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Data-Driven Quality Improvement in Woven Wire Mesh Production Using Machine Learning Algorithms

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Abstract:

Purpose: This paper aims to purpose a Data-Driven Quality Improvement (DDQI) framework for improving production quality by analyzing existing data using machine learning, data visualization, and correlation analysis. The objective is to predict optimal machine settings for different batches of raw materials to enhance process yield and minimize defects. A case study was conducted at a stainless-steel woven wire mesh manufacturing plant in Thailand, using real production data and testing the predicted machine parameters in actual production.

Design/methodology/approach: The framework starts with the integration of existing data into the master database. Next, data visualization and correlation analysis are employed to screen out unimportant factors. Subsequently, machine learning is utilized to model the relationship between process parameters and their corresponding quality characteristics. Finally, the model is used to identify the optimal settings for production parameters that are suitable for new incoming batches based on the raw materials' inspection data.

Findings: The results from implementing the DDQI framework in the case study company showed that it was able to accurately predict the process yield of the wire mesh weaving process. This capability enabled the selection of process parameters that were well-suited to the incoming materials, leading to an increase in process yield to an average of 91.3%. The results indicate that the DDQI framework not only significantly improves the process yield of the case study factory but also facilitates more systematic and planned decision-making regarding production.

Research limitations/implications: The model's performance was limited by the quality and completeness of the historical data. Some complexities in the manufacturing processes could not be captured due to missing variables or unmeasured process aspects. While the Gradient Boosted Tree (GBT) performed well, some batches still exhibited defects, indicating that there is room for model refinement or the inclusion of additional parameters.

Originality/value: This research introduces a novel integration of machine learning, data visualization, and correlation analysis into a practical quality improvement framework. It further provides empirical evidence from a real-world implementation in the wire mesh industry, demonstrating that data-driven optimization can outperform traditional quality tools with minimal disruption to manufacturing.

Keywords: quality improvement, machine learning, predictive models, gradient boosted tree, parameter prediction, production yield, wire mesh manufacturing

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1. Introduction

In today's increasingly interconnected and globalized environment, maintaining competitiveness presents significant challenges for businesses. To remain competitive, organizations must deliver products and services that effectively meet customer needs and expectations (Riepina, 2024). Achieving and ensuring a high level of quality is a critical factor in this regard (Psarommatis, Prouvost, May & Kiritsis, 2020), as lower defect rates lead to customer satisfaction, optimize the utilization of machinery and personnel, and contribute to cost control. Quality improvement tools, which encompass a variety of techniques and methodologies, play a crucial role in enabling organizations to enhance their processes, identify and eliminate defects, and improve efficiency. These tools are widely applied across diverse industries, including manufacturing, healthcare, and services (Carnerud, Mårtensson, Ahlin & Slumpi, 2020; Coughlin & Posencheg, 2023; Fundin, Lilja, Lagrosen & Bergquist, 2025; Jomy, Lin, Huang, Chen, Malik, Hwang et al., 2025; Maani, Putterill & Sluti, 1994; Nicolay, Purkayastha, Greenhalgh, Benn, Chaturvedi, Phillips et al., 2012). There are many different quality tools available, each designed to address specific problems or areas for improvement. Some commonly used quality tools include flowcharts, Pareto charts, cause-and-effect diagrams, statistical process control, Failure Mode and Effects Analysis (FMEA), quality control circles, and Six Sigma. The application of these tools has been associated with significant cost savings in the past.

Traditional quality improvement tools address quality issues by identifying and eliminating the root causes of problems, rather than merely addressing the symptoms. This approach requires a deep understanding of process mechanisms, which is increasingly difficult and time-consuming to obtain in modern, complex manufacturing systems (Yin, Niu, He, Li & Lee, 2020a).To achieve this, the relationships between input factors, such as incoming materials, labor, and machine parameter settings, and quality characteristics, must be thoroughly investigated and modelled to predict the quality level for given input variables (Ramana & Reddy, 2013). However, these relationships are often extremely complex and uncertain (Liu, Liu & Duan, 2020) making analysis much more challenging.

One of the techniques commonly used to model such relationships is the design of experiments (DOE). Various types of experimental designs have been reported to successfully improve quality levels in manufacturing processes (Hanrahan & Lu, 2006), for example, full factorial design (Javorsky, Franchetti & Zhang, 2014; Kadeethum, Salimzadeh & Nick, 2019), fractional factorial design (Montgomery, 1990; Nabaterega, Kieft, Hallam & Eskicioglu, 2022), and the Taguchi method (Ghani, Choudhury & Hassan, 2004; Sukthomya & Tannock, 2005a; Yang & Tarng, 1998). However, these techniques require additional experiments and testing on actual production lines, which not only require further investment but also cause disruptions to production. Moreover, they rely on certain assumptions and often build models using the entire dataset, without splitting the data into separate training and testing sets (Yin et al., 2020a).

Even though traditional quality improvement tools have proven to be useful, better methods to analyze the massive amounts of data collected in industry database emerged (Köksal, Batmaz & Testik, 2011). In the modern manufacturing environment, advances in information technology such as the Internet of Things (IoT), sensor technology, and cloud computing have resulted in an exponential increase in the amount of manufacturing data collected (O'Donovan, Leahy, Bruton & O'Sullivan, 2015). Numerous countries have introduced national strategies to advance manufacturing, such as the Industrial Internet, Industry 4.0, and Made in China 2025. A common goal of these strategies is to achieve smart manufacturing, which requires the integration and coordination of both the physical and digital aspects of manufacturing (Tao & Qi, 2019). Smart manufacturing involves the use of systematic computational analysis to analyze manufacturing data in order to make more informed decisions (Tao, Qi, Liu &

Kusiak, 2018). It is recognized that Industry 4.0 has brought significant changes to traditional quality management practices, giving rise to a new approach known as Quality 4.0 (Oliveira, Alvelos & Rosa, 2024).

At present, machine learning (ML) is playing a critical role in manufacturing digitalization and in the adoption of the Industry 4.0 concept (Chen, Sampath, May, Shan, Jorg, Aguilar-Martín et al., 2023). In recent years, ML has been applied to a wide range of manufacturing applications, including demand forecasting, supply chain optimization, and predictive quality control. A study by Carnerud et al. (2020) revealed that although quality management researchers are generally positive about digitalization, related initiatives and conceptual approaches within the field appear to lag behind current advancements.

The use of ML with manufacturing data has been increased over the past 20 years (Sharp, Ak & Hedberg, 2018). One of the promising applications of ML is manufacturing process modelling, in which process parameters are used as input data and quality characteristics, such as process yield or defect rate, are used as target outputs. Data obtained from the process is split into a training set (for building the model) and a testing set (for evaluating the performance of the model); hence, the performance of the model is more reliable when applying it to new data. ML does not require any assumptions about the data and can cope well with complex and non-linear relationships. Moreover, because the model training process uses only historical (past) data, it can be performed without interfering with or interrupting the ongoing production process. Various ML algorithms have been applied to model manufacturing process; for example, artificial neural network (ANN) (Bhagya-Raj & Dash, 2022; Coit, Jackson & Smith, 1998; Sukthomya & Tannock, 2005b; Venkatesan, Kannan & Saravanan, 2009), support vector machine (SVM) (Ding, He, Yuan, Pan, Wang & Ros, 2021; Rostami, Dantan & Homri, 2015; Yin et al., 2020a; Zouhri, Homri & Dantan, 2022), decision tree (DT) (Barrios & Romero, 2019; Ronowicz, Thommes, Kleinebudde & Krysiński, 2015), deep learning (DL) (Mojahed-Yazdi, Imani & Yang, 2020; Shah, Wang & He, 2020; Wang, Ma, Zhang, Gao & Wu, 2018) and ensemble models (Garrido-Labrador, Puente-Gabarri, Ramírez-Sanz, Ayala-Dulanto & Maudes, 2020; Yin et al., 2020b). As a result, ML has proven to be more suitable for modelling the relationship between process parameters and quality outputs than traditional quality improvement tools in the modern manufacturing environment. Once, the model is well established, it can be used to identify best parameter setting to achieve the desired quality level.

Building on the strength of ML in process modelling and optimization, this research addresses additional challenges that arise in real manufacturing settings, such as raw material variability from multiple suppliers. To reduce the risk of relying on a single supplier, industries often engage multiple suppliers to provide the same type of raw material. This diversity introduces variation, and therefore, it becomes necessary to configure machinery tailored to the characteristics of each raw material.

Setting process parameters in production can be done in several common ways, such as operator experience, trial and error, and DOE. However, each method has its own advantages and disadvantages. Using operator experience enables quick decision-making, but it can introduce bias, human error, and may overlook complex relationships. The trial and error method is easy to carry out but is time-consuming and resource-intensive, and it may not always find the true optimal settings. DOE provides a systematic and statistically valid approach but requires experimentation, which can be costly and resource demanding.

Machine learning offers significant advantages over traditional methods for setting process parameters. ML excels at modelling complex and nonlinear relationships among numerous process variables. This data-driven approach reduces reliance on human intuition, minimizes the risk of error or bias from manual adjustments, and allows for real-time, dynamic adaptation to changing production conditions. Examples of using ML to set process parameters include Tan and Nhat (2022), who used ANN to optimize process parameters for thermoforming and addressed challenges such as defects in the final product, and Dharmadhikari, Menon and Basak (2023), who discussed the application of reinforcement learning to optimize process parameters in additive manufacturing.

This research aims to create a new Data-Driven Quality Improvement (DDQI) framework for analyzing existing data in databases with the goal of improving quality and addressing defects in the manufacturing sector using ML techniques, together with data visualization and correlation analysis. To demonstrate the proposed framework, we conducted a case study with a large-scale manufacturer of stainless-steel woven wire mesh in Thailand. The proposed method begins with the acquisition of data from relevant databases, including supplier data, raw material inspection data, machine parameter setting data from each process, and final product quality inspection data. Then all the data is merged to create a master database. Since the master database is constructed by merging data from various sources, it contains a large number of related attributes. These attributes are then selectively chosen based on the analysis of relationships and visualization. Association rule analysis is also applied to study relationships among defect types. The selected attributes are used to create ML models. When new lots of raw material properties are tested, the test results are combined with the data set of all possible process parameters to create a scoring file for the ML model. This ML model is then used to predict the best-suited machine parameters settings. Additionally, Local Outlier Factor (LOF) is employed to group raw materials with similar characteristics into the same production batches, thereby reducing process variability.

The rest of the paper is organized as follows; the next section discusses background theories, including a literature review of the application of ML in manufacturing and a brief review of the ML methods used in this research. Section 3 describes the research methodology, detailing all the steps of the DDQI framework. Section 4 presents relevant information about the case study company, along with an explanation of the related production process. Section 5 covers the results and discussion from the application of DDQI in the case study company. The final section provides the conclusion.

2. Background Theories

2.1. The Use of Machine Learning in Manufacturing

Machine learning is one of the fields that has recently gained significant attention. It combines concepts and techniques from various fields, including computer science, statistics, artificial intelligence, and data science. With the rapid development of new learning algorithms, ML has been adopted in various fields, including healthcare, manufacturing, education, financial modelling, and marketing (Jordan & Mitchell, 2015).

Machine learning algorithms are commonly categorized into three primary types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning includes algorithms that enable computers to learn from examples. Unsupervised learning consists of algorithms that allow computers to learn patterns on their own. Reinforcement learning involves algorithms in which computers learn through trial and error, gaining insights from actions that result in rewards in order to find the best actions leading to optimal outcomes. The use of these algorithms in manufacturing has been reported in literature (Dogan & Birant, 2021; Rai, Tiwari, Ivanov & Dolgui, 2021; Sharp et al., 2018; Wuest, Weimer, Irgens & Thoben, 2016).

Köksal et al. (2011) categorized the applications of ML in quality improvement into four tasks: description of quality, classification of quality, prediction of quality, and parameter optimization. The description of quality involves analyzing attributes or features that affect a product's quality. For example, Hsu and Chien (2007) applied DT and ANN to extract features from wafer bin maps, aiming to improve yield. Chen, Tseng nd Wang (2005) utilized association rules to identify the root causes of defective products.

Classification of quality is an application where ML is used to predict quality classes. Among the various ML methods, DT and ANN are extensively discussed techniques, as seen in studies by Sik-Kang, Hyoen-Choe and Chan-Park (1999) and Chen, Lee, Deng and Liu (2007). The most common application of ML for quality improvement is in the prediction of quality. Various ML approaches, such as DT (Li, Feng, Sethi, Luciow & Wagner, 2003), ANN (Kurtaran, Ozcelik & Erzurumlu, 2005) and SVM (Fei, Jinwu, Min & Jianhong, 2013), have been reported. Quality optimization is the least commonly applied task compared to its applications in other areas. Common tools found in optimization tasks include genetic algorithms (GA) (Kim, Oh, Lee, Lee & Yun, 2001) and the Taguchi method (Teng & Hwang, 2007).

2.2. Machine Learning Algorithms for Manufacturing Process Modelling

This section briefly describes the ML algorithms used in this research, focusing on their operational characteristics and demonstrated utility in manufacturing process modelling. The algorithms reviewed are Generalized Linear Model (GLM), Decision Tree (DT), Random Forest (RF), Gradient Boosted Tree (GBT) and Deep Learning (DL), Generalized Linear Model is a concept developed by John Nelder and Robert Wedderburn. It has been adapted to work with error distributions that are not necessarily normal (Myers & Montgomery, 1997). The GLM can create models even when the relationship between independent and dependent variables is not linear, using a link function to connect the dependent variable to a linear function. This versatility allows GLM to model various manufacturing datasets effectively. For example, Brinkley, Meyer and Lu (1996) demonstrated the application of GLM combined with nonlinear programming for quality improvement in circuit board manufacturing, significantly reducing defects in the process. Additionally, GLM has been successfully used in predicting semiconductor yield (Krueger, Montgomery & Mastrangelo, 2011) and defects in plasma etching (Boumerzoug, 2010).

Decision Tree, random forest, and gradient boosted tree are tree-based supervised ML techniques. DT use training data to build a tree-like diagram, consisting of internal nodes representing tests on attributes, branches representing outcomes of these tests, and leaf nodes holding class labels. Attribute selection is typically based on information gain, calculated from the difference in entropy before and after a split. A key characteristic of DT that makes it particularly useful for modelling production processes is that their visual, hierarchical structure, which allows engineers and operators to understand how decisions are made. DT also naturally select the most important features (Choudhury, Mondal & Sarkar, 2024), helping to identify key process variables affecting product quality.

Random forest, and gradient boosted tree and GBT are ensemble methods that construct multiple decision trees as base learners. RF creates many decision trees from different subsets of the data, with each tree trained independently and randomly using bootstrap aggregating, or bagging. RF provides the benefits of improved accuracy (Chen, Zhu, Niu, Trinder, Peng & Lei, 2020) and robustness to noise and outliers (Kang, 2023), both of which are often present in real-world manufacturing environments. GBT, on the other hand, trains each tree based on the residual errors of the previous trees and uses the gradient descent algorithm to iteratively update tree parameters to minimize a loss function. GBT offers high predictive power (Wang, Song, Zhao, Wang, Dong, Wang et al., 2022) and the ability to handle complex interactions (Ghazwani & Begum, 2023), making it especially useful in multistage or highly automated manufacturing systems. There have been some reports on the superior performance of GBT over RF (Yoon, 2021).

Deep learning enables computational models consisting of multiple processing layers to acquire representations of data with varying levels of abstraction. DL discovers structure in large datasets by employing the backpropagation algorithm, which guides the ML in adjusting its internal parameters. These parameters compute the representation in each layer based on the representation in the preceding layer. Breakthroughs in image, video, speech, and audio processing have been realized through deep convolutional networks, while recurrent networks have been used particularly with sequential data, such as text and speech (LeCun, Bengio & Hinton, 2015). DL has the ability to learn complex patterns, handle large datasets, and reportedly has superior predictive performance compared to other ML methods (Bakyalakshmi, 2024). The DL algorithm employed in this research is the open-source H2O deep learning algorithm, which is based on a multi-layer feedforward artificial neural network trained with gradient descent using back-propagation.

3. Research Methodology

The content in this section explains the methods for utilizing existing data in the company's database system to address quality problems, as summarized in Table 1.

The research method is divided into four main steps: data collection and preprocessing, dimension reduction, ML model building, and determination of optimal parameters.

3.1. Data Collection and Preprocessing

This step is the first step in collecting data from relevant sources, generally including the following essential data:

- Supplier data: which contains information related to the suppliers of raw materials, such as their past quality rates, specifications, or related drawings.
- Incoming inspection data: which includes various test results performed on incoming materials, such as chemical testing, mechanical testing, and electrical properties testing.

- Production data: which contains information regarding the types of machines and their parameters settings.
- Quality inspection data: which includes the results of final and in-process quality inspections.

Since these data are often stored separately in different databases, immediate integration may lead to errors. Therefore, it is necessary to clean the data beforehand to reduce errors. Common errors encountered include inconsistent records, where different departments refer to the same item with different names. Additionally, it is essential to handle outlier data, which may result from data collection errors, and to replace missing data in order to obtain the most complete dataset possible. Finally, data from various sources are tracked, traced and merged into a single table called the master database.

Main Steps	Detail Steps	Relevance data and tools
Data Collection and Preprocessing	Step 1: Collect data from relevance source	Supplier's data Incoming inspection data Production data Quality inspection data
	Step 2: Data cleansing	Missing data Wrong type data Outlier detection
	Step 3: Trace, Track and Merge all data into master database	n/a
Dimension Reduction	Step 4: Correlation and Visualization Analysis	R value, Visualization graphs
	Step 5: Defect type correlation	Association rule analysis
Machine Learning Model Building	Step 6: Build the ML models using significant parameters with quality characteristic as target	GLM, DL, DT, RF, GBT
	Step 7: Fine tuning the hyper-parameters to improve the performance	n/a
	Step 8: Performance evaluation	Root Mean Squared Error (RMSE) and Relative Error (RE)
Determination of Optimal Parameters	Step 9: Grouping new batch of materials to reduce variation	LOF
	Step 10: Generate all possible combination of controllable factors while keeping uncontrollable factors constant	Cartesian Product

Table 1. The detailed step in the proposed DDQI framework

3.2. Dimension Reduction

Since the master database is created by consolidating multiple databases throughout the factory, it contains a large number of attributes. This step involves reducing the number of attributes by selecting those that are crucial for the results. Including all available attributes in the model-building process can lead to excessive time consumption and may also negatively impact the error of the model.

The selection of attributes can be accomplished in several ways, such as correlation analysis or the use of visualization. Visualizations such as histograms, box plots, and scatter plots are valuable tools for understanding the distribution of each feature, detecting outliers, and identifying potential relationships between features and the target outcome. For example, scatter plots can reveal features that exhibit clear trends in relation to the target classes. These visualizations enable experts to recognize meaningful relationships, groupings, and clusters that may be contextually significant but are not always captured by statistical criteria.

The involvement of human experts with domain knowledge is crucial for interpreting these visual patterns, as they can observe important relationships, such as overlapping categories and nonlinear separations. These insights help guide subsequent analysis steps and model selection. Incorporating domain knowledge ensures that the interpretation of patterns is accurate and relevant, reducing the risk of misinterpretation that could occur if relying solely on automated analysis. Additionally, in this research, we applied association rule analysis techniques to examine the relationship between different types of the defects (Wongwan & Laosiritaworn, 2018).

3.3. Machine Learning Model Building

This step involves creating a predictive model using ML techniques from the data in the master database. The target attribute, which is the attribute that measures a quality characteristic such as the defect rate, the quantity of detects, or the process yield, is defined. The selected attributes from the previous step are then used to build the ML model.

This research uses three types of datasets: training, validation, and test sets, to develop the ML models. The training set is used to teach the model by adjusting its parameters, validation set is used to measure the performance of the model during training, while the test dataset is used after the model is fully trained to provide an unbiased evaluation of its final performance. To prepare the data, we first split the dataset into two parts: 60 % for training/validation and 40% for testing. Training/validation dataset is further split using 3-fold cross-validation approach. The grid search method was used to fine-tune the hyper-parameter of each ML to ensure the best performance. We chose the 60:40 split to achieve a balance between giving the model enough data to learn robust patterns from the training set and having a large, representative test set for reliable performance evaluation. The model with the lowest error metrics was used in the next step.

3.4. Determination of Optimal Parameter

When the new batches of raw material have undergone testing, the LOF method is used with the test results to group raw materials with similar characteristics and send them to the same production batch to reduce variation. Additionally, the test results are combined with the possible production process parameters to generate a scoring file for the ML model of the process in order to generate the results. Therefore, the best machine parameter setting can be determined.

4. Industrial Case Study

A case study of a large-scale manufacturer of stainless-steel woven wire mesh in Thailand was used to demonstrate the proposed method. The company has been in operation for over 20 years, and the demand for wire mesh has increased continuously in both Thailand and abroad. The major weaving type for this case study is the plain weave type, as shown in Figure 1. There are two side views of the stainless-steel woven wire mesh plain weave type shown.

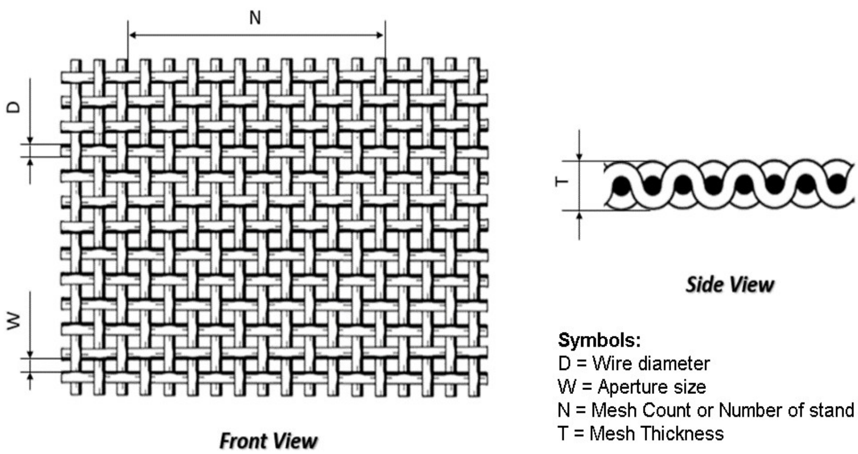


Figure 1. Stainless-steel woven wire mesh plain weave type

The production process of woven wire mesh, shown in Figure 2, consists of eight main processes. The first process is the material receiving process, which is the responsibility of the warehouse (WH) and the quality assurance department (QA). They inspect raw materials and documents from suppliers, checking specifications such as type, quantity, dimensions, appearance defects, and test results. Next, the raw material is forwarded to the second process, the beaming process. This process is the responsibility of the weaving department (BW), where the wire is rolled from pails or drums onto each flange of the bobbin. The number of wires in each flange varies according to the width of the woven wire mesh based on customer requests. The third process is the weaving process, which is the responsibility of the BW department. They assemble the wire with two wire directions, warp and weft, using the woven wire method and different types of weaving patterns such as plain weave or twilled weave. The fourth process is the cutting and inspection process, which falls under the responsibility of the BW and QA departments. This involves rolling the wire mesh into a flat sheet, stretching, cutting, and inspecting for mesh defects by appearance. Width, height, mesh count, and aperture size are also measured during this process. The fifth process is the surface finishing process, which is the responsibility of the surface finishing department (SF). This involves pre-treatment, powder coating, and baking the wire mesh. This process is capable of coating both stainless steel and aluminium materials. The remaining processes are concerned with fabrication, packing, and shipping to the customer.

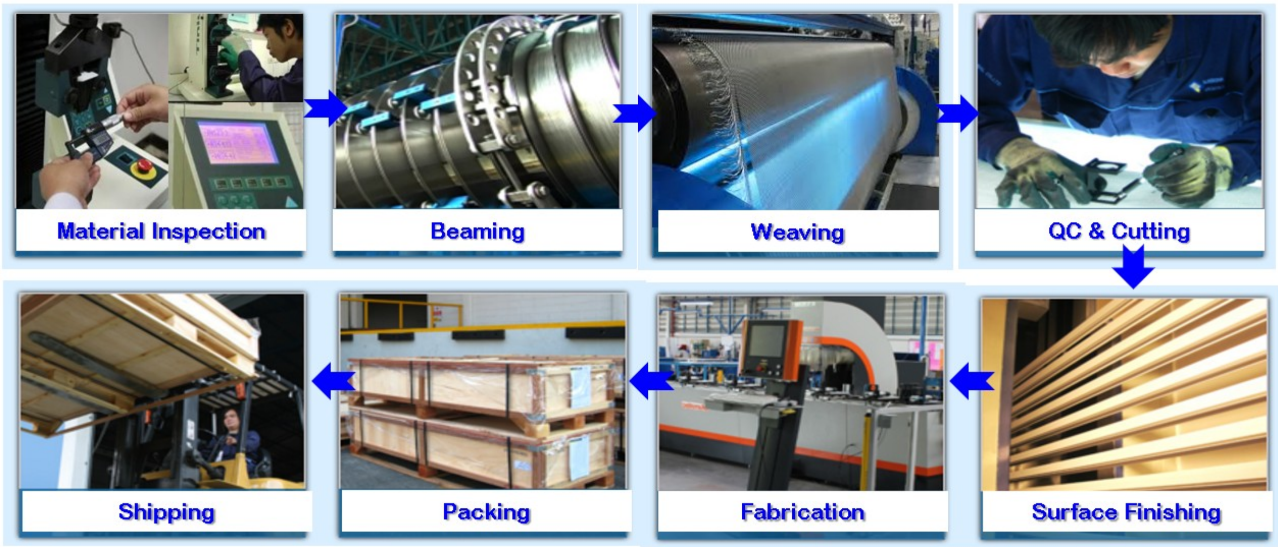


Figure 2. The production process of stainless-steel woven wire mesh, door, and window products

Historical total annual production data from 2006 to 2023 is presented in Figure 3, which shows that the annual production of wire mesh increase steadily from 282,304 square meters in 2006, to 1,060,895 square meters in 2023.

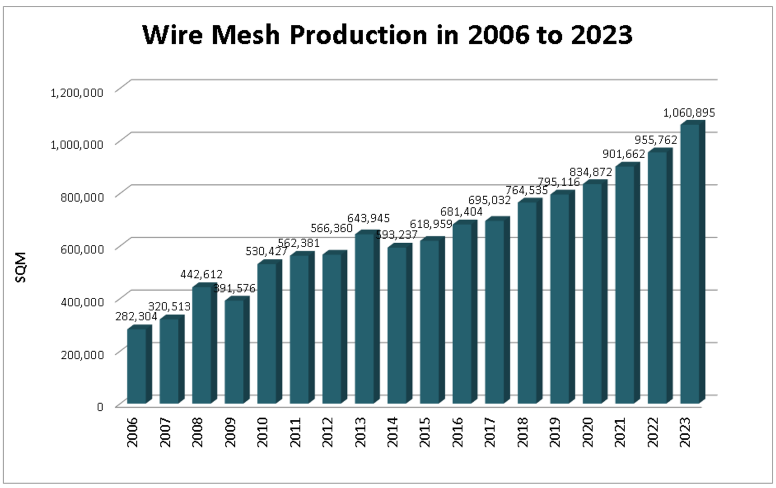


Figure 3. Annual mesh production volume between 2006-2023

The number of defects that occur in the woven wire process has increased every year, as shown in Figure 4. The number of defects increased from 4.9% in 2006 to 9.4% in 2023. Defect problems could affect the delivery schedule, increase production costs per unit, and affect the firm's ability to compete with competitors.

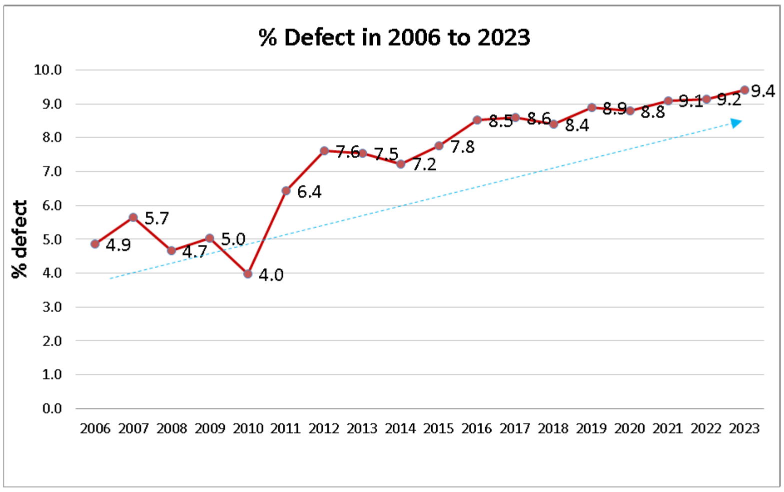
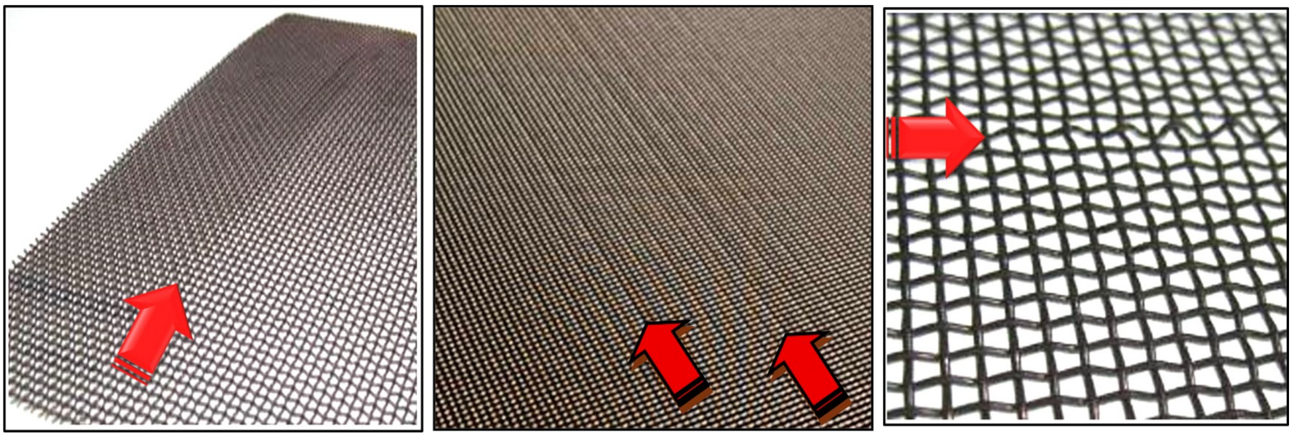


Figure 4. Percentage of mesh defects between 2006 and 2016

There are approximately 16 types of defects. The top three defects considered in this research are mark warp (MW), hard warp (HP) and creeper (CP). These three types of defects account for 53.3%, with MW, HP, and CP constituting 19.9%, 19.3% and 14.1% respectively. Figure 5 shows pictures of the three defect types. MW (Figure 5a) appears as a trace-like pattern resembling a broken net along the warp line. HP (Figure 5b) is a defect where the warp wire forms a raised ridge line that is more visible than the others, and is clearly noticeable across the entire surface of the work. CP (Figure 5c) occurs when the weft wire is serrated, ridged, or not level compared to the normal weave.



a) Mark warp (MW) b) Hard warp (HP) c) Creeper (CP)

Figure 5. Top three defect type

The yearly production yield of the case study company was more than 90%. However, since 2017, the production yield has dropped to between 84.5% and 87.2%, which no longer meets the company's KPI. The reason for the significant drop in production yield is anticipated to be the variation in incoming wire properties. Due to the pressure to reduce costs and the shortage of raw materials, the company has had to seek additional wire suppliers, resulting in the problem of variability in the composition of wires that differ from each manufacturer. These raw materials, when introduced into the production process, require appropriate adjustments to the machinery.

However, there has not been a clear study on the impact of parameters in the production process on quality levels. Consequently, the same set of parameters is used for raw materials from all suppliers, leading to an overall decrease in yield. If the company can adjust the production process parameters to align with the quality of raw materials from each batch provided by different suppliers, the yield of the process should be improved. This will ultimately lead to significant cost reductions.

5. Results and Discussion

5.1. The Master Database

Figure 6 shows the list of attributes that are from six databases. The first section contains information about suppliers, such as the manufacturer's name, specification number, and the type of oil used. The second section is the incoming wire chemical testing results, which include the manufacturer/seller's name, heat number, wire batch number, and the percentage for each element: %C, %Ni, %Si, %P, %S, %Mo, and %Cr. The third section is mechanical properties; every pail (drum) of wire must be tested, and the following must be recorded: wire batch number, pail number, manufacturer name, ultimate tensile strength, elongation after fracture, and offset yield for both warp and weft wire directions. The fourth section is the beaming process parameter settings. There are many factors in the beaming process, including beaming lot number, beaming station number, wire type, beaming shift, beaming width, beaming length, beaming tension level, beaming speed, and warp group number. The fifth section contains data regarding the weaving process, including weaving loom number, width size of the mesh, total weaving length, reed number, weaving tension, weaving speed, weaving timing, weaving bar level, weaving back roll level, and weaving front roll level. Finally, the sixth section is the final product inspection data, which includes mesh roll number, the length of each mesh roll, the calculated total mesh area for each roll, the calculated standard size mesh area for each roll, total scrap wire mesh, percent of production yield for each roll (%STD), percent of scrap for each roll (%Scrap), and the total quantity of defects for each roll (a total of 26 defect types). These data are traced, tracked, and merged to produce the master database, which contains 58 attributes and 9,219 records.

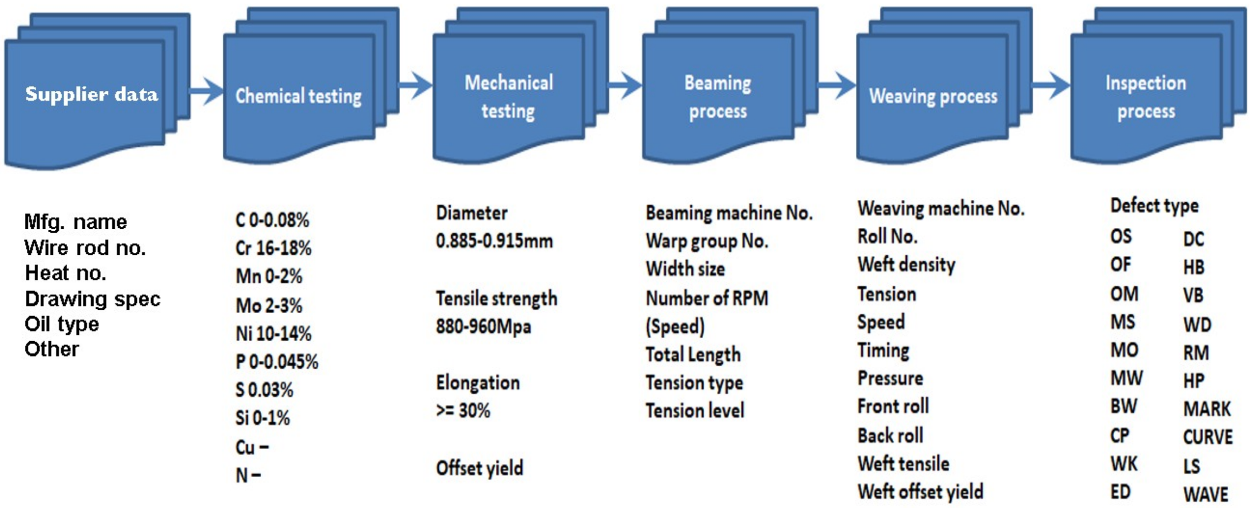


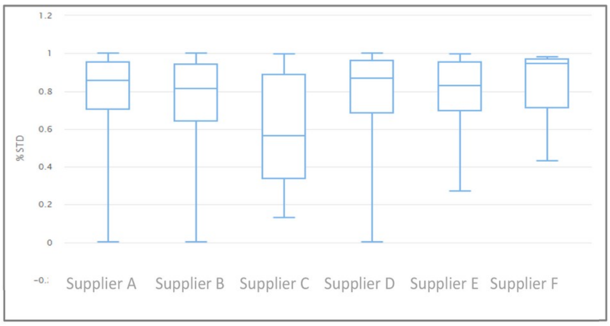
Figure 6. Attributes available in each database

5.2. Visualization and Correlation Analysis

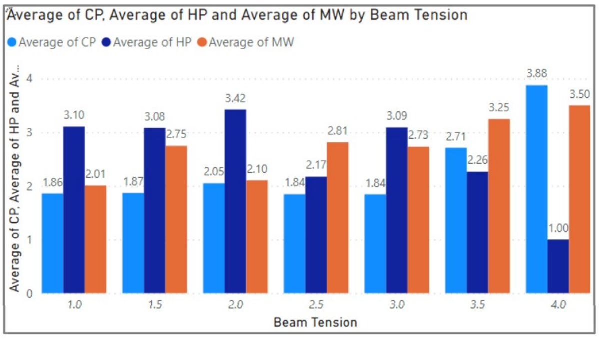
5.2.1. Visualization

Data visualization has been utilized by creating graphs between process parameters (independent variables) and quality characteristics, including production yield, and the occurrence of the defect types CP, HP, and MW. Figure 7 shows some examples of visualization graphs of wire mesh parameters. Figure 7a) is a box plot of production yield percentage (%STD) of the six suppliers. Due to the confidentiality of the suppliers, their names cannot be disclosed here. It can be observed that the median of %STD for every supplier is similar, except for supplier C, which has a significantly lower median, while supplier F has a slightly higher median than the other suppliers. Supplier C shows the highest variation, while supplier F shows a significantly left-skewed distribution.

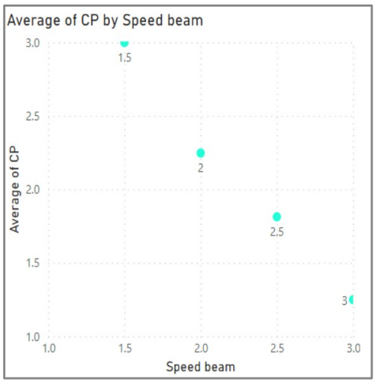
Figure 7b) is a bar chart of the average number of top three defects separated by beaming tension. On average, CP defects occur a maximum of 3.88 times at a beaming tension level of 4.0. Therefore, setting the beam tension at a low level of 1.0 to 3.0 should result in fewer CP defects. HP defects, on the other hand, reach a maximum of 3.42 occurrences at a beaming tension at level of 2.0. Consequently, the beam tension should be set to the highest, specifically at level 4 to minimize HP defects. Regarding the MW defect, it is evident that its occurrence tends to increase if the beam tension level is set too high. MW defects reach a maximum of 3.5 times at beaming tension level 4.0. Therefore, setting the beam tension at a lower level, specifically at 1.0, will result in fewer MW defects. In conclusion, CP and MW defects are more likely to occur at beam tension level 4. However, setting the tension too low can lead to an increase in HP defects. Figure 7 c) d) and e) show the scatter plots between beaming speed and the average number of CP, HP and MW defects, respectively. It appears that CP and HP defects decrease with an increasing beam speed, but this leads to an increase in MW defects.



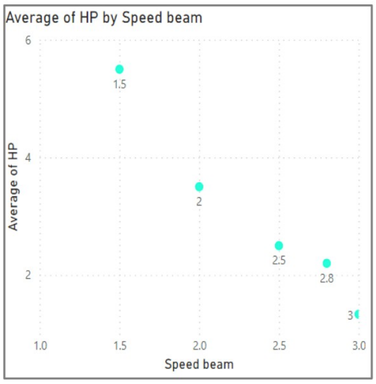
a) Box plot of % production yield separated by type of weft supplier



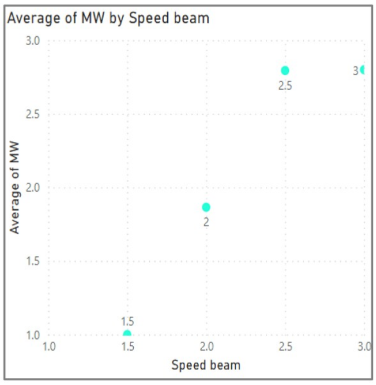
b) Bar chart of the average number of top three defects separated by beaming tension.



c) Scatter chart between beaming speed and average number of CP defect



d) Scatter chart between beaming speed and average number of HP defect



e) Scatter chart between beaming speed and average number of MW defect

Figure 7. Example of visualization graph of wire mesh parameters

Association rule analysis was also used to study the relationship among defect types (Wongwan & Laositritaworn, 2018). It was found that the occurrence of the HP defect is very strongly associated with the OM (Open Mesh) defect, as OM is almost always found whenever HP is present. The results of the study also revealed correlations among HP, OM, and OF (Open Mesh Full) defects. For instance, when HP is present, there is a 59.4 % chance that both OM and OF defects will also occur. These findings can be used to improve production processes by enabling better defect monitoring, addressing root causes, refining inspection methods, and establishing more effective judgment criteria in the future.

5.2.2. Correlation Analysis

Scatter plots were created between the numeric process parameters and quality characteristics. Their correlation coefficients (r) were calculated. In this research, factors with an r value greater than 0.5 were selected. Figure 8 shows the correlation graphs for the average number of MW defect rates and ten independent variables. It was found that all ten factors had r values higher than 0.5, including beaming tension, beaming speed, beaming station, weaving back roll, weaving speed, weaving tension, weaving timing, weaving loom, weaving front roll, and warp tensile.

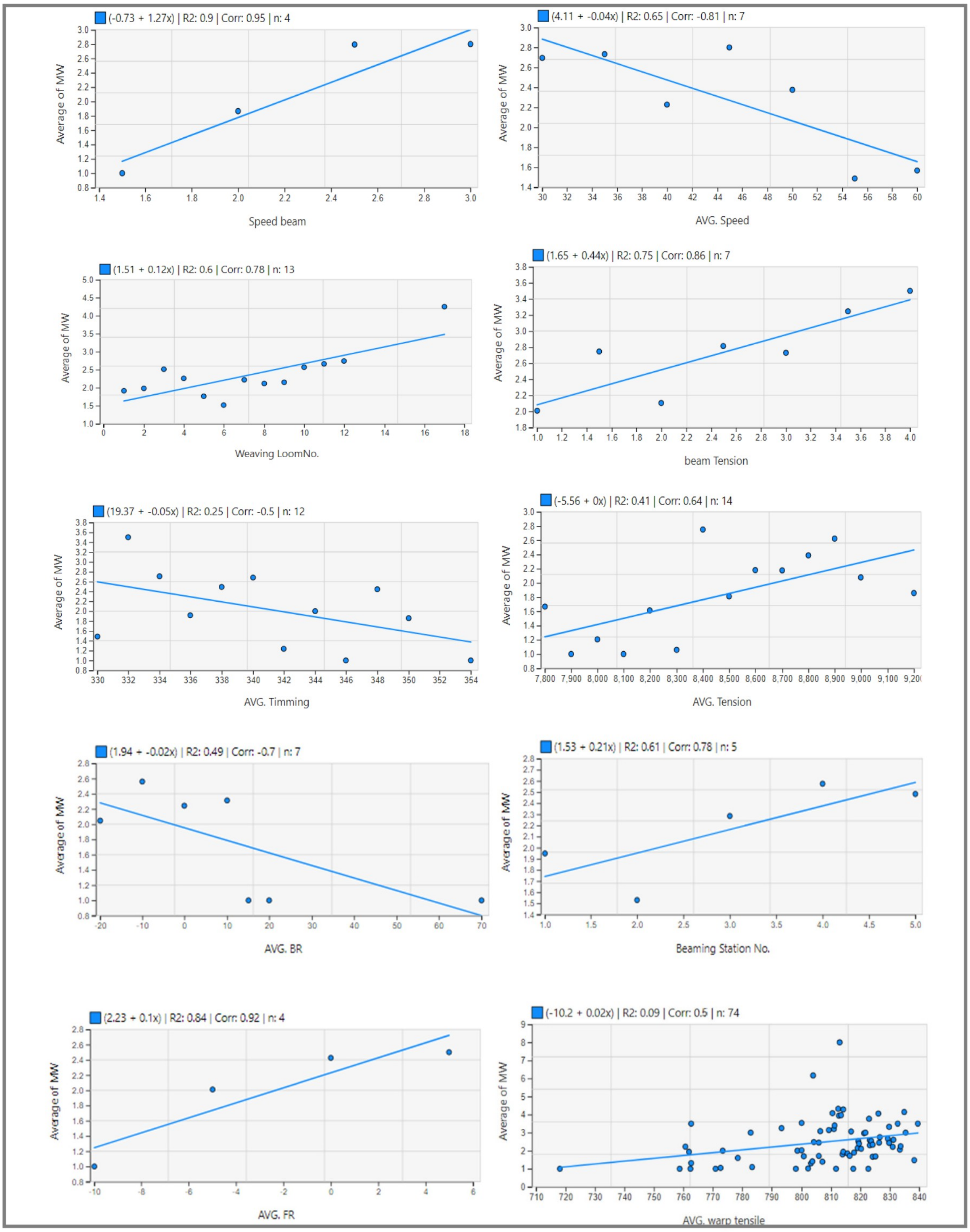


Figure 8. Correlation results and graphs for the MW defect rate

The results of the significant factors are summarized in Table 2. These results will be utilized in the next phase of ML modeling. It is evident that there are conflicting factors that hinder immediate implementation. For instance, beaming speed has an adverse effect on both HP and MW defects. This implies that decreasing beaming speed will increase the HP defect while decreasing the MW defect.

Dependent Variable	Positive Correlation Coefficient	Negative Correlation Coefficient
%STD (Yield)	1. Beaming speed = 0.82 2. Weaving speed = 0.92 3. Warp offset yield = 0.58	1. Weaving tension = -0.66 2. Weaving timing = -0.50 3. Warp elongation = -0.51
HP Defect (Hard Warp)	1. Weaving front roll level = 0.85	1. Beaming tension = -0.76 2. Beaming speed = -0.98 3. Weaving speed = -0.56 4. Weaving back roll level = -0.72
MW Defect (Mark Warp)	1. Beaming tension = 0.86 2. Beaming speed = 0.95 3. Weaving tension = 0.64 4. Weaving front roll level = 0.92 5.Warp tensile = 0.50 6.Beaming station = 0.78 7.Weaving loom number = 0.78	1. Weaving speed = -0.81 2. Weaving back roll level = -0.70 3. Weaving timing = -0.50
CP Defect (Creeper)	1. Beaming tension = 0.76 2. Weaving front roll level = 0.82 3. Weaving timing = 0.54 4.Beaming station = 0.53	1. Beaming speed = -0.99 2. Weaving speed = -0.51 3. Weaving back roll level = -0.83

Table 2. Summary of correlation coefficient analysis results

After completing the visualizing and correlation analysis, a total of 12 significant attributes were identified through visualization, as listed in Table 3. Table 3 summarizes how each factor affects the output variable and which database the variable comes from. It also describes the data type, whether it is real, integer, or nominal. Additionally, it specifies whether the variable values can be adjusted during actual production operations (such as setting parameters for machines) or cannot be adjusted (such as test results for raw materials).

No.	Database	Attributes (independent variable)	Abbreviation	Possible Affected Output (dependent variable)	Data type	Adjustable
1	Beaming process	Beaming tension	B01	CP, HP, MW defect rate	Real	Yes
2		Beaming speed	B02	CP, HP, MW defect rate	Real	Yes
3		Beaming station	B03	MW defect rate	Integer	Yes
4	Weaving process	Weaving speed	W01	HP, MW defect rate	Integer	Yes
5		Weaving tension	W02	MW defect rate	Integer	Yes
6		Weaving back roll level (BR)	W03	CP, HP, MW defect rate	Integer	Yes
7		Weaving front roll level (FR)	W04	CP, HP, MW defect rate	Integer	Yes
8		Weaving time	W05	MW defect rate	Integer	Yes
9		Weaving loom number	W06	MW defect rate	Integer	Yes
10	Mechanical testing	Warp tensile	M01	% Production yield	Real	No
11		Warp elongation	M02	% Production yield	Real	No
12		Warp offset yield	M03	% Production yield	Real	No

Table 3. Summary of important factors from visualization

5.3. Wire Grouping Based on Mechanical Testing

There are two main threads in the weaving process: warp and weft. The warp thread is vertical and positioned from top to bottom. It must be arranged before the weaving process begins and remains stationary throughout the weaving process. On the other hand, the weft thread is horizontal and moves in and out during weaving. The warp threads need to be carefully arranged before weaving since they cannot be adjusted during the process, making them harder to control compared to the weft threads.

The incoming wire undergoes a mechanical property testing process before it is used in production. Based on past data, it has been found that wires entering the process exhibit significant differences in mechanical properties, even if they are sourced from the same supplier. It has been observed that arranging wires with similar mechanical properties for warp direction leads to an improvement in the %STD. However, in the past, the factory categorized wires solely based on the warp tensile value (M01). From the analysis of the relationships in the previous section, it was found that other mechanical properties, such as warp elongation (M02) and warp offset yield (M03), also impact the %STD. To group the wires more accurately, this research applied the LOF value considering M01, M02, and M03 together.

The LOF, a commonly used method for detecting outliers, has been applied to the selection of warp wires. Wires with high LOF values are not used in the warp direction, as they exhibit significantly different characteristics from the group. The objective is to arrange the selected wires in the warp direction to achieve the most uniform characteristics. Table 4 presents the results after calculating the LOF values for the inspection data. A column labelled "Outlier" shows the LOF value for each data point. A lower LOF value indicates that the data point is more similar to others in the group, while a higher value suggests it is more different. Each wire is sorted in ascending order based on its LOF value, and the wires are then arranged in this order along the warp direction of the weaving machine.

ID	Tensile Strength	Offset Yield @0.2%	Elongation at Break	Pail No.	outlier
1	745.1	306.3	63.1	78.0	.906
2	745.6	307.1	65.5	17.0	.922
3	745.2	305.5	64.1	86.0	.934
4	744.8	307.3	62.9	24.0	.935
5	744.3	304.6	64.9	30.0	.937
6	742.7	303.8	64.5	35.0	.981
7	750.8	307.8	63.4	82.0	.983
8	751.0	310.1	64.7	54.0	.998
9	745.2	302.9	65.0	41.0	1.003
10	744.3	308.5	64.8	57.0	1.011
11	747.0	305.3	67.2	44.0	1.029
12	752.5	309.7	66.6	48.0	1.040
13	748.2	306.5	65.0	74.0	1.042
14	741.1	303.0	63.1	70.0	1.043
15	742.8	305.2	60.6	61.0	1.046
16	750.6	310.1	67.1	46.0	1.057
17	749.9	303.7	67.6	45.0	1.060
18	740.8	307.0	62.6	28.0	1.072
19	749.3	311.9	61.6	87.0	1.075
20	758.3	308.9	63.3	1.0	1.086
21	755.0	309.4	69.4	40.0	1.087
22	755.8	310.4	61.9	68.0	1.088
23	751.8	305.3	67.8	37.0	1.089
24	758.5	310.1	66.1	69.0	1.098
25	749.7	302.6	68.2	47.0	1.141
26	753.5	309.9	59.9	73.0	1.141
27	751.6	307.6	59.7	60.0	1.143
28	747.4	304.2	61.9	63.0	1.149
29	754.3	304.7	66.9	12.0	1.157
30	747.0	308.7	59.7	83.0	1.176
31	759.1	308.4	67.7	32.0	1.193
32	743.5	300.4	65.1	6.0	1.216
33	759.0	310.5	68.4	18.0	1.247
34	740.4	306.6	60.8	26.0	1.250
35	745.4	299.7	67.4	14.0	1.262
36	750.2	312.6	59.5	71.0	1.267
37	740.3	303.1	66.5	16.0	1.279
38	743.6	311.0	61.6	22.0	1.298
39	748.6	301.9	71.5	7.0	1.498
40	761.8	312.6	65.9	66.0	1.526
41	755.2	299.3	64.0	15.0	1.768

Table 4. LOF result of wire 0.9mm/ 304

The average M01, M02, and M03 characteristics of the selected wires in the warp direction are combined with all possible setting of machine parameters to create a scoring dataset. This dataset is then employed for ML to predict the %STD value. Subsequently, suitable parameters for the wires in that batch are selected based on the examples that yield high %STD values.

5.4. Selecting Machine Parameters Using ML Techniques

Setting machine parameters in the wire mesh process is divided into two parts: the training phase and the deployment phase, as shown in Figure 9.

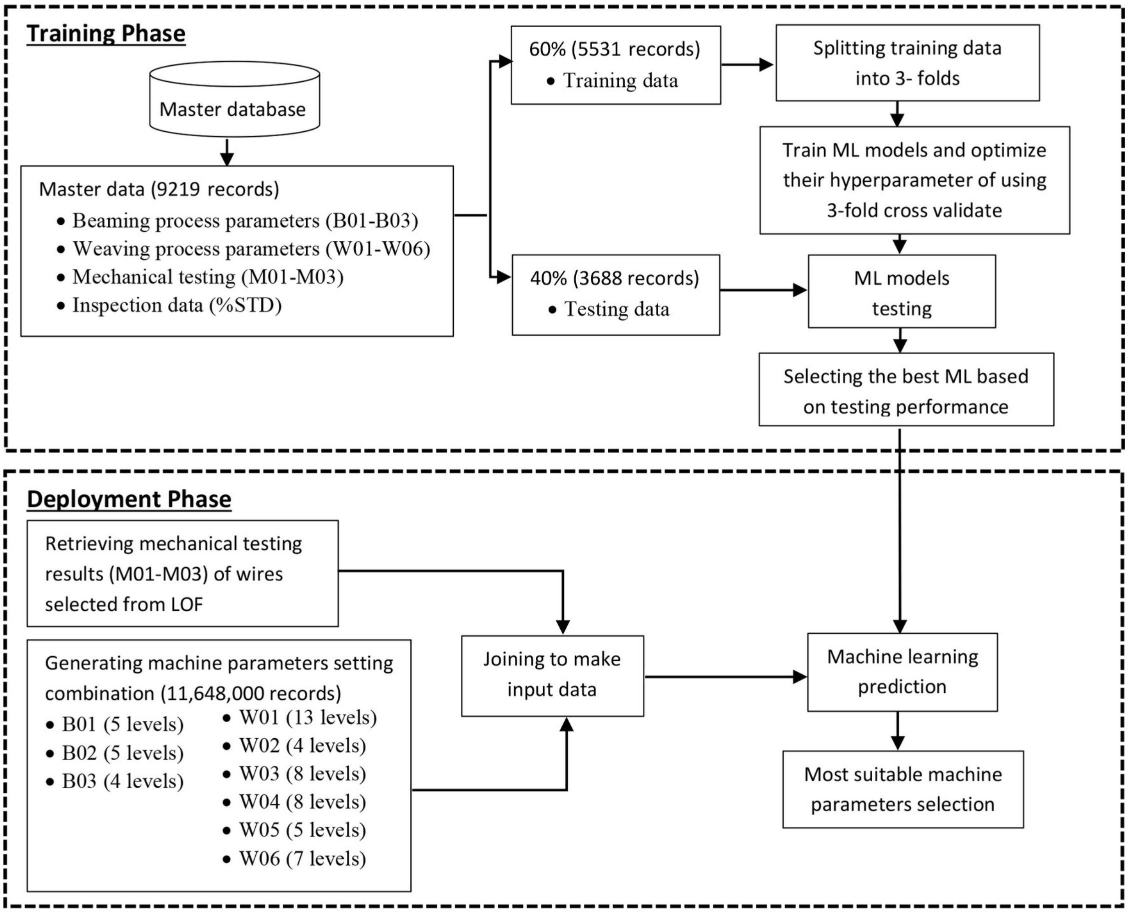


Figure 9. Framework of data flow in wire-mesh's machine parameters setting with ML

5.4.1. Training Phase

To achieve the most accurate models, parameters related to each model type were adjusted using the grid search method. Details of these adjustments are provided in Table 5. For example, the hyperparameter adjusted for the decision tree is the maximal depth, which specifies the length of the longest path from the tree root to a leaf. In this context, the max depth was adjusted from 0 to 26, increasing by 1 each time (a total of 27 runs). It was found that the most suitable value was max depth = 2.

Figure 10 shows a surface plot of GBT grid search results, where the number of trees, maximal depth, and learning rate are plotted on x, y and z axis, while the error rate is displayed by color. From the image, it can be observed that using a low number of trees, maximal depth, and learning rate results in a relatively high error rate, and the point where the lowest error rate occurs is when the number of trees is 90, the maximal depth is 7, and the learning rate is 0.1.

Figure 11 presents an overview of the results comparing different ML models. The bar graph on the left shows the relative error values for each model, with GBT achieving the lowest relative error at 18.0 %. On the right, the bar graph shows the training time for each model, highlighting DT as the fastest to build. Despite its speed, DT has the highest relative error. Since model training can be performed offline before production begins, this study prioritizes predictive error over training time. Therefore, GBT was selected over DT due to its lower error metrics.

ML algorithm	Hyper parameter	Grid search		Optimal value
		Range	Step	
Decision Tree	Maximal depth	0-26	1	2
Random Forest	Number of trees	0-140	40	100
	Maximal depth	0-7	1	7
Gradient Boosted Trees	Number of trees	0-150	60	90
	Maximal depth	0-7	1	7
	Learning rate	0.001-0.100	0.001	0.100

Table 5. Setting of the grid search values to find the best parameters

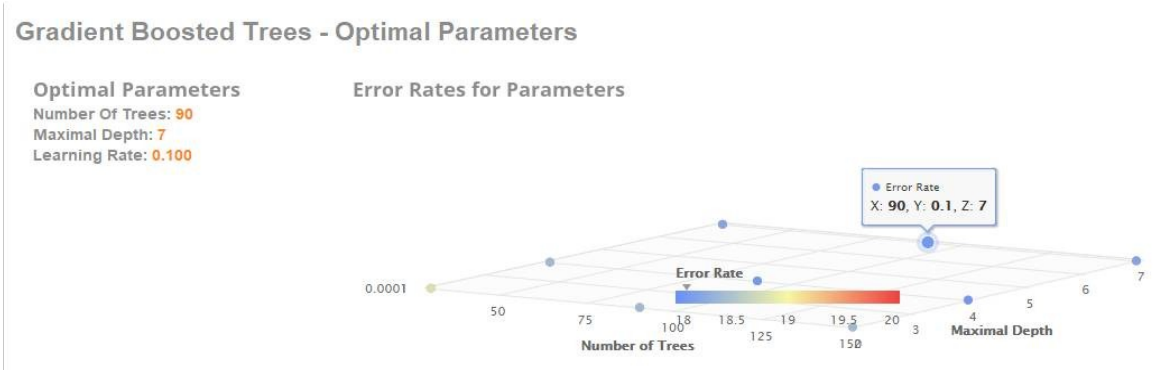


Figure 10. Surface plot of GBT grid search result

However, it is worth noting that even the model with the lowest error (GBT) still has a relatively high error rate. This can be attributed to the inherent complexity of the production process, the large number of influencing variables, and limitations in the factory's data collection capabilities, which restricted the ability to gather comprehensive input data. Despite these challenges, consultation with factory management confirmed that an error in this range is considered acceptable for operational decision-making. This demonstrates that there is room for further enhancement through expanded data collection. The current model provides practical value and meaningful performance gains for the factory's needs.

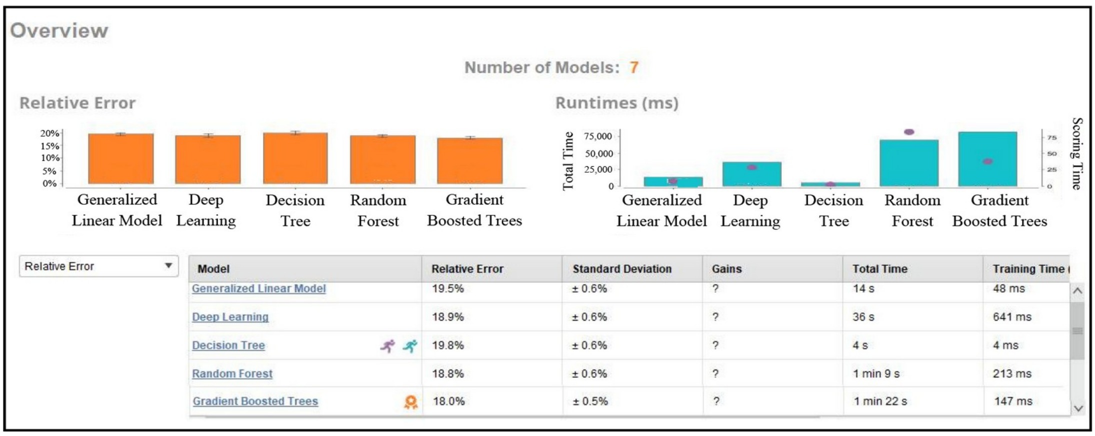


Figure 11. Overview comparison between ML algorithms

Table 6 shows the averages performance metrics for the ML models, with standard deviations indicated in parentheses. It can be observed that GBT is the model with the lowest error, whether measured by RMSE, relative error, absolute error, or squared error. Additionally, this model has low variability (as seen from the standard deviation values) and the highest correlation of results. This makes GBT the best-performing model among all the models compared.

ML algorithm	Performance measurements of held-out test set				
	RMSE	Relative error	Absolute error	Squared error	Correlation
Decision Tree	0.21 (±0.006)	19.8 % (±0.6)	0.21 (±0.006)	0.044 (±0.003)	0.000 (±0.000)
Generalized Liner Model	0.205 (±0.006)	19.5 % (±0.6)	0.205 (±0.006)	0.042 (±0.002)	0.227 (±0.027)
Deep Learning	0.195 (±0.005)	18.9 % (±0.6)	0.195 (±0.005)	0.038 (±0.002)	0.366 (±0.041)
Random Forest	0.195 (±0.005)	18.8 % (±0.6)	0.195 (±0.005)	0.038 (±0.002)	0.394 (±0.029)
Gradient Boosted Trees	0.187 (±0.005)	18.0 % (±0.5)	0.187 (±0.005)	0.035 (±0.002)	0.459 (±0.020)

Table 6. The average and standard deviation of performance metrics on held-out test set

5.4.2. Deployment Phase

After obtaining the wire-mesh process ML model from the previous steps, the next step is to create a dataset for prediction. For this prediction dataset, two types of data will be used. The first part consists of mechanical test data for incoming raw materials in the new wire batches. The second part involves generating combinations of all possible machine setups from the 12 related variables, as listed in Table 7. The total number of records that can be generated is 11,648,000 records (5×5×4×1×3×4×8×8×5×7). The specified levels are determined by experts from the factory.

Parameter	Number of levels	1	2	3	4	5	6	7	8	9	10	11	12	13
B01	5	1	2	3	4	5								
B02	5	1.5	2	2.5	2.8	3								
B03	4	1	2	3	4									
W01	13	1	2	3	4	5	6	7	8	9	10	11	12	17
W02	4	30	40	50	60									
W03	8	7800	8000	8200	8400	8600	8800	9000	9200					
W04	8	330	334	338	342	346	350	354	358					
W05	5	-10	-5	0	5	10								
W06	7	-20	-10	0	10	15	20	70						

Table 7. Possible setting of wire-mesh's machine parameters

Figure 12 shows the influence of each variable on the response, derived from applying the Local Interpretable Model-agnostic Explanations (LIME) technique to the GBT model. Among all factors, weaving speed had the highest positive impact, indicating a strong association with increased yield in the dataset. Other variables with notable negative impacts included weaving time, warp offset yield, warp elongation, and weaving tension, suggesting that higher values of these factors were linked to reduced yields. Several additional factors, such as beaming station, warp tensile, weaving back roll level, and weaving loom number, showed smaller positive contributions to yield. The results highlight the complex nature of the production process and underscore the importance of closely monitoring and optimizing the most influential parameters.

However, the surprising positive effect of weaving speed warrants further investigation, since in most manufacturing processes, increasing production speed usually leads to more defects. This could be due to various reasons. Firstly, it may be influenced by specific data characteristics or external factors not directly controlled within the process. Secondly, the data used to construct the model may have been collected during periods when the speed was below the optimal range, so increasing the speed could have moved the system into a better-performing window. Additionally, using historical data may introduce bias; for example, higher speeds may have only been used with wire from manufacturers with higher standards, which already tend to produce higher yields.

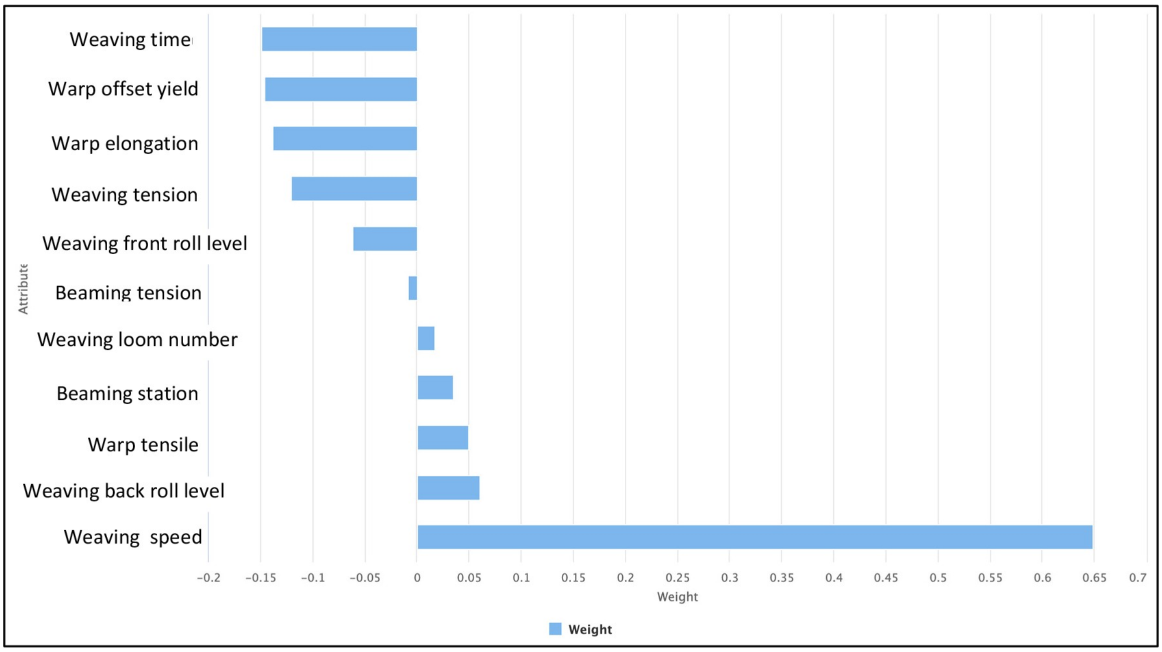


Figure 12. the influence of each variable on the response, derived from applying the LIME technique to the GBT model

Table 8 shows the results of forecasting %STD using GBT. These forecasts have been sorted and filtered to display only combinations that have a yield of greater than 90 %. The results are arranged in descending order based on the %STD. Engineers then consider selecting the most suitable machinery and parameters, taking into account the following key factors:

- **Machine Availability**: Machine availability plays a crucial role in reducing production downtime and increasing operational efficiency. We select beaming and loom machines with the highest current availability, the fewest failures and repairs, and the most consistent operation.
- **Capabilities and Limitations of the Beaming and Loom Machines**: Each beaming and loom machine has different capabilities, such as width, length, and speed, required to meet customer specifications. The predicted machines must be able to accommodate these varying requirements.
- **Manpower**: The skills and availability of personnel significantly influence operational efficiency and the effective utilization of the machines, which may, in turn, impact the final results. For example, if the regular operator of a required loom is absent, the replacement operator should have equivalent skills and experience to maintain consistent performance.
- **Production Settings Affecting Quality and Efficiency**: When yields are equal, we may consider using higher beaming or weaving speeds to increase production rates, as this allows for faster processing.
- **Production Settings Affecting Machine Longevity**: Similarly, if yields remain constant, we may opt for lower beaming or weaving tension. Reduced tension minimizes stress on the machine, decreasing the risk of excessive wear and helping to prolong the machine's lifespan.

Average warp elongation	Average offset yield	Average tensile	Beaming station	Beaming speed	Beaming tension	Weaving loom number	Weaving speed	Weaving tension	Weaving time	Weaving front roll level	Weaving back roll level	Prediction (%STD)
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9000.0	334.0	-10.0	10.0	0.901
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9000.0	334.0	-10.0	20.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9000.0	334.0	-10.0	70.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9000.0	334.0	-5.0	10.0	0.901
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9000.0	334.0	-5.0	20.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-5.0	70.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-10.0	10.0	0.901
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-10.0	20.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-10.0	70.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-5.0	10.0	0.901
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-5.0	20.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	50.0	9200.0	334.0	-5.0	70.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-10.0	10.0	0.909
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-10.0	15.0	0.907
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-10.0	20.0	0.917
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-10.0	70.0	0.917
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-5.0	10.0	0.909
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-5.0	15.0	0.907
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-5.0	20.0	0.917
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	330.0	-5.0	70.0	0.917
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-10.0	10.0	0.918
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-10.0	15.0	0.916
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-10.0	20.0	0.922
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-10.0	70.0	0.922
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-5.0	10.0	0.918
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-5.0	15.0	0.916
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-5.0	20.0	0.922
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	334.0	-5.0	70.0	0.922
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	338.0	-10.0	20.0	0.905
64.6	306.7	749.1	1.0	1.0	1.0	1.0	60.0	9000.0	338.0	-10.0	70.0	0.905

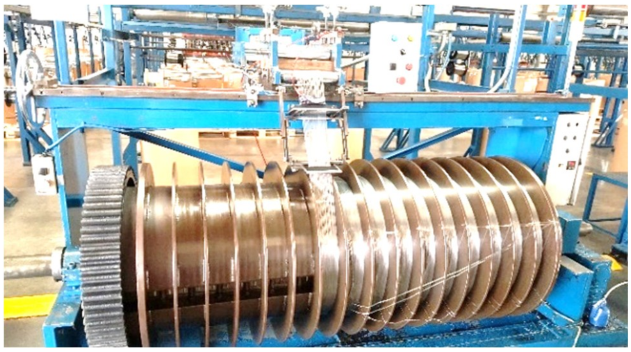
Table 8. Examples of prediction results for a set of new incoming wire

After obtaining the suitable parameters, they were then tested in the actual process by conducting a total of 12 beam tests. Figure 13 illustrates the machine setup for the testing, with Figure 13a) showing the arrangement of wires in the warp direction according to the values obtained from LOF. Figure 13b) illustrates the machine setup for beaming, with three relevant variables: beaming tension (B01), beam speed (B02) and beaming station (B03). Figure 13c) illustrates the adjustment of the weaving machine, which involves a total of six variables: weaving speed (W01), weaving tension (W02), weaving back roll level (W03), weaving front roll level (W04), weaving time (W05) and weaving loom number (W06). Figure 13d) shows the inspection area after the weaving process. The quality control inspector checked for major blemishes in each roll through visual inspection and measured the wire properties in accordance with the quality control inspection record.

Process control and monitoring were applied to critical points. This step ensures that each stage of the manufacturing process experimentation is controlled in accordance with the chosen prediction results. Beaming tension, beaming speed, weaving speed, weaving tension, weaving timing, weaving front roll level, and weaving back roll level were all controlled and monitored. During deployment, all processes related to quality or experimental results are subject to process control and performance monitoring with hourly, shift, and daily reports. After successfully setting up the system, we implemented the new system with a new set of incoming wire of a 0.9mm/304 wire mesh product, totaling 12 beams, and the results are shown in Table 9. The experimental result shows that the average yield of beam lot no. 5 is the lowest at 70.2 %, while beam lot no. 10 has the highest yield at 97.3 %. The overall average is 91.3 %, which surpasses the company's KPI target of 90 %.

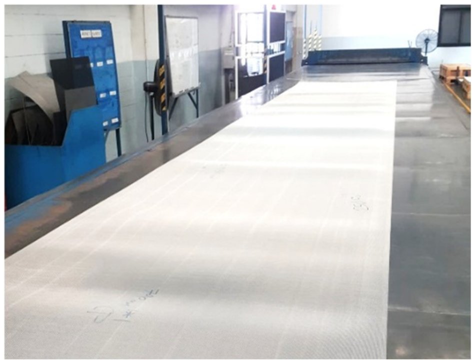
In comparing the %STD values obtained from the prediction using GBT with those derived from the actual production process (in Table 9), some differences are evident. In this regard, the %error has been calculated based on the discrepancy between the two values. CP defects were found in beam lot no. 1, 4, and 5. Both CP and HP defects were found in beam lot no. 5, while OF defects were found in beam lot no. 3. The defects that occurred directly affected productivity, especially in the beam lot no. 5, where two types of defects occur, causing the yield to be the lowest of all beams at 70.2 %. Given the data from Table 9, we calculate the confidence level equals to 4.19. Therefore, the 95 % confidence interval for the population means is approximately (87.11, 95.49), which means that the average of the population falls within this interval.

a) Arranging the wire according to LOF result



b) Setting up the beaming process

c) Setting up the weaving process



d) Quality inspection

Figure 13. Machine setup and quality inspection of the 12 testing beam

Beam Lot No.	Wire Maker Warp	Wire Batch No.	Average warp elongation	Average offset yield	Average tensile	Beaming station	Beaming speed	Beaming tension	Weaving loom number	Weaving speed	Weaving tension	Weaving time	Weaving front roll level	Weaving back roll level	Actual %STD	Prediction %STD	Error %	Defect
1	CFW	MTC-04	64.6	306.7	749.1	B03	2	1.0	1	50	8500	336	0	0	79.2	91.9	16.0%	CP
2	CFW	MTC-04	64.6	306.7	749.1	B03	2	1.0	1	50	8000	336	0	0	94.4	91.3	-3.3%	no defect
3	CFW	MTC-04	64.6	306.7	749.1	B03	2	1.0	1	50	8200	336	0	0	93.3	90.8	-2.7%	OF
4	CFW	MTC-04	64.6	306.7	749.1	B03	2	1.0	1	50	8200	336	0	0	95.4	90.8	-4.8%	CP
5	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.5	1	50	7900	336	-5	0	70.2	91.3	30.1%	HP, CP
6	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.5	1	50	7900	336	-5	0	90.2	91.3	1.2%	no defect
7	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.5	1	50	7900	336	-5	0	96.9	91.3	-5.8%	no defect
8	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.5	1	50	7900	336	-5	0	89.4	91.3	2.1%	no defect
9	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.5	1	50	7900	336	-5	0	95.5	91.3	-4.4%	no defect
10	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.0	1	50	7900	336	-5	0	97.3	91.4	-6.1%	no defect
11	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.0	1	50	8000	336	-5	0	96.9	91.9	-5.2%	no defect
12	CFW	MTC-04	64.6	306.7	749.1	B03	2	2.0	1	50	8000	336	-5	0	96.3	91.9	-4.6%	no defect
														AVG.	91.3	91.4		
														MIN	70.2	90.8		
														MAX	97.3	91.9		

Table 9. Actual %STD vs prediction Results of 12 beams

To understand the underlying cause of the error, we examined the production data and found that the diameter of some wires after weaving, specifically at the point where the effect of beam lot no. 5 occurred, was smaller than that of the adjacent wires. Normally, the rate of diameter reduction after weaving is in the range of 5 to 10 percent. However, in some tanks where beam lot no. 5 produced HP, the diameter reduction rate after weaving reached 15 percent, resulting in an unusually high amount of HP waste. The rate of diameter reduction after weaving depends on how well the wire manufacturer controls the parameters and consistency of the cold drawing process, which is not directly controlled in the wire weaving process.

While the overall error metrics are low, the acceptability of residual errors must be carefully considered, especially when larger errors indicate potential assignable causes in the process. In cases like beam lot no. 5, residual errors serve as indicators of underlying production issues and highlight the value of using predictive models as diagnostic tools for process improvement.

6. Conclusion

This research introduces novel DDQI approaches to address defects problems by analyzing existing production data with ML along with data visualization and correlation analysis. The goal is to establish a predictive model for production yield and process settings. During the creation of the master database, data and information were collected from various processes. The key emphasis in database creation lies in ensuring the correctness and accuracy of data for each process, which is traceable throughout every production step.

Once the master database is complete, correlation analysis is conducted to identify insignificant factors. Association rules may also be employed to investigate relationships between defects. Insignificant factors are then excluded from the master database, retaining only significant factors for constructing the training dataset used to train the prediction model. In the prediction model training process, multiple data mining and ML algorithms are utilized, and the best algorithm is chosen. The subsequent step involves generating a new dataset by combining new inspection data with all levels of controllable factors in production settings. These combinations are then applied to the best prediction model. The production process settings associated with the highest yield records are chosen for implementing the actual production process. Resource availability, such as machines and equipment, is also considered when selecting process settings.

To demonstrate the framework, we utilized a case study involving the stainless-steel woven wire mesh process. The master database encompassing a total of 38 factors. After screening factors through visualization and correlation analysis, 12 factors remained. These were employed to develop ML models for predicting production yield, with the GBT model chosen based on the lowest error. New incoming wire inspection data were used to group wires with similar mechanical properties to minimize variation. Inspection data were then combined with all possible production parameter settings to generate a scoring dataset for the GBT. The actual implementation on 12 beam lots resulted in actual yields ranging from 70.2 % to 97.3 %, with an average yield of 91.3 %. This demonstrates a significant improvement in production yield.

The proposed DDQI framework can be applied with relatively low cost and minimal disruption to the process, as it makes use of existing data in the database and requires no additional experimentation. It can be implemented in any manufacturing process, even when the process is operating at its maximum capacity. The DDQI determines parameter settings based on empirical evidence rather than subjective opinion, making the decision-making process more reliable. Moreover, it employs ML, with the ability to model complex patterns and relationships that may be challenging to capture using traditional quality control methods. This feature makes it suitable for processes with advanced technology and intricate relationships. The model exhibits high adaptability, allowing it to cope with dynamic environments. If the nature of the process changes, the model can be retrained with new data. Therefore, the DDQI can be used to optimize processes, reduce waste, and enhance overall efficiency with relatively low cost and minimal process disruption.

Although the main objective of the case study company, which is to reduce defective products, has been achieved, the performance of the GBT model with a relative error of 18% indicates that there is still room for improvement. This could potentially be achieved by collecting additional relevant data to better capture the complexity of the production process, as well as by expanding the analysis to include other types of ML models. Additionally, the current approach estimates all parameters simultaneously, which may not fully exploit the sequential nature of the process. It may be beneficial to divide the process into distinct stages and estimate parameters in process-specific groups. This stage-wise approach may help reduce the prediction burden on the ML model and potentially reduce error metrics.

The DDQI is applicable across all manufacturing industries. However, it is crucial to note that the master database should consist of all factors potentially impact quality performance but only significant factors to the quality characteristic of interest should be selected for model building. The inclusion of insignificant factors may impact training time and error metrics. Ultimately, the model can only be as good as the data used to train it.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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