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Computer-based data processing approaches to production scrap management

Abstract

The aim of this study was to design and empirically validate a predictive approach for classifying scrap types and forecasting scrap volume in brake calliper remanufacturing, oriented toward operational decision-making. We addressed three research questions: (1) which “red-flag” defects most strongly increase the risk of high scrap (“Large”); (2) whether scrap category is driven by the accumulation of multiple defects or by single catastrophic defects; and (3) whether logistic regression provides sufficient performance and interpretability for industrial use, or whether more complex machine-learning models are justified. The analysis used real industrial data (435 cases, 34 defect-related features with discrete values: 0/1 and, in some cases, counts). The baseline model (logistic regression) achieved 79% accuracy and an AUC of 0.773, confirming its practical usefulness in a production environment. Coefficient analysis indicated, among others, that the defect “power-supply leakage” is a strong predictor of the “Norm” class ($OR \approx 4.64$ for “Norm” vs. “Large”), while defect-profile analysis revealed an accumulation trajectory (mean 7.3 defects for “Large” vs. 3.5 for “Norm”), distinct from a catastrophic trajectory (immediate disqualification). The study shows that interpretable models can support decision processes in remanufacturing, reducing scrap and supporting circular-economy and Industry 4.0 goals.

1. INTRODUCTION

Rapid global population growth and lifestyle changes make limited natural resources an increasingly important issue for modern production systems. At the same time, high levels of consumption, combined with fast technological development, increase demand not only for energy, but also for materials and resources used to manufacture food, mechanical components, and technologically complex products. As a result, the industry must adapt to new environmental, economic, and social requirements, and traditional paradigms of design, production, and product use are often insufficient (Ponte et al., 2019).

In response, the concept of sustainable development and the circular economy has gained importance. This approach aims to maximise the value of products and components through reuse, remanufacturing, and recycling, while minimising waste generation and the use of primary resources. In mechanical engineering, circular-economy implementation requires integrating advanced monitoring and data-analysis technologies, MES (Manufacturing Execution Systems), ERP (Enterprise Resource Planning), and predictive maintenance methods to optimise both manufacturing and remanufacturing processes. This enables companies to improve operational efficiency while meeting environmental and economic constraints, in line with Industry 4.0/5.0 expectations (Parker et al., 2015; Yang et al., 2018).

Remanufacturing is a key circular-economy practice. It restores products at the end of their life cycle (End-of-Life, EoL). The process typically includes disassembly of returned products, thorough cleaning, and detailed inspection of components. Parts suitable for repair are regenerated, while components that do not meet technical requirements are replaced with new ones. Finally, the product is reassembled and functionally tested to achieve a condition comparable to that of a new product and to ensure compliance with industrial standards (Fofou et al., 2021). A simplified remanufacturing process is shown in Figure 1 (Pizoń et al., 2024).

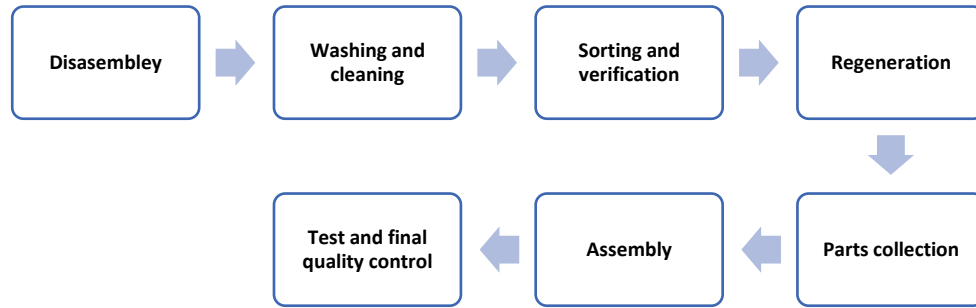


Fig. 1. Simplified remanufacturing process (Pizoń et al., 2024)

Remanufacturing is particularly effective for complex electromechanical and mechanical products, where recovered cores retain significant added value. This value can be substantial compared to both the current market value and the original manufacturing cost, making remanufacturing economically attractive, especially in sectors that rely on precise and advanced technologies (Ijomah, 2009).

In remanufacturing, End-of-Life (EoL) products are treated as input materials (cores), thereby introducing substantial uncertainty (Guide et al., 1997). EoL products experience different loads during use, leading to large differences in condition and wear. Immediately before and during remanufacturing, it is difficult to accurately assess core quality. Additional challenges include estimating processing time, the probability of remanufacturing success, and the risk of accidental damage or core failure. Uncertain quality also makes cost estimation difficult and increases overall complexity (Zhao et al., 2019).

In the era of Industry 4.0, product development cycles are shorter and products are increasingly customised. This creates challenges for smart production systems, and similar difficulties appear in remanufacturing, where process variability increases uncertainty. Despite these challenges, production systems must remain flexible and continuously adapt to changing conditions (Garcia et al., 2011). With real-time observation, such information can be used to adjust production strategies (Paschko et al., 2023).

Properly selected IT systems support data centralisation, resource optimisation, and monitoring of sales and purchasing processes. They also enable real-time production management, control of technological operations, tracking of machine performance, and rapid identification of deviations from production norms (Teixeira et al., 2022).

2. LITERATURE REVIEW ON PRODUCTION SCRAP AND SCRAP MANAGEMENT

The literature emphasises that production planning in remanufacturing is more difficult than in traditional manufacturing, because the input stream is constrained by core availability and characterised by uncertain quality and variable resource demand. These factors directly affect processing times and costs, as well as multi-period decisions regarding remanufacturing, holding, and salvage (Goodall et al., 2019).

Remanufacturing planning requires decision methods that explicitly account for uncertainty. On the one hand, life-cycle strategies and information-sharing mechanisms improve “remanufacturability” and access to operational data; on the other hand, planners must consider core-quality variability, grading/salvage costs, and capacity constraints over time (Jiang et al., 2014). Multi-stage stochastic programming is often cited as a useful foundation, as it supports quality-class-dependent decisions (grade–remanufacture–hold–salvage) and ensures the feasibility of plans across different quality realisations. Complementary approaches such as Material Flow Analysis and scenario analysis help structure production scrap streams and quantify trade-offs between material and energy recovery, linking operational decisions to circular-economy indicators (Lv et al., 2021; Ponte et al., 2021).

In remanufacturing, inspection is essential to ensure quality and reliability. Detailed verification points are typically placed at critical stages of the process to facilitate core classification and quality grading (Aksoy & Gupta, 2005). This approach limits economic losses by removing cores that would fail qualification later in the process (Litwin et al., 2024).

A typical remanufacturing process includes at least three key inspection stages: core inspection before disassembly, component inspection after disassembly, and final assessment after reassembly. The main goal

of core inspection is to determine feasibility and economic viability, and to collect information needed to plan the process, including component inventory management (Guide, 2000).

During initial inspection, information is collected on the core configuration (model/version, bill of materials, technical requirements), its quality condition, and predictive indicators of remanufacturability. Post-disassembly inspection evaluates components for reuse/repair/scrap, often using measurements and non-destructive testing. Control also includes checks performed during remanufacturing, followed by verification after reassembly and before final tests, to validate compliance with technical and functional requirements (IFIP, 1998).

Effective information management is crucial for supervising remanufacturing. Data are collected at different stages from MES systems and manual records. This enables a more complete analysis of input conditions, operation progress, and outcomes at each stage of the remanufacturing process.

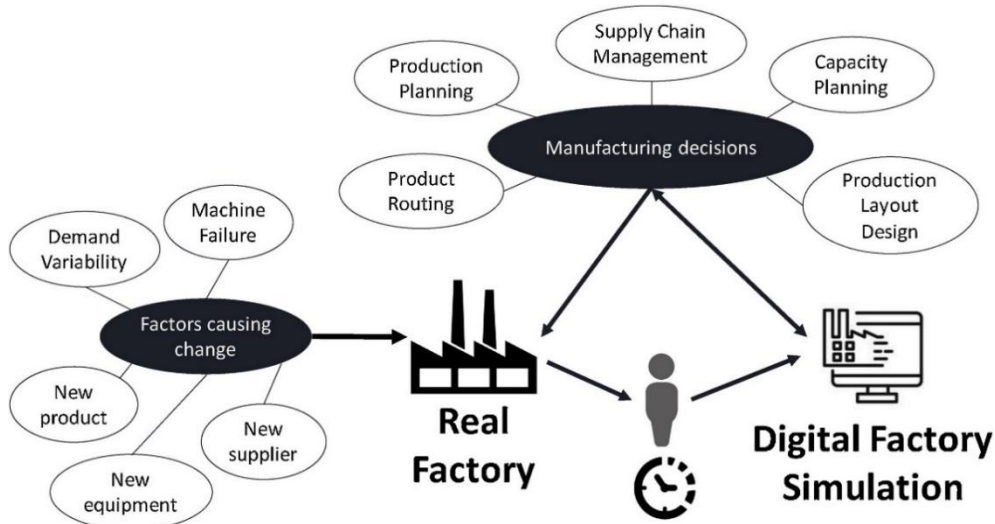


Fig. 2. Current simulation workflow, highlighting the dependence on manual information updates between the real factory and the simulation (Goodall et al., 2019)

To support dynamic planning and production control, simulation models should automatically adapt to real conditions and a changing environment. This requires digital tools ranging from ad hoc databases and technical documentation to formal ERP and MES systems, so that models can be fed with current data and their structures and parameters updated automatically (Wójcik & Gola, 2025). Such a simulation environment supports credible evaluation of process variants and operational decisions, even by non-specialist users, while maintaining informational consistency and traceability of changes (Goodall et al., 2019). Figure 2 presents a simulation workflow highlighting the dependence on manual updates to information between the real factory and the simulation.

3. RESEARCH PROBLEM AND RESEARCH GAP

The main research problem is the lack of effective predictive tools that enable accurate classification and forecasting of scrap volume in remanufacturing based on defect data. Current industrial practice is largely reactive (defects are identified after they occur), which limits preventive actions and hinders optimal process planning. Therefore, a model is needed that not only predicts scrap levels but also identifies key defects (“red flags”) that have the highest impact on scrap generation, enabling proactive quality management and improved operational efficiency.

Previous research on scrap management in manufacturing and remanufacturing indicates a lack of integration between defect analysis and scrap-volume forecasting. Most existing approaches focus on either quality assessment or scrap quantity, while ignoring relationships between defect type and the magnitude of its impact on scrap generation.

The identified research gap, therefore, concerns the need to develop an integrated, machine-learning-based predictive model that enables:

- • classifying scrap based on observed defects,

- • estimating the contribution of defects to total scrap volume,
- • providing practical recommendations for process improvement in line with Industry 4.0 and the circular economy.

The objective of this study is not to develop a complete Digital Twin system, but to establish and validate an analytical foundation for future intelligent decision-support systems supporting brake caliper remanufacturing.

4. MATERIALS AND METHODS

4.1. Input data analysis

This study used production data collected by the authors directly from an industrial plant performing brake calliper remanufacturing (operational records from quality control and process sheets; shared for research after anonymisation and aggregation of internal identifiers). The dataset reflects real production conditions, including variability in End-of-Life core quality and differences in defect profiles (Tab. 1).

Tab. 1. Input data used in the study

Order No.	BOM ID	Product Subgroup	Disassembly Quantity	Sorting Quantity	Sorting Scrap	Workstation	Defect Name
POE76595	LUC-86-0828B	HANDBRAKE	9	4	5	BCRB1_L2	Exceeded Housing Working Length
POE76595	LUC-86-0828B	HANDBRAKE	9	4	5	BCRB1_L2	Mechanical Damage of the Housing
POE76595	LUC-86-0828B	HANDBRAKE	9	4	5	BCRB1_L2	Returned Core – Completely Different Part Number
POE76595	LUC-86-0828B	HANDBRAKE	9	4	5	BCRB1_L2	Incorrect Insert (Not Our Insert)
POE76596	LUC-86-0607-1B	HANDBRAKE	40	25	15	BCRB1_L2	Chinese Housing/body
POE76596	LUC-86-0607-1B	HANDBRAKE	40	25	15	BCRB1_L2	Severe Housing Corrosion
POE76596	LUC-86-0607-1B	HANDBRAKE	40	25	15	BCRB1_L2	Damaged Supply Thread (Insert Installation Not Possible)
POE77402	LUC-86-0815	HANDBRAKE	41	32	9	BCRB1_L2	Severe Housing Corrosion
POE77402	LUC-86-0815	HANDBRAKE	41	32	9	BCRB1_L2	Cylinder Corrosion
POE77402	LUC-86-0815	HANDBRAKE	41	32	9	BCRB1_L2	Claw Corrosion
POE77402	LUC-86-0815	HANDBRAKE	41	32	9	BCRB1_L2	Incorrect Quantity Reported from Previous Workstation
POE74099	LUC-83-0903	FIXED	12	2	10	BCRB1_L2	Severe Housing Corrosion
POE74099	LUC-83-0903	FIXED	12	2	10	BCRB1_L2	Mechanical Damage of the Housing
POE72753	LUC-83-1641	FIXED	10	8	2	BCRB1_L2	Cylinder Corrosion
POE72753	LUC-83-1641	FIXED	10	8	2	BCRB1_L2	Mechanical Damage of the Housing

Each observation represented a single remanufactured brake calliper identified by a unique production record. During the inspection process, multiple defects could be assigned to the same component; therefore, the dataset was structured with one row per brake calliper rather than per defect. Each brake calliper was

described by 34 defect-related variables (discrete values: 0 indicates no defect; positive values indicate occurrence and, for some defects, the count within the given unit). This representation captures the complete quality profile of each unit and enables analysis of defect co-occurrence across process stages without duplicating observations. The target variable WasteType had two categories: "Norm" (standard scrap) and "Large" (increased scrap volume). The data reflect real plant proportions: 62.3% of cases were classified as "Norm" and 37.7% as "Large" (Figure 3).

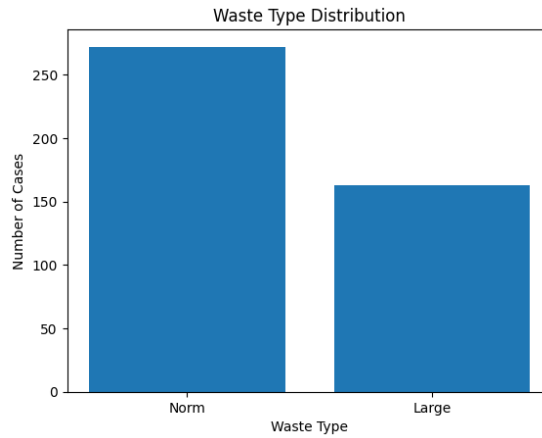


Fig. 3. Distribution of waste types in the industrial dataset (N=435)

For deeper analysis, defects were divided into two groups based on the stage at which they were detected (Figure 6: Norm vs Large). The first group (“Defekt1_”) included 17 defect types identified during initial visual inspection and functional tests—mainly power-supply leaks, body corrosion, cracks or mechanical deformations, and thread defects. Examples are shown in Figure 4. The second group (“Defekt2_”) also included 17 variables describing defects revealed only during more advanced technical analysis, such as welding issues, damage to cooperating elements, or deformations resulting from earlier repairs. This distinction supports both frequency analysis and assessment of defect impact, depending on the detection moment within the product life cycle. Figure 5 presents the fifteen most frequent defects recorded during brake calliper remanufacturing.



a) Claw corrosion



b) Severe body corrosion



c) Damaged power-supply thread

Fig. 4. Examples of defects

The analytical procedure began with data cleaning to remove incomplete or erroneous records and verify the accuracy of binary variables. Since all explanatory variables were binary (0/1), no feature scaling or normalisation was required prior to model development. Next, an exploratory data analysis (EDA) was performed to identify the most frequent defects, assess their interdependencies, and indicate potential relationships between primary and secondary defect groups. At this stage, correlation analysis was also conducted to preliminarily identify defects that may strongly influence the occurrence of the “Large” scrap class.

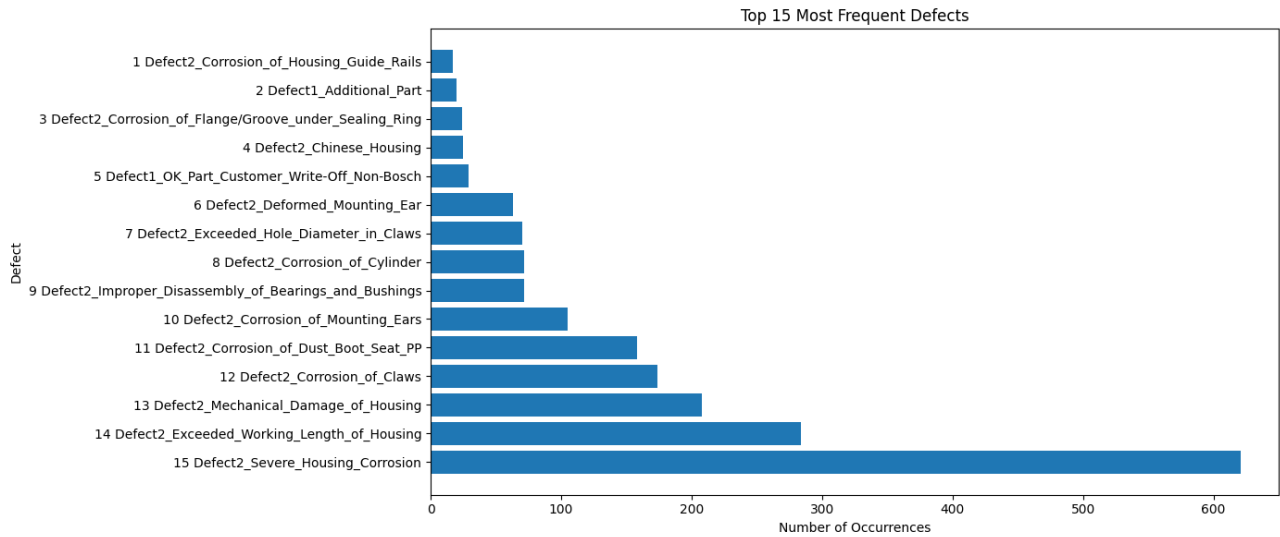


Fig. 5. Top 15 most frequent defects recorded during brake-caliper remanufacturing

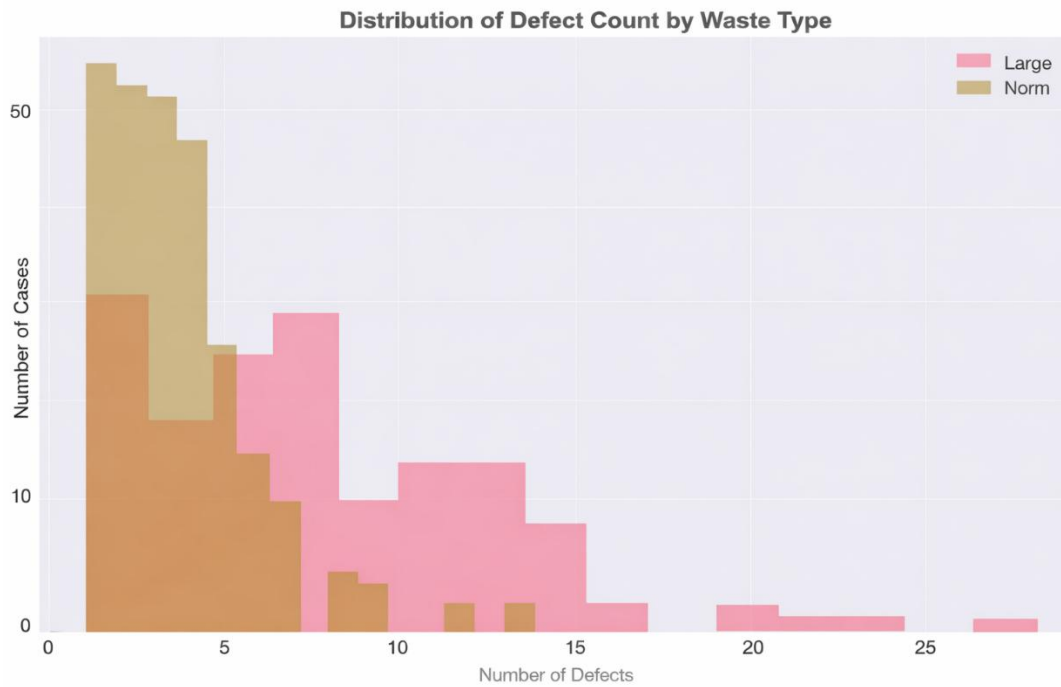


Fig. 6. Defect-count distribution per unit by waste type (Norm vs Large)

4.2. Data preprocessing

First, data completeness was verified. All 34 defect variables contained no missing values. Therefore, the full number of observations could be retained without imputation, increasing the reliability of subsequent analyses.

Next, the target variable was label-encoded: “Large” was mapped to 0 and “Norm” to 1. This coding was selected to support intuitive interpretation of logistic regression coefficients: a positive coefficient increases the probability of the class “Norm”, while a negative coefficient indicates a higher risk of the class “Large”.

The data were then split into training and test sets in an 80/20 proportion. The training set contained 348 cases and was used to estimate model parameters. The test set contained 87 cases and was used only for performance evaluation. Stratification preserved the “Norm”/“Large” class proportions in both sets, reducing the risk of non-representative splits. For reproducibility, the random state was set to 42. A stratified hold-out

validation strategy was adopted to preserve the original class distribution in both subsets while evaluating the model on previously unseen data.

No normalisation or standardisation was applied. The predictors are discrete (mostly 0/1 and, in some cases, counts >1), where 0 denotes absence of a given defect. Because logistic regression works well with such inputs and the original scale supports direct interpretation of defect effects, keeping the data in their native form was methodologically and practically justified.

4.3. Model and algorithm

To build a predictive model that classifies scrap type in the remanufacturing process, logistic regression was selected as the baseline method. The choice was motivated by computational efficiency and full interpretability—an important requirement in industrial environments where model-based decisions must be transparent for engineers and managers.

Logistic regression enables explicit estimation of how each input variable (defect) influences the probability of belonging to a given scrap category. Coefficient values indicate both the direction and strength of the effect: positive coefficients increase the probability of “Norm”, while negative coefficients indicate a higher risk of “Large”. This transparency is a key advantage over more complex machine-learning models that often operate as black boxes.

An additional advantage is fast inference and low computational cost, which is relevant for potential real-time deployment in production systems. The model outputs probabilities, so it can indicate borderline cases that may require additional verification before an operational decision is made.

The logistic regression model was implemented using the Scikit-learn library in Python. Logistic regression was selected because it provides an interpretable baseline model that estimates the influence of individual defects while maintaining competitive performance in binary classification problems. The model was configured with `max_iter = 1000` to ensure convergence and `random_state = 42` for reproducibility. The “lbfgs” solver (Limited-memory Broyden–Fletcher–Goldfarb–Shanno) was used for its stability and speed on small-to-medium datasets. Although it supports multiclass problems, it was applied here to binary classification.

Model training minimised the cross-entropy loss, reducing the difference between true labels and predicted probabilities. Convergence was reached after 32 iterations, indicating well-conditioned data and appropriate hyperparameter settings. Predicted probabilities greater than 0.5 were assigned to the “Norm” class, while lower probabilities were classified as “Large”. The intercept was 2.2479, reflecting a baseline tendency toward the “Norm” class, consistent with its prevalence in the dataset.

Model quality was evaluated using complementary metrics. The combination of threshold-dependent (accuracy, precision, recall, and F1-score) and threshold-independent metrics enabled a comprehensive assessment of model performance under industrial operating conditions. Overall performance was measured by accuracy. Class-specific effectiveness was assessed using precision, recall, and F1-score, enabling the identification of asymmetric errors, such as missing “Large” cases or incorrectly flagging “Norm” as “Large”.

To analyse error structure, a confusion matrix was used. In addition, the ROC curve and AUC were computed to assess class separability independent of the decision threshold. A higher AUC indicates better probabilistic predictions and stronger discrimination between “Norm” and “Large”.

Finally, training and test results were compared to assess generalisation and detect potential overfitting. The absence of meaningful differences in accuracy confirmed that the model is stable and not overfit to the training data.

All computations and visualisations were prepared by the authors in Python (pandas, scikit-learn, matplotlib), so the procedure can be reproduced directly or automated within quality-management systems (e.g., daily/shift reporting).

5. RESULTS

The results confirm that the developed logistic regression model is effective for predicting scrap category in brake calliper remanufacturing. The analysis combined predictive performance evaluation with interpretation of model coefficients, which helps explain mechanisms contributing to increased scrap volume.

5.1. Model performance

The logistic-regression model showed good stability and generalization, achieving accuracy of 78.74% on the training set and 79.31% on the test set. The small difference (0.57 percentage points) indicates no overfitting and suggests that the model learned general relationships between defects and scrap type rather than noise.

The ROC AUC was 0.773 (Figure 7), which indicates good discrimination in an industrial context. This means the model ranks true “Large” cases higher than “Norm” cases with 77.3% probability. The result is clearly above random classification (AUC = 0.5) and meets typical practical-use thresholds (AUC > 0.7).

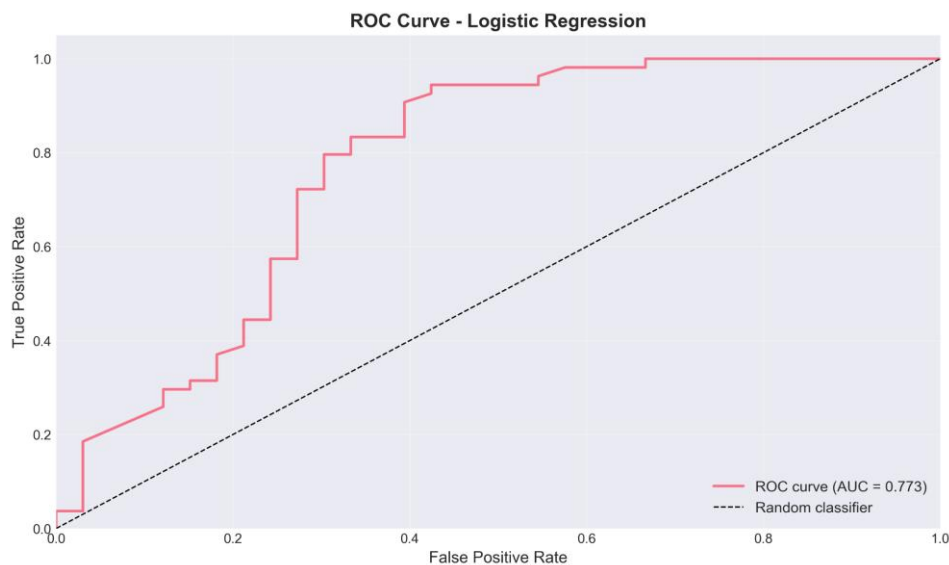


Fig. 7. ROC curve for logistic regression (AUC=0.773)

5.2. Confusion-matrix analysis

The confusion matrix for the test set Figure 8 (87 cases) shows the error structure. The model correctly identified 20 “Large” cases and 49 “Norm” cases, corresponding to 79.31% correct classifications.

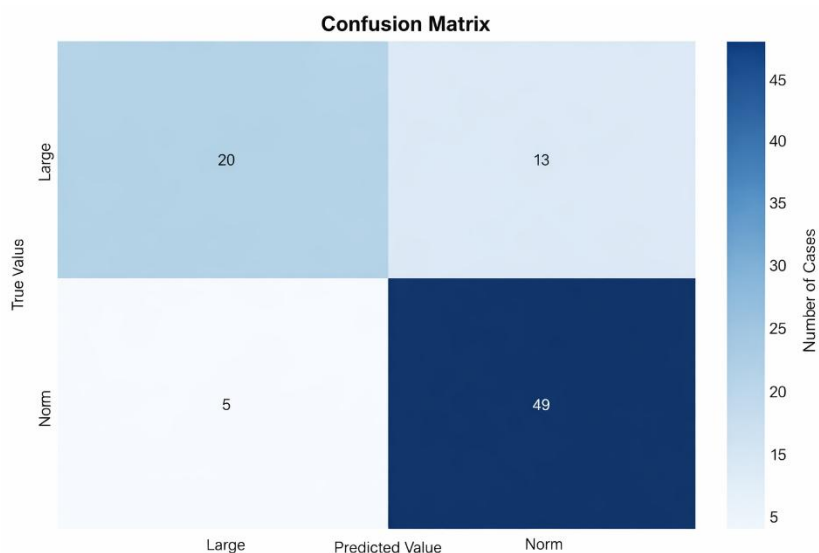


Fig. 8. Confusion matrix for logistic regression on the test set (n=87)

Two error types were observed. In 5 cases, the model produced false alarms for “Large” (false positives: true “Norm”, predicted “Large”), which operationally means directing a unit for additional verification. More

critical are misses of “Large” cases: 13 false negatives (true “Large”, predicted “Norm”), which may allow units requiring intensified handling to proceed without an adequate response.

5.3. Class-wise metrics

For class “Large” (increased scrap), precision was 0.80, meaning that 80% of units predicted as “Large” truly belonged to this class. Recall was 0.61, indicating that the model detected 61% of all actual “Large” cases. The F1-score was 0.69.

For class “Norm”, precision was 0.79, recall 0.91, and F1-score 0.84. This indicates that the model identifies standard-scrap cases well and rarely misclassifies “Large” units as “Norm”.

This class asymmetry can be acceptable in industry: the model is relatively conservative and, in ambiguous cases, tends to flag “Large”, increasing additional inspections but reducing the risk of missing high-scrap units.

5.4. Feature importance analysis

Logistic regression coefficients were analysed to quantify the influence of individual defects on scrap classification. Because labels were encoded as “Large” = 0 and “Norm” = 1, positive coefficients increase the probability of “Norm”, while negative coefficients indicate a higher risk of “Large” (Figure 9). The strongest predictors of “Large” scrap were defects with the most negative coefficients: “No assembly possible” (coef = -0.817), “Cracked Housing” (coef = -0.809), and “Damaged/corroded surface around supply port” (coef = -0.734). Further risk-increasing predictors included “Incorrect disassembly of bearings and bushings” (coef = -0.681) and “Exceeded hole diameter in claws” (coef = -0.567).

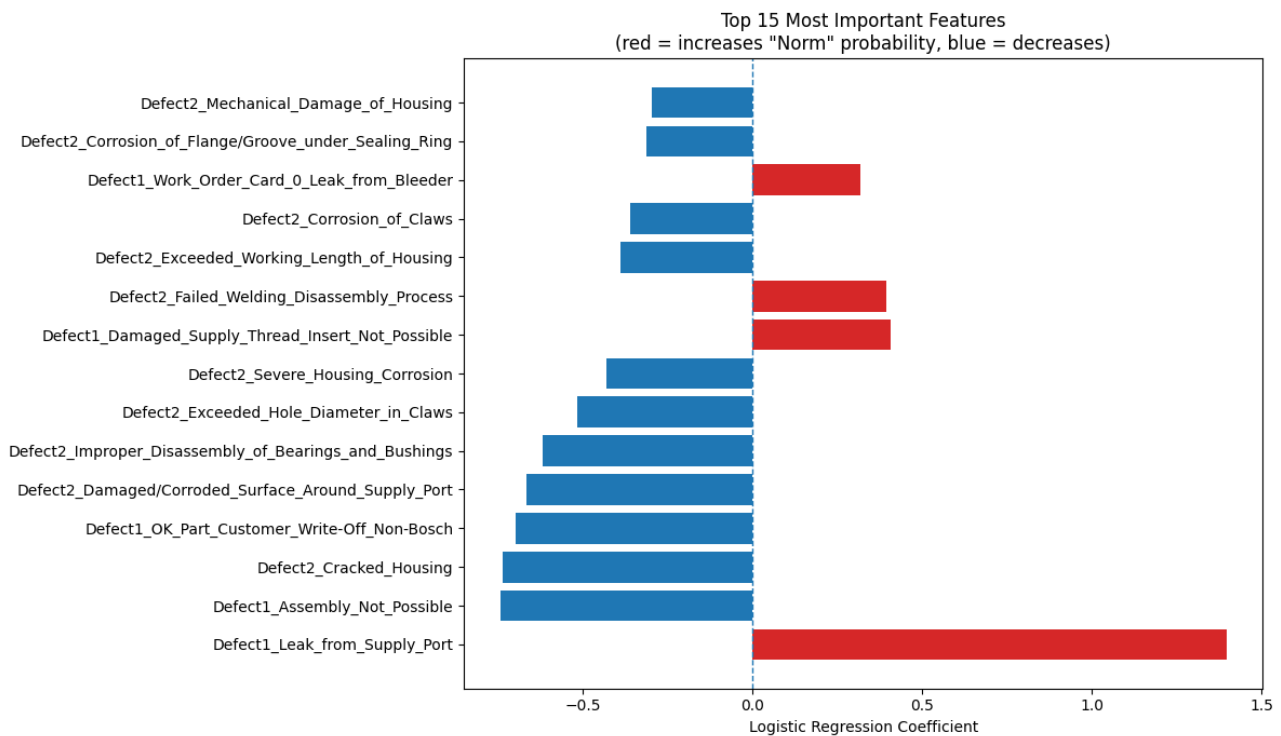


Fig. 9. Top 15 features by logistic-regression coefficient (positive increases “Norm”, negative increases “Large” risk)

Defects with positive coefficients increased the probability of “Norm”, suggesting problems that are relatively easier to repair or typically lead to standard scrap levels. The largest positive coefficient was observed for “Leak from supply port” (coef = +1.535), corresponding to $OR = \exp(1.535) \approx 4.64$ for “Norm” vs. “Large”, holding other features constant. Other positive predictors were “Damaged supply thread – insert not possible” (coef = +0.451) and “Failed welding disassembly process” (coef = +0.434).

5.5. Key findings

Several key phenomena were observed. First, a cumulative defect effect was found: units classified as “Large” had, on average, 7.3 defects, while “Norm” units had 3.5. This indicates that increased scrap is typically not caused by a single failure but by the accumulation of multiple smaller defects.

Second, among the highest positive coefficients (favouring “Norm”), defects related to the power-supply subsystem dominate (leaks and thread damage). This suggests they are frequent but often manageable within the standard remanufacturing route.

Third, catastrophic defects (e.g., cracked housing, no assembly possible) are among the strongest predictors of “Large” scrap (most negative coefficients). This supports early quality gates (triage) to stop processing quickly and avoid unnecessary labour and material costs.

Finally, the coefficient structure is asymmetric: of the 34 variables, 10 had positive coefficients and 23 had negative coefficients. Most absolute values were small (<0.5), supporting the observation that single defects often have a limited effect, whereas combinations determine the final scrap category. Figure 10 presents the distribution of logistic-regression coefficients for 34 defect-related features.

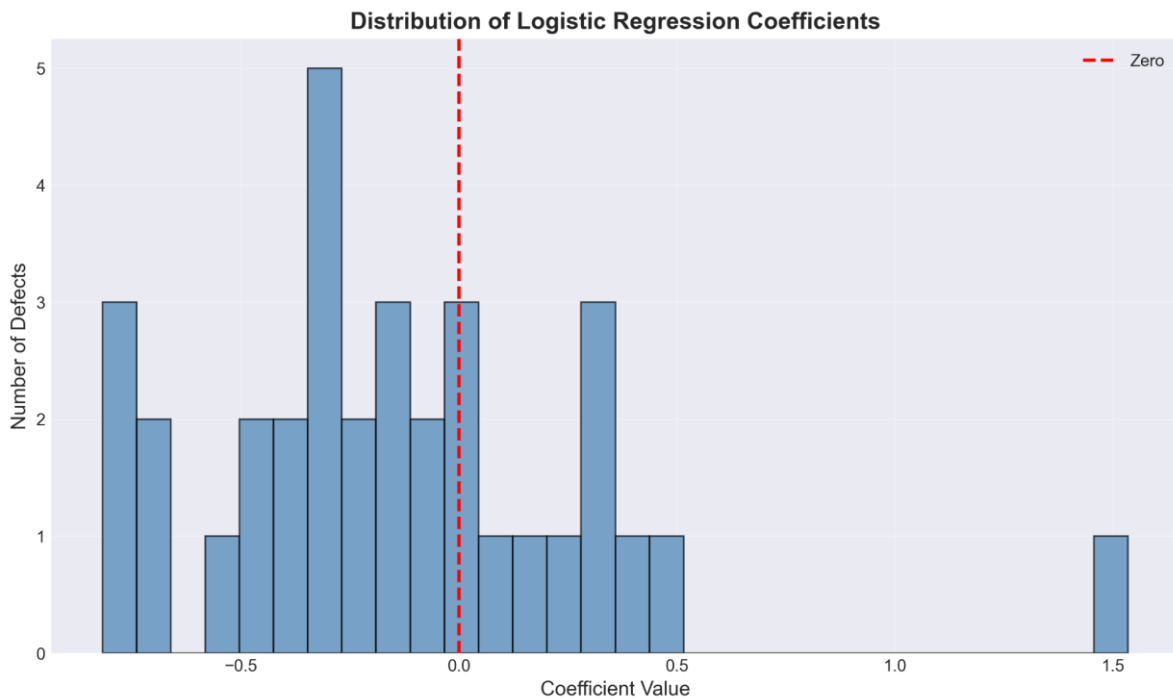


Fig. 10. Distribution of logistic-regression coefficients for 34 defect-related features

5.6. Interpretation in the production-process context

The logistic-regression coefficient of +1.535 for the defect “Power-supply leakage” is operationally important. After transforming the logit to odds ($\exp(1.535) \approx 4.64$), the presence of this defect increases the odds of classifying a unit as “Norm” by about 4.6 times, holding other variables constant. In practice, this indicates that, in the analysed plant, leakage is often detected and handled within the standard remanufacturing path, rather than being a direct driver of increased scrap. Nevertheless, it remains a key quality signal and should be monitored systematically.

From an engineering perspective, three complementary mechanisms can explain this relationship:

1. Damage-propagation mechanism: leakage can initiate a cascade (contamination, surface degradation, accelerated corrosion of body/claws/cylinders) and secondary damage to moving parts, which supports defect accumulation.
2. Systemic-problem marker: leaks may indicate component-quality issues (e.g., seals, threads) and can reveal lot-related problems or parameter drift at a supplier.

3. Assembly-related causes: incorrect tightening torque, improper seating of power-supply elements, or missing short-cycle leak tests can contribute to leakage. This points to operator training, revision of standard work instructions, and equipment support (e.g., torque-controlled tools and quick leak tests).

Model interpretation also suggests two distinct scrap-formation trajectories. The first, typical of the “Large” class, is an accumulation path: on average, 7.3 defects per unit, often centred on sealing problems, progressing corrosion, and secondary damage appearing at later remanufacturing stages. Units move through the system “collecting” defects until a disqualifying threshold is reached. The second is a catastrophic trajectory: a single critical defect (e.g., cracked body, no assembly possible) leads to immediate rejection before secondary defects accumulate.

The results support two complementary quality-control strategies:

- Anti-accumulation path (prevention): focus on sources of leakage and corrosion. Practically, this includes mandatory leak tests after assembly (short pressure cycle), SPC for tightening torque, poka-yoke solutions for critical joints, traceability of seal/thread batches, and regular supplier audits. Threshold escalation rules are also useful: a detected leak automatically routes a unit to an intensified verification path.
- Fast disqualification path (triage): strengthen incoming inspection for catastrophic defects. Short, high-sensitivity visual/functional checklists, vision support, and clear STOP criteria reduce unnecessary processing: detection of a cracked body or no-assembly condition ends the process immediately.

6. DISCUSSION

The results confirm that logistic regression can serve not only as a predictive tool but also as a valuable analytical tool for understanding the mechanisms underlying waste generation in regeneration processes. The combination of satisfactory prediction quality (accuracy $\approx 79\%$, ROC AUC = 0.773) with high interpretability makes the model particularly useful in industrial settings, where transparency and the ability to explain results are of key importance.

One of the most important findings is the asymmetry in classification quality between the ‘Normal’ and ‘Large’ classes. The model identifies standard cases very well, whereas its ability to detect cases of elevated waste levels is moderate. This is typical of classification problems in industry, where more complex and less homogeneous classes are harder to capture. From a practical point of view, this suggests the need for further refinement of the model, e.g., by fine-tuning the decision threshold, applying cost-based approaches, or using ensemble methods. A significant contribution of this work is the interpretation of the regression coefficients, which enables the model’s statistical outcomes to be directly related to engineering phenomena observed in the remanufacturing process.

The identified effect of defect accumulation is a key finding of this study. The significantly higher number of defects in the ‘Large’ cases confirms that waste generation is a process-driven and cumulative phenomenon. This implies that quality degradation should be analysed as the result of the interaction of multiple factors, rather than isolated events. In this context, the logistic regression model effectively captures the combined influence of multiple variables.

The results also indicate two distinct trajectories of defect accumulation: a cumulative and a catastrophic. This has significant implications for the design of quality systems, suggesting the need to apply differentiated control strategies depending on the type of defects.

From an industrial implementation perspective, the proposed model can support decision-making at multiple stages of the remanufacturing process. After defects are identified during inspection, the model can estimate the probability that a component belongs to the “Large” waste category and help operators select the appropriate processing route, such as standard remanufacturing, additional inspection, or early rejection. Such an approach has the potential to improve the consistency of quality assessment, reduce subjective decision-making, and increase process standardisation. Furthermore, integration of the model with Manufacturing Execution Systems (MES), Enterprise Resource Planning (ERP), and Business Intelligence tools would enable continuous monitoring of defect trends and support data-driven process improvement in accordance with Industry 4.0 principles.

Limitations of the study include reliance on data from a single production environment, which may limit the generalizability of the results. In the future, it would be reasonable to consider more advanced machine learning methods and the integration of the model with real-time monitoring systems.

7. CONCLUSIONS

Interpreting the model coefficients enabled the translation of statistical relationships into engineering conclusions. Catastrophic defects, such as a cracked body or an inability to assemble the product, were clearly identified as factors leading to immediate rejection. In turn, frequently occurring defects in the power supply system (e.g., leaks) are usually handled through the standard remanufacturing pathway; however, they may serve as significant indicators of systemic issues, such as process instability, variability in supply quality, or assembly errors.

In the broader context of Industry 4.0 and the circular economy, the proposed methodology aligns with the shift in remanufacturing processes towards intelligent, data-driven systems. By increasing process transparency, improving resource utilisation, and reducing waste, this approach supports the implementation of sustainable production principles.

In summary, the research confirms that interpretable machine learning models, such as logistic regression, can significantly improve the efficiency of regeneration processes and deepen our understanding of them. In future work, it is advisable to extend the model to include additional process parameters, integrate it with real-time monitoring systems, and apply more advanced analytical methods to further improve predictive quality and implementation capabilities.

Conflicts of Interest

The authors declare no conflict of interest.

REFERENCES

- Aksoy, H. K., & Gupta, S. M. (2005). Buffer allocation plan for a remanufacturing cell. *Computers & Industrial Engineering*, 48(3), 657–677. <https://doi.org/10.1016/j.cie.2003.03.007>
- Fofou, R. F., Jiang, Z., & Wang, Y. (2021). A review on the lifecycle strategies enhancing remanufacturing. *Applied Sciences*, 11(13), Article 5937. <https://doi.org/10.3390/app11135937>
- Garcia, A. R., Filipe, S. B., Fernandes, C., Estevão, C., & Ramos, G. (2011). Enabling manufacturing competitiveness and economic sustainability. In *Proceedings of the 4th International Conference on Changeable, Agile, Reconfigurable and Virtual Production (CARV2011)* (pp. 2–5).
- Goodall, P., Sharpe, R., & West, A. (2019). A data-driven simulation to support remanufacturing operations. *Computers in Industry*, 105, 48–60. <https://doi.org/10.1016/j.compind.2018.11.001>
- Guide, V. D. R., Jr. (2000). Production planning and control for remanufacturing: Industry practice and research needs. *Journal of Operations Management*, 18(4), 467–483. [https://doi.org/10.1016/S0272-6963\(00\)00034-6](https://doi.org/10.1016/S0272-6963(00)00034-6)
- Guide, V. D. R., Kraus, M. E., & Srivastava, R. (1997). Scheduling policies for remanufacturing. *International Journal of Production Economics*, 48(2), 187–204. [https://doi.org/10.1016/S0925-5273\(96\)00091-6](https://doi.org/10.1016/S0925-5273(96)00091-6)
- Ijomah, W. L. (2009). Addressing decision making for remanufacturing operations and design-for-remanufacture. *International Journal of Sustainable Engineering*, 2(2), 91–102. <https://doi.org/10.1080/19397030902953080>
- IFIP International Federation for Information Processing. (1998). *Advances in production management systems*. Springer. <https://doi.org/10.1007/978-0-387-35304-3>
- Jiang, Z., Fan, Z., Sutherland, J. W., Zhang, H., & Zhang, X. (2014). Development of an optimal method for remanufacturing process plan selection. *The International Journal of Advanced Manufacturing Technology*, 72(9–12), 1551–1558. <https://doi.org/10.1007/s00170-014-5783-x>
- Litwin, P., Gola, A., Wójcik, Ł., & Cioch, M. (2024). Optimization of the flow of parts in the process of brake caliper regeneration using the System Dynamics method. *Processes*, 12(1), Article 16. <https://doi.org/10.3390/pr12010016>
- Lv, Y., Li, C., Zhao, X., Li, L., & Li, J. (2021). A novel approach for remanufacturing process planning considering uncertain and fuzzy information. *Frontiers of Mechanical Engineering*, 16(3), 546–558. <https://doi.org/10.1007/s11465-021-0639-1>
- Parker, D., Riley, K., Robinson, S., Symington, H., Tewson, J., Jansson, K., Ramkumar, S., & Peck, D. (2015). *Remanufacturing market study for Horizon 2020* (Grant Agreement No. 645984). European Remanufacturing Network.
- Paschko, F., Knorn, S., Krini, A., & Kemke, M. (2023). Material flow control in remanufacturing systems with random failures and variable processing times. *Journal of Remanufacturing*, 13(2), 161–185. <https://doi.org/10.1007/s13243-023-00126-z>
- Pizoń, J., Wójcik, Ł., Gola, A., Kański, Ł., & Nielsen, I. (2024). Autonomous mobile robots in automotive remanufacturing: A case study for intra-logistics support. *Advances in Science and Technology Research Journal*, 18(1), 177398. <https://doi.org/10.12913/22998624/177398>
- Ponte, B., Cannella, S., Dominguez, R., Naim, M. M., & Syntetos, A. A. (2021). Quality grading of returns and the dynamics of remanufacturing. *International Journal of Production Economics*, 236, Article 108129. <https://doi.org/10.1016/j.ijpe.2021.108129>
- Ponte, B., Naim, M. M., & Syntetos, A. A. (2019). The value of regulating returns for enhancing the dynamic behaviour of hybrid manufacturing-remanufacturing systems. *European Journal of Operational Research*, 278(2), 629–645. <https://doi.org/10.1016/j.ejor.2019.04.019>

- Teixeira, E. L. S., Tjahjono, B., Beltran, M., & Julião, J. (2022). Demystifying the digital transition of remanufacturing: A systematic review of literature. *Computers in Industry*, 134, Article 103567. <https://doi.org/10.1016/j.compind.2021.103567>
- Wójcik, Ł., & Gola, A. (2025). Utilization of artificial intelligence and machine learning technologies in regeneration processes control and optimization: A literature review. *Applied Computer Science*, 21(1), 1–15.
- Yang, S., Raghavendra, M. R. A., Kaminski, J., & Pepin, H. (2018). Opportunities for Industry 4.0 to support remanufacturing. *Applied Sciences*, 8(7), Article 1177. <https://doi.org/10.3390/app8071177>
- Zhao, J., Peng, S., Li, T., Lv, S., Li, M., & Zhang, H. (2019). Energy-aware fuzzy job-shop scheduling for engine remanufacturing at the multi-machine level. *Frontiers of Mechanical Engineering*, 14(4), 474–488. <https://doi.org/10.1007/s11465-019-0560-z>