

RANDOM FOREST-BASED WASTE PREDICTION IN SUSTAINABLE GRAPHIC PRODUCTION WITHIN INDUSTRY 4.0

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Abstract

Graphic production systems generate significant material waste due to defective prints, registration errors, inefficient material utilization, and suboptimal energy management. In printing processes, waste levels can exceed 10%, contributing to environmental burden and increased operational costs. Within Industry 4.0 environments and ESG-oriented production management, companies require measurable, data-driven mechanisms for resource optimization. The aim of this research is to develop and evaluate a Random Forest-based predictive model for production waste forecasting in sustainable graphic systems using key performance indicators as operational inputs.

A supervised Random Forest regression model was developed to predict waste levels. Because publicly accessible industrial datasets are unavailable due to confidentiality constraints, simulated KPI data was generated to reflect realistic production variability. Input variables include material waste percentage, machine efficiency, number of defective prints, energy consumption, and equipment downtime. The synthetic dataset incorporates controlled variability and inter-variable correlations to approximate real production conditions. The data was divided into training and testing subsets, and cross-validation was applied to ensure model robustness. Model performance was evaluated using mean absolute error, mean squared error, and the coefficient of determination.

The Random Forest model achieved an R^2 value of 0.89, indicating strong explanatory power, with an overall prediction accuracy of 87.32% and a mean absolute error of 3.17%. Simulation scenarios demonstrate substantial waste reduction potential under AI-supported optimization. In the printing process, waste levels decreased from 12.7% to 5.8%, representing a 54.3% reduction. Early detection mechanisms identified 36% of potential waste events prior to occurrence, enabling proactive intervention. Additional simulation results indicate projected improvements in energy

efficiency, defect prevention, and overall cost reduction, estimated at 8%, 12%, and 6%, respectively.

The findings confirm that Random Forest-based predictive modeling can function as an operational tool for ESG-aligned waste management in Industry 4.0 graphic production. KPI-driven monitoring combined with predictive analytics enables early identification of inefficiencies, improved production planning, and systematic reduction of material losses. The model is suitable for integration with sensor systems and production management platforms in smart manufacturing environments, supporting both environmental sustainability and economic performance.

Keywords: *ESG framework, Industry 4.0, key performance indicators, Random Forest, waste prediction.*

Introduction

Graphic production systems are increasingly expected to operate with lower levels of material waste, reduced energy consumption, and a smaller environmental footprint, while still maintaining high quality and cost efficiency. In practice, this is not easy to achieve. Waste in printing and related processes occurs for several reasons, including defective prints, color mismatches, registration errors, and inefficient use of materials and equipment. In many cases, waste levels exceed 10%, which directly increases operational costs and contributes to environmental impact. Under current regulatory and market conditions, such inefficiencies are becoming less acceptable.

The development of Industry 4.0 has introduced new possibilities for improving these processes. Contemporary production environments are supported by interconnected machines, sensor systems, and digital management platforms that enable continuous data collection. This creates a foundation for more precise monitoring and analysis of production performance. Predictive models play an increasingly important role in such environments by enabling data-driven decision-making and improving production efficiency through advanced analytics (Kusiak, 2023). At the same time, ESG requirements are placing additional pressure on companies to measure and report environmental indicators such as waste generation, energy use, and resource efficiency. Key performance indicators represent a fundamental tool for implementing and monitoring sustainability strategies in production systems (Hristov & Chirico, 2019). Machine learning approaches are increasingly used to identify key drivers and improve ESG-related performance indica-

tors in complex operational environments (Dwivedi et al., 2023). In manufacturing systems, key performance indicators also play a central role in measuring sustainability and supporting circular economy strategies (Aljamaal et al., 2024), particularly in relation to quality-related indicators that directly influence production efficiency and waste generation (Zuher, 2024). In this context, traditional reactive approaches are no longer sufficient, and there is a clear need for predictive and data-driven solutions.

Artificial intelligence, particularly machine learning, offers a practical way to address these challenges and has been widely recognized as a key enabler of advanced manufacturing systems (Ördek et al., 2024). Its application in smart manufacturing environments enables improved process control, predictive capabilities, and enhanced production efficiency (Rajesh et al., 2022). Predictive models can identify patterns in production data and estimate future outcomes based on current conditions. This makes it possible to detect potential inefficiencies before they lead to actual waste. Among different machine learning methods, Random Forest is often used in similar contexts because it can handle complex relationships between variables and does not rely on strict assumptions about data distribution. It is also relatively robust when working with noisy or heterogeneous data, which is common in production environments.

However, the application of such models in graphic production is limited by the availability of suitable datasets. Industrial data is often confidential, fragmented, or inconsistent, which makes it difficult to use in research. For this reason, this study is based on synthetic data designed to reflect realistic production conditions. The dataset includes controlled variability and correlations between variables, allowing the model to be trained and evaluated in a consistent and reproducible way. While this approach does not replace real production data, it provides a useful framework for testing predictive models.

The main objective of this research is to develop and evaluate a Random Forest-based model for predicting waste levels in graphic production systems. The model uses key performance indicators as input variables, including material waste percentage, machine efficiency, number of defective prints, energy consumption, and equipment downtime. The analysis focuses on whether such a model can support waste reduction and improve resource efficiency within an Industry 4.0 environment aligned with ESG principles. Model performance is evaluated using standard regression metrics, and the results are interpreted in terms of their practical relevance for production systems.

The contribution of this study lies in combining KPI-based monitoring with predictive modeling in the context of graphic production. The results show how machine learning can support earlier detection of inefficiencies and provide a basis for more informed production decisions. In this way, the proposed approach contributes to both operational efficiency and sustainability objectives.

Methodology and equipment

The methodological framework for developing and evaluating the predictive model for waste estimation in graphic production systems combines the definition of relevant operational indicators, the construction of a synthetic dataset that reflects realistic production conditions, and the application of a Random Forest regression model. The objective is to establish a consistent relationship between production parameters and waste generation and to evaluate the predictive capability of the model using standard regression metrics.

Definition of Key Performance Indicators

The predictive model is based on a set of key performance indicators that describe the operational state of the production system. These indicators capture material efficiency, process stability, and production quality, which are the primary sources of waste generation.

Each production instance is represented by a feature vector:

$$\mathbf{x}_i = [w_i, e_i, d_i, c_i, t_i] \quad (1)$$

where w_i denotes material waste percentage, e_i machine efficiency, d_i number of defective prints, energy consumption, and t_i equipment downtime.

The target variable represents the total waste level associated with the corresponding production state. For clarity, the selected KPIs are summarized in Table 1.

The selected set of indicators enables a consistent representation of production conditions by integrating material, operational, and quality-related factors into a unified input space. This structure provides the basis for modeling the relationship between process parameters and waste generation in subsequent stages of the analysis.

Table 1. Key Performance Indicators Used as Input Variables.

KPI	Role	Description
Material waste percentage	Share of raw material lost during production	Direct waste indicator
Machine efficiency	Ratio of actual to theoretical output	Process performance
Defective prints	Number of rejected units	Quality-related loss
Energy consumption	Energy usage per production unit	Resource efficiency
Equipment downtime	Duration of production interruptions	Operational instability

Synthetic Data Generation

The predictive model requires a dataset that captures the variability and interdependencies of production parameters in graphic systems. Since real industrial datasets are not publicly available due to confidentiality constraints, a synthetic dataset was constructed to approximate realistic operating conditions. The objective of this approach is to preserve statistical properties of production processes while enabling controlled experimentation and reproducibility. Controlled variability and correlations between variables were introduced to reflect realistic interactions between production parameters under both stable and unstable operating conditions.

Each observation is defined as a realization of the KPI vector under stochastic variability. The generation process assumes that production states fluctuate around a nominal operating point, represented by a mean vector of expected KPI values.

This relationship is modeled as:

$$x_i = \mu + \varepsilon_i \quad (2)$$

where μ denotes the vector of expected values for all KPIs and represents a stochastic deviation from this baseline. The variability component is modeled as a multivariate normal distribution, which is commonly used to represent correlated stochastic processes in multivariate data analysis (Hair et al., 2019):

$$\varepsilon_i \sim \mathcal{N}(0, \Sigma) \quad (3)$$

where Σ is the covariance matrix that encodes dependencies between variables. This formulation allows the dataset to reflect realistic interactions be-

tween production parameters, such as increased defect rates under reduced machine efficiency or higher energy consumption during unstable production phases.

To better approximate real production behavior, the target variable is not treated as independent but is modeled as a function of the input KPIs. The waste level is therefore expressed as:

$$y_i = f(x_i) + \delta_i \quad (4)$$

The function f represents an unknown nonlinear mapping between production KPIs and waste generation, which justifies the use of a nonparametric model such as Random Forest. The term δ_i represents an additional noise component capturing unobserved influences and measurement uncertainty.

The dataset includes a wide range of operating conditions by introducing controlled variability across all dimensions of the input space. This ensures that the model is exposed to both stable and unstable production scenarios. The complete dataset is partitioned into training and testing subsets, and k-fold cross-validation is applied to evaluate model generalization and robustness.

This data generation framework provides a consistent and flexible basis for training and validating the predictive model while maintaining realistic assumptions about production variability and system behavior.

Random Forest Model Formulation

The prediction of waste levels is performed using a Random Forest regression model, which is well suited for modeling complex and nonlinear relationships between multiple production variables. Random Forest belongs to a class of tree-based machine learning algorithms that combine multiple decision trees to improve predictive performance and robustness (Sheppard, 2019). Similar applications of process knowledge-based Random Forest regression have shown its suitability for predictive control in nonlinear production processes with multiple operating conditions (Sun et al., 2022).

In the context of this study, the model approximates the functional relationship between the KPI vector and the corresponding waste level defined in the previous section.

The Random Forest model consists of an ensemble of decision trees, where each tree is trained on a bootstrap sample of the dataset. For a given input vector x_i , the predicted waste level is obtained as the average of individual tree predictions:

$$\hat{y}_i = \frac{1}{B} \sum_{b=1}^B T_b(x_i) \quad (5)$$

where $T_b(x_i)$ denotes the prediction of the b -th decision tree and B represents the total number of trees in the ensemble. This aggregation reduces variance and improves model stability compared to a single decision tree.

Each decision tree partitions the input space by recursively applying binary splits. At each node, the algorithm selects the optimal split by minimizing the variance of the target variable within the resulting subsets. This is equivalent to minimizing the mean squared error at the node level:

$$\text{MSE}_{node} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_{node})^2 \quad (6)$$

where \hat{y}_{node} is the mean value of the target variable within the node.

To introduce diversity among trees and prevent overfitting, Random Forest applies random feature selection at each split. Instead of evaluating all input variables, only a subset of features is considered, which leads to different tree structures and improves generalization performance. Similar approaches combining Random Forest with optimization techniques have been successfully applied in engineering prediction tasks involving complex and nonlinear relationships (Chen et al., 2023; Wengang et al., 2021).

From a regression perspective, the model can be interpreted as an approximation of the conditional expectation of the target variable:

$$\hat{y}_i \approx \mathbb{E}[Y | X = x_i] \quad (7)$$

This interpretation is consistent with the formulation introduced in the previous section, where the waste level is modeled as a nonlinear function of the KPI vector. The Random Forest model therefore provides a data-driven approximation of the unknown function $f(x_i)$, enabling accurate prediction of waste levels under varying production conditions. This capability allows the model to capture complex interactions between operational indicators that are difficult to represent using conventional linear approaches. The ensemble structure, combined with bootstrap sampling and feature randomness, makes the model robust to noise and suitable for datasets with complex interdependencies between variables. This is particularly important in graphic production systems, where process variability and measurement uncertainty are inherent characteristics.

Evaluation Metrics

The performance of the proposed model is evaluated using standard regression metrics adapted to the prediction of waste levels in graphic production systems. In this context, y_i represents the observed waste level, while \hat{y}_i denotes the corresponding prediction obtained from the Random Forest model.

The mean absolute error is defined as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

This metric provides a direct measure of the average deviation between predicted and actual waste levels and is expressed in the same units as the target variable. It allows for intuitive interpretation of prediction accuracy in terms of percentage deviation.

The mean squared error is defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (9)$$

This metric assigns greater weight to larger deviations and is therefore sensitive to extreme prediction errors. It is particularly useful for assessing model stability under conditions with higher variability.

The coefficient of determination is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

where \bar{y} denotes the mean observed waste level. This metric quantifies the proportion of variance in waste levels explained by the model and provides an overall measure of predictive performance. In regression analysis, the coefficient of determination is often considered a more informative indicator of model performance compared to alternative error-based metrics (Chicco et al., 2021).

In addition to these metrics, model performance is interpreted in relation to practical thresholds relevant to production systems. Lower error values and higher R^2 indicate that the model successfully captures the relationship between production parameters and waste generation, supporting its applicability in predictive optimization scenarios.

Model Implementation Process

The implementation of the predictive model involves data preparation, model training, parameter configuration, and validation, with the aim of ensuring consistent and reproducible model behavior. Particular emphasis is placed on the model's ability to generalize across different production scenarios. The model implementation and simulation procedures were performed in a Python-based environment using standard machine learning and data analysis libraries suitable for regression modeling and statistical evaluation. The implementation process is structured to ensure stable model performance under varying production conditions and different combinations of operational parameters.

The overall workflow of the proposed model is illustrated in Figure 1.

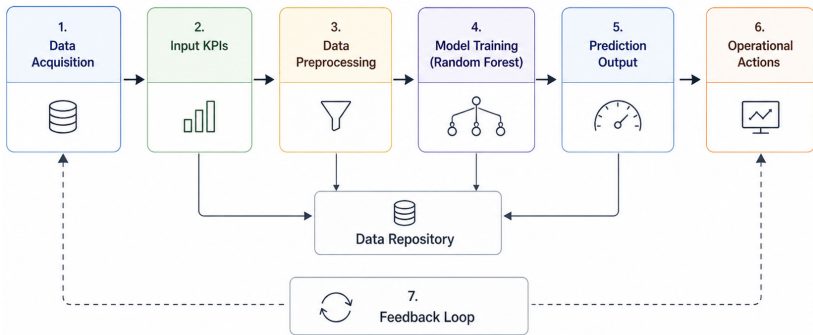


Fig. 1. Workflow of the AI-Based Waste Prediction Model.

The presented workflow summarizes the main stages of the model, from data acquisition and preprocessing to prediction and feedback. Each of these stages is described in detail in the following subsections, with emphasis on their role in ensuring reliable waste prediction and model generalization. The workflow also illustrates the continuous interaction between data analysis, prediction, and operational decision-making within the proposed framework.

Data Preparation

The generated dataset was first prepared for model training by ensuring consistency across all input variables. Since the selected KPIs are expressed in comparable and interpretable units, no additional normalization was required. However, the dataset was inspected to verify the absence of invalid or extreme values that could negatively affect model performance.

The complete dataset was divided into training and testing subsets. The training subset was used to construct the model, while the testing subset was reserved for evaluating predictive performance. This separation ensures that model evaluation is performed on previously unseen data.

Model Training

The Random Forest model was trained using the KPI vectors defined in Section 2 as input features and the corresponding waste levels as the target variable. The training process follows standard supervised learning principles, where the model learns the mapping between input features and target values through repeated exposure to labeled data (Howard & Gugger, 2020). During training, multiple decision trees were constructed using bootstrap sampling, where each tree was trained on a randomly selected subset of observations.

At each split within a tree, a random subset of input features was considered. This mechanism reduces correlation between trees and improves the robustness of the ensemble. The model therefore learns a diverse set of decision rules that capture different aspects of the relationship between production parameters and waste generation.

The training process results in an ensemble model that approximates the underlying nonlinear function $f(x_i)$ introduced in the methodological formulation.

Hyperparameter Configuration

The performance of the Random Forest model depends on several key parameters, including the number of trees, maximum tree depth, and the number of features considered at each split. These parameters were selected to balance model complexity and generalization performance.

A sufficiently large number of trees was used to stabilize predictions and reduce variance. Tree depth was limited to prevent overfitting, ensuring that the model captures general patterns rather than noise in the data. Feature selection at each split was controlled to maintain diversity among trees.

The final parameter configuration was determined based on validation performance, with the goal of achieving stable and consistent predictions across different subsets of the data.

Model Validation

To evaluate model robustness, k-fold cross-validation was applied during the training process. The dataset was partitioned into multiple subsets, and the model was trained and evaluated iteratively, using a different subset as validation data in each iteration.

This approach reduces the dependence of the results on a single data split and provides a more reliable estimate of model performance. The evaluation metrics defined in Section 2 were computed across all validation folds, and the average values were used as the final performance indicators.

The final model was then evaluated on the test dataset to assess its predictive capability under unseen production conditions. This step ensures that the model is not only accurate on training data but also applicable to real-world scenarios.

Results and Discussion

This section presents the results of the proposed Random Forest model and their interpretation in the context of waste prediction, production efficiency, and sustainability. The analysis integrates predictive performance, simulated waste reduction, and system-level implications relevant to Industry 4.0 environments.

Model Performance and Prediction Capability

The predictive model achieved a coefficient of determination of 0.89, indicating that a substantial proportion of the variance in waste levels is explained by the selected KPIs. This result confirms that the relationship between production parameters and waste generation can be effectively captured using a nonlinear ensemble approach. The high explanatory power of the model suggests that the selected operational indicators provide a reliable representation of production behavior and waste formation mechanisms.

The mean absolute error was 3.17%, representing the average deviation between predicted and observed waste levels. This level of error is acceptable in production environments characterized by inherent variability and measurement uncertainty. The mean squared error remained within a stable range, confirming the absence of large deviations and indicating model robustness. Together, these metrics demonstrate that the model maintains stable predictive performance across different production conditions.

The overall prediction accuracy reached 87.32%, defined as the proportion of predictions within an acceptable deviation range. In addition, the model demonstrated the ability to identify 36% of potential waste events before occurrence. This early detection capability enables proactive intervention and represents a shift from reactive quality control toward predictive process management. Such predictive capability is particularly important in production systems where delayed detection can lead to cumulative material and energy losses.

Simulation results further indicate a strong potential for waste reduction across production stages. The most significant improvement was observed in the printing process, where waste levels decreased from 12.7% to 5.8% (Figure 2).

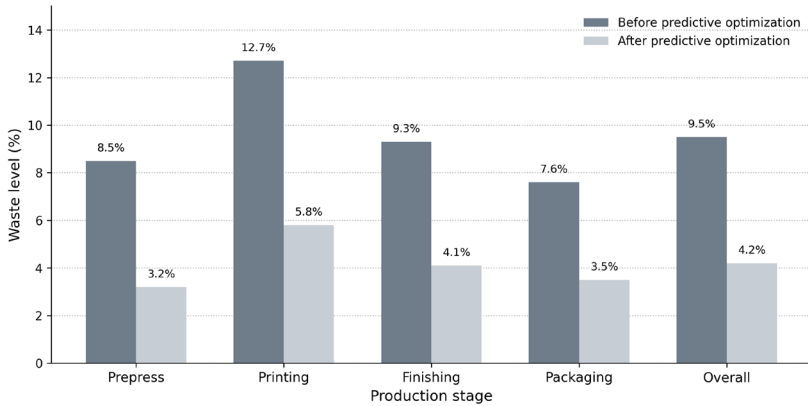


Fig. 2. Comparison of Waste Levels Before and After Predictive Optimization Across Production Stages

Similar trends were observed in prepress, finishing, and packaging, confirming that waste generation is influenced by the overall production system rather than isolated processes.

Operational Impact and System Integration

The application of the predictive model leads to measurable improvements in multiple dimensions of production performance, which is consistent with the use of machine learning techniques for improving sustainability and control in industrial processes (Ahmed & Raihan, 2024). The simulation results indicate an overall waste reduction of approximately 11%, reflecting the direct impact of predictive optimization on material usage. Energy consumption was reduced by 8%, while the number of defective prints decreased by 12%. These improvements resulted in an estimated cost reduction of 6%, demonstrating that waste minimization is closely linked to broader operational efficiency.

Beyond direct prediction, the model provides additional value through pattern recognition. By analyzing production data across multiple observations, the system identifies recurring relationships between KPIs and waste generation. This enables root cause analysis and supports systematic process

adjustments. The continuous comparison between predicted and observed outcomes establishes a feedback mechanism that allows for iterative improvement and adaptation.

The integration of the model into production environments is consistent with Industry 4.0 principles. Data collected from sensor systems can be used as input for real-time prediction, while integration with Manufacturing Execution Systems and Enterprise Resource Planning platforms enables alignment with operational planning and control. Human–AI collaboration remains an essential component, as operators interpret model outputs and implement corrective actions based on domain knowledge.

From a sustainability perspective, the results indicate that predictive waste reduction contributes to reduced environmental impact through lower material consumption and energy use. At the same time, improved efficiency enhances economic performance and supports the transition toward more sustainable and data-driven production systems.

Implementation Challenges and Limitations

Despite the positive results, several challenges must be considered. The use of synthetic data limits the direct applicability of the model to real production environments, as actual data may contain additional variability and complexity not fully captured in the simulation.

Data quality represents a critical constraint. Inconsistent or incomplete production data can reduce model accuracy and require additional preprocessing. The successful implementation of the model therefore depends on reliable data acquisition systems and standardized data management.

Organizational factors also influence adoption. The introduction of AI-based systems may require workforce training and adaptation, as well as acceptance of data-driven decision-making processes.

Finally, system integration presents technical challenges, particularly when connecting legacy equipment with modern Industry 4.0 infrastructures. These limitations indicate that further research is needed to validate the model using real production data and to support its implementation in operational environments.

Conclusion

This study demonstrates that predictive modeling based on key performance indicators can be effectively applied to estimate and reduce waste in graphic production systems. The results confirm that the relationship between production parameters and waste generation can be modeled using a Random Forest approach, even in the absence of real industrial datasets.

The model achieved a high level of predictive performance, with strong explanatory power and acceptable error levels. The simulation results indicate that the application of such a model can lead to substantial reductions in material waste, as well as improvements in energy efficiency, process stability, and overall production performance. In addition to prediction accuracy, the model enables early detection of inefficiencies, which allows for proactive intervention and more consistent production outcomes.

Beyond waste prediction, the results show that the model can support pattern recognition and systematic process optimization. By identifying recurring relationships between production parameters and waste generation, the system provides a basis for continuous improvement and more informed decision-making.

The proposed framework aligns with Industry 4.0 principles by enabling data-driven monitoring, integration with production systems, and support for real-time decision-making. At the same time, it contributes to ESG objectives by reducing environmental impact and improving resource efficiency, while maintaining economic viability.

However, the findings should be interpreted in light of the study's limitations. The use of synthetic data introduces constraints related to realism and generalizability, and further validation using real production data is required. Future research should focus on integrating the model into real production environments, including real-time data acquisition, system interoperability, and adaptive model updating.

Overall, the results indicate that machine learning-based waste prediction has strong potential as a practical tool for optimizing graphic production processes. Its application supports the transition toward more efficient, stable, and sustainable production systems.

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