Optimization Model for Textile Dye Microenterprise Production Processes and Return Reduction Using Taguchi, ANN, Kanban, and RFID–Poka-Yoke

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Abstract

This research seeks to improve the production process of a micro and small enterprise focused on the manufacture of textile dyes, a sector that commonly faces high return dates due to formulation errors, labeling mistakes, and inadequate task management. Deficiencies were identified in the control of mixing parameters, imbalance in workload distribution, and failures in final label verification, all of which affect product quality and operational efficiency. The proposed model applies combination of lean methodologies and digitalization: the Taguchi method to optimize parameter control, Artificial Neural Networks to generate predictive models to responses under dyeing conditions and identify combinations with similar absorbance levels to replicate, Kanban for task management, and RFID with Poka-Yoke to ensure correct labeling. As a result, returns due to labeling errors decreased by 27.78%, followed by a 26% increase in value flow, a coefficient of determination of 0.799, and a mean squared error of 0.0213, which indicates an optimistic fit for a nonlinear systema. Additionally, the social evaluation highlights improvements in occupational safety, job formalization, and product traceability, contributing to a more efficient production model for the small-scale chemical textile industry.

1 Introduction

The chemical sector in Perú, particularly the dye and pigment subsector, plays a crucial role in the industrial economy, representing 1.0% of chemical product exports in 2023. This subsector experienced a 4.6% growth in dye and pigment production, reaching 856,446 thousand kilograms[1], however, the industry continues to face persistent challenges in maintaining product quality. Defects related to irregular textures, unstable viscosity, improper coloration, and deficiencies in formulation and labeling significantly affect both the visual performance and commercial value of paints and dyes[2].

These quality problems impact customer satisfaction, production costs, and the competitiveness of companies in the subsector, as nonconforming batches often lead to rework, scrap, product returns, accounting for 32.6% of defects, the situation is critical for micro and small enterprises (MSEs), which often lack standardized quality control systems, structured process monitoring, rework, scrap, and robust task management frameworks[3-4]. In dye production, variability in mixing parameters, inconsistent raw material handling, and inadequate verification mechanisms increase the risk of producing nonconforming batches, which compromise the product uniformity and market competitiveness[5].

Previous studies addressed similar quality and problems by combining Lean methodologies, planning systems and technological solutions, like an App Inventor to alert operators in case a mistake happens[6], however, its mains dependent on a manual supervision, that requires continuous training and demand periodic evaluations. However, several authors have applied Taguchi design of experiments, and they achieved improvements in color fixation, but it was focused on single-objective and had dealing with multi-objective trade-offs dimensions, which has led to suggest complementing Taguchi with another multicriteria method[7-9]

Motivated by these gaps, this study aims to identify solutions to optimize the dye production processes, reduce defects in manufacturing, and ensure better quality and consistency in the final product, which can be adapted to different industries and company sizes. The contribution integrates design of experiments with a new methodology that can obtain a performance with comparative scenarios to support multi-objective decision-making in dye production, also using lean-based improvements with technological tools to achieve a more controlled and partially automated process.

2 Literature Review

2.1 Quality, Logistics and Returns Issues in MSEs

The returns within micro enterprises (MSEs) are caused by structural deficiencies in quality management and logistics. It is identified that in a chemical MSE, 13% of returns were due to errors in storage, product quantity, and delivery times[6]. Meanwhile, 5.05% of their returns are attributed to non-standardized processes, as they lack adequately documented order reports[10], which demonstrate administrative disorganization. 8.33% of returns in his chemical company resulted from incorrect labeling[5-11]. Also, at the supply chain and logistics levels, it showed that 16% of returns are due to the unavailability of raw materials within remanufacturing processes[12]. Finally, in the textile sector it has been demonstrated that the lack of integrated planning and material records limits the final quality of products[12-14].

2.2 Defect Reduction with Poka-Yoke and Kanban

address issues related to product returns. They have been used to prevent errors in inventory management[10], leading to a reduction in returns caused by process instability, a 30% improvement in data accuracy, and more efficient management. In other enterprises, their implementation resulted in an increase in process capability from 1.278 to 2, thereby decreasing the rate of defective products[15-16], which represents a cost saving of 25.23% due to lower labor expenses and reduced returns[11]. Additionally, one company was able to reduce its order return rate using Poka-Yoke from 13% to 8%, representing a 38.5% improvement[17]. Finally, studies highlight that integrating Poka-Yoke with Kanban can reduce defects by 20% to 50%, strengthening Kanban's effectiveness in workflow management and increasing confidence in the visual process[18].

2.3 Application of ANN for Optimization and Prediction in Dye Process

Artificial Neural Networks (ANNs) are useful for modeling complex parameters in dyeing processes, and their application has significantly reduced textile simulation time from 8 minutes to just 15 seconds[19]. Cross-validation was performed to avoid overfitting and ensure reliable predictions[20] and integrating ANNs with traditional methods such as Taguchi helps reduce external variability, enabling more realistic dyeing simulations, improving result accuracy, and facilitating the identification of critical parameters[21]. In another study, ANN was used to predict the adsorption efficiency of methyl orange, achieving a coefficient of determination (R^2) of 0.9971 and a maximum relative error (RE) of 8.24%, demonstrating high predictive accuracy[8]. Finally, ANN was applied after reducing experimental runs with the Taguchi method, achieving predictions very close to experimental values—for example, for P-FBP-AC at 1000 mg/L, 2 g/L, and 15 min, the experimental removal was 96.8%, while ANN predicted 95.75%[22].

2.4 Optimizing Color Fixation in the Dyeing Process

Poor color fixation in the dyeing process is related to the interaction between the chemical properties in the dye, the fabric, and the dyeing conditions[23], and 70%–80% of fixation problems originate from the dye formulation, influenced by factors such as pH, temperature, and unstable reagents. Fiber structure and porosity are essential for achieving adsorption levels above 90%[24]. Furthermore, the relationship between dye concentration and exhaustion percentage affects color fixation, with reported exhaustion values of 75.25%. Implementing methodologies such as Taguchi and ANOVA have improved parameter optimization and increased accuracy in the identification of optimal conditions[25]. In another study, the Taguchi technique was applied to generate optimal and controlled data, reporting improvements of 15%–30% in treatment performance after implementation[26], and additional research confirmed improvements of 7.49%, demonstrating its relevance for standardizing conditions without requiring many experimental tests[7].

3 Methodology

3.1 Conceptual Model

returns by focusing on input analysis and the control of key parameters, such as the dye's chemical formulation, which is adjusted using techniques like Taguchi and the LSSVR machine learning model to achieve a 5%–10% improvement[27-28]. Furthermore, artificial neural networks can be used to generate samples that enhance fixation simulations without the need for direct experimentation, allowing for reproducible and comparable combinations that achieve fixation values approaching 1. The formula $A = \varepsilon \times c \times l$ is implemented in order to obtain a better percentage of fixation and find better values, and obtains a better final interpretation of the dye absorption. Furthermore, tools such as RFID and Poka-Yoke are used to optimize labeling and reduce human error, increasing productivity by 20%–50%[18]. The model also incorporates control methodologies such as VSM and Kanban, which reduce customer complaints and improve process efficiency[29].

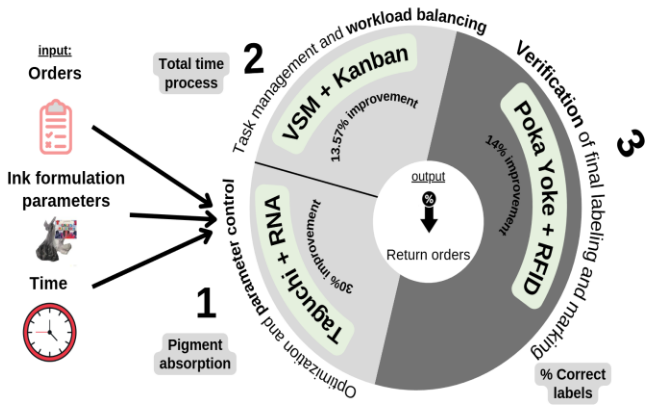

Fig. 1 Production Optimization Model

3.2 Description of Components

3.2.1 Formulation and Control of Parameters: The goal of developing and achieving parameters that meet standards and improve ink absorbency is based on Taguchi and RNA techniques. These techniques increase the efficiency, fixation, and quality of the product, considering parameters such as pH, concentration, temperature, and time, whose characteristics are crucial for identifying potential improvements in the manufacturing process.

The statistical calculation of sample quantities for experimentation is most easily achieved with the Taguchi method, allowing for an experimental design without missing or excess samples. Similarly, the techniques used provide greater control over the parameters, facilitating the development of efficient extraction methods.

3.2.2 Task Management and Workload Balancing: RNA allows for the generation of simulated data, thereby reducing the dependence on extensive experimental trials. This approach enables the evaluation of a broad range of parameter combinations and facilitates the identification of optimal operating conditions that can be consistently reproduced and compared, resulting in fixation values close to unity and enhancing process robustness.

During the simulation phase, model performance is assessed through the comparison of coefficients of determination (R), establishing a minimum threshold of $R > 0.8$ to ensure satisfactory predictive capability. To this end, different modeling techniques are analyzed, including linear and non-linear regressions, decision tree models, and ensemble methods such as random forests. The final model selection is based on its fit quality and predictive strength, ensuring an accurate representation of the process behavior.

The efficiency of better coordination in the delivery of finished products, along with an improved analysis that identifies key activities to increase productivity percentages, is supported using the Kanban tool, which fulfills this objective. Likewise, the ability to visualize and identify processes that require improvement to meet the component objective is presented; therefore, the Value Stream Mapping (VSM) tool is used.

Other studies present a logical sequence for using these tools to reduce non–value-added activities, representing 6.74%[30]. Using both tools in chronological order to achieve better functioning, aiming to develop activities that enhance the operational process. For this reason, Value Stream Mapping (VSM) is used first, the use of the Kanban tool, which reinforces the idea of applying VSM initially to obtain a global view of the process and then rigorously structuring the Kanban cards, thereby increasing process organization[31]. After conducting a general analysis, key improvement activities are identified through visualization of the operational flow. Therefore, the use of both techniques generates efficiency and increases product quality by reducing unnecessary time spent on performing other simultaneous activities.

3.2.3 Labelling and Final Labelling Verification: The implementation of tools that improve the effective recording of color codes, product types, and inventory accuracy involves incorporating devices into the operational process, such as RFID and Poka-Yoke, to achieve greater organization, reduce labeling errors, and ensure a correct finished product.

After the analysis, it was considered that the structured use of a complementary tool within products to obtain proper registration and provide usefulness within the operational process, with the objective of reducing bottlenecks and losses caused by incorrect labeling. These devices are part of a monitoring and control system that provides real-time data recording of activities[30]. Likewise, evaluates and confirms the efficient sequence of implementation, demonstrating improvements in monitoring and tracking of products, achieving an 81% enhancement due to the support provided[32].

3.3 Application Flowchart to Validate

The operational process system presents activities in which sequences of incorrect movements occur, preventing the continuous flow of product manufacturing. Based on an analysis that identifies negative effects in the labeling, packaging, and final delivery stages, these issues reduce the productivity of the process flow. For this reason, an analysis of these components is conducted with the aim of minimizing negative effects and achieving a continuous operational flow.

The process begins with the visualization and identification of incorrect movement frequencies, using the VSM tool, which represents the process flow through diagrams and scales. The flow outlines the details of the process, making it possible to visualize incorrect activities through a preliminary diagnosis that includes operators, tools, time records, and measurements, enabling the identification of critical points for improvement. Once the current state and deficiencies have been identified, Kanban cards are incorporated into a visual board to maintain inventory control, and the exact value of the parameter with the characteristics needed for its use in the operational process is analyzed.

In this way, the activities of receiving, filling, and label application are carried out using Poka-Yoke and RFID tools. This approach enables more efficient barcode identification and establishes a connection with the Poka-Yoke device, which defines the attributes each label must contain and allows proper application to the product. Subsequently, if the opposite situation occurs, an RFID-linked device such as a scanner is used. This device is responsible for visualizing and recording the correct attributes for each type, color code, and product, allowing the system to determine whether the labeling is correct or incorrect.

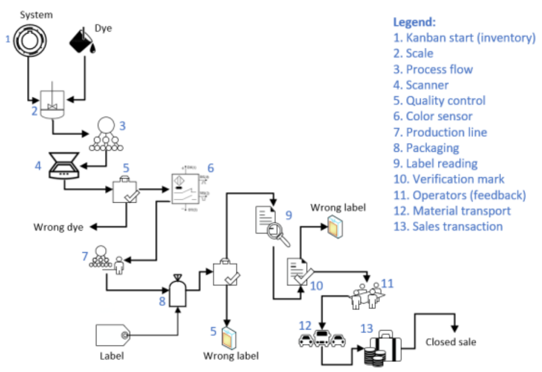

Fig. 2 Flowchart of the three components

4 Results

Using Poka-Yoka devices resulted in a 6.1% improvement. There was a better organization in registering the correct product code with barcode, which can identify faster than see the book and same time verify with formulation, that take more time and more issues of confuse. Using a macro simulator, make a total improvement of 27.78% in returned products, that achieved using scanning and recording devices. Using those records, Table I presents the better results of the operation process and make a continuous process, without error-free workflow. Finally, after analysing several samples and interpreting the experimental design, a 22.47% improvement was observed. This represents an improvement in the percentage of absorption compared to the original ink.

Table 1 Absorption Improvement Validation Calculations – Component 1

Metric	Calculation	Result	Absorbance
Total orders	2179	2179 units	
Returns due to fastening (AS IS)	2179 x 32.11%	700 units	0.87
Returns due to fastening (TO BE)	2179 x 22.47%	490 units	1.05
Reduction of returns	700-490	210 units	
Improvement percentage	(210/700) x 100	30%	

According to the indicators found in Table 2, the number of returned orders registered in August decreased due to the tools used. Greater focus and efficient record-keeping were identified, with incorrect products being returned before packaging. This improved quality control activity, implemented with the new devices, resulted in a 26% improvement. This is evident in our focus month (august), where 250 total orders were identified, of which 36 were returned. After the implementation of these devices, the same total number of orders was registered, but with a decrease of 10 orders due to returns, representing a 3.5% improvement.

Table 2 Reduction of number of incorrect final products – Component 2 and 3

Metric	Min Value	Max Value
Indicator 1	3.82	8.49
Indicator 2	-1.68	2.32
Indicator 3	-0.426	1.37
Indicator 4	0.492	4.14

The validation model identifies the main problem, which is nonconforming finished product, because of two causes. One of them is unfixed dye in dyed fabric (%) caused by little formulation time and no verification of the quality of the inputs used to prepare the mixture, which causes the fixation to fail. Likewise, the fixation time is shorter than the standard range that should be met, which is why there are many returns related to the formulation process. The second is the Incorrect product delivery The low formulation time and the lack of quality verification of the raw materials used in the mixture cause the fixation process to fail, and the fixation time itself is below the standard range required, leading to a high number of returns associated with formulation errors. Additionally, this problem is aggravated by the absence of a complete registry of the entire color range and the insufficient ability to distinguish between similar colors, which generates labeling and delivery mistakes; therefore, RFID and Poka-Yoke tools are implemented to strengthen the process, improve identification, and ensure accurate labeling through color codes and product type registration. The improvement in in indicator 4, with a value of 2.37, indicates a decrease in the number of returned orders due to incorrect labeling. This result demonstrates the effectiveness of implementing the poka-yoke and Taguchi devices, thus confirming the validity of this implementation and its high-level improvement and efficiency in reducing returns.

5 Discussion

The selection of the extraction method varies depending on the parameters used. According to [34], the process was carried out using a 1:2 ratio, a temperature of 50–60°C, and a time of 20–30min, achieving only a yield of 0.237%. In contrast, in the experiment considered pH (4-10) along with temperatures of 60–90°C, consistent with[35] and [36], resulting in a more efficient dyeing process with a precision of 7.49%.

The results also highlight the role of error-proofing mechanisms such as Poka-Yoke in improving operational reliability, particularly in labeling and formulation stages where human error was recurrent. The device-based interventions significantly reduced mislabeling and formulation mistakes, contributing to a 41% improvement in process consistency[31]. This suggests that the root causes of returns were strongly linked to manual handling and verification tasks, reinforcing the importance of system-dependent rather than operator-dependent controls. The formulation stage was identified as the most energy-intensive step, contributing substantially to the overall carbon footprint. According to the formulation methodologies aimed at enhancing absorption, different investigations recommend employing a solvent-based method (ethanol and water) combined with an extraction process[33]. This extraction is applied to reduce the number of pressurization and depressurization cycles and to maximize the bioactive components of the ink. In contrast to the referenced method, the present study demonstrates the efficiency of the lyophilization technique, which not only enables a comparative colorimetric analysis but also prevents material loss throughout the process[5].

Following the implementation of Poka-Yoke tools, devices such as a colorimeter and a QR code barcode scanner, the objective of reducing incorrectly labeled products by 27.97%, improving absorption by 4%, and decreasing the excessive use of incorrectly applied labels and wasted supplies was achieved[19]. This demonstrates that Poka-Yoke, Kanban, and Value Stream Mapping (VSM) tools can be implemented regardless of company size, if product quality remains optimal.

This finding is like articles such as two articles that have similar attributes. However, it differs from other authors, which found that implementation takes time and the percentage of success does not exceed 20%.[5-31]

6 Conclusion

The improvement project is economically viable and sustainable, strengthening the company's financial stability by reducing operational costs and losses associated with product returns. Additionally, the implementation of devices for both formulation control and labeling accuracy resulted in a 41% improvement, demonstrating the significant impact of parameter control and error-prevention mechanisms on overall process performance. It is defined according to the percentage of absorption, a possible path optimizing the investment cost, and a better input used to increase the fixation of the dye. The improvement of reduced returned orders is presented with the support of devices, thus automating the process and developing organization in the products.

7 Recommendations

To enhance the performance of the natural dyeing process, it is recommended to implement energy-efficiency measures by optimizing equipment usage times, especially during the formulation stage. Additionally, identifying the target unit at the end of each simulation will facilitate accurate time recording and improve data accessibility. Clearly defining the objectives to be analyzed will also help ensure the precision of the results and strengthen the reliability of the simulation outcomes. In addition, it is analyzed and presented to consider the ambient temperature in the approach to reading the samples, since it determines the proportion in the reading.

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