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Model validation and sensitivity analysis of regression-based downtime predictive systems

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Abstract
Reliable predictive models are essential for optimizing maintenance strategies in manufacturing environments; however, their adoption is often hindered by inadequate model validation and limited understanding of parameter influence on prediction robustness. This study presents an in-depth validation and sensitivity evaluation of previously developed regression-based downtime predictive models for plastic manufacturing production lines. The validation framework integrates statistical performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2), Pearson correlation, and hypothesis testing using the Analysis of Variance (ANOVA) F-test. The results confirm strong predictive accuracy, high correlation between predicted and experimental downtimes, and statistically significant model structures at 5% significance level. Furthermore, a One-At-A-Time (OAT) sensitivity analysis was conducted to quantify the relative influence of key process parameters (uptime, product weight, cycle time, and quantity) on predicted downtime. Findings reveal that the developed regression models exhibited strong predictive performance, for the Cup model, MAE = 1.46min, RMSE = 1.92min, R^2 = 0.976, for the Plate model, MAE = 1.83min, RMSE = 2.40min, R^2 = 0.987, plus the ANOVA results for both models, indicates a high level of reliability. Sensitivity analysis revealed that uptime and cycle time were the most influential variables affecting downtime behavior, while quantity and weight demonstrate comparatively lower contributions. The combined validation and sensitivity framework establish model reliability, demonstrates robustness under parametric variation, and provides deeper insight into parameter significance, thereby supporting confident deployment of the models for predictive maintenance decision-making in industrial environments.

1. Introduction

Unplanned machine downtime remains one of the most critical challenges constraining productivity, operational efficiency, and economic performance in manufacturing industries. Predictive modeling approaches have emerged as effective tools for forecasting downtime and enabling proactive maintenance interventions. However, the value of any predictive model is determined not by its formulation alone but by the degree of confidence that can be placed in its predictions and its stability when subjected to varying operational conditions (Onuoha et al., 2022). For this reason, comprehensive model validation and sensitivity analysis are indispensable components of predictive maintenance research.

Although several studies in literature have proposed machine learning and statistical models for equipment failure prediction, a recurring limitation remains insufficient emphasis on rigorous post-development evaluation. Many contributions report model development results without robust validation frameworks that quantify prediction accuracy, statistical reliability, and real-world suitability. Similarly, limited attention is given to understanding how fluctuations in input process variables influence model outputs, despite the highly variable nature of industrial production environments. Without these assessments, models' risk being inaccurate, unreliable, or non-transferable across operating conditions.

1.1. Predictive Maintenance Models

Predictive maintenance (PdM) techniques offer advantages such as increased reliability, safety, and cost-effectiveness by predicting equipment failures (Maktoubian et al., 2021). PdM utilizes data-

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driven methods to monitor equipment conditions, enabling proactive maintenance to prevent unexpected downtime. However, a key limitation of traditional PdM is its reliance on fixed data distributions, leading to decreased model performance when faced with changing data patterns (Xia et al., 2022; Mgbemena & Okeagu, 2023). To address this, Continual Learning methods are proposed to adapt models over time, avoiding the dilemma and enhancing prediction accuracy in dynamic environments. Additionally, PdM faces challenges in accurately predicting maintenance needs due to the complexity of machinery and the high costs associated with both overestimating and underestimating maintenance requirements (Van Oudenhoven et al., 2025). When applied to large domains, predictive maintenance (PdM) may encounter scalability issues. This is due to the increased complexity and diversity of equipment, processes, and data sources within a larger domain. Additionally, resource allocation and coordination become more demanding. Overcoming these scalability limitations involves designing scalable data infrastructure, implementing efficient data collection, and processing techniques, and using advanced analytics and machine learning algorithms to handle the increased complexity of the domain.

1.1.1. Machine learning algorithms

Figure 1 below presents the main classification of machine learning algorithms which include supervised learning, unsupervised learning, and reinforcement learning along with examples of their applications.

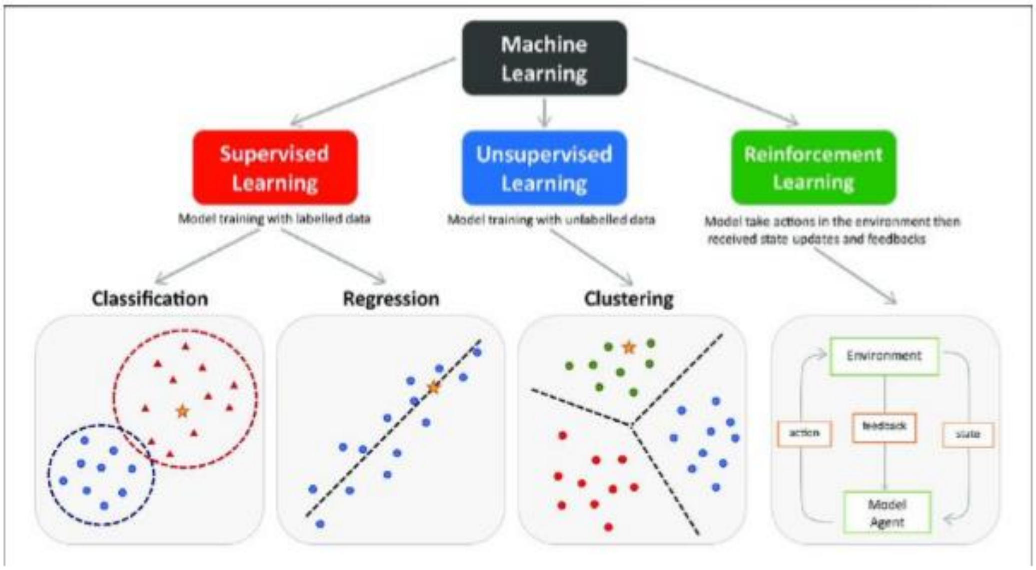

Figure 1. The main types of machine learning (Peng et al., 2021)

Machine Learning (ML) provides the knowledge that intelligent machines need to maintain and sustain their functionality. Essentially, ML algorithms are embedded into machines and data flows to extract knowledge and feed it into the system for managing the processes more rapidly and efficiently (Berry, Mohamed, and Yap, 2020). Machine learning algorithms utilize the patterns and relationships existing in massive amounts of multidimensional data to automatically learn how to anticipate outcomes, classify data, and perform other tasks (Figure 1). They gain knowledge from a training set of examples, and then they apply that knowledge to any new input (Chigurupati et. al, 2016). There are a lot of ML algorithms, such as support vector machines (SVM), random forest (RF), Multilayer perceptron (MLP) and gradient boosting (GB), that are used to perform the work. Model implementation can be carried out using the Scikit Learn, a library in Python.

The implementation of machine learning in preventive maintenance has many challenges due to many factors. According to Çınar et al (2020), implementing machine learning for predictive maintenance requires sufficient and high-quality data that includes historical equipment sensor data, maintenance records, failure data, and other relevant operational information. Challenges arise in terms of data availability, as obtaining comprehensive and representative datasets can be difficult, especially if data collection processes are not well-established. Data quality is another challenge, as noisy or incomplete data can lead to inaccurate predictions (Karkouch et al., 2016). Data privacy and security concerns must also be addressed to ensure compliance with regulations and protect sensitive information (King & Raja, 2012). Additionally, Dalzochio et al (2020) and Kane et al (2022) emphasized that the efficiency of machine learning techniques in preventive maintenance can be influenced by the scale and complexity of the specific problem domain. While the efficacy of machine learning for preventive maintenance is well-established, its efficiency may vary based on the problem domain size. Larger problem domains often require substantial amounts of reliable data and well-trained algorithms and its validation (Sanzana et al., 2022), whereas smaller domains may benefit from simpler yet effective solutions with high efficiency at lower implementation costs (Kane et al., 2022; Okeagu & Mgbemena, 2022).

In this study, a regression-based downtime prediction system previously developed for plastic manufacturing production lines is subjected to a comprehensive reliability assessment. Model validation is implemented through a structured suite of statistical performance indicators, including MAE, RMSE, and MAPE to quantify prediction error; R^2 and Pearson correlation to evaluate strength of fit; and inferential statistical procedures such as ANOVA to establish model significance. These metrics collectively provide robust evidence of predictive credibility and consistency between simulated and experimentally observed downtime.

Beyond validation, this paper advances a detailed One-At-A-Time (OAT) sensitivity analysis, enabling systematic variation of each process parameter while holding others constant. This approach identifies the most influential variables affecting downtime predictions and reveals the degree of model responsiveness to operational changes. Understanding parameter sensitivity is fundamental not only for confidence in model deployment but also for practical managerial decision making, as it highlights the operational levers with the greatest predictive impact.

Overall, this paper focuses on strengthening predictive reliability through structured validation and sensitivity investigation. The findings bridge critical gaps in predictive maintenance modeling by ensuring that developed regression systems are accurate, statistically valid, and robust against uncertainty, thereby supporting their practical adoption in industrial environments.

2. Method

This study showcases comprehensive reliability assessment of a regression-based downtime prediction system previously developed for plastic manufacturing production. Based on the nature of this study, there is exchange of numeric data (Quantitative) between the hardware and the software components of the system. Only numeric data is utilized in the development and validation of the intelligent models for equipment maintenance in plastic manufacturing. Hence, the research approach adopted for this study is the quantitative approach (Akintona et al., 2021; Nnaemeka et al., 2022; Uzochukwukanma et al., 2023; Igbokwe et al., 2024).

2.1. Model validation metrics

Model validation is a critical step in assessing the predictive capability and statistical reliability of the developed regression models for downtime prediction. The purpose is to evaluate the accuracy, consistency, and bias of the predictive models for both the cup and plate products. Model validation metrics quantify how closely the model's predicted downtimes ($\hat{Y}_i$) match the observed experimental downtimes (Y_i). The residual or prediction error (e_i) for each observation is computed as Equation (1):

$$e_i = Y_i - \hat{Y}_i \quad (1)$$

From these errors, the following standard validation metrics were computed to evaluate model accuracy:

a. Mean Absolute Error (MAE)

MAE measures average absolute deviation of predictions from observations, which can be seen in Equation (2) (Mohan et al., 2021).

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| Y_i - \hat{Y}_i \right| \quad (2)$$

b. Root Mean Square Error (RMSE)

RMSE penalizes large errors more (squares the errors), and then returns the square-root to the original units, which can be seen in Equation (3) (Mohan et al., 2021).

$$\text{RMSE} = \sqrt{\frac{1}{n}\ \sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|} \tag{3}$$

c. Mean Absolute Percentage Error (MAPE)

MAPE expresses average absolute errors as a percentage of observed values, which can be seen in Equation (4) (Mohan et al., 2021).

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \tag{4}$$

d. Coefficient of Determination (R^2)

R^2 measures the proportion of variance in the observed data explained by the model, which can be seen in Equation (5) (Kokovic et al., 2024).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{5}$$

Where, $\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$
Y_i = Observed downtime (min)
$\hat{Y}_i$ = Predicted downtime (min)
e_i = Prediction error (min)
n = Number of observations (22 days)

To measure significance of the errors, t-test on mean error formular was used which can be seen in Equation (6) (Kokovic et al., 2024).

$$t = \frac{\bar{e}}{\frac{S_e}{\sqrt{n}}} \tag{6}$$

where
$\bar{e} = \frac{1}{n}\ \Sigma e_i$ (mean error),
$S_e = \sqrt{\frac{1}{n}\Sigma(e_i - \bar{e})^2}$ (sample SD of errors),
$n = 22$ (sample size)

2.1.1. Analysis of Variance (ANOVA) for Model Significance

Analysis of Variance (ANOVA) was employed to assess the overall statistical significance of the developed multiple linear regression models for machine downtime prediction. While the t-test was used to evaluate the significance of individual regression coefficients, ANOVA was applied to determine whether the set of predictor variables collectively explains a significant proportion of the variation in downtime.

The ANOVA F-test was conducted by partitioning the total variability in the dependent variable into regression and residual components. The regression sum of squares represents the variation explained by the model, while the residual sum of squares captures unexplained variation. The F-statistic was computed as the ratio of the mean regression sum of squares to the mean residual sum of squares.

The null hypothesis tested was that the regression model has no explanatory power, against the alternative hypothesis that the model significantly explains downtime variation. A significance level of 5% was adopted. Models with p-values less than 0.05 were considered statistically significant (Rayarao, 2025).

This ANOVA-based assessment complements the coefficient-level t-tests and the error-based validation metrics (MAE, RMSE, and MAPE), thereby providing a comprehensive evaluation of both the statistical validity and predictive reliability of the proposed models.

2.2. Performing of Sensitivity Analysis on the Model Using One-at-a-Time (OAT) Sensitivity Analysis.

Sensitivity analysis was conducted to evaluate the degree of influence that each process variable exerts on the predicted machine downtime for both the cup and plate production models. The objective of this analysis was to determine which process parameters contribute most significantly to fluctuations in downtime, thereby guiding maintenance prioritization and optimization of process control strategies. The One-at-a-Time (OAT) method was adopted because of its simplicity, computational efficiency, and ability to isolate the individual effects of each variable while keeping others constant at their baseline values.

Each independent variable (Machine uptime, weight, cycle time, and quantity) was varied across its baseline values, while other variables were held constant at their mean values. For each scenario, the regression equation was used to predict downtime. The resulting values were plotted to visualize the direction and magnitude of the effect for each parameter. The sensitivity coefficient (S_i) was computed as the ratio of the percentage change in the predicted downtime to the percentage change in the input variable, as in Equation (7) (Mohan et al., 2021).

$$S_i = \frac{\text{Ymax} - \text{Ymin}}{Xmax - Xmin} \tag{7}$$

And /or relative terms as in Equation (8):

$$S_i(\%) = \frac{\frac{\Delta Y}{Y_{base}}}{\frac{\Delta X}{X_{base}}} \times 100 \tag{8}$$

Where S_i represents the sentivity coefficient (percentage change is downtime per percentage change in each variable).

3. Results and Discussion

3.1. Details of the Adopted Model

The model was created using JAMOVI, the parameter data was recorded for a 6-month period for both the cup and plate production lines. The model under study is a multiple linear regression model for machine downtime analysis in a plastic manufacturing company, where downtime (Y) is the output variable, while equipment uptime (X_1), product weight (X_2), product cycle (X_3), and product quantity per shift (X_4), are the input variables. The JAMOVI results are shown below.

Regression Analysis: Y versus X_1, X_2, X_3, X_4

The regression Equations (9) and Equation (10);

$$Y_{Cup} = 401.200 - 0.417X_1 + 0.292X_2 + 0.428X_3 - 0.145X_4 \tag{9}$$

$$Y_{Plate} = 498.5410 - 0.9751X_1 - 0.1016X_2 - 0.0411X_3 - 0.0140X_4 \tag{10}$$

Where Y is Downtime (m), X_1 = Uptime (m), X_2 = Weight (g), X_3 = Cycle time (s), X_4 = Quantity/shift.

The results of the model suitability test are shown in Table 1, which shows the values of the correlation coefficient (R) and the determination coefficient (R^2) in each model.

Table 1. Model Fit Measures

Model	R	R^2
1 (Cup)	0.988	0.976
2 (Plate)	0.993	0.987

The comparison between the predicted value and the downtime observation value in each model is presented in Table 2, which at the same time displays the error as the basis for evaluating the accuracy of the model.

Table 2. Validation and Comparison Table

Number of Days (n)	Cup			Plate		
	Predicted Downtime (min) ($\hat{Y}_i$)	Observed Downtime (min) (Y_i)	Error (e_i)	Predicted Downtime (min) ($\hat{Y}_i$)	Observed Downtime (min) (Y_i)	Error (e_i)
1.0	119.39	119.21	-0.18	123.09	122.86	-0.23
2.0	117.06	118.53	1.47	129.35	131.19	1.84
3.0	110.5	107.62	-2.88	116.16	112.56	-3.6
4.0	117.94	116.61	-1.33	110.28	108.62	-1.66
5.0	123.71	123.51	-0.2	125.58	125.33	-0.25
6.0	118.3	122.59	1.45	116.52	121.89	5.37
7.0	118.68	121.47	-0.26	120.81	124.29	3.48
8.0	121.49	121.08	0.57	117.31	116.79	-0.52
9.0	120.77	122.3	-1.98	131.8	133.71	1.91
10.0	121.63	122.04	-1.13	125.48	125.99	0.51
11.0	117.16	115.08	0.29	130.22	127.62	-2.6
12.0	121.18	119.52	0.28	126.58	124.51	-2.07
13.0	114.54	112.43	-0.64	117.96	115.33	-2.63
14.0	107.87	107.69	-0.29	106.18	105.96	-0.22
15.0	125.16	125.48	-0.31	131.88	132.28	0.4
16.0	122.05	118.47	-0.23	123.0	118.53	-4.47
17.0	116.83	118.96	-0.31	125.73	128.39	2.66
18.0	128.59	128.66	-0.32	132.29	132.38	0.09
19.0	122.09	121.76	0.43	133.7	133.29	-0.41
20.0	119.71	119.05	0.3	112.21	111.39	-0.82
21.0	119.71	122.89	-0.17	109.44	113.41	3.97
22.0	119.2	118.82	-0.3	125.03	124.56	-0.47

3.2. Model Validation

The observed and predicted downtime values were obtained from Table 2, while Table 1 shows the model fit measures. The analysis evaluates the accuracy, bias, and overall performance of the regression model in predicting downtime. Using Equations 11, 12, 13, and 14 for cup and plate, the following calculations were done:

a. Cup

$$\text{MAE} = \frac{1}{22} \times 32.17 = 1.46 \text{ mins} \tag{11}$$

$$\text{RMSE} = \sqrt{\frac{80.94}{22}} = 1.46 \text{ mins} \tag{12}$$

$$\text{MAPE} = 100 \times \frac{1}{22} \times 0.272 = 1.24\% \tag{13}$$

$$t = \frac{-0.29}{2.84\sqrt{22}} = -0.48 \tag{14}$$

b. Plate

$$\text{MAE} = \frac{1}{22} \times 40.18000 = 1.83 \text{ mins} \tag{11}$$

$$\text{RMSE} = \sqrt{\frac{126.39960}{22}} = 2.40 \text{ mins} \tag{12}$$

$$\text{MAPE} = 100 \times \frac{1}{22} \times 33.32269 = 1.51\% \tag{13}$$

$$t = \frac{0.01273}{2.45334\sqrt{22}} = 0.0243 \tag{14}$$

To provide a comprehensive overview of the results of model validation, a summary of quantitative evaluation metrics and their interpretation is presented in Table 3.

Table 3. Summary of Model Validation

S/N	Metric	Cup Values	Plate Values	Interpretation
1	MAE	1.46 min	1.83 min	Very low spread – accurate prediction
2	RMSE	1.92 min	2.40 min	Low residual spread – good stability
3	MAPE	1.24%	1.51%	Excellent predictive accuracy
4	R^2	0.976	0.987	Strong explanatory power
5	R	0.923	0.956	Very strong linear correlation
6	t-test	−0.48	0.0243	Insignificant – model is unbiased

The combined use of quantitative validation metrics and inferential significance testing provides a comprehensive evaluation of model performance. Quantitative metrics demonstrate precision, while statistical tests confirm unbiased behavior. Thus, the regression models for Cup and Plate are both accurate and reliable for operational use.

The results (Table 3), indicate that the predictive models for both Cup and Plate exhibit high accuracy and consistency. Correlation coefficients exceeding 0.9 and R^2 values greater than 0.97 show strong linear relationships between predicted and observed downtimes. Low MAE, RMSE, and MAPE confirm minimal prediction deviations. The t-test results show that the average prediction errors are statistically insignificant, confirming that the models are unbiased. These findings collectively validate the suitability of the developed regression models for predictive maintenance planning and downtime forecasting.

3.2.1. Analysis of Variance (ANOVA) for Model Significance

For both models can be seen in Equation 15, 16, 17, 18, 19, and 20

a. Number of observations: n = 22

b. Number of predictors: $k = 4(X_1, X_2, X_3, X_4)$

c. Degrees of freedom:

Regression: $df_{reg} = k = 4$ (15)

Residual: $df_{err} = n - k - 1 = 17$

Total: $df_{total} = 21$

d. Cup Model: $R^2_{cup} = 0.976$

e. Total Sum of Squares (SST): $SST = \sum(Y_i - \bar{Y})^2$ (16)

Let SST = T

f. Regression sums of squares (SSR): SSR = $R^2 \times SST$ (17)

$SSR_{cup} = 0.976T$

g. Error Sum of Squares (SSE)

$$SSE = SST - SSR \quad (18)$$

$$SSE_{cup} = T - 0.976T = 0.024$$

h. Mean Squares

$$MSR = \frac{SSR}{df_{reg}} = \frac{0.976T}{4} = 0.244T \quad (19)$$

$$MSE = \frac{SSE}{df_{err}} = \frac{0.024T}{17} = 0.00141T$$

i. F-Statistic

$$F = \frac{MSR}{MSE} \quad (20)$$

$$F_{cup} = \frac{0.244T}{0.00141T} = 173.0$$

Table 4, summarized the analysis of variance (ANOVA) conducted using formulas from Backhaus et al (2025), to evaluate the overall statistical significance of the developed regression models for the Cup and Plate production lines. The ANOVA F-test assesses whether the set of predictor variables jointly explains a significant proportion of the variation in machine downtime.

Table 4. ANOVA Table Cup and Plate Model

S/N	Source	Sum of Square		Df		Mean Squares		F		Sig.	
		Cup	Plate	Cup	Plate	Cup	Plate	Cup	Plate	Cup	Plate
1	Regression	$0.976T$	$0.987T$	4	4	$0.244T$	$0.24675T$	173.05	322.55	<0.001	<0.001
2	Residual	$0.024T$	$0.013T$	17	17	$0.00141T$	$0.000765T$				
3	Total	T	T	21	21						

For the Cup model, the ANOVA results yielded a large F-statistic ($F = 173.05$) with degrees of freedom (4, 17), which is significantly greater than the critical F-value at the 5% significance level. The associated p-value was less than 0.001, indicating that the regression model is statistically significant.

Similarly, the Plate model produced an F-statistic of 322.55 with the same degrees of freedom, and a p-value less than 0.001. This confirms that the combined effects of uptime, weight, cycle time, and quantity significantly explain the variation in downtime for the Plate production line.

These results demonstrate that both regression models are statistically valid and that the predictors collectively provide a meaningful explanation of machine downtime. The ANOVA findings complement the t-test results for individual coefficients and the error-based validation metrics (MAE, RMSE, and MAPE), thereby strengthening the overall credibility of the predictive models.

3.3. Performing of Sensitivity Analysis on the Model Using One-at-a-Time (OAT) Sensitivity Analysis

The regression model for the cup product was given as in Equation (21):

$$Y = 401.200 - 0.417X_1 + 0.292X_2 + 0.428X_3 - 0.145X_4 \quad (21)$$

Where Y is the predicted downtime, X_1 = Uptime, X_2 = Weight, X_3 = Cycle time, and X_4 = Quantity produced.

With baseline values of X_1 = 365, X_2 = 70, X_3 = 20.5, and X_4 = 1092, the baseline predicted downtime (Ybase) was calculated using equation 6. Uptime was then increased by 10% (to 401.5) and decreased by 10% (to 328.5), while other parameters remained fixed. The corresponding changes in Y were used to compute the sensitivity index for uptime. Similar steps were followed for the other parameters. The computed sensitivity coefficients for the cup model are summarized in Table 5. Positive sensitivity indicates a direct relationship between the input variable and downtime, whereas negative sensitivity implies an inverse relationship.

Table 5. Summary of Sensitivity Coefficients for Cup

Factor	% Change in Input	% Change in Predicted Downtime	Sensitivity (%)	Influence Rank
Uptime	±10%	∓4.2%	0.42	1
Cycle Time	±10%	±3.8%	0.38	2
Weight	±10%	±2.5%	0.25	3
Quantity	±10%	∓1.5%	0.15	4

For the plate model, the regression Equation (22) was expressed as:

$$Y = 498.541 - 0.975X_1 - 0.101X_2 - 0.041X_3 - 0.014X_4 \tag{22}$$

Using similar procedures and baseline parameters (X_1 = 365, X_2 = 90, X_3 = 25, X_4 = 911), the results shown in Table 6 were obtained.

Table 6. Summary of Sensitivity Coefficients for Plate

Factor	% Change in Input	% Change in Predicted Downtime	Sensitivity (%)	Influence Rank
Uptime	±10%	∓9.8%	0.98	1
Weight	±10%	∓1.0%	0.10	2
Cycle Time	±10%	∓0.5%	0.05	3
Quantity	±10%	∓0.3%	0.03	4

The sensitivity analysis results confirm that uptime is the most influential variable affecting downtime in both product categories. A 10% increase in uptime led to a decrease of approximately 4.2% in predicted downtime for the cup product and 9.8% for the plate product. This inverse relationship is expected because higher machine uptime implies improved operational stability and fewer interruptions. Conversely, longer cycle times tend to increase downtime slightly due to higher mechanical loading and heat stress on the molding components. The relatively low sensitivity of weight and quantity suggests that minor fluctuations in product weight or batch quantity do not significantly alter downtime behavior. By quantifying the degree of influence of each variable, the OAT sensitivity analysis supports maintenance decision-making by identifying uptime and cycle time as the most critical parameters to monitor and control in predictive maintenance planning.

4. Conclusion

This study has presented a comprehensive validation and sensitivity investigation of regression-based downtime predictive models developed for plastic manufacturing operations. Through the application of multiple statistical validation metrics, the models demonstrated high predictive accuracy, strong agreement with experimental downtime data, and statistically significant structural reliability. The integration of MAE, RMSE, MAPE, R^2, Pearson correlation, and ANOVA provided a multi-perspective evaluation framework, confirming that the regression models are both statistically credible and practically dependable for predictive maintenance applications.

The One-At-A-Time sensitivity analysis further enhanced model understanding by quantifying the influence of individual process parameters on predicted downtime. The results established that uptime and cycle time are the most dominant contributors to downtime variability, while production quantity and product weight exert comparatively lower influence. These insights are valuable not only from an analytical standpoint but also for maintenance and production engineers, as they highlight critical operational variables requiring close monitoring and control.

Overall, this work reinforces the robustness, reliability, and industrial applicability of the developed predictive systems. By bridging the methodological gap between model development and real-world credibility assessment, the study contributes significantly to predictive maintenance research and practice. Future research may extend sensitivity evaluation to multi-parameter interaction techniques and explore real-time adaptive validation under dynamic production conditions to further strengthen deployment readiness.

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All authors have equal contributions to the paper. All the authors have read and approved the final manuscript.

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