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ORIGINAL ARTICLE

Investigation of failures in rotational moulding using historical production dataset and machine learning

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Abstract

Rotational moulding (RM) is a versatile manufacturing process widely used for producing lightweight, seamless plastic components, but its potential is often constrained by challenges in optimizing production parameters for diverse product geometries and simultaneous batch production. This study addresses the pressing need for a data-driven approach to enhance RM efficiency and reduce defects under non-optimal process conditions. Leveraging historical production data from a medium-sized RM enterprise, an Ensemble Learning-based machine learning (ML) model was developed to predict failure probabilities across 390 product-process combinations. Input parameters are heating temperature, speed, mould volume, product mass. The model achieved an accuracy of 97.17%, identifying optimal parameter ranges for minimizing defects. The results revealed that deviations between machine and product-specific conditions, particularly in heating temperature and rotational speed, significantly increased failure probabilities. Products with intermediate sizes and masses were most susceptible to failures, while extreme values of mould volume occupancy showed a lower likelihood of failures. Notably, the study highlighted the critical importance of maintaining minimal delta heating temperature and speed ratio disparities to ensure product quality. This approach offers a robust framework for optimizing RM processes without costly sensorization, making it especially beneficial for small- and medium-sized enterprises.

Keywords Rotational moulding · Machine learning · Failure prediction · Design for manufacturing

1 Introduction

Rotational moulding (RM) is a versatile plastic manufacturing process that offers unique advantages, such as the production of large, lightweight, and seamless parts with exceptional structural integrity. RM involves heating and rotating a mould filled with polymer powder to form hollow components, making it particularly suited for diverse applications, from storage tanks to medical devices [1]. Recent studies highlight RM's potential to meet growing demands for customized solutions, with benefits aligned with trends in light-weighting and energy efficiency [2, 3]. Additionally, RM allows for the simultaneous production of multiple parts with varying designs using rotating carousel arms, improving productivity [4]. The process's ability to minimize material waste and accommodate complex geometries positions RM as a promising alternative to traditional methods, with ongoing research further expanding its applicability [5].

The complexities inherent in RM introduce substantial challenges that hinder process optimization. A primary issue is the wide variety of geometries and dimensions that RM accommodates, complicating the development of standardized testing protocols. This diversity necessitates tailored testing approaches, often resulting in difficulties in achieving meaningful results across different designs. Moreover, the multitude of variables involved

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(e.g., volume, shape, rotational speed, mass, temperature) increase the complexity to be managed to ensure product quality and consistency. Understanding the influence of individual parameters on part quality, specifically the tolerance ranges necessary to avoid defects, is essential for determining the right combination of settings within these limits. The use of sensors techniques, such as thermal imaging, face limitations due to the dynamic nature of the process and varying thermal properties of materials, complicating accurate temperature monitoring and control [4, 6]. Conducting extensive testing across a wide range of components is often impractical due to time and resource constraints. The lengthy cycle times associated with RM necessitate a careful balance between production efficiency and quality assurance. As companies maintain extensive catalogues of parts and seek to implement dynamic production schedules, identifying optimal process parameters becomes increasingly critical for enabling the simultaneous printing of components with differing shapes and sizes while minimizing failures and defects [7].

Hence, a comprehensive analysis of how the failures of products produced through RM are influenced by process parameters and products features is essential to adequately understand the process within the industrial reality. This can be the basis for planning production by increasing quality and increasing rates through the definition of combinations of products on the machine.

However, in the literature, the different studies analysing the RM process proposing predictive methods, based on mathematical and statistical models, simulation software and machine learning (ML) (see Sect. 2.2) have several limitations that do not allow them to fully solve this problem:

- The data used to build the models are mostly secondary or, if primary, were obtained from measurements in laboratory tests. In this context, the considered products are of a rather standard shape, such as a box [8]. The limit in this case is both in the validation of the method and in its application in industrial context, where those who print with rotational moulding typically have a large catalogue of products and manage many orders [9].
- The machines considered in the construction of the methods mostly print only one part at a time. Therefore, when the methods explore the influence of off-design process parameters on the part, they consider arbitrary conditions or those dictated only by the limits of the machine [10]. In this way, off-design conditions in printing that arise from the need to print multiple products together, or from compromises between the different required process parameters, are not considered.
- There are several studies that use ML to support production planning, both with the aim of maximizing production and reducing defects, by directly interpreting production data, for example from dashboards, instead of using specific laboratory tests in ad hoc environments with lots of sensors [11]. However, the environments in which ML has already been applied according to this logic, such as semiconductors and automotive, are more automated, standardized and digitalized compared to RM that is poorer in structured data to apply ML effectively.
- There is no study that simultaneously addresses the problem of maximizing production and avoiding defects by combining different parts. There are also studies that plan production without investigating the quality of the obtained parts [12] and studies that study the quality of a single part at a theoretical level, without dealing with the needs of maximizing occupancy [13].

This study aims to advance the theoretical understanding of RM process failures by examining the influence of different key process parameters: temperature, rotational speed, and product attributes (i.e., shape, size, and mass), on the occurrence of failures in RM products. While previous literature has focused on single parameters or restricted with laboratory-scale tests, this research addresses the multidimensional interplay within RM by considering different product families and industrial conditions. Hence, the main contribution of this work is to bridge the gap between the theoretical and industrial RM applications to provide a fundamental knowledge for production planning and quality control applications.

To gather extensive industrial data on failures across various printing scenarios and many different products, the production was monitored over several months at a company. Additionally, ML was employed to analyse the collected data and generate predictions for failure occurrences in untested product-process configurations.

Training an ML-based approach on historical production data eliminates the need for costly and invasive sensors or laboratory tests. This is particularly beneficial for RM, where such requirements pose significant challenges for small and medium-sized enterprises (SMEs) reliant on extensive product catalogues. The method provides actionable insights for aligning batch configurations and process parameters, identifying temperatures and rotation speeds that enable failure-free production of diverse products in the same batch. By correlating failure probabilities with process conditions and part characteristics, it establishes tolerance criteria for grouping parts and streamlining batch assignments.

This approach is particularly valuable for maximizing production efficiency by enabling the simultaneous manufacturing of diverse products, thereby addressing the constraints posed by a limited number of moulds. Such scenarios are common in SMEs, especially those engaged in customer-driven, on-demand production. In these cases, it is often necessary to produce a wide variety of products, many of which fall outside the standard catalogue. Due to the lack of multiple moulds for identical products and the challenge of maintaining consistent process parameters, manufacturers must operate under off-design conditions and seek compromises during production. The proposed method provides a robust framework for navigating these challenges, ensuring efficient and failure-free operation even under suboptimal conditions.

2 Literature background

2.1 Overview of rotational moulding

RM is often regarded as a niche process within the plastics industry, yet its distinct advantages merit greater attention from the scientific community. Unlike more widely used techniques such as injection or blow moulding, RM utilizes a unique method that involves heating and rotating a mould filled with polymer powder to produce hollow components. These parts are characterized by exceptional structural integrity and design flexibility, making RM particularly well-suited for large, lightweight, seamless items free from internal stresses. Applications of RM span various industries, from storage tanks to complex medical devices [1].

Recent studies emphasize RM's potential to address the increasing demand for customized solutions across sectors like automotive and consumer goods. The process's versatility fosters innovation and aligns with trends toward lightweighting and energy efficiency in product design [2, 3]. As sustainability becomes a key priority for manufacturers, RM's ability to produce intricate geometries with minimal material waste presents it as a compelling alternative to traditional methods. Ongoing research into novel materials and process optimization further expands RM's applicability, positioning it to play a critical role in the future of plastic manufacturing [3].

The RM process involves the uniform distribution of molten material in a rotating heated mould, resulting in hollow plastic parts. Its key benefits include low tooling costs, the creation of complex seamless shapes, and consistent wall thickness. RM is especially effective in producing durable components from low-density polyethylene and can accommodate various geometries and sizes, from small objects to large tanks, by adjusting parameters like heating and cooling temperatures, as well as rotational speed [4]. The geometric properties and structural integrity of the moulded parts are closely linked to the dynamics of heating, cooling, and centrifugal forces at play [6].

An additional advantage of RM is its capacity to simultaneously produce multiple parts with different designs using rotating carousel arms that hold several moulds. To do this, it is necessary to find the right compromise between the process parameters. In this way it is possible to boosts the productivity, especially considering the typically low added value of the components produced.

The RM process can be summarized through the following four stages (Fig. 1).

1. Mould Charging: This initial stage involves the precise introduction of powdered polymeric material into a meticulously cleaned and prepared metallic mould cavity. The quantity and distribution of polymer powder are critical, as they directly influence the final product's morphological and mechanical characteristics.
2. Bi-axial Rotation and Thermal Plasticization: Upon mould loading, the mould is simultaneously rotated about two perpendicular axes and transferred into a high-temperature controlled oven. This bi-axial rotation mechanism ensures uniform heat transfer and material distribution. As the polymer approaches its glass transition temperature and melting point, it undergoes a complex phase transformation, transitioning from a particulate solid to a molten state with rheological properties governed by thermal gradients and rotation kinematics.
3. Cooling and Structural Consolidation: Following thermal plasticization, the mould undergoes a controlled cooling process while maintaining continuous bi-axial rotation. This stage is crucial for achieving dimensional stability and microstructural integrity. As evidenced by [14], cooling methodologies include forced air convection, external evaporative cooling, external water spray cooling. Each cooling technique presents unique heat transfer characteristics that influence the final mechanical properties of the product, thermal stress distribution, and surface morphology.
4. De-moulding: The final stage involves the carefully controlled extraction of the solidified polymeric component from the mould, minimizing potential structural deformations or mechanical stresses induced during demoulding [15].

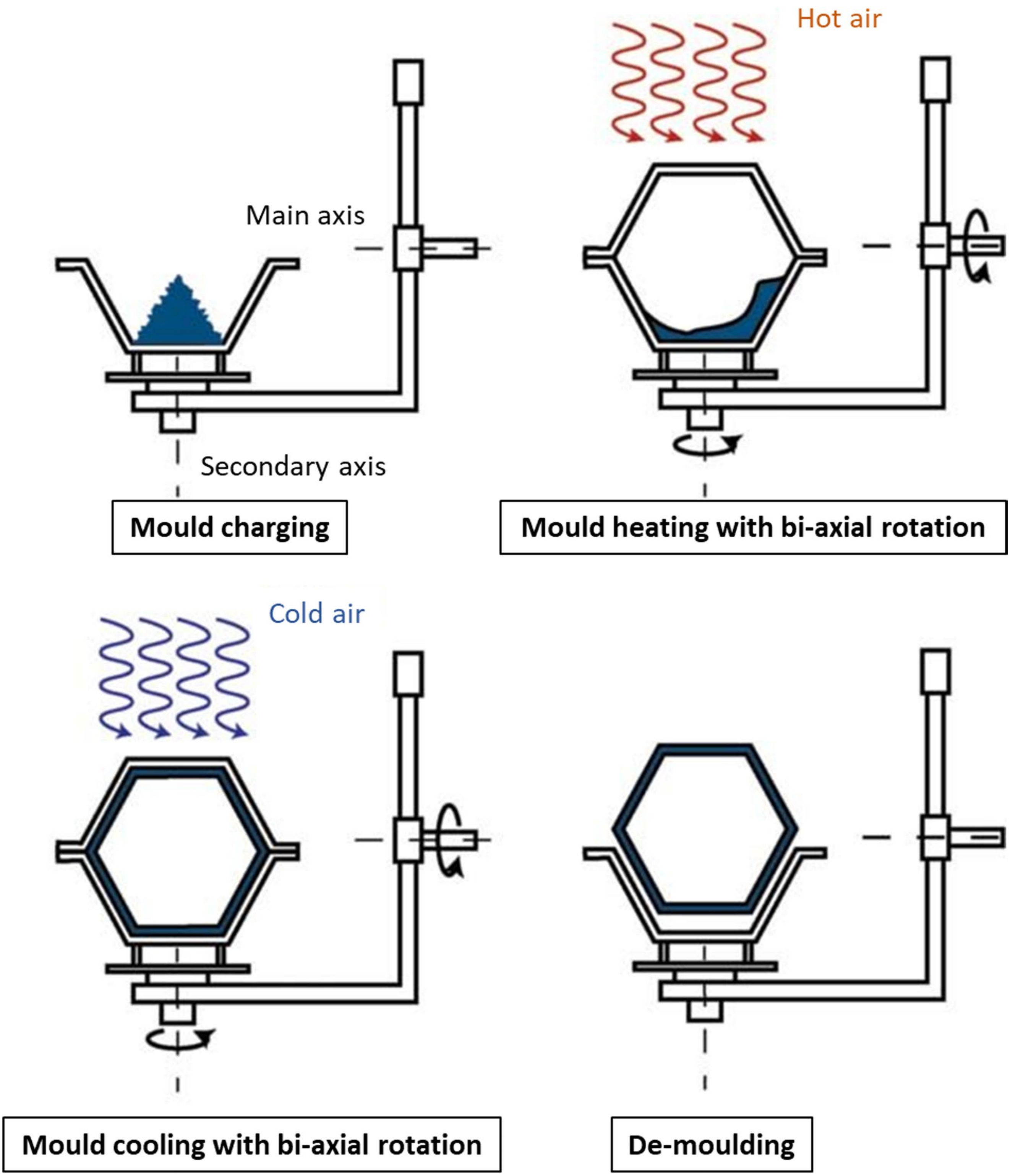

Fig. 1 Graphical representation of the RM process, adapted from [15]

2.2 Failures in rotational moulding

The product failures in RM can arise from a variety of factors encountered during the production process, many of which can significantly impact the quality and functionality of the final product. One of the most common issues is inadequate temperature regulation. Precise heating and cooling cycles are critical to ensuring the proper melting, flow, and solidification of the material. When heating is insufficient, the polymer may not fully melt, resulting in poor surface finishes, voids, or incomplete coverage within the mould. Conversely, excessive heating can degrade the material, leading to discoloration, brittleness, or an uneven surface texture. In the cooling phase, inadequate control can result in warping, residual stresses, or dimensional inaccuracies, as the material contracts unevenly [16].

Another source of failure stems from defects in the mould itself. Surface imperfections, such as scratches, dents, or uneven textures, can transfer directly onto the moulded product. These defects not only diminish the aesthetic appeal but can also introduce weak points that compromise the structural integrity of the final product. Furthermore, improperly maintained or poorly designed moulds may lead to difficulty in releasing the product, increasing the likelihood of damage during demoulding [17].

Operational parameters, such as rotation speed and timing, also play a crucial role in the success of RM. The rotational motion of the mould ensures the even distribution of molten material across its interior surfaces. However, incorrect rotation speeds or durations can lead to uneven wall thickness. Thin sections may result in weak spots prone to failure under stress, while overly thick sections can add unnecessary weight and material cost. Properly calibrated equipment and adherence to production specifications are essential to achieving uniformity and consistency in the finished product [4].

2.3 Studies supporting rotational moulding

In order to understand which approaches have been proposed in the literature to support the RM printing process, relevant studies were collected and analysed following a systematic procedure. The studies have been collected from Scopus and Google Scholar, launching the following search query in title, abstract and keywords fields: "((rotational W/1 moulding) OR rotomoulding) AND (simulation OR (machine W/1 learning) OR (artificial W/1 intelligence) OR ((computat* OR numeric* OR mathemat*) W/1 (model or method or algorithm)))". The collected studies were manually analysed, keeping only those that use predictions to suggest the most suitable printing parameters in relation to product geometry, to ensure product quality or high productivity.

From the analysis of the collected studies, it emerges that Baxendale et al. (2021) [12] and Ozdagoglu et al. (2013) [18] aim to maximize machine occupancy during printing, suggesting how to combine the parts, while all the other studies aim to guarantee the quality of the produced part. No study considers both goals, looking for a compromise. The goal of guaranteeing quality is declined in different ways that can be classified into two categories: avoiding geometric or surface defects [10] and guaranteeing mechanical properties of the part, such as tensile, impact and flexure strength [2].

The inputs of the proposed methods include theoretical and empirical rules and data such as mathematical models of heat transfer or experimental test data collected from the literature [19]. Other studies instead use direct data obtained after printing by measuring the characteristics of the obtained part [20] or during printing, measuring parameters such as the internal temperature of the part through thermal cameras [21].

The methods provide as output the process parameters that can be set to improve the part quality or increase the production, such as heating temperature and time [22], cooling temperature and time [13] and rotation speed [8]. These parameters are provided individually or together, suggesting the most strategic combinations. In addition, the production scheduling in batches can also be provided as output [12].

The proposed methods search for correlations between two or more parameters, typically one related to the process, such as heating temperature or rotation speed, and one related to the quality of the product, such as thickness. The correlation is searched through the implementation of simulations based on numerical models developed ad hoc and implemented in commercial software [13], mathematical or statistical models [12] and ML [20].

The application of the proposed methods is almost always at a laboratory level and considering the printing of a single product, with the exception of the methods of Baxendale et al. (2021) [12] and Shirazian et al. (2024) [20] which are applied in real industrial applications on machines that print multiple products at a time.

The results of the analysis of the considered studies according to the considered features are reported in Table 1.

Table 1 Studies proposing methods to support RM process

Study	Goal	Input	Output	Method	Model and tool	Application level
[19]	Avoid product deformation and superficial defects	Theoretical and empirical rules and data from the literature	Heating temperature, heating time	Prediction of the product failures based on the increase in its internal temperature	Computational fluid dynamic simulation	Laboratory scale, single product
[21–24]	Reduce product sinkhole area percentage, ensure product tensile, impact and flexure strength	Direct data measured during printing	Heating temperature, heating time, rotational speed	Prediction of the product failures based on the increase in its internal temperature	Machine learning	Laboratory scale, single product
[10]	Avoid product surface and geometrical defects	Theoretical and empirical rules and data from the literature, direct data collected after printing, direct data measured during printing	Heating time, cooling time	Prediction of the filling of the mould during printing based on theoretical rules	Numerical model embedded in simulator software	Laboratory scale, single product
[12, 18]	Maximize machine occupancy	Direct data collected after printing	Production scheduling	Combination of the product in batches based on the similarity of heating times	Mixed Integer Programming mathematical model	Production scale, multiple products
[2]	Ensure product tensile, impact and flexure strength	Direct data collected after printing	Heating time	Predicting oven residence time for ensuring certain product tensile, impact and flexure strength	Machine learning	Laboratory scale, single product
[8]	Ensure product uniform thickness	Direct data collected after printing	Rotation speed	Analysing the relation between product thickness and rotation speed	Statistical analysis	Laboratory scale, single product
[25]	Ensure product uniform thickness	Theoretical and empirical rules and data from the literature	Rotation speed	Simulating the flow of material inside the mould	Mathematical model	Laboratory scale, single product
[20]	Ensure product tensile, impact and flexure strength	Direct data collected after printing	Heating time	Predicting products quality based on the internal temperature	Machine learning	Production scale, multiple products
[13]	Avoid product deformation	Theoretical and empirical rules and data from the literature	Cooling temperature, cooling time	Simulation of the product warpage during cooling based on theoretical rules	Numerical model embedded in simulator software	Laboratory scale, single product

3 Materials and methods

The method used to obtain the failure predictions of the considered products consists of different phases. First, products and their features (i.e., mould volume, product mass, most suitable heating temperature and speed ratio) are collected. Historical data about the failures of the considered products under different printing conditions, i.e., different heating temperature and speed ratio set in the machine, are collected by monitoring industrial production. These historical data are used to select the ML algorithm among different alternatives based on the accuracy and training the model for predicting the features of the products under all the combinations of printing conditions. Finally, the obtained results are analysed and discussed, by studying the intersections between predicted failures and product features and process parameters. Figure 2 presents the flowchart of the proposed method.

In the following sub-sections, the first three steps of the proposed method are explained in detail, while Sect. 4 and Sect. 5 are dedicated to step 4 - results analysis.

3.1 Define input/output

The considered products are all made of low-density polyethylene (LDPE), printed with steel moulds and they are different in terms of size, shape and mass. These products have been chosen to reflect the typical production of companies in the sector and to ensure a case study that is as varied and heterogeneous as possible. Based on their shape, the products were classified into 13 models with the same design and different dimensions. These models were then grouped into 5 families based on geometric similarity.

- **Alpha**: spherical shaped products, with a small opening, such as lamps or jars.

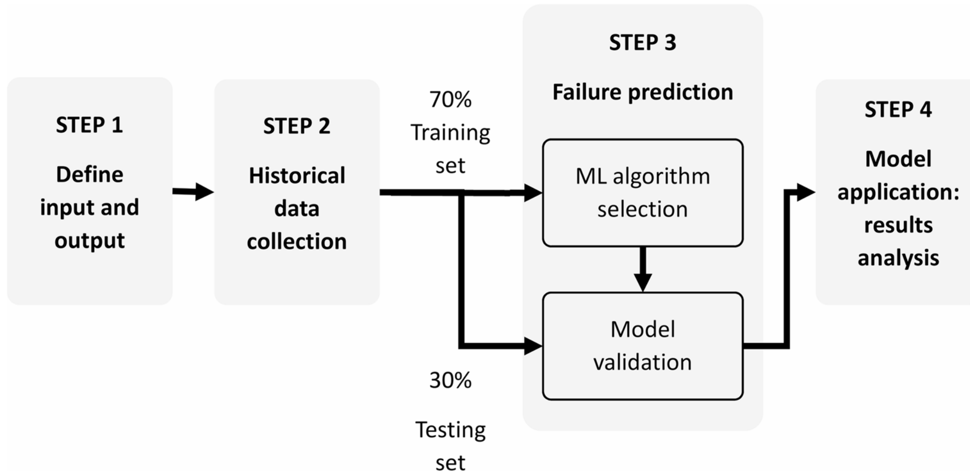

Fig. 2 Presents the flowchart of the proposed method

- **Beta**: cylindrical shaped products, such as tanks or spools.
- **Gamma**: are cubic-shaped pieces, almost completely closed on all sides, come pouffes and armchairs.
- **Delta**: are pieces of parallelepiped shape, open on one side, like boxes, trunks and bins.
- **Epsilon**: flat products, in which two dimensions are significantly larger than the third, such as bases, walls and doors, for example of portable toilettes.

Figure 3 illustrates the product models and families under consideration, displaying the name of each model along with the number of products associated with it.

For each product, the most suitable heating temperature was provided by the company. All the printing temperatures are all contained between 200 and 220 °C, while the process time is set equal to 20 min for all the products, and it is defined by the company. Regarding the rotation speed of the mould during printing, the speed ratio parameter related to the two axes of the machine (see Fig. 2) has been adopted. The value of the speed ratio was assigned to each piece in relation to the criteria established by [4]: the parts with a speed ratio equal to 2 are rings, tires, mannequins, flat shapes, while those with a speed ratio equal to 3 are Cubes, balls, rectangular boxes, most regular 3-D shapes.

Table 2 in the appendix reports the characteristics of the considered products.

Figure 4 provides the distribution of most heating temperature, speed ratio, mould volume occupancy and mass of the considered products. The mould volume occupancy parameter quantifies the extent to which the mould fills the available cavity within the moulding machine. It is expressed as a percentage and represents the ratio of the mould external volume to the maximum capacity of the moulding machine's processing volume that can be utilized.

The addressed problem deals with the determination of the failure probability, for different products under different printing conditions. 39 products, typically printed with RM have been considered. Product features and their optimal process parameters were identified during the collaboration with Roplast Srl, a medium-sized company specializing in RM, operating in northern Italy for over 40 years, producing both catalogue and custom-made products. The products have different shape, dimension, mass, heating temperature, speed ratio, and volume occupancy of the mould. The printing parameters for testing the failure probability of the products were chosen to replicate common process conditions where multiple products are typically printed simultaneously, maximizing productivity while balancing trade-offs. In particular, the considered parameters are the following:

- Heating temperature: 200, 205, 210, 215, 220 °C, where the selected extremes are equal to the lowest and highest most suitable heating temperatures of the considered products, so as to simulate all possible couplings between the products in the machine.
- Speed ratio: 2, 3, in relation to the considered products. The speed ratio is equal to the ratio between the rotation speed of the main axis of the machine, divided by the difference in rotation speed between the main axis and the secondary axis.

Consequently, the product-temperature-speed ratio combinations for which the failure probabilities have been predicted are 390. These product types and printing conditions have been defined to reflect typical RM production [4].

3.2 Historical data collection

The historical data used to train the ML model comprise a comprehensive dataset of printed product combinations,

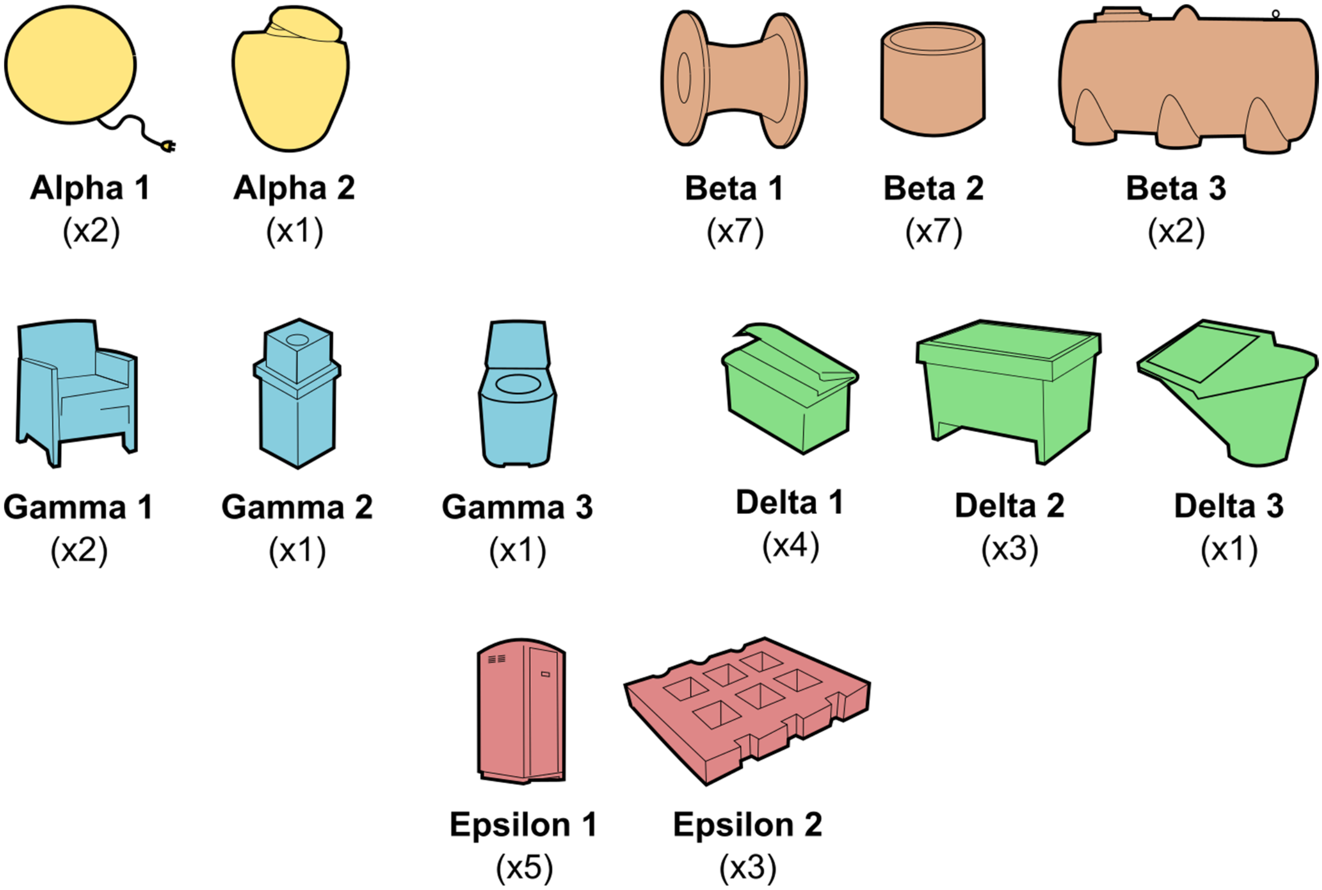

Fig. 3 Families of the considered products

each defined by specific values for mould volume occupancy, product mass, heating temperature, and speed ratio, along with recorded instances of failure or success under these conditions. These data were obtained through monitoring actual production processes at Roplast. All the products are manufactured using the same machine, i.e., a two-axis Polivinil model designed and produced by Rotomachinery-Group. For each product, information was collected regarding the quality or otherwise of its printing as a function of temperatures and speed ratios different from the preferable ones.

Overall, the historical data, i.e., the printing combinations of each product of the catalogue considered, with its own or different heating temperatures and speed ratios, are 522. Of these, 29 were found to be with a failure, i.e., they were rejected in relation to the company's standards and are printed again. Such failures were superficial, dimensional or breakages during extraction, not due to incorrect handling by the operator.

Figure 5 presents an overview of the printing combinations considered in the historical data, including machine parameters and the classification of printed products into families.

3.3 Failure prediction

ML was employed to estimate the failure probability of a printed product, expressed as a binary outcome (YES/NO), based on the input parameters: heating temperature, speed ratio, mould volume occupancy, and product mass. The implementation involved training and evaluating a suite of ML algorithms using MATLAB [26]. A 70% portion of the historical dataset was used for training, and the remaining 30% for testing, to assess predictive accuracy.

Our research focused on applying established classification algorithms to this specific problem. We evaluated a range of models to identify the most effective approach for predicting failure probabilities in rotational moulding. The selection of algorithms and their performance was based on class-wise metrics, including Accuracy, Precision, Recall, and F1 Score, to provide a comprehensive assessment.

- Accuracy was quantified as the proportion of correct predictions relative to the total number of predictions made. This metric reflects the model's overall effectiveness in reproducing the observed outcomes in the historical dataset. It was calculated using the formula:

Table 2 Considered products and features

Name	Mould volume occupancy [%]	Product mass [kg]	Heating temperature [°C]	Speed ratio
Alpha 1 A	20	2.7	205	3
Alpha 1 B	25	6.5	205	3
Alpha 2	8	0.35	200	3
Beta 1 A	8	0.25	200	3
Beta 1 B	8	0.45	200	3
Beta 1 C	8	0.55	200	3
Beta 1 D	8	1	200	3
Beta 1 E	8	1.2	200	3
Beta 1 F	8	1.7	205	3
Beta 1 G	8	0.35	200	3
Beta 2 A	25	3.5	200	3
Beta 2 B	25	9	215	3
Beta 2 C	50	18	215	3
Beta 2 D	35	12	210	3
Beta 2 E	50	14	210	3
Beta 2 F	25	6	205	3
Beta 2 G	35	11	210	3
Beta 3 A	25	9	220	3
Beta 3 B	25	5.8	220	3
Delta 1 A	25	7.5	220	3
Delta 1 B	35	7.5	220	3
Delta 1 C	12.5	1.2	210	3
Delta 1 D	12.5	1.4	210	3
Delta 2 A	25	12.5	210	3
Delta 2 B	25	8.5	220	3
Delta 2 C	10	0.4	205	3
Delta 3	35	7.5	210	3
Epsilon 1 A	50	10	205	2
Epsilon 1 B	35	6.5	205	2
Epsilon 1 C	25	6.5	205	2
Epsilon 1 D	35	6.5	210	2
Epsilon 1 E	25	4.7	215	2
Epsilon 2 A	50	14	210	2
Epsilon 2 B	50	17	215	2
Epsilon 2 C	35	6	220	2
Gamma 1 A	25	4	210	3
Gamma 1 B	50	10	215	3
Gamma 2	25	6	215	3
Gamma 3	4	0.08	200	3

$$Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positives + False\ Negatives}$$

- Precision, particularly for the positive class ('YES', indicating a failure), was emphasized due to the imbalanced nature of our dataset and the critical need to minimize false alarms. This metric assesses the reliability of the model's positive predictions and was computed as:

$$Precision_{YES} = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

Several classification algorithms, recognized for their effectiveness in similar tasks, were assessed.

- **Decision Trees**: Tested across various levels of complexity (Fine, Medium, Coarse Trees) for their ability to capture patterns and generalize.
- **Logistic Regression**: Explored in different forms (Binary GLM, Efficient, Kernel-based) to model class probabilities and handle non-linear relationships [28, 29].
- **Support Vector Machines (SVMs)**: A range of SVM algorithms, including linear and kernel-based variations (e.g., Linear, Quadratic, Cubic, Gaussian), were assessed for their robustness and ability to handle complex relationships in high-dimensional spaces [30].
- **Ensemble Learning**: Algorithms like AdaBoost, Bagged Trees, and RUSBoost were investigated for their ability to combine multiple models, improve robustness, and mitigate overfitting, particularly for imbalanced datasets [31].
- **Artificial Neural Networks (ANNs)**: Various architectures (Narrow, Medium, Wide, Bilayered, Trilayered Networks) were tested for their capacity to learn intricate patterns from data [32, 33].
- **Naive Bayes**: Tested in Gaussian and Kernel variations, suitable for continuous data and complex probability distributions, respectively [34].

The selection of the best-performing algorithm was based on predictive accuracy, precision, recall, and F1 score on the testing set, as detailed in Table 3.

Figure 6 reports the normalized confusion matrices about the prediction of the failure (YES/NO) in the products of the ML algorithms reported in Table 3.

Although the decision tree classifier performed relatively well in this study, this does not necessarily imply that the problem is trivial. The combination of low-dimensional input data and strong correlations between some features and failure occurrences creates a classification task with distinct decision boundaries that even simpler models (e.g., decision trees) can capture effectively. As aforementioned, decision trees fundamentally partition the feature space using straightforward rules that align with the manufacturing thresholds and ranges that influence failure.

As seen in Table 3; Fig. 6, ensemble learning methods, such as AdaBoost, improve upon decision trees by combining multiple weak learners to reduce variance and avoid overfitting, thereby achieving better generalisation and robustness across the dataset. This is the main reason behind the slightly higher accuracy and F1 scores shown in Table 3 when ensemble learning is compared to decision trees.

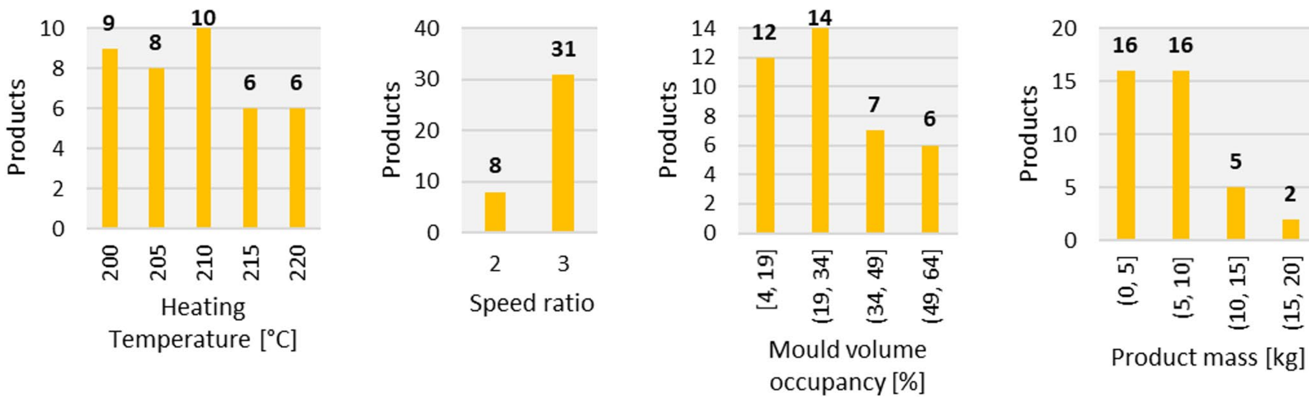

Fig. 4 Distributions of heating temperature, speed ratio, mould volume occupancy and mass of the considered products

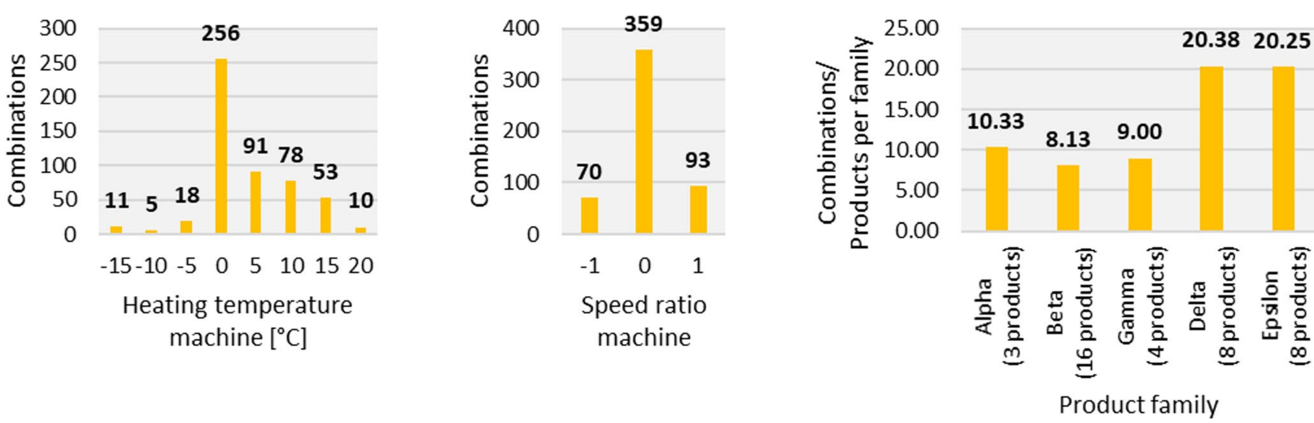

Fig. 5 Overview of the printing combinations in the historical data

Overall, the scores provided in Table 3 reflect a problem structure where key features provide strong predictive signals, allowing even simple methods to achieve a good performance, while ensemble learning enhances stability and predictive reliability.

A critical methodological consideration was addressing the significant class imbalance inherent in the historical dataset. As discussed in Sect. 3.2, the 522 historical production combinations contained only 29 recorded failures, corresponding to 5.5% of the total instances. Such distribution is a common and expected challenge in real-world defect detection applications where failures are rare events. Relying solely on overall accuracy as a performance metric can be highly misleading in such scenarios, as a model can achieve high accuracy by simply predicting the majority class (i.e., "no failure") for all instances. To overcome this challenge, the following are implemented:

- Several ML algorithms were tested, as reported in Table 3; Fig. 6. A key example is the Ensemble Random Under-Sampling Boost (RUSBoost) algorithm, which is explicitly tailored for unbalanced datasets, as reported in [31].
- Performance evaluation of ML algorithms included class-wise precision, recall, and F1 scores to provide a more balanced assessment of algorithm performances. The prioritization of these metrics ensured that the

Table 3 Comparison of different ML algorithms in terms of failure prediction accuracy, precision, recall and F1 scores

ML algorithm	Accuracy	Failure class	Precision	Recall	F1 Score
Ensemble Learning (AdaBoost)	97.17%	NO	97.44%	99.63%	98.52%
		YES	89.47%	54.84%	68.00%
Decision Tree	96.46%	NO	97.24%	99.06%	98.14%
		YES	76.19%	51.61%	61.54%
Narrow Neural Network (ANN)	96.28%	NO	96.89%	99.25%	98.06%
		YES	77.78%	45.16%	57.14%
Fine Gaussian SVM (SVM)	95.75%	NO	96.03%	99.63%	97.79%
		YES	81.82%	29.03%	42.86%
Efficient Logistic Regression (Kernel)	93.81%	NO	94.79%	98.88%	96.79%
		YES	25.00%	6.45%	10.26%
Ensemble Random Under-Sampling Boost (RUSBoost)	85.31%	NO	98.70%	85.58%	91.68%
		YES	24.51%	80.65%	37.59%

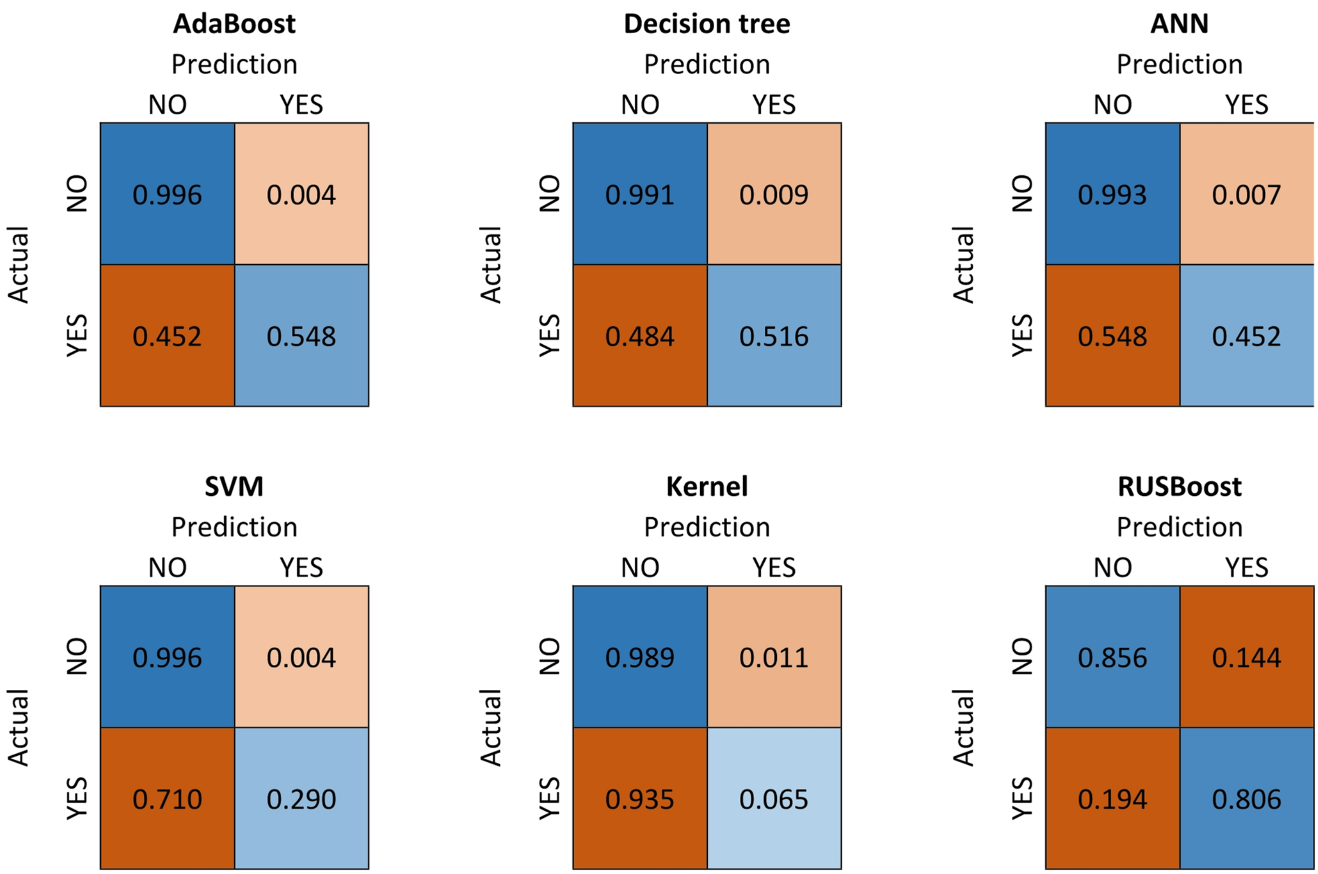

Fig. 6 Normalized confusion matrices of the considered ML algorithms for the prediction of the failure in the products

selected algorithm was the one that effectively learned the complex pattern of the failure events. The final performance of the selected ensemble learning (AdaBoost) model validates the success of this methodological approach in overcoming the data imbalance challenge.

4 Results

The failures probability predicted through ML for the considered products according to the considered process configurations are reported in Table 4. The following sections analyse the results, focusing on the influence of each parameter (heating temperature, speed ratio, mould volume, product mass, and product shape) as well as their interactions.

Figure 7 illustrates the average failure rate of the products in relation to heating temperature, examining the influence of the temperature set on the machine, the most suitable temperature for the piece based on industrial experience, and the differences between the two temperatures.

As can be seen from Fig. 7, for the machine heating temperature, a clear trend is observed, with failure rates decreasing as the temperature increases from 200 °C to 220 °C. The highest failure rate of 17% is observed at 200 °C, while the lowest rate of 6% occurs at 220 °C. This suggests that higher machine temperatures contribute to improved process stability. In contrast, the product heating temperature shows a less consistent trend. Failure rates remain low at intermediate temperatures, such as 205 °C (5%), but rise sharply at 220 °C (37%), indicating a potential threshold beyond which the product temperature negatively impacts process quality. The delta heating temperature, defined as the difference between machine and product heating temperatures, shows the most pronounced relationship with failure rates. Large negative deltas, such as −20 °C, correspond to a failure rate of 58%, while values near 0 °C minimize the failure rate to nearly 0%. These findings emphasize the importance of temperature alignment between the machine and the product to reduce defects.

Figure 8 illustrates the average failure rate of the products in relation to the speed ratio set in the machine (speed ratio machine), the speed ratio theorical of the product according to industrial experience (speed ratio product), and the differences between the two speed ratios.

As can be seen from Fig. 8, for the speed ratio set in the machine, an increase from 2 to 3 results in a rise in the

Table 4 Total failure rate of the considered products and failure rate in relation with delta heating temperature, delta heating time and delta speed ratio

Name	Total	Delta heating temperature [°C] = Heating temp machine - Heating temp product									Delta speed ratio = Speed ratio machine - Speed ratio product		
		−20	−15	−10	−5	0	5	10	15	20	−1	0	1
Alpha 1 A	30%	n.a.	n.a.	n.a.	0%	0%	50%	50%	50%	n.a.	0%	60%	n.a.
Alpha 1 B	0%	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	0%	0%	n.a.
Alpha 2	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 1 A	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 1 B	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 1 C	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 1 D	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 1 E	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 1 F	0%	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	0%	0%	n.a.
Beta 1 G	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Beta 2 A	70%	n.a.	n.a.	n.a.	n.a.	0%	50%	100%	100%	100%	80%	60%	n.a.
Beta 2 B	0%	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	0%	0%	n.a.
Beta 2 C	0%	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	0%	0%	n.a.
Beta 2 D	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Beta 2 E	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Beta 2 F	0%	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	0%	0%	n.a.
Beta 2 G	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Beta 3 A	60%	100%	100%	100%	0%	0%	n.a.	n.a.	n.a.	n.a.	60%	60%	n.a.
Beta 3 B	60%	100%	100%	100%	0%	0%	n.a.	n.a.	n.a.	n.a.	60%	60%	n.a.
Delta 1 A	0%	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	n.a.
Delta 1 B	60%	100%	100%	100%	0%	0%	n.a.	n.a.	n.a.	n.a.	60%	60%	n.a.
Delta 1 C	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Delta 1 D	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Delta 2 A	10%	n.a.	n.a.	50%	0%	0%	0%	0%	n.a.	n.a.	20%	0%	n.a.
Delta 2 B	0%	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	n.a.
Delta 2 C	0%	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	0%	0%	n.a.
Delta 3	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Gamma 1 A	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%	n.a.
Gamma 1 B	0%	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	0%	0%	n.a.
Gamma 2	40%	n.a.	100%	100%	0%	0%	0%	n.a.	n.a.	n.a.	40%	40%	n.a.
Gamma 3	0%	n.a.	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	0%	0%	n.a.
Epsilon 1 A	0%	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%
Epsilon 1 B	0%	n.a.	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	0%	0%
Epsilon 1 C	10%	n.a.	n.a.	n.a.	50%	0%	0%	0%	0%	n.a.	n.a.	0%	20%
Epsilon 1 D	60%	n.a.	n.a.	100%	0%	0%	100%	100%	n.a.	n.a.	n.a.	60%	60%
Epsilon 1 E	0%	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	n.a.	0%	0%
Epsilon 2 A	0%	n.a.	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	0%	0%
Epsilon 2 B	0%	n.a.	0%	0%	0%	0%	0%	n.a.	n.a.	n.a.	n.a.	0%	0%
Epsilon 2 C	40%	50%	50%	50%	50%	0%	n.a.	n.a.	n.a.	n.a.	n.a.	0%	80%

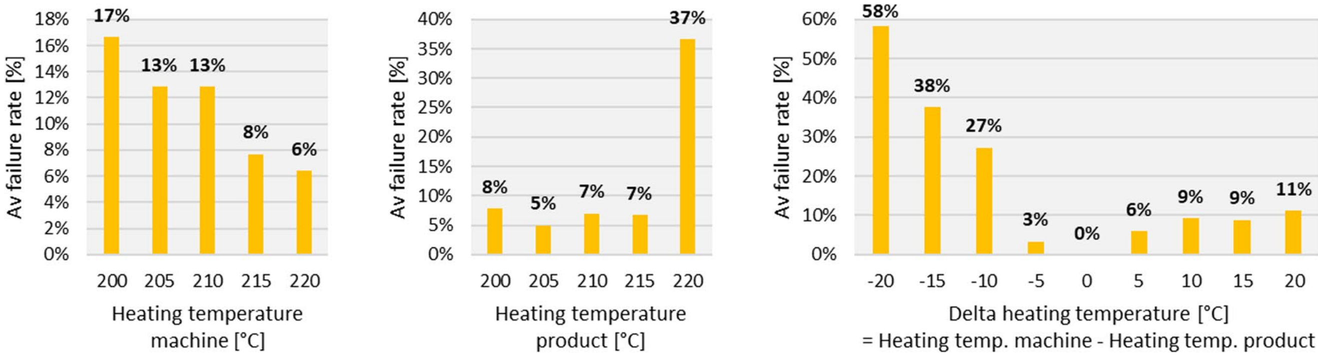

Fig. 7 Average failure rate of the products in relation to the heating temperature

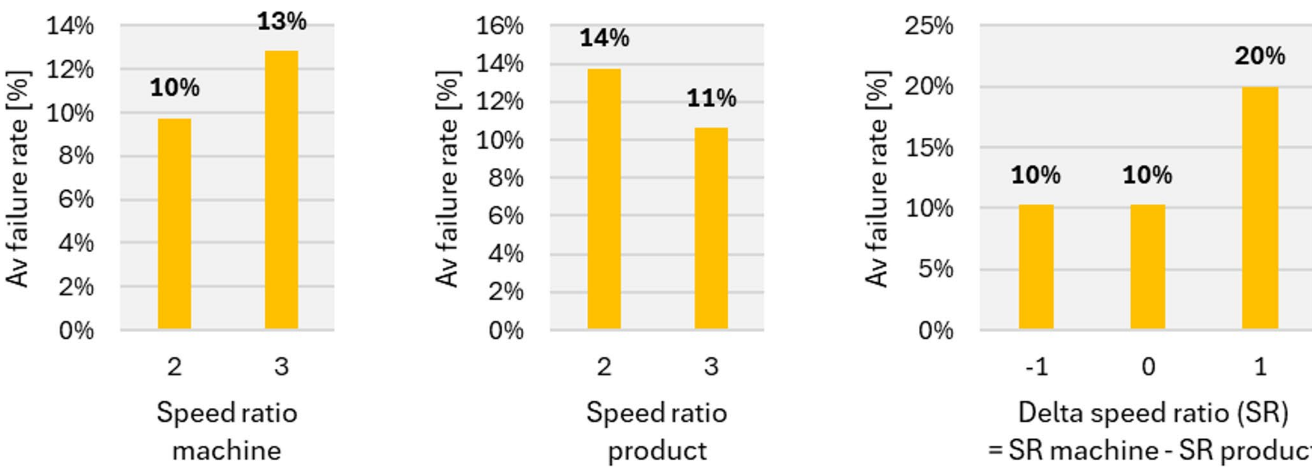

Fig. 8 Average failure rate of the products in relation to the speed ratio

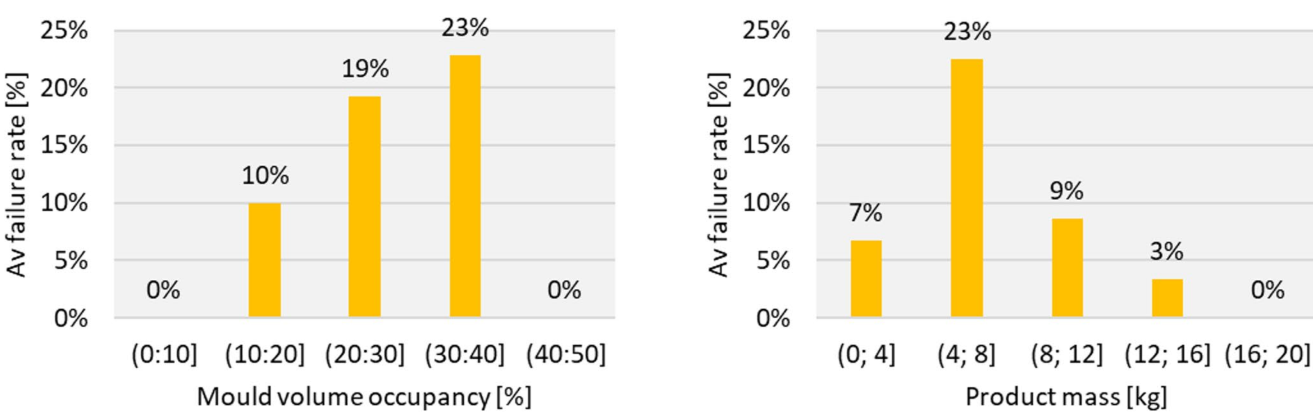

Fig. 9 Average failure rate of the products in relation to mould volume occupancy and product mass

failure rate from 10% to 13%. A similar trend is observed for the product speed ratio, where the failure rate increases from 10% at a speed ratio of 2 to 14% at a speed ratio of 3. The delta speed ratio, representing the difference between machine and product speed ratios, demonstrates a distinctive behaviour. A delta of 1 corresponds to the highest failure rate (20%), while deltas of 0 and −1 result in lower and comparable failure rates of 10%. These results therefore suggest that products with different speed ratio (2) have a higher failure rate, both when printed at their optimal rotation speed and, even more so, when printed at a higher speed.

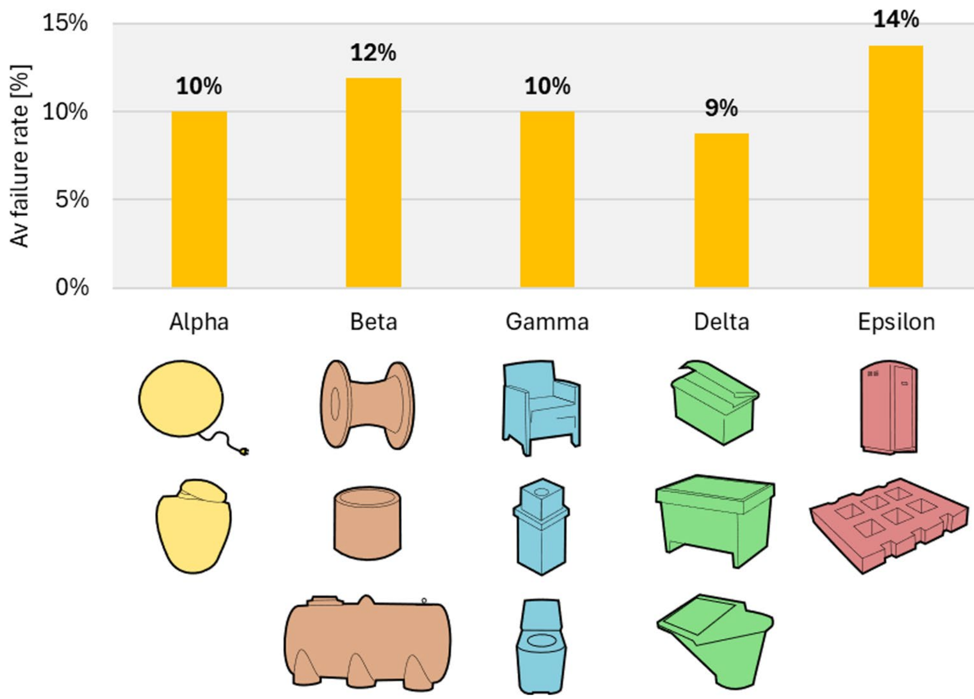

Fig. 10 Average failure rate in relation to product family

Figure 9 shows the average failure rate in relation with the mould volume occupancy in the machine and the product mass.

From analysing Fig. 9, it emerges that for mould volume occupancy, failure rates increase significantly as occupancy ranges from 10 to 20% (10%) to 30–40% (23%), while both lower (0–10%) and higher (40–50%) ranges result in no observed failures (0%). This suggests a nonlinear relationship where mid-range mould volume occupancy may lead to suboptimal outcomes due to potential inconsistencies in material flow or thermal management. Similarly, product mass exhibits a distinct trend, with failure rates peaking at 4–8 kg (23%) and progressively decreasing as product mass increases, reaching 0% in the 16–20 kg range. The sharp rise in defects at lower mass ranges may be indicative of challenges in achieving uniformity during processing, while heavier products could benefit from enhanced stability in material behaviour.

Figure 10 shows the average failure rate in relation with product geometry (i.e., the product families).

For what concerns the influence of product geometry on average failure rate (see Fig. 10), while most product types (Alpha, Gamma, Delta) show comparable failure rates of 9–10%, the Beta and Epsilon categories exhibit elevated rates of 12% and 14%, respectively. The higher predicted failure rate of the Epsilon family could be related to the fact that the products of this family are the only ones that have the optimal speed ratio equal to 2, while for the other products the speed ratio is 3. Therefore, the products of the Epsilon family are quite different from the other products in terms of geometry. The 12% failure rate of the Beta family could be attributed to its long, hollow cylindrical geometry, which results in a narrow optimal processing window. This shape is particularly sensitive to deviations in heating temperature and rotational speed, as it poses challenges in achieving uniform melt distribution along its elongated axis and ensuring consistent cooling. Such inconsistencies can lead to increased internal stresses or incomplete material fusion, ultimately compromising product integrity.

Figure 11 shows the average failure rates in the intersections between delta temperature and delta speed ratio.

From the comparison between delta temperature and delta speed ratio (see Fig. 11), it emerges that the intersections with the highest failure rate are those in which the delta temperature is negative and when there is a delta speed ratio different from zero.

Figure 12 shows the average failure rate of the intersections between product features (i.e., product family, mould volume occupancy in the machine, product mass) and process parameters (i.e., delta temperature, delta time and delta speed ratio).

The analysis of the failure rates of the different intersections shown in Fig. 12 highlights some critical issues. With negative delta heating temperatures (i.e., heating temperature machine – hearing temperature product) the failure probability tends to increase for different product families, for different mould volume occupancy and for different product masses. The increase in failure rate is particularly increasing also for positive failure rates when the mould volume occupancy is between 10% and 30%. These data

		Delta speed ratio		
		-1	0	1
Delta temperature [°C]	-20	60%	50%	100%
	-15	44%	33%	33%
	-10	29%	23%	40%
	-5	0%	0%	25%
	0	0%	0%	0%
	5	4%	6%	14%
	10	5%	11%	20%
	15	7%	12%	0%
	20	11%	11%	n.a.

Fig. 11 Average failure rates in the intersections between delta temperature and delta speed ratio

also confirm how crucial it is to reduce the delta heating temperature to lower the failure probability, regardless of the product to be realized. The trend of the failure probability as a function of the different intersections with the delta speed ratio is more heterogeneous. Only a few peaks emerge when the delta speed ratio is equal to +1 and the mould volume occupancy is between 30% and 40% and when the product mass is between 4 kg and 8 kg. Reading the columns matrix, we can notice the low failure probability (even zero) for particularly small (< 10%) or high (> 40%) mould occupancy volumes. The same is true for pieces with large mass (> 12 kg). Among the product families, it is worth noting the good results of the Gamma and Delta, in which the failure probability is present but is concentrated only when the delta heating temperature is <−10 °C.

5 Discussion

5.1 Failure probability vs. product and process features

This study presents a comprehensive analysis of failure probabilities in rotational moulding, incorporating a wide range of product attributes and process parameters. In contrast to previous laboratory-scale investigations, often limited to single variables or standardized geometries (see Sect. 2.3), our approach is based on real-world industrial data from a medium-sized enterprise, capturing the complexity and variability of actual production environments.

The results highlight the pivotal role of heating temperature and rotational speed ratio in determining defect rates. Discrepancies between machine settings and product-specific optimal conditions emerged as key contributors to failures. Notably, when the machine's heating temperature

		Product family					Mould volume occupancy [%]					Product mass [kg]				
		Alpha	Beta	Gamma	Delta	Epsilon	(0:10]	(10:20]	(20:30]	(30:40]	(40:50]	(0; 4]	(4; 8]	(8; 12]	(12; 16]	(16; 20]
Delta heating temperature	-20	n.a.	100%	n.a.	33%	n.a.	n.a.	n.a.	50%	75%	n.a.	n.a.	63%	50%	n.a.	n.a.
	-15	n.a.	50%	50%	33%	n.a.	n.a.	n.a.	43%	75%	0%	n.a.	58%	25%	n.a.	0%
	-10	n.a.	29%	33%	21%	30%	n.a.	0%	39%	42%	0%	0%	56%	17%	17%	0%
	-5	0%	0%	0%	0%	13%	0%	0%	4%	7%	0%	0%	8%	0%	0%	0%
	0	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	5	17%	4%	0%	0%	14%	0%	17%	6%	20%	0%	7%	13%	0%	0%	0%
	10	17%	8%	0%	0%	20%	0%	17%	17%	20%	0%	10%	17%	0%	0%	n.a.
	15	17%	11%	0%	0%	n.a.	0%	50%	25%	0%	0%	13%	0%	0%	n.a.	n.a.
	20	0%	14%	0%	n.a.	n.a.	0%	n.a.	100%	n.a.	n.a.	11%	n.a.	n.a.	n.a.	n.a.
Delta SR	-1	0%	13%	10%	10%	n.a.	0%	0%	24%	15%	0%	5%	23%	10%	10%	0%
	0	20%	11%	10%	8%	8%	0%	20%	17%	17%	0%	8%	18%	9%	0%	0%
	1	n.a.	n.a.	n.a.	n.a.	20%	n.a.	n.a.	10%	47%	0%	n.a.	32%	0%	0%	0%

Fig. 12 Average failure rates in the intersections between products features and process parameters

falls below the optimal requirement for a given product, the likelihood of defects increases significantly. This underscores the importance of precise thermal control, which directly affects polymer sintering, degradation, and crystallization. Rotational speed also plays a critical role: excessive speeds can cause chaotic powder movement, compromising uniformity, while insufficient speeds may prolong cycle times and hinder effective heat transfer. Products in the Beta family, characterized by elongated hollow cylindrical shapes, exemplify the challenges posed by complex geometries. Their narrow processing windows make them particularly sensitive to deviations in temperature and speed, increasing the risk of internal stresses and incomplete fusion.

Further analysis revealed a non-linear relationship between mould volume occupancy and failure rates. Mid-range occupancy levels were associated with higher defect probabilities, likely due to uneven material distribution or suboptimal thermal dynamics. Similarly, product mass exhibited a distinct trend, with intermediate weights correlating with increased failure risks.

A key innovation of this research lies in its practical applicability for small and medium-sized enterprises. By employing machine learning models trained on historical production data, we offer a data-driven method for optimizing batch configurations and aligning process parameters, without the need for costly sensorization or extensive lab testing. The model effectively identifies optimal temperature and rotation speed settings, enabling defect-free production across diverse product types processed concurrently.

This investigation enables a nuanced discussion of failure probabilities in rotational moulding, considering both process parameters (temperature and speed) and product characteristics (geometry, volume, mass). The realism and diversity of the dataset mark a significant advancement over prior studies, which typically focus on isolated aspects under controlled laboratory conditions.

The analysis of products with varying shapes, sizes, and masses confirms that these attributes independently affect failure probability, regardless of process settings. As shown in Fig. 8, items with intermediate dimensions and weights are more prone to defects, while smaller and larger products exhibit greater tolerance to parameter variations. This observation is supported by the absence of comparative studies in the literature addressing failure probabilities across different RM products. Reference [4] notes that, as in other moulding techniques, maintaining consistent wall thickness is crucial to minimizing internal stresses and defects. The small products examined here feature simple geometries that promote uniform thickness, while larger items mitigate abrupt thickness transitions through generous connection radii. This insight aligns with findings in Fig. 9, where flatter products (Epsilon family), characterized by smaller radii, experienced higher failure rates.

Figures 6 and 10, and 11 illustrate the critical importance of correctly setting the heating temperature. Failure risks are notably higher when the machine temperature is below the product's optimal threshold. Heating temperature governs key polymer behaviours, melting, adhesion, and coalescence, ensuring structural integrity and mechanical performance. Insufficient heating leads to incomplete sintering and poor product quality, while excessive temperatures may cause degradation, reducing impact resistance and tensile strength [16].

Figures 7 and 10, and 11 demonstrate that both overestimation and underestimation of the speed ratio elevate failure risks, with underestimation being particularly detrimental. This must be interpreted in context: increasing the speed for products with an optimal ratio of 2 is more harmful than reducing it for those with a ratio of 3. These findings are consistent with empirical observations by [35], which show that excessive rotation induces chaotic powder motion, compromising wall thickness uniformity and mechanical properties. Conversely, lower speeds, while less damaging, may still affect heat transfer efficiency.

5.2 Limitations, implications and future developments

The dataset used to train the predictive model, while representative of a medium-sized RM enterprise, may not capture the full diversity of RM applications across different industries and materials. The study predominantly focuses on LDPE and specific product families, potentially limiting the generalizability of the findings to other polymer types or more complex geometries. The predictive model relies on historical production data, which inherently reflects the constraints and biases of existing operational practices. This dependence may affect the model's ability to extrapolate to entirely novel conditions or unconventional designs. While the proposed approach eliminates the need for extensive sensorization, it does not account for real-time process variations, such as unforeseen machine or environmental fluctuations, which could influence defect rates. Finally, the study focuses on static optimization of batch parameters, without exploring dynamic adjustments during the production cycle that could further enhance efficiency and quality.

The findings of this study have implications for RM, particularly for SMEs that face challenges in adopting advanced production optimization tools. By leveraging ML models trained on historical production data, this approach eliminates the need for costly and invasive sensors or laboratory-scale testing, which are often prohibitive for SMEs. This represents a shift towards data-driven production planning that is both cost-effective and scalable, enabling wider accessibility to advanced manufacturing technologies.

A key contribution of this study is the introduction of actionable insights for batch configuration and process parameter alignment. The method identifies optimal temperature and rotation speed settings that enable failure-free production for diverse products processed simultaneously. By correlating failure probabilities with process parameters and part characteristics, it establishes tolerance criteria to group parts into compatible production batches. These insights lay the groundwork for the development of a production planning configurator, a tool that can automate and streamline batch assignments by balancing trade-offs between heating temperatures and speed ratios. This advancement has the potential to significantly enhance efficiency, reduce defects, and minimize material waste, aligning with sustainability goals. In this way, it is possible to integrate the RM configuration of [12] that was specific for maximizing machine occupation considering structural constraints but no product failures.

Looking ahead, future developments could focus on extending this methodology to encompass a broader range of RM applications, materials, and product geometries. Incorporating real-time monitoring and adaptive control systems would further enhance the predictive capabilities of the model, allowing for dynamic adjustments to process parameters during production. In this sense, integration with ML trained on real industrial data can reduce the number and invasiveness of sensors, thus avoiding having to resort to tests in sensorized laboratories that reduce the significance of the results [8]. Additionally, expanding the dataset to include data from other RM enterprises and machines would improve the generalizability and robustness of the model across different industrial contexts.

Integrating this approach with emerging technologies, such as digital twins or IoT-enabled systems, could open new opportunities for real-time simulation and optimization of RM processes, as already done in injection moulding of plastic parts [36]. By creating a comprehensive framework that combines ML-based predictions with real-time feedback, the RM industry could move closer to achieving fully automated and defect-free production. These future advancements would not only benefit SMEs but also pave the way for the widespread adoption of intelligent manufacturing systems in the RM sector.

6 Conclusions

This study demonstrates the potential of machine learning (ML) as a transformative tool for optimizing production planning in rotational moulding (RM). By leveraging historical production data and predictive algorithms, the approach presented addresses two critical and often conflicting objectives: maximizing machine utilization and minimizing defect rates. Unlike previous studies, which focus narrowly on either production efficiency or quality assurance, this research integrates both dimensions, providing a holistic framework for RM optimization.

The findings underscore the significant impact of process parameters, particularly heating temperature and rotation speed, on the failure probability of moulded parts. The results reveal that deviations between machine settings and optimal product-specific conditions are a primary driver of defects. For instance, mismatches in heating temperature or rotational speed ratios are strongly correlated with increased failure probabilities, particularly for products with intermediate sizes and masses. These insights emphasize the necessity of aligning process parameters with the specific needs of the products being manufactured.

The use of ML, specifically the Ensemble Learning method, achieved an impressive predictive accuracy of 97.17%. This highlights the robustness of ML-based approaches in navigating the inherent complexity of RM processes, characterized by the interplay of multiple variables, such as product geometry, material properties, and machine dynamics. By identifying parameter tolerances and compatible batch configurations, the proposed method reduces reliance on costly and invasive sensorization, making it particularly advantageous for small- and medium-sized enterprises.

The implications of this work extend beyond immediate production improvements. The methodology paves the way for the development of advanced configurators capable of automating batch assignments and parameter settings, thus significantly enhancing the scalability and adaptability of RM operations. Furthermore, the integration of this approach into industrial practices can support broader goals of sustainability by reducing material waste and energy consumption, aligning RM with global trends toward greener manufacturing.

Future research should explore the generalizability of this methodology across different RM systems and materials, as well as its potential integration with real-time monitoring and control systems. Expanding the dataset to include a wider range of product families and industrial scenarios would further strengthen the predictive capabilities of the model, ensuring its applicability in diverse contexts.

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James McGree: Validation, Writing – review & editing.
Paul Corry: Validation, Writing – review & editing.
Christian Spreafico: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Supervision.

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Data availability The data that support the findings of this study are available from the corresponding author, CS, upon reasonable request.

Declarations

Competing interests The authors declare that they have no competing interests.

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