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Integrating between Taguchi methodology and boosted decision trees machine learning: a case study in enhancing quality electrical conductor manufacturing

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Abstract

This study introduces an integrated approach that combines Taguchi methodology and machine learning techniques to enhance production quality in electrical cable manufacturing. The Taguchi method was employed to identify critical factors such as compaction percentage, wire diameter, raw materials, assembly procedures, and operating voltage, converging on an optimal solution. Various decision-making algorithms, including decision trees, random forests, boosted decision trees, linear regression, and k-star, were utilized alongside evaluation metrics like sensitivity, F1-score, and accuracy. The integration of Taguchi and machine learning facilitated the identification of key process parameters and their optimal settings, significantly improving the quality and efficiency of cable manufacturing. The optimal solution achieved included a 666 kg/km weight, 2.64 cm diameter, and a 30% compaction rate, reducing the poor quality cost from 5% to 1.7%. This synergistic approach allowed for the optimization of critical process factors, resulting in significant improvements in product quality and reductions in defects and costs.

Keywords: machine learning, decision tree algorithms, electric cables, doe, ANOVA,Taguchimethod.

1. Introduction

Power cables have gained prominence in electrical power delivery due to their reduced environmental impact, compliance with public concerns, and high reliability, particularly for offshore renewable energy transmission. Moreover, underground energy transmission was recognized as a method to provide reliable power supplies at a lower total cost, driving the increasing demand for high-quality power cables. In the context of electricity market reformation and liberalization, the reliability of these cables is crucial for maintaining an uninterrupted, quality power supply. Consequently, developing improved testing and measuring technologies has become essential in manufacturing high-quality power cables to meet the growing electrical demand.

Furthermore, selecting materials and production methods significantly influences conductor conductivity and weight, impacting performance and cost-effectiveness. Achieving repeatability and reproducibility in conductor design is crucial for quality and reliability, particularly in advanced packages and assemblies with lead-free wetting and higher process temperature requirements. Additionally, the manufacturing system design plays a vital role in product quality, with reconfigurable manufacturing systems offering various configuration alternatives that affect the final product.

Cable chain systems can impact precision and articulation as manufacturing equipment and studies have shown that eliminating cable chains can improve accuracy and reduce articulation. Moreover, the miniaturization of conductor tracks and circuit carriers in electronic packaging can increase component temperatures and accelerate system degradation, emphasizing the critical importance of efficient thermal management for ensuring long-term reliability in electronic systems. This paper is structured as follows: section 2 explains the literature review. Section 3 is devoted to applying Taguchi and machine learning methodology. Section 4 provides results and a discussion, and section 5 concludes the research.

2. Literature review

The Taguchi method has been widely applied in various manufacturing contexts, including flexible manufacturing systems performance optimization [10], component machining [11], and IT infrastructure security risk assessment [12]. Its versatility extends to optimizing manufacturing processes for diverse products such as printed circuit boards [13], and light-storing ceramics [14].

This method offers significant benefits, systematically optimizing product quality and reducing costs [15]. Studies

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have demonstrated its efficacy in yielding better finishing and improved surface roughness in manufacturing processes [16]. Furthermore, the Taguchi method has been successfully employed to minimize total cost under stochastic breakdowns in manufacturing processes [17]. Researchers have integrated the Taguchi method with other techniques to enhance its effectiveness in manufacturing optimization. These combinations include response surface methodology [18], neural networks [19], and texture profile analysis [20]. This integration of methodologies demonstrates the adaptability and continued relevance of the Taguchi method in addressing complex manufacturing challenges.as illustrated in Fig. 1.

The Taguchi method's capability to optimize product designs and manufacturing processes and its effectiveness in enhancing the efficiency and stability of quality control measures suggests its potential as a valuable tool in electric conductor manufacturing. By leveraging this method, manufacturers may improve their electric conductors' quality, cost-effectiveness, and performance [13].

In electric conductor manufacturing, the Taguchi method has been utilized to determine the optimal combination of wire diameters, raw materials, and resistances. For instance, in electrochemical machining (ECM) processes, Kumar et al. applied the Taguchi method to optimize insulation process parameters, including the gap between work material and tool, discharge current, and electrolyte concentration. They applied voltage to achieve optimal surface finish insulation [14], [15]. The method has demonstrated its potential to enhance efficiency and cost-effectiveness in electric conductor manufacturing by minimizing the reduction rate in production, thereby lowering overall production costs [16]-[19]. Chen et al. further investigated the effect of simultaneously changing influential parameters of the electrodeposition method using a hybrid approach with response surface methodology (RSM) [20], highlighting the method's applicability in improving the quality and performance of final electric conductor products. Moreover, the Taguchi method's application in electrical machine design indicates its potential for use in the manufacturing process of electric conductor insulation [21-23]. The Taguchi method and Analysis of Variance (ANOVA) combination could contribute significantly to various aspects of electricity.

Many researchers studied Quality Control added to Machine learning techniques, such as deep learning models, are employed for automated defect detection and classification in conductor manufacturing, leading to improved product quality and reduced manufacturing costs [24]., and also, these models learn from diverse datasets of defect images or videos, enabling the detection of various defect classes and promoting time savings while achieving improved accuracy [25].

Additionally, Machine learning (ML) has emerged as a powerful tool for predicting and improving the quality of conductor manufacturing. ML methods predict work piece quality in early manufacturing stages, potentially leading to significant savings in time, cost, and resources [26]. In industrial applications, such as at Bosch Rexroth AG, ML has been employed to predict the diameter and roundness of bores in manufacturing processes [27]. In the automotive industry, ML techniques, including linear regression and Long Short-Term Memory (LSTM) networks, predict the quality of spot-welding processes, enabling root cause analysis and preventive actions [26]. ML offers an efficient approach to learning models for quality prediction directly from large amounts of measured process data, as demonstrated in the abrasion-resistant material manufacturing process [27].

The global demand for reliable and efficient electrical infrastructure necessitates high-quality electric cables. However, achieving consistent quality in electrical conductor manufacturing remains a significant challenge, often resulting in material waste and increased production costs. Noncompliant conductors can lead to overheating, electrical losses, reduced service life, and even safety hazards.

This study addresses this critical issue by proposing a novel hybrid approach that combines the powerful statistical methods of Taguchi methodology with the predictive capabilities of machine learning (ml) techniques. Our objective is to optimize the electrical cable manufacturing process by:

1. Minimizing excess material consumption: reducing material waste is essential for cost reduction and environmental sustainability.
2. Identifying influential parameters: identifying the critical factors that impact conductor quality will allow for targeted process improvements.
3. Calculating cost implications: quantifying the cost savings associated with implementing the optimized process will demonstrate the economic viability of the proposed approach.

By integrating Taguchi's robust design principles with ml's ability to analyze large datasets and predict outcomes, we aim to develop a comprehensive framework that effectively pinpoints and optimizes critical process factors, ultimately leading to improved product quality, reduced defects, and enhanced cost-effectiveness in electrical cable production. Demonstrated The effectiveness of this hybrid approach was a case study focusing on a specific cable type.

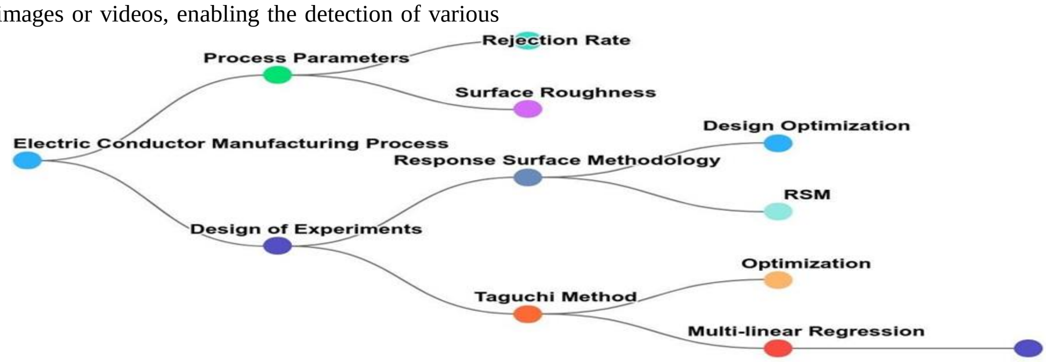

Figure 1. Relation of effect parameters

3. Methodology

This research paper proposes a synergistic framework combining Taguchi methodology with machine learning (ML) techniques to optimize the manufacturing process for electrical conductors, aiming to enhance product quality and minimize material consumption.

3.1. Taguchi Method

The Taguchi methodology forms the basis of our experimental design. It leverages statistical Modeling to systematically examine the relationships between crucial input factors, such as compaction percentage, wire diameter, raw material composition, assembly procedures, operating voltage, and critical output responses like conductivity, tensile strength, and weight. Using Taguchi principles, strategically designed experiments were conducted to generate data that elucidate the complex interactions within the conductor manufacturing process. Taguchi's quality control method is a prominent approach in engineering. It highlights the essential roles of research and development (R&D) and product design and development in minimizing defects and failures in manufactured products. Widely used for quality optimization, this method reduces variation and defects in products and processes. A key aspect of this approach is robust design, which involves creating products or processes that are resilient and capable of performing effectively under various conditions, thereby reducing the influence of external factors.

This study's primary experimental objective is to decrease conductor weight while ensuring electrical resistance remains at or below 0.125 ohms. The investigation targets critical variables that affect these outcomes, applying a significance level (α) of 0.05. The factors under consideration include compaction percentage with levels set at 15, 20, 25, and 30 and wire diameter with levels set at 2.63, 2.64, 2.66, and 2.67 mm. To achieve a robust experimental design, the study requires 80 samples, calculated as 5*4^2, to account for the two factors with four levels each. This sample size ensures a comprehensive representation of the conditions under investigation. An experimental data sheet was prepared to record the response values for each of the 80 trial conditions, essential for analyzing and determining mean response metrics.

3.2. Data Collection

The parameters that influence the performance and quality of electrical cables are multifaceted and have been extensively studied in literature. The choice of conductor material and its cross-sectional area directly impact the cable's resistance, current-carrying capacity, and thermal dissipation characteristics, with larger conductor sizes reducing power losses and improving efficiency [39]. The insulation material and wire diameters also play a crucial role, as the dielectric properties and wire diameter affect the cable's voltage rating and ability to withstand electrical stress while balancing cost, weight, compaction percentage, raw material composition, assembly procedures, operating voltage and the required level of protection [40]. Additionally, the cable's overall construction, including shielding and armoring layers, can impact its electromagnetic compatibility and mechanical resistance to external factors such as abrasion, impact, and corrosion [28]. Data was collected over one year using a control chart and process capability to measure the performance of defects, which is the material consumed over the upper specification limit. (if use = 2000 kg and actual 2500kg, then weight consumed =500kg, and any weight less than the lower specification limit with specific resistance is considered the best condition).

3.3. Manufacturing processes

The cable manufacturing process shown in Figure2 can be described as follows:

1. Raw Material: Start with raw material for cable production.
2. Drawing: The raw material is drawn into wires.
3. Stranding: The wires are stranded together to form a conductor.
4. Insulation Decision:
- If Medium Voltage (MV), the conductor is used for the Overhead Transmission Line (O.H.T.L), and the process ends.
- If Low Voltage (LV), proceed to Insulation.
5. Insulation: The cable is insulated.
6. Screening: The cable is screened for additional protection (for high-voltage cables).
7. Assembly: The insulated wires are assembled.
8. Bedding: A bedding layer is applied to the cable for mechanical protection.
9. Armored Cable Decision:
- If the cable needs to be Armored, proceed to armoring.
- If no armor is required, the process ends.
10. Armoring: Armoring is applied to protect the cable from physical damage.
11. Sheathing: A sheath is applied over the armored cable for environmental protection.
12. Testing: The cable is tested for quality and performance.
13. Warehouse: The tested cables are stored in a warehouse.
14. Delivery: The finished cables are delivered to the customer.

The main two processes are drawing and stranding. The drawing process is a mechanical process to reduce the wire diameter by tension force between 17 to 33 % of the first diameter by passing the wire through several dies of a specific sequence till we get the required diameter. In the stranding process, one wire was in the center of the conductor; a second layer containing several wires was stranded around it, so the conductor of cables consists of several strands of wire in a circular cross-section. Figures 3 (a and b) present systematic diagram for the drawing and stranding processes.

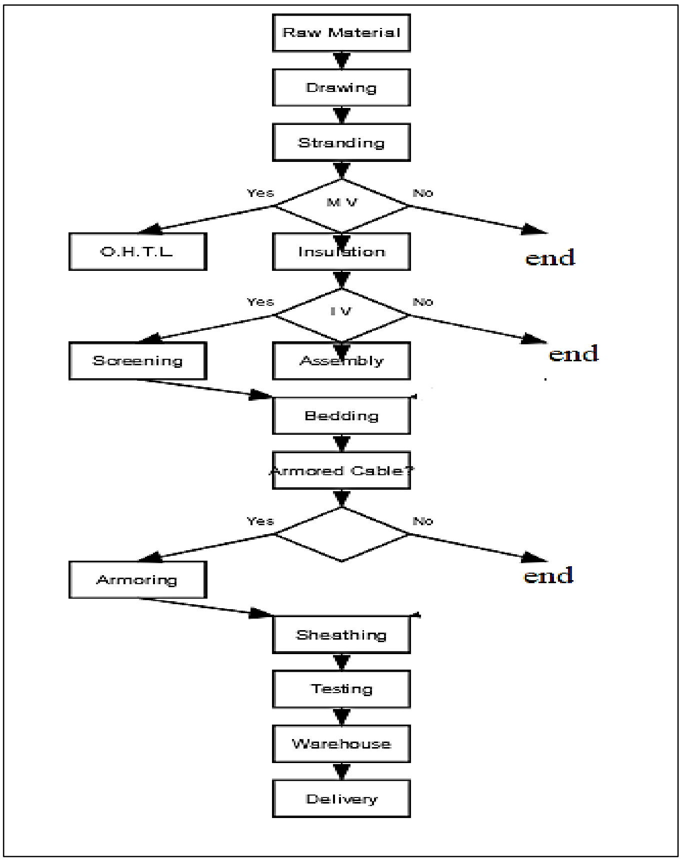

Figure 2. Flow chart of the cable manufacturing process

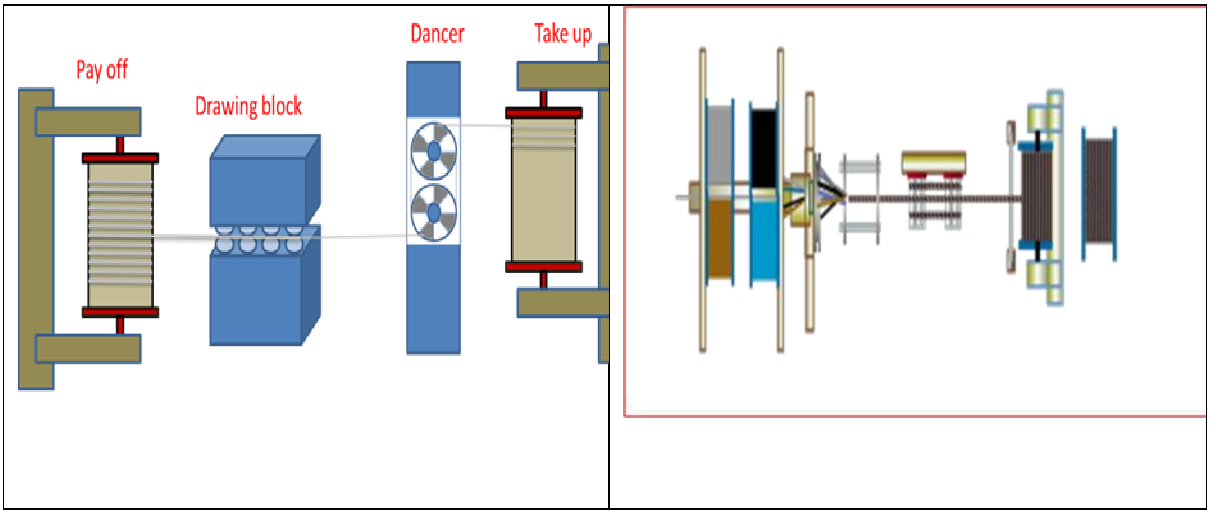

Figure 3. a) drawing process b) standing process

3.4. Problem Definition

A dedicated team comprising the authors, operators, quality personnel, production engineers, and management was established. This team engaged in multiple brainstorming sessions and meetings to thoroughly define the problem and gather relevant data. Historical preliminary data were collected to understand the nature and scope of the existing issue. The team employed demand rate criteria to evaluate different cable types, as this metric substantially impacts financial performance. Specifically, data on the average annual demand rate over one year for various cable types were gathered. Pareto analysis determined that the medium voltage line had the highest demand, representing 39.2% of the total market. As a result, the project was primarily focused on the medium voltage line.

The problem can be summarized as the company's challenge in managing an increase in material consumption during the manufacturing of its products, leading to an overall increase in the weight of the cables, higher manufacturing costs, and diminished process efficiency. In response, top management resolved to establish a team tasked with applying Taguchi methodologies integrated with hybrid machine learning to address and resolve this issue. Table 1 outlines the scope of improvement costs and the defect percentage relative to costs for each process.

Table 1. Over cost and defect of each process

material	over cost (l.e)	cost %*	defect (kg)	defect rate%
conductor	29168	22	36	0.1%
insulation	30040	22	1163	3.6%
copper tape (screening)	30054	22	1437	4.5%
polypropylene filler	5764	4	4305	13.4%
polypropylene tape	496	0.37	449	1.4%
PVC sheathing	9414	7	9082	28.2%
armoring	14138	10	3830	11.9%
PVC bedding	13222	9	11939	37%
total	132300	100	32241	100%

After determining defect rates, deciding the cost of material, and assessing the importance and effect of processes on cable, a selection matrix was used to rate the factors and their potential impact cable weight. Based on these ratings, a priority order was set to determine the vital few from the trivial many—Table2.

It shows a weight for each factor according to its importance in affecting cost for every process and a value for these factors (cost, significant parameters, etc.), as shown in Table 3. To find the total effect of every process on the overall cable manufacturing product, the weight for each factor is multiplied by its value for the process, and collection for every factor is performed. The overall process weight is given byeq.1.

$$\mathrm{opw} = \sum_{i=1}^{n} \mathrm{piwi} \quad (1)$$

pi is the process value for factor i, and wi is the weight for factor i. The percentage contribution for every process was divided by the overall process weights for all processes.

These lection matrix shows that the drawing and stranding processes have the most significant ratings (19%and20%), which means that the conductor is the core and essential part of the cable manufacturing process. Therefore, we have decided to work with these two processes for improvement.

3.4.1. Cause and effect matrix

In describing the problem, all measurable variables, including inputs and outputs, were incorporated into the cause-and-effect matrix. This matrix assigns weights to each output variable (y) according to its significance. Subsequently, each input variable (x) was assessed based on its correlation with the respective output variables. The calculations, grounded in both importance and correlation, identify the input variables with the highest scores as the most suitable candidates for data collection, as illustrated in Table 3. The results indicate that wire diameter, elongation, tensile strength, resistivity, and raw material diameter are the most critical factors influencing the conductor's performance. Among the manufacturing process outputs, conductor weight and resistance are identified as the most significant.

Table 2. Selection matrix of processes

selection matrix						
	cost	sigma level	effect on cable	management	total	percent
importance	8	5	9	5		
processes	ratings					
drawing	9	8	10	10	252	19%
stranding	10	9	10	10	265	20%
insulation	7	6	5	7	166	13%
screening	6	4	3	7	130	10%
assembly(filler)	1	5	4	2	79	6%
assembly(tape)	3	5	6	2	113	9%
bedding	3	6	6	3	123	9%
sheathing	2	6	5	4	111	8%
armoring	2	2	3	3	68	5%

Table 3. Cause and Effect Matrix

Process Step	**Process Input**	**Importance to Y's**	**Wire Breaker**	**Engine**	**Table**	**Central Runner**	**Central W/W**	**Ingrid Arm**	**Layer Arm**	**Interstrand**	**Total**
Drawing	Conductor Type	50	0	0	6	9	6	6	6	9	795
	Resistivity	30	0	0	6	9	6	6	6	9	720
	Raw Material Diameter	20	9	9	6	0	0	0	0	0	915
	Raw Material Tensile	10	9	9	3	0	0	0	0	0	615
	Raw Material Elongation	10	9	9	3	0	0	0	0	0	615
Stranding	Wire Diameter Tensile Strength	50	9	9	3	9	9	9	9	9	1245
	Compaction Percent	15	9	3	3	9	9	9	9	9	1275
total		210	120	120	60	120	120	60	60	570	210

The causes of increasing conductor weight could be summarized as follows:

- Due to the absence of a standardized brake setting, operators continuously adjust the compaction percentage during manufacturing. This practice contributes to increased open lay length, as depicted in Table3.
- Occasionally, the conductor's resistance exceeds the specified requirements during the stranding process. To rectify this, operators insert larger wire diameters into the conductor's center, which results in an increase in conductor weight.
- Additionally, when the drawing machine's dies become scratched, operators increase the distance between the rolls to prevent further wire scratching. This adjustment, however, leads to an increased conductor diameter and weight.

3.5. Machine learning methodology

This section provides an overview of the machine learning (ML) methods employed to compare the accuracy of combined models with individual models to predict the quality of electrical cables. The process involved dividing the dataset into training and testing sets, with 70% of the data used for training and 30% for testing to evaluate the efficiency of the proposed ML algorithm.

Figure 4 presents a typical ML workflow, outlining key stages in constructing and assessing a model. This workflow includes data collection, preprocessing, essential feature selection, and training dataset creation. The model is subsequently trained, cross-validated, and optimized before deployment. Cross-validation plays a critical role in this process, as it allows for performance assessment and enhancement by using a separate validation dataset to refine the model.

Standard ML algorithms—such as decision trees, random forests, linear regression, and K-star—are selected based on the problem's specific requirements, which enhances the overall effectiveness of the ML approach, as illustrated in Figure 4. The iterative process of model retraining and optimization further contributes to the development of the final deployed mode.

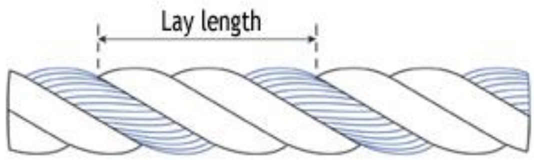

Figure 4. Lay length

On the other hand, several machine learning algorithms were employed, including decision trees, random forests, boosted decision trees, linear regression, and K-star algorithms. Each of these algorithms plays a distinct role in model construction and is selected based on the specific requirements and characteristics of the problem. This target selection enhances both the versatility and effectiveness of the overall machine-learning approach, as illustrated in Figure 5.

3.5.1. Performance Evaluation Methods

3.5.1.1. Model performance and evaluation metric.

Several evaluation metrics were employed: specificity, sensitivity, f1-score, and area under the receiver operating characteristic curve. The confusion matrix considered includes true positives and false positives), true negatives and false negatives

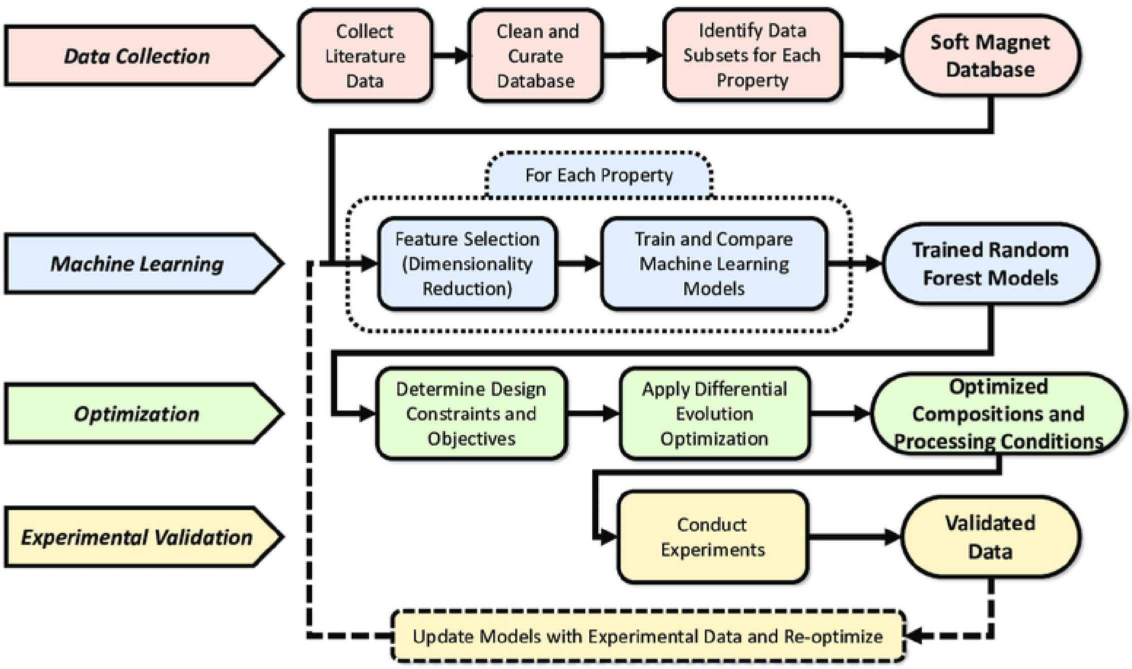

Figure 5. Layout of machine learning

$$\text{CapAccuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (3)$$

$$\text{recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

$$\text{F} - \text{Score} \;\; = \frac{2*\text{Sensitivity}*\text{Specificity}}{\text{Specificity+Sensitivity}} \quad (5)$$

3.5.2. Bidirectional Symbiosis

Crucially, the Taguchi methodology and the ML component operate synergistically and bi-directionally. The Taguchi experiments provide ML algorithms with structured and comprehensive data, enabling them to build highly accurate predictive models. Conversely, the insights gleaned from the ML models inform the Taguchi methodology, guiding the design of future experiments and refining the optimization process.

This bidirectional symbiosis allows the framework to:

- **Broaden ML's predictive power:** The ML models benefit from the systematic and statistically sound data generated by the Taguchi approach.
- **Enhance Taguchi's systematic experimental approach:** The insights from ML models will guide the selection of parameters and levels in future experiments.

4. Result and decision

4.1. Taguchi Methodology Results

The Taguchi analysis identified open lay length as the primary factor contributing to the increase in conductor weight. Additionally, key parameters influencing the outcomes were identified, prompting the decision to conduct an experimental study to optimize these parameters. The parameters under consideration included compaction percentage, which refers to the pressure applied to the brakes to reduce speed when a specific resistance is required, and wire diameter, which is the diameter of the wire drawn from the machine for stranding.

Analysis of interaction plots for the response graph indicated that the optimal parameter settings were a compaction percentage of 4% and a wire diameter of 2 mm. These settings were expected to yield minimal weight while maintaining an acceptable resistance level.

The data revealed that, at a compaction percentage of 30%, a diameter of 2.64 mm resulted in a weight of 630 and a resistance of 0.121. A similar trial at the same compaction level with a slightly larger diameter of 2.67 mm resulted in a weight of 640 and a resistance of 0.119. Under different conditions, a 20% compaction with a diameter of 2.63 mm produced a weight of 665 and a resistance of 0.120. Another trial with 30% compaction and a diameter of 2.66 mm yielded a weight of 645 and a resistance of 0.121.

These variations in diameter, weight, and resistance across different compaction percentages highlight the relationships among these variables in the experimental trials. They provided valuable insights into the relationship between process parameters and resulting weight and resistance values, supporting informed decision-making in optimizing conductor manufacturing processes. The results of this experimental design are illustrated in Figures 6 and 7.

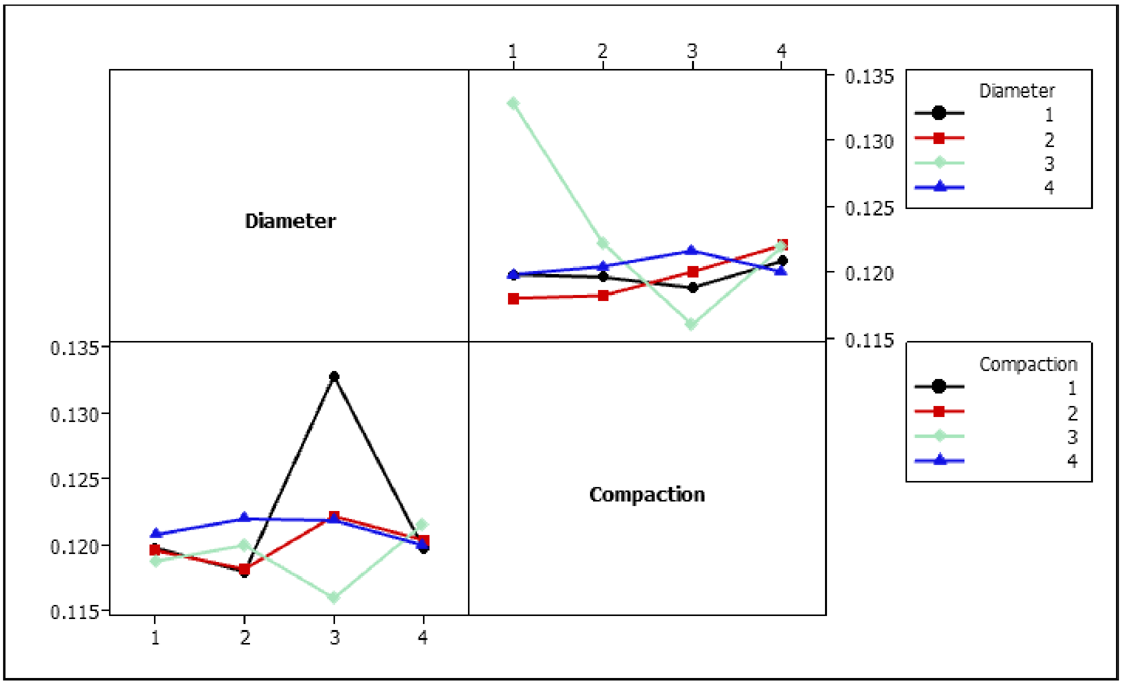

Figure 6. Interaction plot for resistance

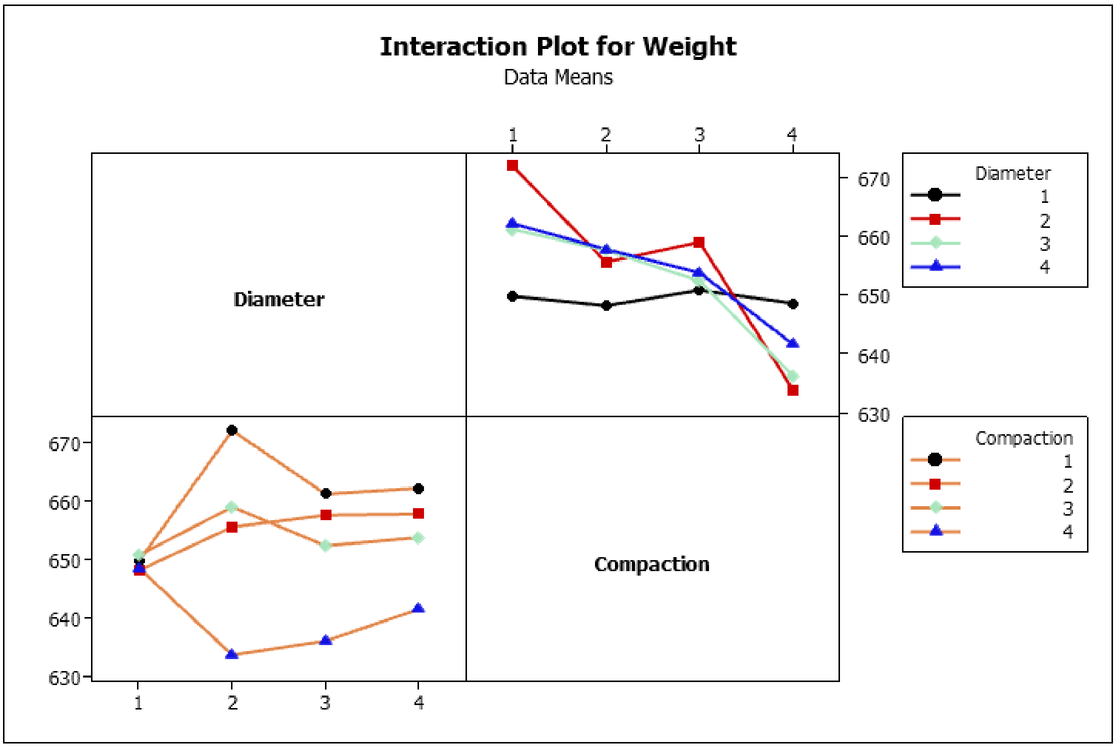

Figure 7. Interaction plot for weight

4.2. Regression analysis

Regression analysis identifies the empirical mathematical relationship between the cause (independent input variables) and effect (output response). This technique is used to fit experimental data into an equation or model, with the objective of estimating the relationship between the output response and independent variables. The coefficient values used in the analysis are presented in Tables 4 and 5.

4.3. Analysis of Variance

Analysis of Variance (ANOVA) is a statistical method used to determine whether significant differences exist between multiple sample groups by comparing the variation within sample groups (often referred to as “noise”) to the average differences between the groups. ANOVA focuses on variability and involves calculating several measures of this variability.

An ANOVA analysis was conducted using specialized software to assess the relative significance of individual factors. In Tables 4 and 5, "DOF" represents the degrees of freedom, "SS" is the sum of squares, "MS" is the mean squares or estimated variance, and "F" is the variance ratio. The results from the ANOVA analysis, as shown in Table 4, provide insights into the relationship between weight and the parameters of diameter and compaction.

Table 4. ANOVA analysis

SOURCE	DF	SS	MS	F	P
diameter	3	378	126	5.75	0.0175
compaction	3	4799	1599	72.97	0.000
interaction	9	2000	222	10.14	0.000
error	64	1403		21	
total	79	8581			

Based on the optimum value for weight and resistance, as shown in Figures 8 and 9, the values 2.64 cm for diameter and 30% for compaction give the optimum solution, predicted value weight, and resistances of 666 kg/km and 0.1224 ohms, respectively.

Table 5. ANOVA Table for Resistance versus Diameter and Compaction

source	DF	SS	MSS	F	P
diameter	3	.000120623	.00003107	0.82	0.480
compaction	3	0.0001770	.00008379	0.69	0.5493
interaction	9	0.0006290	.00008379	1.63	0.4530
error	64	0.004489	.00007379		
total	79				

4.4. Machine Learning Models Results

This research aimed to develop and evaluate machine learning models for classifying quality products. The dataset used for this evaluation consisted of 20% of the total data. we assessed the performance of these models based on various performance metrics, including sensitivity, f1-score, and accuracy)

4.4.1. Comparison of Decision Tree Machine Learning Models for Performance Evaluation

In this section, various well-known machine learning models are evaluated to classify product quality into two identified classes. A binary classification task has been designed based on the features analyzed in Section 3.1.

Figure 8 presents a detailed table with the performance metrics of five machine learning models employed for a classification task. The metrics reported are accuracy, f-score, and recall, each with distinct implications for model evaluation. Accuracy represents the percentage of instances correctly classified by the model, with higher values indicating better performance. The f-score is a harmonic means of precision and recall, reflecting a balance between these two measures, where higher values are preferable. Recall quantifies the percentage of actual positive cases that the model correctly identified, and higher recall is desirable.

Examining the model performances, the decision tree model exhibits good accuracy at 92% but relatively low f-score and recall compared to other models, suggesting potential issues with precision or a tendency to miss positive cases. The random forest model achieves slightly lower accuracy at 90% but demonstrates a better f-score and significantly higher recall than the decision tree, indicating a more favorable balance between precision and recall and an enhanced ability to capture positive instances. The boosted decision trees model performs similarly to the random forest, with a good f-score and slightly lower recall. Conversely, the linear regression model has the lowest accuracy but the highest f-score and recall, which is unusual for a classification model employed as linear regression was typically for regression problems. This anomaly may be attributable to a mismatch in model selection or potential overfitting of the data.

Overall, the random forest and boosted decision tree models perform best in this scenario, balancing accuracy, f-score, and recall. Furthermore, these models were generally better choices for classification tasks. The decision tree model may benefit from tuning its parameters to improve recall, while the linear regression model warrants further investigation to determine if the data requires different preprocessing for better results.

4.4.2. Selection Feature

This study was conducted to enhance the understanding of defect importance analysis and to assist manufacturers in more effectively evaluating trends in the electrical conductor production process. To achieve this, decision tree models were employed to assess defect significance, determining the critical score for each variable involved in predicting the final product's quality. As shown in Figure 9, the selected defects were compaction and wire diameter. A defective score plot was developed to provide a relative score for each variable, with the faults ranked in descending order of importance. By examining the decision tree coefficients, it is possible to identify the primary characteristics used in categorization. In this case, the increase in compaction coefficient corresponds with the findings of the statistical analysis. This result aggregates the findings from Section 4.4 as described in references (29-31).

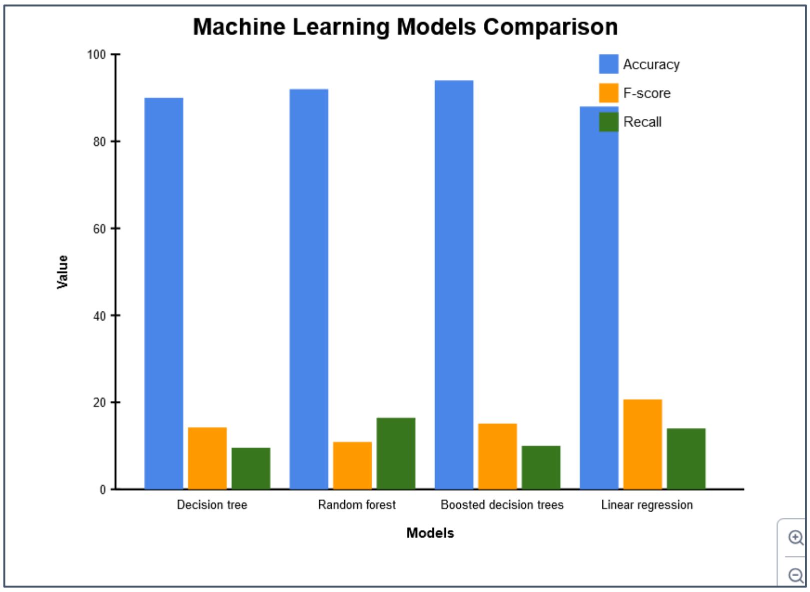

Figure 8. Performance of ml classification models

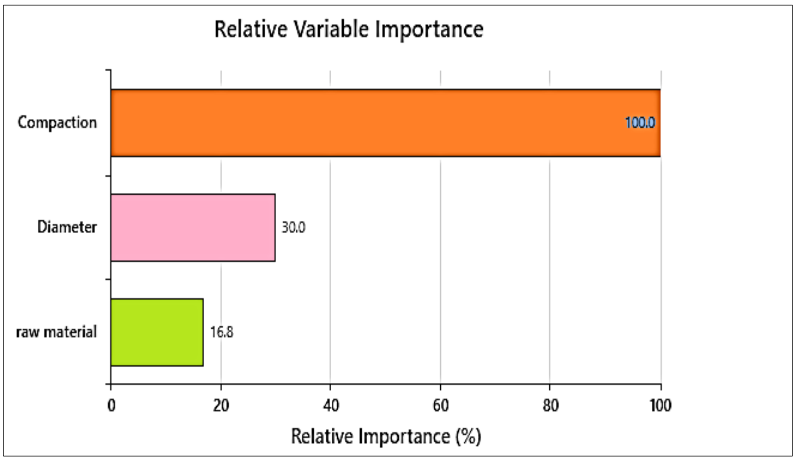

Figure 9. Features of models

4.4.3. Tornado Sensitivity Analysis

The impact of reducing conductor weight on the overall weight of other materials within a cable. The total cable weight decreased from 9321 kg/km to 8895 kg/km, resulting in a significant saving of 426 kg/km. Achieved. This reduction was primarily by directly decreasing the conductor's weight by 63 kg/km. However, the effects extended beyond the conductor, with additional weight reductions in other components. The insulation, bedding, and sheathing materials saw reductions of 79 kg/km, 44 kg/km, and 70 kg/km, respectively, suggesting that the smaller conductor size allowed for less material usage in these surrounding layers while maintaining functionality. Furthermore, the armoring weight decreased by 95 kg/km, likely due to the reduced overall cable diameter, which required less armoring material for protection. The weight reductions in screening and filling materials were relatively minor at 22 kg/km and 28 kg/km, respectively, indicating that these components were less directly affected by conductor size. The thriving weight reduction through conductor modification offers significant cost savings in cable manufacturing and transportation, enhances efficiency in handling and installation, and provides environmental benefits by reducing material consumption, contributing to sustainability efforts (ref. 32-33), illustrated in Figure 10.

5. Discussion

The Revised Discussion Section is Divided into Two Sub-Sections: Theoretical implications and Practical Implications as Follows:

5.1. Theoretical Implications

The graph illustrates that the wire diameter initially decreases as the compaction percentage increases, reaching a minimum of approximately 23.5% compaction. However, further increases in compaction lead to an increase in wire diameter. This bell-shaped relationship between compaction and wire diameter is crucial for optimizing the electrical conductor manufacturing process, as noted in references (30-32).

The data presented in the tables shows that at 30% compaction, the wire diameter ranges from 2.64 to 2.67 mm, with corresponding weights between 630 and 645 grams and electrical resistances between 0.119 and 0.121 ohms. At 20% compaction, the wire diameter is 2.63 mm, the weight is 665 grams, and the resistance is 0.120 ohms, as shown in Figure 11.

Understanding the trade-offs between compaction, wire diameter, weight, and electrical resistance is crucial for ensuring the quality and performance of the final electrical conductor. The goal is to identify the optimal compaction level that results in the desired wire characteristics, balancing the various factors to meet the application's requirements. These results align with the practical and experimental findings presented in Sections 4.3 and 4.4.

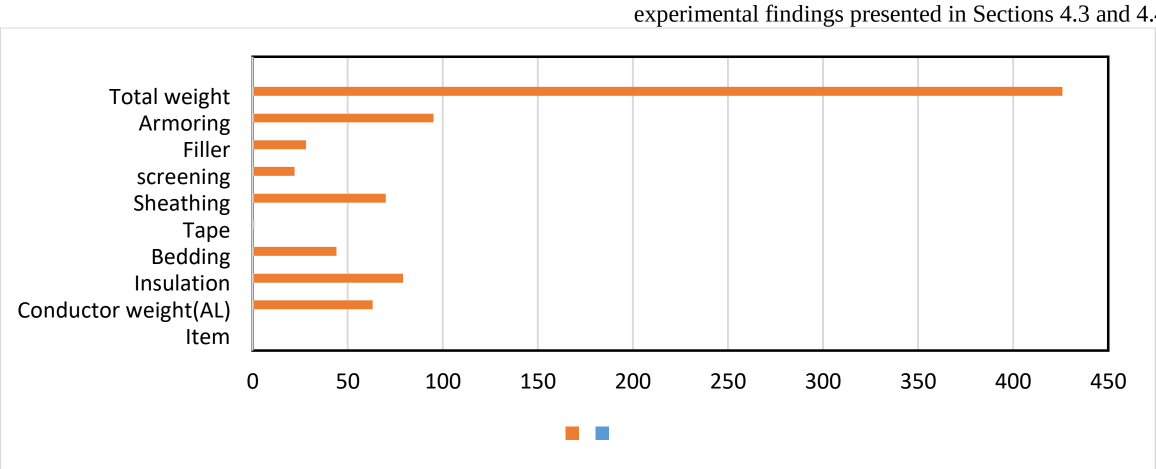

Figure 10. Tornado sensitivity analysis

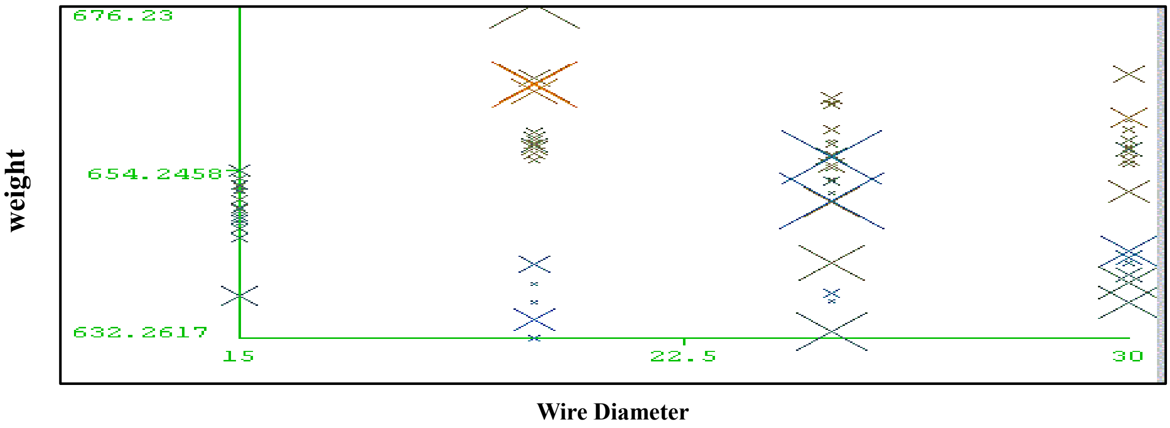

Figure 11. The built model predicted

Training Set (Left Panel): The scatterplot indicates that the data points closely follow the green dashed line, representing the ideal scenario where the fitted values match the actual values. This alignment suggests that the model has effectively captured the patterns within the training data, although minor deviations from the line point to some prediction errors.

Test Set (Right Panel): In contrast, the scatterplot for the test set reveals a more excellent dispersion of points around the green dashed line, indicating that the model's predictive accuracy diminishes when applied to unseen data. This increase in scatter may indicate overfitting, where the model performs well on the training data but struggles to generalize to new data.

Moreover, the scatterplots highlight a potential overfitting issue, where the model demonstrates satisfactory performance on the training set but exhibits reduced accuracy on the test set. As shown in Figure 12, exploring strategies such as regularization, increasing the dataset size, or simplifying the model to enhance its generalization capability may be advisable.

Comparison of Capabilities in Cable Manufacturing: Taguchi Methodology and Hybrid Machine Learning Approaches

In this study, we utilized Taguchi methodologies of hybrid machine learning to tackle the challenges of elevated material consumption and defect rates in cable manufacturing, particularly emphasizing the drawing and stranding processes. These methodologies enabled us to pinpoint critical factors affecting cable weight and cost, such as wire diameter, raw material quality, and process control. Our analysis indicated that the drawing and stranding processes were responsible for significant material waste and cable weight, accounting for 19% and 20% of the overall effect, respectively. Consequently, we prioritized these processes for optimization to achieve cost reduction. In contrast, the study by D.C. Sheridan et al. and R.K.Roy adopted a different approach by integrating Taguchi methods with AI and traditional optimization techniques to address similar issues of process inefficiencies and material defects in insulation, sheathing, and armouring, Ref. (10). Both studies underscore the importance of process variability in influencing defects and material waste, finding that precise process control during the drawing stage is essential for minimizing defect rates. For instance, our research identified that variability in wire diameter due to operator adjustments led to increased conductor weight and defects, while Y. Zhang's study observed that tension control and material quality issues resulted in higher defect rates and material wastage (1,11).

5.2. Practical implications

The increase in conductor's weight results from several factors. Firstly, the absence of a specific value for brake settings leads operators to continuously adjust the compaction percentage during manufacturing, causing fluctuations in the open lay length. Secondly, during the stranding process, conductor resistance occasionally exceeds the required level, prompting operators to insert larger wire diameters into the conductor's center to address the issue, inadvertently increasing the overall weight. Additionally, scratches on the dies of the drawing machine force operators to widen the distance between rolls to prevent further wire damage, which increases the diameter and contributes to the conductor's increased weight.

5.3. Confirmation experiments

Confirmation experiments are conducted to verify the factors and levels selected in an experiment that influence a product or process to behave in a specific manner. Ten confirmation experiments are performed at the process's optimal settings, as agreed upon in Section 2 and presented in Table 6.

Table 6. displays the process data collected for the improved process conditions.

TRIAL NO.	COMPACTION	DIAMETER	WEIGHT	RESISTANCE
1	30	2.64	630	0.124
2	30	2.64	628	0.1225
3	30	2.64	640	0.123
4	30	2.64	613	0.124
5	30	2.64	625	0.122
6	30	2.64	680	0.125
7	30	2.64	644	0.1245
8	30	2.64	618	0.121
9	30	2.64	655	0.119
10	30	2.64	621	0.123

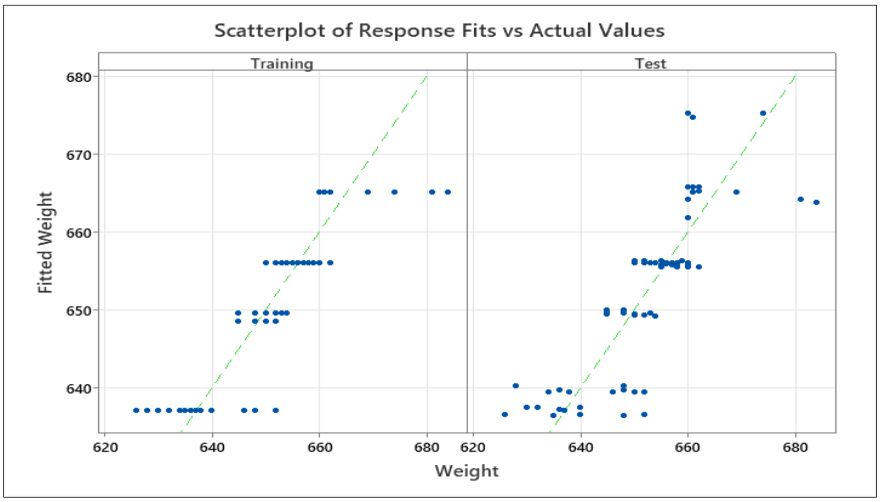

Figure 12. Scatter of response

6. Conclusion

This study has shown how integrating Taguchi methodology with machine learning techniques can effectively optimize the manufacturing process of electrical cables. By carefully analyzing and adjusting key factors like compaction percentage, wire diameter, and material usage, the study identified optimal settings that significantly improved product quality and manufacturing efficiency. For example, the optimized process parameters reduced material usage, with the total cable weight decreasing by 426 kg/km, and reduced production costs, lowering the cost of poor quality from 5% to 1.7%. These improvements were achieved without compromising the quality of the final product. This approach deepened the understanding of the factors influencing the manufacturing process and provided a practical framework that can be applied to similar industrial processes. The findings indicate that this integrated method can help manufacturers reduce defects, lower costs, and maintain high product standards, ultimately contributing to more efficient and sustainable production practices. Furthermore, defect analysis and corrective actions have significantly improved the processes by eliminating the elements that cause defects. This improvement is sustainable, leading to a permanent enhancement in quality. The cost of poor quality (coq) has been significantly reduced from 5% over cost to 1.7% over cost, a reduction of 66%.

A statement of data availability

Data is provided within the manuscript.

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