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An Integrated Framework for Predictive Quality in Injection Molding: Combining Explainable AI and Time Series Analysis in a German Industry Case Study

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Abstract: In the era of Industry 4.0 and the emerging vision of Industry 5.0, ensuring consistent product quality is crucial, particularly in complex manufacturing processes like injection molding. This study integrates Explainable AI (XAI) with time series analysis using real-world data from a German injection molding facility to enhance predictive accuracy and process interpretability. Results demonstrate that combining explainability techniques, such as SHAP, with time series features improves model performance, reducing the Mean Squared Error (MSE) from 0.01025 to 0.00251 and increasing the R-squared from 0.9886 to 0.9972, while revealing hidden patterns in process dynamics. Global SHAP analysis identified key factors influencing quality, while local SHAP insights highlighted the role of setting parameters—those directly adjustable by operators—in mitigating deviations. Time series analysis further enhanced decision-making by enabling proactive interventions before process fluctuations compromised stability. By structuring decision-making into key steps—identifying influential parameters, prioritizing adjustable ones, and incorporating temporal insights—this study provides a roadmap for integrating XAI into quality control. The findings reinforce the value of human-centric AI, ensuring transparency and empowering operators to optimize industrial processes effectively.

Keywords: Modeling of Manufacturing Operations, Predictive Quality, Data-Driven Decision-Making, Human-AI Interaction, Artificial Intelligence

1. INTRODUCTION

The integration of new information and communication technologies (ICTs), central to Industry 4.0 (I4.0) and Industry 5.0 paradigms, is increasingly prioritized in both academia and industry. I4.0 enhances competitiveness by allowing companies to precisely customize processes and products, significantly improving overall operational efficiency (Costa et al., 2023). In this context, Machine Learning (ML) plays a pivotal role in uncovering production patterns, supporting predictive maintenance, quality control, and advancing sustainability and supply chain efficiency (Rai et al., 2021). Indeed, quality control benefits greatly from this shift: with enhanced data collection, quality engineers can access extensive measurement data, improving their ability to detect defects that might otherwise go unnoticed (Godina and Matias, 2019). Moreover, recent advancements in ML have significantly enhanced virtual measurement capabilities, enabling the acquisition of quality information without direct reliance on physical instruments. (Zhang et al., 2024). By leveraging predictive quality models, which use ML methods to predict quality characteristics from process data (Cramer, Huber and Schmitt, 2022), recurring patterns linked to specific metrics can be identified, supporting data-driven decisions to enhance product standards (Tercan and Meisen, 2022). However, while the predictive capabilities of ML models in manufacturing quality control are well-studied, the mechanisms driving model predictions often remain unexplored. This lack of transparency is critical, as understanding model decisions is essential for building trust in ML systems and generating insights (Presciuttini, Cantini and Portioli-Staudacher, 2024). Explainable Artificial Intelligence (XAI) has emerged as a crucial approach to improve AI transparency, helping human experts to better manage advanced AI systems, enhancing human-AI collaboration; ensuring that AI tools provide actionable and trustworthy insights for expert decision-making by developing more comprehensible models (Rehse, Mehdiyev and Fettke, 2019). XAI comprises methods that offer clear insights into how an AI model functions, whether at a specific instance level or across the entire system (Hoenig et al., 2024). In predictive quality contexts, predicting outcomes alone is insufficient; understanding how parameter settings influence predictions is essential. XAI extracts these insights, supporting data-driven quality improvements (Buschmann et al., 2023).

1.1 Research aim and contribution

Ensuring transparency in manufacturing quality control is essential, particularly in plastic injection molding, where

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process parameters frequently fluctuate, increasing the risk of defects and unpredictable costs (Silva et al., 2022). Thermoplastics injection molding enables the production of complex industrial components, yet achieving optimal quality requires continuous monitoring and fine-tuning of key process parameters (Nagorny et al., 2017). These processes involve intricate, yet not fully characterized, variable interactions. In this context, ML enables improved outcomes. Given the high production frequency of parts, early error detection is critical to avoiding significant losses. (Párizs et al., 2022). This study contributes to the growing field of XAI in manufacturing by combining a specific XAI method, namely SHapley Additive exPlanations (SHAP) and time series analysis to real data collected from an injection molding facility. In the manufacturing domain, gathering data directly from production machines through real experiments is often time-consuming and costly. While simulated data provide a valuable and faster alternative, they may simplify complex realities and, as a result, may not capture all the nuances of real production processes (Tercan et al., 2018). Therefore, our work aims to demonstrate the practical application of XAI in a real-world industrial setting, offering both theoretical value and practical relevance for enhancing predictive quality in manufacturing. Also, XAI principles are central to the vision of Industry 5.0, which prioritizes human-centricity and sustainable innovation (Xu et al., 2021). By serving as fundamental enablers, these principles empower human operators to interact effectively with AI systems, fostering not only efficiency but also trust and collaboration. Furthermore, AI-driven explainability enhances resilience by enabling more reliable predictions, allowing operators to anticipate and mitigate disruptions in dynamic manufacturing environments. This approach aligns with the European Union's regulatory frameworks, such as the AI Act, which emphasizes the need for trustworthy and transparent AI systems in industrial contexts. In addition, previous studies highlighted the need to investigate advancements in XAI techniques tailored to the manufacturing sector, including hybrid approaches that blend more traditional AI methods with XAI to achieve optimal transparency and interpretability maintaining high performance (Moosavi et al., 2024). In line with this direction, our study adopts a combined approach, integrating SHAP for global and local explainability with time series feature extraction for parameter monitoring. By applying this hybrid approach, we provide targeted insights that allow operators to monitor and adjust these variables promptly, providing then guidelines for improving quality in injection molding processes. Beyond enhancing technical outcomes, it fosters a human-centric approach, allowing operators to align data-driven insights with their expertise for more effective decision-making. To the best of the authors' knowledge, no previous studies have integrated SHAP-based methods with time series analysis for manufacturing quality control, making this the first hybrid method to provide both explainability and dynamic monitoring in a real industrial setting. The goal of this work aligns with the company's objective: to understand how to maintain consistent weight in produced components and to identify the main factors driving the predictions. The weight of the produced part is of particular interest as it serves as a primary indicator for all geometric quality characteristics. If the weight falls within the tolerance range, there is a high probability that other characteristics will also align with their specifications. Additionally, measuring the weight of each part is quick and cost-effective, making it feasible to record this dataset without requiring extensive measurement procedures. The remainder of this work is structured as follows: Section 2 presents the materials and methods, detailing the workflow adopted. Section 3 presents the results. Finally, Section 4 provides a discussion of the key findings and suggests operators how to leverage the results for data-driven decision-making. Finally, Section 5 concludes the study along with directions for future research.

2. MATERIAL AND METHODS

2.1 Dataset Description

The data used in this study was collected from a German injection molding facility over two weeks in 2022. The dataset includes both setting parameters that can be adjusted during the process and process parameters that reflect the operational conditions. Table 1 illustrates the features included in the dataset. The 'Time Series Data' column specifies whether a time series is available for each input feature.

Table 1. Variables

Feature name	Parameter Type	Time series data
Injection Velocity	Setting	
Cooling Time	Setting	
Set Pressure	Setting	Yes
Mold Temperature	Setting	Yes
Melt Temperature	Setting	Yes
Cycle Time	Process	
Melt Cushion	Process	
Pressure Max	Process	Yes
Clamping Force	Process	
Volume	Process	
Torque Max	Process	
Weight	Target	

2.2 Data analysis and Machine Learning model

The data was scaled transforming each feature to have a mean of zero and a standard deviation of one. By setting boundaries at the 1st and 99th percentiles, we identified significant weight deviations, representing observations that may represent anomalies or critical cases for quality control. Then, to predict component weight, we trained a Random Forest (RF) model using only the static input features. The RF model, which uses an ensemble of decision trees, is well-suited for capturing complex interactions between variables, providing an advantage over traditional bagged ensembles due to its ability to lower bias by building each tree using only a subset of features sampled from the overall dataset (Sankhye and Hu, 2020). The model's performance was evaluated using the Mean Squared Error (MSE) and the R-Squared metrics. MSE is a standard metric in regression tasks that quantifies the average squared difference between predicted and actual values; a lower MSE indicates better model accuracy by reflecting smaller prediction errors. R-Squared complements this by measuring the proportion of variance in the target variable that is explained by the model.

2.3 Key Variable Analysis with Random Forest Feature Importance and SHAP

With the initial model trained, we conducted a deeper analysis of feature importance to understand the specific impact of each variable.

1) *Random Forest Feature Importance*: First, we leveraged the inherent feature importance scores from the RF model. These scores rank the features by their influence on the target prediction, providing an overview of which variables contribute most significantly to component weight. This high-level insight helped to identify key predictors and provided a foundational understanding of variable relevance in the model.

2) *Global and Local SHAP Analysis:* SHAP was employed to achieve both global and local interpretability. SHAP values quantify the contribution of each feature to the model's predictions, offering a consistent explanation framework. The global SHAP summary plot was used to visualize the average impact of each feature across all observations. In contrast, SHAP force plots were used due to their focus on local analysis, highlighting the specific contributions of individual features to the prediction of a single observation. In this context, the local view was useful to pinpoint the variables most responsible for deviations. This combination of global and local analyses not only enhances model transparency but also empowers operators to interpret predictions at both the macro and micro levels, enabling data-driven and targeted interventions.

2.4 Time Series Analysis on Setting Parameters

In this stage, we first identified the influential setting parameters—adjustable inputs in the injection molding process—to understand their impact on the target variable variations. Then, we analyzed the time series data for these key parameters and extracted features that describe their behavior over time. The inclusion of time series features, such as skewness, mean, and linear trend, adds another layer of interpretability. Finally, we trained a new RF model integrating these extracted time-series features, evaluating their importance in predicting the target outcome through SHAP analysis.

3. RESULTS

3.1 Data analysis and Random Forest results

Figure 1 illustrates the boxplot of the scaled weight distribution, with the orange and blue dashed lines marking the boundaries of the 1st and 99th percentiles, respectively. Red points denote observations identified as outliers based on the percentile-based definition. Regarding the model evaluation, the trained RF achieved a MSE of 0.01025 and an R-Squared of 0.9886, demonstrating its effectiveness in predicting the weight of components based on static input features.

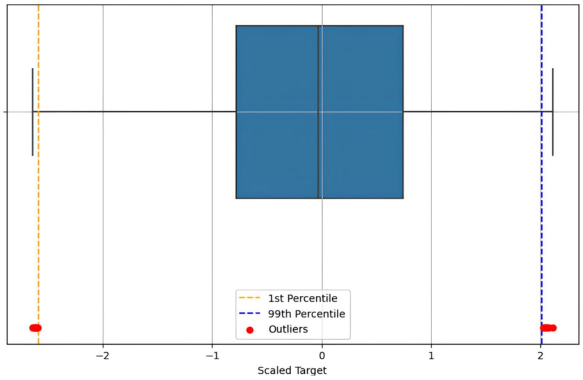

Fig. 1. Distribution of the scaled weight

3.2 Key Variable Analysis with Feature Importance and SHAP results

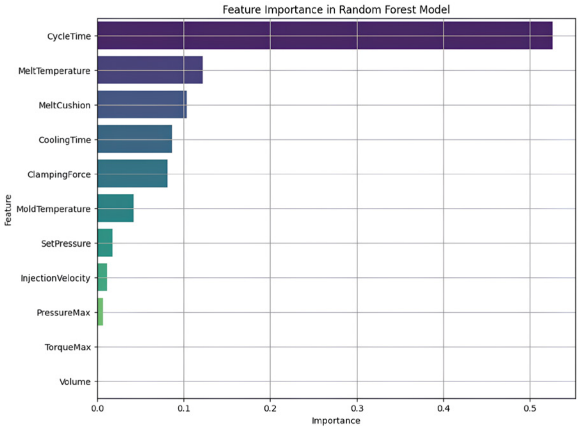

Fig. 2. Feature importance in RF model

Figure 2 presents a bar chart derived from the RF model, ranking the importance of each feature in predicting the target variable. The chart shows the relative contribution of each input variable, with Cycle Time emerging as the most impactful feature, followed by Melt Temperature. These findings help identify the parameters that are crucial in determining the component weight. Conversely, lower-ranking features such as Torque Max demonstrate minimal influence in the prediction process. Figure 3 presents the SHAP summary plot, which illustrates the global impact of each feature on the model's predictions. Features are ordered by their importance, similar to the RF feature importance plot. However, the SHAP plot provides additional insights by showing the direction and magnitude of each feature's effect on individual predictions. The color gradient (ranging from blue for low values to red for high values) highlights how feature values are associated with the target, revealing whether a feature positively or negatively influences the model's output. For instance, for this specific process, we not only confirm that Cycle Time is the most important feature, but we also gain additional insights into how it affects the model's predictions, showing whether higher or lower values of Cycle Time tend to increase or decrease the predicted component weight. For example, red points (higher values of Cycle Time) may generally correspond to higher predicted weights while blue points (lower values of Cycle Time) may correspond to lower predicted weights. Following this global analysis, we employed SHAP at the local level to examine specific instances of observations that exhibited deviations outside the defined normal ranges to understand how individual features, particularly setting parameters, contributed to these extreme predictions. This local interpretability allows for a more precise evaluation of the possible causes of these deviations, providing actionable insights to operators for fine-tuning specific parameters to improve consistency and prevent further deviations.

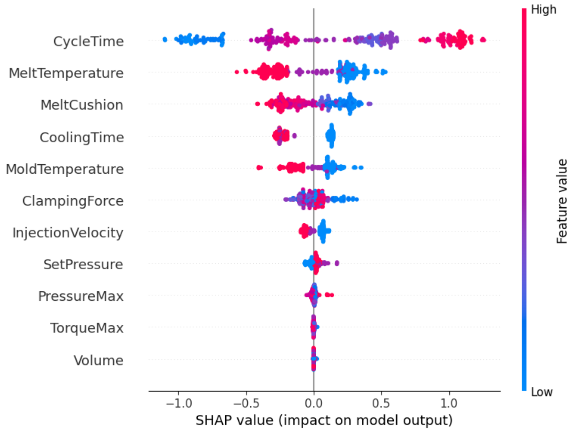

Fig. 3. SHAP summary plot

Fig. 4 illustrates the SHAP force plots for two identified observations classified as outside the normal ranges, highlighting the specific contributions of each feature to the predictions for these anomalous cases. Both plots emphasize that Cycle Time is the most significant positive contributor, driving the predictions upward, while Cooling Time slightly offsets the predicted weight with a negative contribution. Considering whether the deviations fall above or below the normal range and analyzing the direction in which specific variables influence the outcome, we can derive actionable insights to guide corrective measures. This enables us to strategically adjust the influential parameters to bring observations back within acceptable ranges, as determined by comparing the target variable to its specific tolerance limits. By identifying deviations that exceed these predefined thresholds operators can implement targeted adjustments to stabilize the process and maintain product consistency. Such an approach enhances decision-making by providing interpretable guidance for interventions.

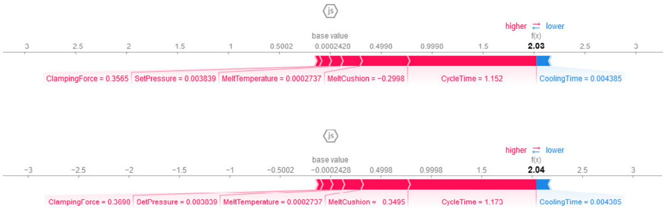

Fig. 4 SHAP force plot for two deviations

Focusing specifically on the setting parameters, as these are the variables that can be directly adjusted by operators to influence the outcomes, we identified Melt Temperature and Set Pressure as the most relevant features for further analysis. Melt Temperature stood out due to its consistently high importance across both global analyses, such as the RF feature importance (Figure 2) and SHAP summary plot (Figure 3), and its strong directional influence on the target variable. On the other hand, Set Pressure, while ranked lower in global analyses (Figures 2 and 3), demonstrated a contributing role in explaining deviations for specific anomalous observations, as evidenced by the SHAP force plots (Figure 4). In these plots, Set Pressure showed a measurable impact on the prediction, indicating its potential to influence outcomes in cases where its values deviate from thresholds. Accordingly, we proceeded to analyze the time series behaviour of these parameters to extract additional insights.

3.3 Time series feature extraction and analysis results

We extracted a comprehensive set of 12 features for each time series, Melt Temperature, and Set Pressure, using metrics such as mean, standard deviation, quantiles, skewness, and trends. Each extracted feature was prefixed with the parameter name (p1_ for Set Pressure and t2_ for Melt Temperature) to maintain traceability in the combined dataset. These extracted time series features were integrated into the scaled dataset of static input variables and the target variable. To assess the impact of the extracted time series features, we trained a new RF model using the combined dataset. The model was evaluated using the MSE achieving a value of 0.00251 and an R-squared of 0.9972, a significant improvement compared to the MSE of 0.01025 and R-squared of 0.9886 obtained without time series features. To further interpret the contributions of the time series features to the model's predictions, we applied SHAP global analysis, illustrated in Fig. 5.

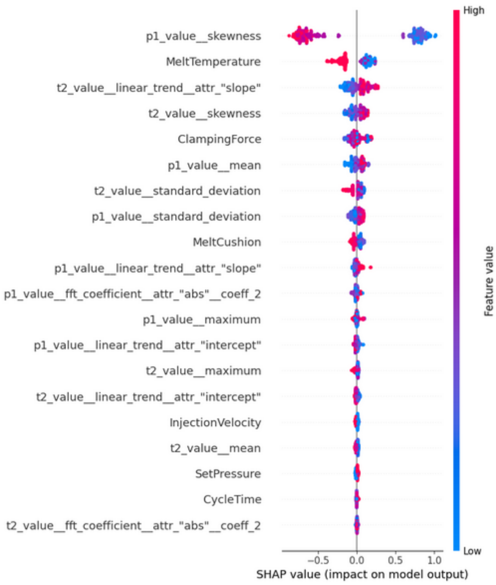

Fig. 5 SHAP summary plot for the integrated dataset

Many of the top-ranked features are derived from the time series data demonstrating the added value of including time series analysis in the model. The static feature Melt Temperature remains highly important, confirming its relevance even in the extended feature set. The prominence of Set Pressure skewness as the most important feature underscores its distribution symmetry critical role during the process, while Melt Temperature skewness indicates the relevance of its time series asymmetries. The relevance of the standard deviation for both setting parameters indicates the importance of their variability or fluctuation during the production process, suggesting that maintaining consistent their values could be crucial for achieving stable weight. The significant reduction in the importance of Cycle Time following the integration of time series features suggests that its role in determining component weight becomes considerably less pronounced when considered alongside the temporal fluctuations and trends of other variables. This indicates that the influence of "Cycle Time" is less decisive when dynamic variations in these other parameters are accounted for, highlighting the value of incorporating time series data to uncover previously underseen relationships within the process.

4. DISCUSSION

The results of this study provide a structured approach for integrating XAI time series analysis into quality control processes, offering actionable guidelines for operators aiming to maintain consistency in production outcomes. The analysis highlights a sequence of steps that operators can follow to better understand and manage process variables:

1. *Identify Critical Parameters*: By applying RF feature importance and SHAP global analysis, we demonstrated how specific variables contributions and their directional influence on the target variable can be identified.

2. *Analyze Deviations Locally and Focus on Actionable Parameters*: As highlighted by our results, SHAP local analysis provides granular insights into which variables drive deviations, enabling operators to take corrective actions tailored to individual anomalies. For instance, even variables that appeared less significant in the global analysis, such as Set Pressure, demonstrated a critical role in explaining specific anomalous observations at the local level. The operator's knowledge can further enrich this step by contextualizing the identified anomalies. Once the critical parameters are identified, operators could prioritize those that can be directly modified—typically the setting parameters, such in our case the Melt Temperature. By focusing on adjustable variables. operators can take practical steps to mitigate deviations and optimize the process. This prioritization ensures that effort is concentrated on variables that can be controlled, rather than those that passively reflect the process state. In this context, combining analytical results with human expertise enhances the interpretability and practical applicability of the insights, ensuring that adjustments are aligned with real-world scenarios.

3. *Integrate Time Series Insights:* Building on the identification of actionable parameters, time series features provide a dynamic perspective on parameter behavior, enabling operators to monitor trends and implement preemptive adjustments. As demonstrated in our results, incorporating time series insights shifts the focus from static snapshots to understanding how parameters evolve over time. For instance, while Cycle Time emerged as highly influential in static analyses, the inclusion of dynamic features for other parameters offered deeper insights into their temporal behavior. Identifying maximum values of specific parameters as critical, for example, allows operators to proactively adjust the process before these variables approach thresholds that could compromise stability, thereby maintaining consistency in production outcomes.

The steps outlined above emphasizes the complementarity of advanced analytics and human expertise, embodying a human-centric approach to industrial processes. Operators can leverage insights from the model to guide interventions while simultaneously using their experience to fine-tune these actions.

5. CONCLUSION

In this study, we demonstrated the application of XAI techniques to real-world data from a German injection molding facility, achieving both enhanced predictive quality and deeper process interpretability. By integrating SHAP for global and local explainability with time series feature extraction, we uncovered hidden patterns in parameter behaviours that would have remained undetected using only static features. The inclusion of time series features improved the model's predictive accuracy and revealed critical dynamic insights in adjustable parameters like Set Pressure and Melt Temperature. This work also underscores the relevance of adopting human-centric AI approaches in data-driven models for operations and supply chains. Operators are empowered to better understand the relationships between parameters and outcomes, fostering proactive quality control and adaptive interventions that support operational excellence. This human-centered perspective is critical for ensuring that AI tools complement human expertise rather than replacing it, driving sustainable improvements in industrial performance.

From a theoretical perspective, this study introduces a hybrid approach that combines traditional AI methods with XAI to enhance transparency without compromising performance. The findings not only demonstrate the value of combining temporal and static data but also pave the way for future research into mixed methodologies, further advancing decision support systems for complex industrial operations. From a managerial perspective, the proposed guidelines offer a roadmap for implementing human-centric AI in industrial environments. Managers can adopt the proposed methodology to create a more resilient production environment, ensuring long-term competitiveness and sustainability in their operations. While this study highlights the value of integrating static and time series features within an XAI framework for predictive quality, certain limitations must be acknowledged. First, the analysis was conducted using data from a single injection molding facility. Future research could explore similar methodologies across diverse manufacturing processes to validate and extend the applicability of the proposed approach. Also, this study focused primarily on component weight as the target variable, however, other quality dimensions may also benefit from a similar analysis. To further enhance explainability, also in addressing the risks associated with overconfident models, additional XAI techniques could be explored. These methods could provide deeper insights into the reliability of predictions, ensuring interpretation that supports robust and informed decision-making. Finally, conducting user studies to evaluate how operators could effectively use the proposed approach can help refine these tools, ensuring they align with practical needs. This human-centric focus is essential for fostering the integration of AI into manufacturing workflows.

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