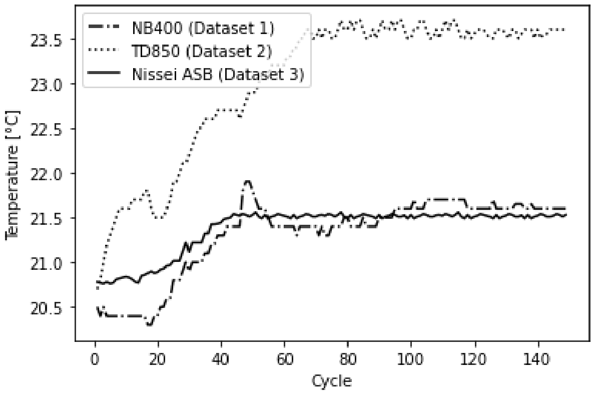

Fig. 4. Example of temperature variation in the different processes sampled between 9am and 12pm to observe the change during the day and the difference between locations.

spindle, the higher the humidity, the longer the material has to be in the oven before being placed in the spindle. In this case, the relevance of the tests carried out has not yet been noticed, but it will be interesting in the future to compare the realities between summer and winter and check if it makes a difference in terms of the process, or just in relation to the stewing time.

V. Conclusion and Future Work

In this study, experimental data were collected from three different injection processes working on three machines of different brands and with different materials (PP, ABS, and Tritan). In order to relate the process variables with the quality of the parts, typical problems were induced, like resistor failure, water turning off, mold carburetor failure, among others.

Two of the machines are conventional injection machines and one of the machines is stretch and blow injection. This machine consists of a conventional injection part and a stretch and blow part. In the presented study we find that there are variables that are transversal to the 3 processes even though they are different materials and parts working with different machines. These variables are Maximum Injection Pressure, Nozzle Temperature, Z1 Temperature, Z2 Temperature, Z4 Temperature (Z3 in Nissei ASB case because it only has 3 resistors on the spindle), Cushion and Ambience Temperature. Additionally and specific to the blowing machine, the temperature variables of the pots and M2 must also be taken into account. There are still other variables that have been shown to be relevant from time to time and that can be taken into account in the representation of an injection process.

Another conclusion of this work is that using a hybrid methodology, which takes into account supervised and unsupervised methodologies to select the variables with the greatest impact on the process, we managed to have a better performance in terms of predicting the quality of the parts produced. Using this methodology, we reduced the number of features on average by 73%, which represents not only gains in terms of performance but also in terms of writing flow to the cloud, computing time, among other things.

Regarding the introduction of meteorological variables in the monitoring of the process, it is clear that the ambience temperature has an impact on the processes.

In the future, we intend to carry out tests with more machines and different materials to reinforce the use of the hybrid methodology and reinforce the conclusion about the number of variables transversal to all the processes to be monitored. Regarding the ambient humidity, it will be interesting to monitor it in different seasons of the year (summer and winter) in order to understand if it only affects the material's stewing time or if it also affects the behavior of the process parameters.

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