0-DMF: A Decision-Support Framework for Zero Defects Manufacturing

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Abstract: Manufacturing companies are increasingly focused on minimising defects and optimising resource consumption to meet customer demands and sustainability goals. Zero Defect Manufacturing (ZDM) is a widely adopted strategy to systematically reduce defects. However, research on proactive defect-reducing measures remains limited compared to traditional defect detection approaches. This work presents the 0-DMF decision support framework, which employs data-driven techniques for defect reduction through (1) defect prediction, (2) process parameter adjustments to prevent predicted defects, and (3) clarifying prediction factors, providing contextual information about the manufacturing process. For defect prediction, Machine Learning (ML) algorithms, including XGBoost, CatBoost, and Random Forest, were evaluated. For process parameter adjustments, optimisation algorithms such as Powell and Dual Annealing were implemented. To enhance transparency, Explainable Artificial Intelligence (XAI) methods, including SHAP and LIME, were incorporated. Tailored for the melamine-surfaced panels process, the methods showed promising results. The defect prediction model achieved a recall value of 0.97. The optimisation method reduced the average defect probability by 28 percentage points. The integration of XAI enhanced the framework's reliability. Combined into a unified tool, all tasks delivered fast results, meeting industrial time constraints. These outcomes signify advancements in predictive quality through data-driven approaches for defect prediction and prevention.

1 INTRODUCTION

As the industrial sector pursues higher profits and meets growing customer demands, optimising production processes and manufacturing high-quality products becomes essential. Additionally, implementing effective waste reduction strategies is crucial for achieving sustainability goals. By minimising waste, companies can not only enhance their environmental footprint but also improve operational efficiency and cost-effectiveness.

The emergence of Industry 4.0 has introduced a profound era of digitalisation, transforming industrial processes through advanced technologies and the generation of unprecedented volumes of data. These technologies can be exploited to create real-time monitoring approaches to prevent process problems and malfunctions. Recently, smart decision-support systems have been applied in manufacturing for various applications, including defect reduction and process optimisation.

Defect occurrence in manufacturing has far-reaching implications, compromising product quality and increasing operational costs due to rework. The wastage of resources, including materials and energy, further adds to the financial burden and environmental impact. Tackling defects in a proactive and preventive way is crucial to minimise the concerns of modern companies. The Zero Defect Manufacturing (ZDM) concept stands out as one of the most applied strategies in dealing with defects, demonstrating positive impacts in industrial settings (Fragapane et al., 2023).

This work aims to develop a smart decision-support framework, 0-DMF (Zero-Defects Manufacturing Framework), tailored for reducing defects in the wood-based panels industry. The framework will achieve this by applying prediction and prevention defect strategies, encompassing three main tasks: (1) real-time defect prediction using Machine Learning (ML) algorithms, (2) real-time process parameter adjustments to prevent predicted defects by applying optimisation algorithms, and (3) detailed analysis of prediction factors using Explainable Artificial

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Intelligence (XAI). The unified decision-support tool promises to enhance decision-making for industrial operators, contributing to improved process efficacy and waste reduction.

This paper is organised as follows: Section 2 presents the literature review. Section 3 highlights the framework's implementation. Section 4 discusses the main results. Finally, Section 5 provides the conclusions and future work.

2 LITERATURE REVIEW

The following literature review overviews the ZDM concept, ML applications for process quality monitoring, optimisation of process parameters, and XAI methods. The section concludes with a summary of the primary conclusions drawn from the reviewed studies.

2.1 Zero Defect Manufacturing

ZDM is widely employed as a strategy to reduce defects in industrial processes (Caiazzo et al., 2022). It includes four foundational strategies: Detection, Repair, Prediction and Prevention. Detection and Repair are more traditional methods, with Detection involving the identification of defects and Repair focusing on reworking defective products whenever feasible. The Prediction strategy aims to anticipate defect occurrence, and Prevention seeks to avoid defects, usually by employing quality control and inspection tools.

Production parameters demonstrate intricate and complex relationships. To effectively implement ZDM in response to these complex production challenges, AI techniques and modern technologies are indispensable (Lin and Chen, 2024). Therefore, the effectiveness of ZDM depends significantly on exploiting new manufacturing technologies introduced by Industry 4.0, making it particularly suitable for deployment in smart manufacturing environments.

A recent survey on ZDM practices highlighted significant positive impacts on throughput time, product quality, and waste reduction (Fragapane et al., 2023). Prevention emerged as the most effective strategy, positively influencing production quality performance. However, despite these identified benefits, the application of the Prevention strategy remains limited, making it the least implemented of the four strategies. Addressing this gap, exploiting the available modern technologies, could lead to more effective defect management and improved overall production performance.

2.2 ML-Based Solutions for Defect Prediction in Manufacturing

The complexity of modern processes, combined with abundant data, strongly promotes the adoption of data-driven techniques. ML algorithms have proven to be highly effective in analysing complex systems and addressing issues within the manufacturing domain, such as quality prediction or process parameter optimisation.

A recent study of ML applications in manufacturing identifies supervised learning as the dominant ML type for process quality optimisation and monitoring (Kang et al., 2020). Regression tasks are often prioritised for quality optimisation, while classification and anomaly detection tasks are used for product failure detection. Binary classification is usually preferred over multiclass classification for defect prediction tasks (Kang et al., 2020; Rožanec et al., 2022; Takalo-Mattila et al., 2022).

Commonly employed ML methods for defect prediction include Random Forest (RF), Decision Trees (DT), Support Vector Machines (SVM), and gradient boosting algorithms such as CatBoost and XGBoost (XGB) (Schmitt et al., 2020; Gonçalves et al., 2021; Tiensuu et al., 2021; Dias et al., 2021; Caiazzo et al., 2022; Rožanec et al., 2022; Takalo-Mattila et al., 2022). Among these, boosting algorithms have shown particularly positive outcomes.

Due to the relative rarity of defects in manufacturing processes, the resulting datasets are usually imbalanced. To address this issue, data balancing techniques like oversampling, undersampling, or using the Synthetic Minority Over-sampling Technique (SMOTE) are often applied (Dias et al., 2021; Gonçalves et al., 2021; Kang et al., 2020). Given this imbalance, appropriate evaluation metrics such as recall and precision are crucial for accurate model assessment.

2.3 Real-Time Process Parameter Optimisation

In an industrial setting, a recipe is a set of process parameter values combined to manufacture a product (Gonçalves et al., 2021). Although unlikely, recipe adjustments may become necessary if a defect is likely to occur. Real-time recipe recommendations are crucial for addressing potential defects and enhancing product quality, aligning with the ZDM Prevention strategy.

To explore the potential parameter adjustments and find optimal solutions for reducing the probability of defect occurrence, optimisation algorithms such as the Powell Method, Basin Hopping, Nelder-Mead Method, and Dual Annealing can be considered (Dias et al., 2021; Çevik Onar et al., 2016; Ezugwu et al., 2020). In industrial contexts, optimising parameter values for defect prevention requires a focus on timeliness, given the limited time frame available for adjustments. The selected optimisation methods must be able to deliver results quickly, enabling operators to implement necessary process adjustments without compromising efficiency or product integrity. Hence, achieving a balance between optimisation effectiveness and computational efficiency is crucial for successful defect prevention.

2.4 Explainable Artificial Intelligence

Many industrial operators lack formal education in AI-related domains, which can lead to trust issues with solutions generated by opaque traditional AI models (Fragapane et al., 2023). XAI methods address this challenge by providing insights into how AI models make decisions, enhancing transparency and interpretability (Hoffmann and Reich, 2023).

XAI techniques such as Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), and Partial Dependence Plots (PDP) have been integrated into quality assurance and defect reduction frameworks in related studies. While researchers widely agree on the benefits of integrating XAI in manufacturing decision-support tools, adoption in industrial contexts remains limited (Hoffmann and Reich, 2023). Overcoming this barrier is crucial for exploiting the full potential of XAI to enhance operational decision-making.

2.5 Gap Analysis

The reviewed studies emphasise the effectiveness of ML algorithms, especially gradient-boosting-based ones, in predicting product quality within manufacturing contexts. The application of optimisation algorithms is crucial for generating real-time recipe recommendations aimed at preventing defects. Moreover, integrating XAI methods significantly enhances model transparency, positively influencing their reliability. However, significant gaps persist. Firstly, despite proven effectiveness, there's a limited adoption of the Prevention strategy in ZDM compared to other strategies, suggesting a need for further research. Additionally, efforts to enhance the adoption of XAI methods in manufacturing settings are needed to improve model transparency and interpretability. Addressing these gaps can result in more accurate, useful, and transparent decision-support frameworks for manufacturing.

3 IMPLEMENTATION

The 0-DMF draws inspiration from successful strategies identified in the reviewed studies. The framework's structure, depicted in Figure 1, is organised into distinct groups of activities: (1) analysis of process and production flows, involving the collection and processing of the data; (2) modelling of processes, where the framework establishes a relationship between different process parameters and their impact on product quality; and (3) specification and development of the graphical unified decision support tool, aiding operators in real-time process monitoring, resulting in (4) a zero-defect product.

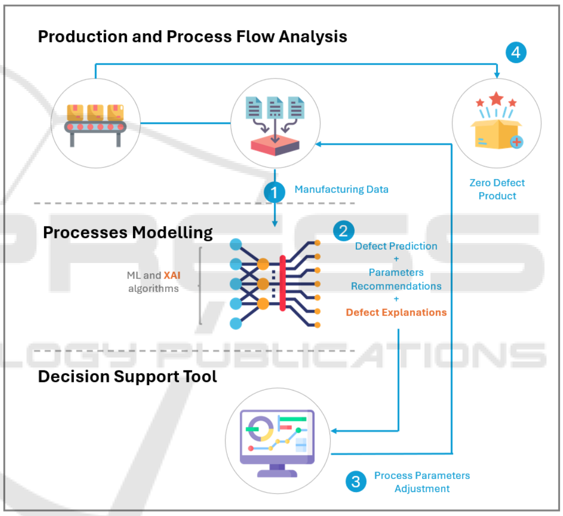

Figure 1: Proposed 0-DMF structure.

0-DMF was implemented in Python, using libraries such as Pandas, NumPy, SciPy, and Scikit-learn.

3.1 Use Case Overview

Wood panels, particularly melamine-surfaced boards, serve a variety of purposes, one of those being decorative applications. These boards consist of wood-based panels coated with paper impregnated with melamine resin. During manufacturing, the process involves pressing the melamine-impregnated paper onto the raw board surface under controlled conditions of pressure and temperature (Dias et al., 2021). Achieving proper adhesion and ensuring high-quality final products requires precise control of these parameters (Gonçalves et al., 2021). The proposed framework, tailored for a Portuguese manufacturer specialising in wood-based panels, aims to optimise the melamine impregnation process.

3.2 Data Analysis and Pre-Processing

The data pertaining to the melamine impregnation process was collected from sensors placed across two identical production lines from January 2022 to February 2024. This data was in tabular format and consisted of 77 distinct feature columns. The separate datasets were consolidated into a single unified dataset to facilitate more accurate analysis and insights, resulting in a total of 105,000 samples.

A "Defect Code" was associated with each sample, serving as an identifier for the type of defect that occurred during the process. Samples produced with no defects were assigned the "0" defect code. Initially, 91 different codes were identified. However, the analysis revealed that many of these actually corresponded to the same defect description despite having different defect codes. To address this issue samples, with repeated descriptions were merged, retaining the code with the most samples, reducing the number of distinct defect codes to 60. However, predicting the type of defect that the panel had using 60 classes in a classification task would overly complicate the process. As a solution, all defect codes and descriptions were grouped into 7 defect categories based on similar properties. This categorisation ensured a more manageable classification.

Given that the dataset had not undergone any prior cleaning or processing, further preparation was required to be suitable for subsequent modelling. Initially, irrelevant features, duplicated columns, and those with a majority of missing or invalid values were removed. After, the Pearson correlation coefficient was calculated for each pair of feature columns. One feature from each pair with a coefficient equal to or greater than $|0.9|$ was removed to eliminate redundancy. Categorical feature columns were then converted to a numerical representation, as most ML algorithms require numerical inputs to process the data effectively. The mapping between each category and its numerical representation was saved in an external file to ensure consistency in later processing. Following this, samples with missing or invalid values were discarded, and boxplots were utilised to identify and eliminate samples with outlier values.

After completing the data cleaning and pre-processing, the final dataset contained approximately 72,000 samples, indicating an initial reduction of nearly 30%. Only around 2% of the samples represented defects, resulting in an imbalanced dataset. The number of feature columns was reduced from the initial 77 to 50.

3.3 Defect Prediction and Explanation Modelling

Four ML methods were evaluated to predict defective wood panels. Given the availability of labelled data and its tabular format, supervised learning methods were implemented, focusing on classification tasks. Specifically, CatBoost, RF, XGB, and an ensemble combining CatBoost, XGB, and RF were tested. These algorithms were implemented using libraries such as Scikit-learn, CatBoost, and XGBoost. Hyperparameter tuning and model optimisation were conducted using the Scikit-learn GridSearchCV method.

The implemented models were trained to perform three different types of classification:

- Binary classification: Predicting whether a sample is likely to be defective.
- Multiclass classification (1): Predicting the specific defect type for a sample previously identified as defective.
- Multiclass classification (2): Predicting the defect category for a sample previously identified as defective.

The dataset underwent a chronological train-test sampling split. The training dataset contained approximately 56,000 samples, while the testing dataset comprised around 15,500 samples. As previously discussed, the available dataset was imbalanced, with defective samples representing only 2% of the data. This can negatively impact model training, compromising both its accuracy and efficiency. To mitigate this issue, the SMOTE algorithm was applied to the training data to balance class occurrences. Figure 2 showcases the significant variances observed among the different defect types before applying the SMOTE algorithm.

The model's performance was evaluated using recall and precision metrics, given the imbalanced nature of the dataset. Emphasis was placed on recall as it focuses on minimising false negatives, ensuring that the model is proficient at identifying all actual defects.

An added layer of transparency and interpretability was integrated using XAI methods. Local model-agnostic techniques, specifically LIME and SHAP, were employed for this purpose. LIME uncovered the specific "rules" or conditions that influenced each prediction, while SHAP highlighted the contribution of each feature to the model's predictions.

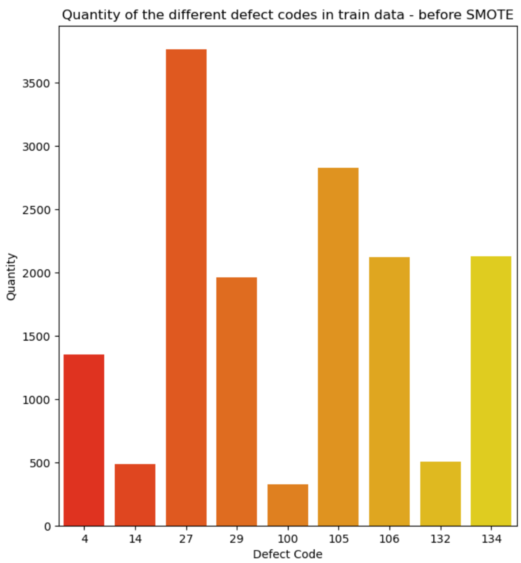

Figure 2: Frequency of the most recurrent defect types (represented by their codes) before applying SMOTE data balancing.

3.4 Real-Time Recipe Recommendation

Recognising that not all process parameters are immediately adjustable or adaptable within a short time frame, consultations with field specialists led to the identification of 10 real-time adjustable variables. To meet the real-time constraint, the optimisation algorithm was tasked with ideally identifying optimal parameter values within a two-minute window.

Four algorithms were tested to find optimal process parameters: Dual Annealing, Nelder-Mead, Powell, and Basin Hopping, all implemented using the SciPy Optimize module. Search intervals were established for each adjustable feature based on the distribution of values observed in non-defective historical samples. However, since practical constraints must be considered, the optimisation search was constrained within ±20% of the current feature value, within the absolute interval, to facilitate real-time adjustments.

Objective functions, namely Mean Squared Error (MSE), LogCosh, and Mean Absolute Error (MAE), were employed to guide the algorithms in minimising the current defect probability relative to a target probability. These functions were evaluated across different target defect probability values (0%, 10%, and 50%), with MSE also assessed without a specific target defect probability.

3.5 Web Application

To enhance the decision-making process, a Flask web application was developed to integrate the prediction, explanation, and optimisation tasks. The MQTT (Message Queuing Telemetry Transport) protocol was implemented to ensure seamless communication between the production line and the application, as it is known for its lightweight and efficient messaging capabilities, which are particularly suitable for IoT scenarios. The application manages raw samples through the following steps:

- **Data Acquisition and Pre-Processing:** Raw samples are received by the application and undergo cleaning and data processing;
- **Prediction and Explanation:** The clean sample is processed through the prediction and explanation modules to provide real-time defect predictions and insights. Upon processing, the sample and corresponding predicted defect probability are stored in a PostgreSQL database;
- **Recipe Recommendation:** Based on the predicted defect probability, the optimisation module suggests process parameter adjustments to minimise it.

For more intuitive insights, a graphical user interface (GUI) was developed. It facilitates the observation of real-time predictions, explanations, and statistics. Users can also access historical data, filtering samples based on date and time ranges. The statistics displayed on the GUI are retrieved through SQL queries, ensuring the accuracy of the presented data. Graphical components of the interface were developed using HTML, JavaScript and CSS. Detailed GUI mockups were created beforehand using Figma, allowing detailed planning before the implementation.

4 RESULTS AND DISCUSSION

The framework's performance was assessed using real production data from wood-panel's melamine impregnation process.

4.1 Defect Prediction and Explanation

Table 1 presents the results of the implemented ML algorithms for the three classification tasks. The performance is shown both with and without the application of the SMOTE algorithm for data balancing.

Upon analysis, it is evident that binary classification performed exceptionally well across all metrics.

Table 1: Results of the employed Machine Learning algorithms for defect prediction.

	CatBoost		**RF**		**XGB**		**Ensemble**	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Binary	0.9664	0.9663	0.9631	0.9629	0.9582	0.9589	0.9659	0.9657
Binary (with SMOTE data balancing)	0.9652	0.9651	0.9548	0.9547	0.9574	0.9582	0.9657	0.9655
Multiclass Defect Types	0.2087	0.2190	0.1929	0.2437	0.2513	0.2113	0.2033	0.2113
Multiclass Defect Types (with SMOTE data balancing)	0.1959	0.1933	0.2174	0.2233	0.2233	0.2014	0.2203	0.2043
Multiclass Defect Categories	0.5788	0.4455	0.5974	0.6373	0.5803	0.4629	0.5956	0.4779
Multiclass Defect Categories (with SMOTE data balancing)	0.5469	0.4661	0.5231	0.4384	0.5360	0.4430	0.5705	0.4480

The CatBoost model, in particular, achieved the highest scores, with a recall of 0.9664 and a precision of 0.9663, indicating a high efficiency in predicting defect occurrence. In contrast, multiclass classification based on defect types achieved poor results across all metrics. Although the classification considering categorised defects performed better, the highest precision achieved was 0.637, and the highest recall was 0.5974 with the RF model. These results are still considerably low for a classification task as they can lead to many misclassifications. Given the poor results of the multiclass classifications, a Principal Component Analysis (PCA) was conducted on the data. The PCA revealed that the defective sample's data is not sufficiently differentiable, with minimal variance between different defect types and categories. This lack of distinct separation likely contributed to the inferior classification performance. Considering these findings, only binary classification was included in the final system.

Overall, the application of the SMOTE data balancing technique did not achieve significant improvements in the results. This is likely due to the lack of distinguishability between classes, causing the synthetic data generated by SMOTE to inaccurately represent true class boundaries. As a result, the models struggled to differentiate between classes, reducing the effectiveness of the data-balancing.

The inclusion of the plots generated by XAI provides operators with useful information about the manufacturing process. The SHAP waterfall plot, exemplified in Figure 3, illustrates the impact of the nine most influential features on model prediction. The LIME bar plot displays the main rules influencing the prediction outcome. These explanations were only generated for samples with a defect probability exceeding 50%.

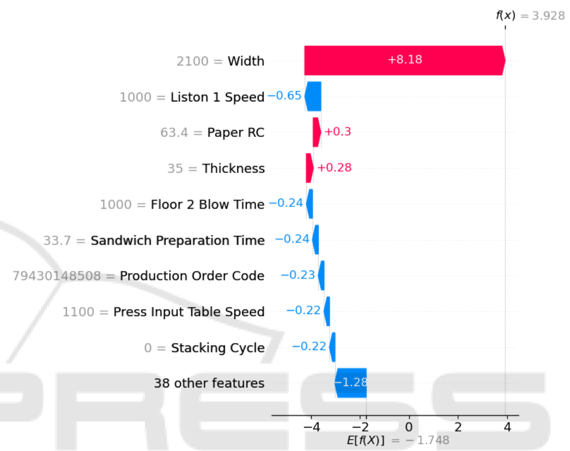

Figure 3: SHAP waterfall plot illustrating feature impact in the prediction.

4.2 Real-Time Recipe Recommendation

The evaluation of the algorithm's effectiveness was conducted across 8 subsets of the testing dataset, categorised based on different ranges of defect probabilities. The performance of each algorithm, considering each of the different objective functions, was assessed across these ranges, and the time taken to reach a solution was measured. The results considering the MSE objective function are presented in Table 2. Dual Annealing emerged as the most effective algorithm, achieving an average defect probability reduction of 28 percentage points (p.p.) and reaching up to 49.70 percentage points reduction in the [60, 70[% range.

The ranges of [60, 70[% and [70, 80[% consistently showed the highest reduction percentages across all algorithms and objective functions. This is likely because samples in these ranges are still relatively close to the threshold between defective and non-defective, making them more easily influenced by optimisation. Small adjustments can push them from one category to the other. The initial defect

Table 2: Effect of recipe recommendation algorithms on predicted defect probability, considering the MSE objective function.

Defect Probability Range	Avg. Defect Probability Before (%)	Dual Annealing			Powell			Nelder-Mead			Basin-Hopping		
		Avg. Defect Probability After (%)	Avg. Reduction (p.p.)	Avg. Duration (s)	Avg. Defect Probability After (%)	Avg. Reduction (p.p.)	Avg. Duration (s)	Avg. Defect Probability After (%)	Avg. Reduction (p.p.)	Avg. Duration (s)	Avg. Defect Probability After (%)	Avg. Reduction (p.p.)	Avg. Duration (s)
10% - 30%	18.22%	4.38%	13.84	1.31	5.60%	12.62	2.95	17.17%	1.04	1.02	25.38%	-7.16	0.37
30% - 50%	40.96%	11.18%	29.78	1.32	13.34%	27.63	3.09	27.31%	13.65	1.05	33.09%	7.87	0.40
50% - 60%	54.49%	17.01%	37.48	1.38	22.03%	32.46	2.95	36.47%	18.02	1.02	41.17%	13.32	0.41
60% - 70%	65.07%	15.37%	49.70	1.32	24.45%	40.62	2.38	38.39%	26.69	1.02	42.12%	22.96	0.40
70% - 80%	74.95%	30.95%	44.01	1.32	36.22%	38.74	2.60	45.86%	29.09	1.03	52.43%	22.53	0.40
80% - 90%	85.99%	53.24%	32.75	1.32	57.66%	28.33	2.34	66.68%	19.30	1.03	70.69%	15.30	0.40
90% - 95%	93.13%	58.58%	34.54	1.30	64.12%	29.01	2.21	77.75%	15.38	1.03	79.47%	13.65	0.43
95% - 99%	98.01%	89.49%	8.51	1.31	91.61%	6.39	1.25	95.30%	2.71	0.70	96.58%	1.42	0.23
99% - 100%	99.70%	97.69%	2.01	1.33	98.44%	1.26	1.56	99.34%	0.36	0.62	99.50%	0.20	0.24

probabilities for samples in these ranges indicated a high likelihood of defects. Post-optimisation, probabilities were reduced to approximately 15% and 30%, significantly increasing the likelihood of defect-free panels. In contrast, the reduction was less effective for the highest defect probability ranges (over 80%), with the final defect probabilities still exceeding 50%. Nonetheless, any reduction in the defect probability improves the outcome.

When comparing the outcomes of the different algorithms across various objective functions, the MSE function delivered the most significant reductions. Setting a target defect probability of 0% consistently produced better results. Oppositely, when no target probability was specified, the outcomes were inferior, indicating potential convergence issues with the algorithms. All optimisation durations were within the two-minute constraint per sample. Basin Hopping was the quickest optimisation method, while Powell was the slowest, with average durations of 2 to 3 seconds. Based on these findings, considering that all algorithms produced results within the defined time limit, Dual Annealing with the MSE objective function and a target defect score of 0% was considered the optimal choice for the framework's recipe recommendation module.

4.3 Web Application

To evaluate the functionality of the developed Flask web application, a simulated MQTT publisher was established to dispatch raw production testing samples every 70 seconds. Using the Python Time module, measurements were conducted to capture the average execution time of the application for performing the required tasks. These tasks include pre-processing, prediction, explanation, optimisation, saving samples to the database, and retrieving analytics from the database, each completed in less than two seconds. This setup effectively meets the requirement for real-time insights, as all tasks are comfortably completed well within the two-minute timeframe.

The final GUI comprises four distinct dynamic pages. Figure 4 provides a visual representation of the implemented GUI.

5 CONCLUSIONS AND FUTURE WORK

In today's manufacturing landscape, companies increasingly rely on sophisticated systems to evaluate product quality, aiming to optimise processes and reduce waste for enhanced sustainability and economic viability. This paper introduced the 0-DMF decision-support framework to help achieve zero defects manufacturing, specifically tailored to the wood panels processing industry. By integrating defect prediction, explanation of predictions, and process parameter adjustments to mitigate defect occurrence, this framework successfully provides real-time insights for end-users. The employed ML algorithms for defect prediction achieved promising results, accurately identifying most defect occurrences. The optimisation algorithms quickly identified optimal process parameters, giving operators sufficient time to implement changes and reduce defect probability. Additionally, the integration of XAI methods enhanced the framework's transparency and reliability. With these positive outcomes, 0-DMF promises enhancements to modern industrial processes, contributing to the progression and sustainability of contemporary industrial practices.

Future framework development should focus on considering more advanced alternative approaches to distinguish between defect types and allow for effective multiclass classification. Developing a more generalised version of the tool to enhance its applicability across various manufacturing processes is also essential.

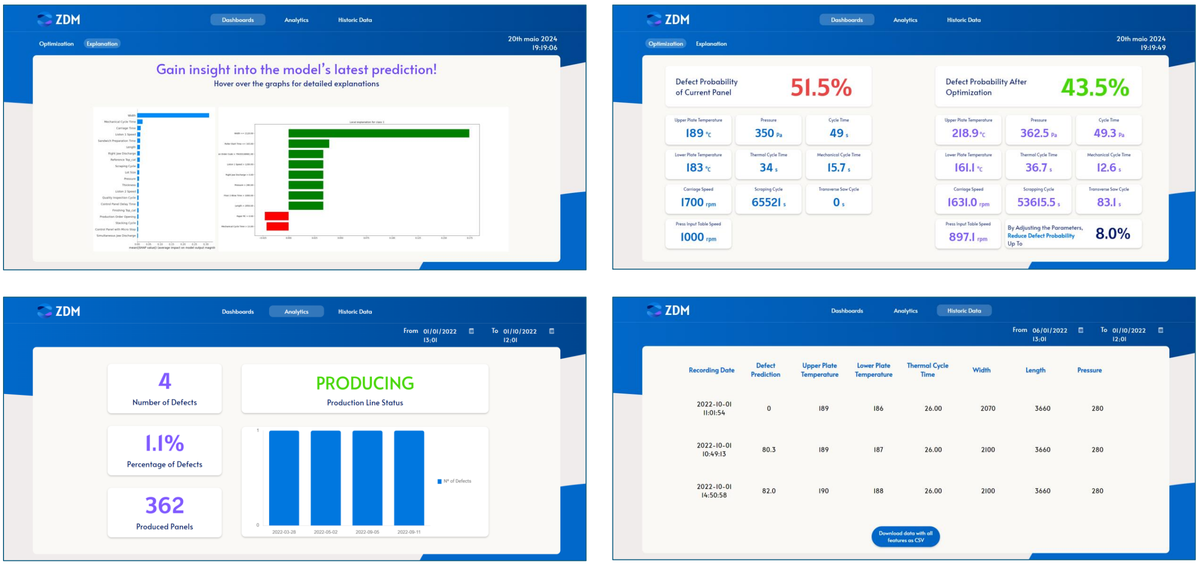

Figure 4: Implemented decision-support framework's GUI.

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