

Data-Driven Optimization of Resistance Spot Welding Processes for Advanced Manufacturing Quality and Industrial Reliability

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Abstract: Production changes can be challenging to ensure consistent production quality and operating conditions. The study is aimed at exploring the potential of an approach based on data to support process assessment and optimization through the application of resistance spot welding. 4,186 measurements from 495 welds and 13 variables (pressure, welding time, electrode angle, force, current, material thickness, pull strength, nugget diameter, Good, Bad, Explode) were analyzed using a quantitative exploratory analysis in R. Variation, quality, and defect patterns were explored using Boxplots, Scatter plots, Category comparisons, and a correlation heatmap. Welding time was identified as a factor that affected the pull strength and nugget diameter, and the categories showed variations with the time conditions. The results indicated unusual readings on the sensors, as well as repeated readings, which need to be interpreted carefully. Based on these results, the paper proposes a framework that links data preparation, process analysis, quality evaluation, and operating decisions. The framework is designed to help identify promising conditions, not a proven optimum. The findings show potential pathways for reducing waste and costs and minimizing production delays that merit investigation in practice, as they connect settings to quality outcomes. Recommendations need to be controlled, validated, and have better data quality before they are applied in production.

Keywords: Production, Quality, Operating Condition, Process, Optimization, Data

Introduction

A. Background of Study

Digitalization of processes has become a common occurrence across industries, and a similar aspect has been observed in the manufacturing industry. Digital platforms permit the producers of manufacturing companies to understand the process efficiently, which further helps in controlling it based on data. A data-oriented process has reduced the value of the producer's historical experience in advanced manufacturing techniques. The report of McKinsey sheds light on the application of machine learning and predictive modelling using data with an intent to convey the mutual positive impact on the productivity of manufacturing processes [1]. The industry revealed that the application of data processing using machine learning aligns the high-production critical mechanism with the parameters required for maintaining quality and performance. Differences in the raw materials and a constantly changing production environment are unavoidable factors in the manufacturing process that producers and organizations always consider. Subsequently, the equipment settings and pattern of process changes vary with the type of manufacturing product. An assessment of data makes the requirements very clear about the process that can be easily trusted. Data-driven procedures reveal those relationships among the manufacturing parameters that are not very apparent in the conventional method. Technological evolution in the modern advanced manufacturing system has improved data assessment and the productive outcome, which further influences the quality of the manufacturing process.

B. Data-Driven Process Optimization in Advanced Manufacturing

The optimization of data-driven processes happens in the manufacturing industry with the help of production data and analytical techniques to assist in decision-making of the organization's administration. Researchers revealed that the industry uses data in its decision-making process to bring a smart initiative through which operational quality can be improved along with cost savings [2]. Effective production outcomes give the company competitive advantages, and data optimizes the entire production process. It has been observed in the modern industry that a high volume of data is generated using digital tools and sensing technologies. However, the relevance of data plays a crucial role in providing accurate decisions to efficiently optimize the process. The aforementioned fact emphasized the administrations or production manager to apply analytical techniques, such as exploratory studies, to reveal the productivity of data values and variables.

C. Problem Statement

The manufacturing of a product happens under a very dynamic environment where the operation standards, product specifications, and expected production volume are within a defined time limit and frequently change with the business requirements. These process variations mutually create a situation that brings the workforce to a position where their skill levels do not meet the new standard criteria. Consequently, a problem of quality inconsistency emerges across the production of items, and sometimes it leads to the production of defective material. As a result, the manufacturing industry starts experiencing production inefficiency due to multiple loopholes developed from the environment described in the aforementioned sentences. Likewise, the manufacturing industry also faces challenges in its waste management that not only impact in terms of environmental sustainability but also compromise the profitability of businesses.

D. Objectives of the Study

The accomplishment of this research work fulfills the following objectives given below:

- To explore the necessary parameters for the manufacturing process by adopting a data-driven approach

- To identify the optimized conditions for the manufacturing process for better performance

F. Significance of the Study

The study is important because it can help to understand and enhance the performance of manufacturing processes. The analysis of the process parameters and quality outcomes can reveal the relationships between the parameters, which can be used to identify the critical parameters and their significant influence on manufacturing quality. Knowing these parameters can help manufacturers to prevent adverse situations in the process and ensure more consistent production results. The results can be used to help enhance process stability and production consistency by defining patterns of process parameters that are correlated with consistent and acceptable manufacturing performance. Moreover, the study serves as a basis for the development of a data-driven optimization framework which will be capable of organizing process information, determining favorable operating conditions, and assisting in an evidence-based decision-making procedure. The aforementioned structure can enable manufacturing companies to make better process modifications, improve their quality management, minimize process uncertainties, and enhance manufacturing reliability by analyzing the available manufacturing data in a systematic manner.

Literature Review

A. Artificial Intelligence and Data-Driven Manufacturing

AI has also been making a mark in manufacturing by moving from traditional process modelling to models that can learn from operational data. Ghahramani et al. [3] reported that AI-based modelling offers mechanisms for studying manufacturing processes based on the data acquired during manufacturing, so as to be able to study complex process relationships without relying on the entire mathematical processes. Their work is significant as the manufacturing systems often have nonlinear interactions between process parameters, equipment conditions and production results, which may be hard to describe using conventional manufacturing models. The data-driven approach does, however, give rise to an important methodological issue since the usefulness of the AI models is largely dependent on the quality, representativeness and context in which production data is available. Errors in measurement, missing data or process specific biases in historical observations can lead to a model that appears to be accurate, but that gives unreliable results when the manufacturing conditions change. The study thus reinforces the analytical usefulness of AI, and indirectly the fact that data availability is not enough to ensure meaningful optimization of the process. In a data-driven manufacturing system, there is a need for evaluation procedures to be in place to ensure that the patterns that are detected in algorithms can be separated from temporary or context-dependent relationships. Such an outlook is especially applicable to process optimization, since not only is prediction needed, but careful consideration of the relationships that emerge from production data is also essential.

The shift to manufacturing is not only the use of AI as an analytical tool but also the adoption of AI in the context of customization of production environments. According to Wan and others [4], AI and customized manufacturing rely on the integration of several technologies that can enable flexible manufacturing, intelligent decision-making, and adaptability to evolving customer and operational needs. It would seem that the value of AI is in how it relates to manufacturing infrastructure, data collection systems, and production processes. This offers a more comprehensive understanding of data-driven manufacturing, where optimization does not just target one production parameter, but also multiple parameters of manufacturing operations. However, highly customized environments may make analysis more complex, as product configuration changes can affect the link between the process and the quality. A model developed under one set of production conditions may thus not be applicable to another set of

conditions unless the data are sufficiently varied. LazaroIU et al. [5] also link AI decision-making with IoT sensing networks and CPM systems, indicating that real-time sensing can enhance manufacturing intelligence decisions. The use of sensing technologies opens the door to real-time monitoring and decision-making with more responsiveness, but also raises the need for a reliable data flow and proper systems integration. Data-driven manufacturing thus needs to be considered as a unified analytical environment where each of the three key elements of sensing, data processing, and decision mechanisms has an impact on each other and on the effectiveness of AI-supported manufacturing management.

Production logistics are becoming increasingly digitalized, giving another facet to the transition to data-driven production. Jeong [6] refers to the increasing use of artificial intelligence, digital twins and simulation for a shift in approach from purely model-based systems to systems that are capable of integrating operational information into production and logistics analysis. Digital twins are especially relevant in this context because they can link physical manufacturing processes with digital representations to facilitate experimentation and monitoring. But, the use of simulation and AI introduces challenges around the consistency of virtual representations with production conditions. When recommendations are made by AI but the digital representation is not a good reflection of the equipment, process variation, or any changing operational constraints, then the AI-generated recommendations will repeat the limitations of the underlying model. Likewise, the more data is produced does not guarantee the solution of process uncertainty as large datasets can still be missing some rare defects, some unusual operating conditions, and some new sources of variation. These constraints suggest a need for a constantly updated analytical model and production data that is used in data-driven manufacturing. In terms of process optimization, the literature therefore focuses on the identification of relevant relationships between process variables, quality outcomes, and operational performance, acknowledging that the analysis of these process characteristics by means of AI technology has to be sensitive to the changing manufacturing conditions. The above-mentioned approach can be an important part of the understanding process of explaining the variation of the process by a more advanced analysis before the development of more advanced predictive and/or optimization models of the process.

B. Manufacturing Process Variation and Quality Management

Process variation in manufacturing is a major problem as it can affect the product characteristics and production stability/quality. Evans [7] is a proponent of optimization using response surface methodology, which offers a systematic approach to understanding the relationship between factors that can be controlled during the process and the factors that represent the performance. The benefit of this approach is that it helps to shift process improvement from observation to the way that the manufacturing conditions interact with each other to affect the outcome. But manufacturing processes do not usually react to just one parameter alone; interactions between the temperature, pressure, speed, material characteristics, and other operating conditions can lead to nonlinear effects. Optimizing one parameter while neglecting interactions could yield a seemingly better setting but not perform well when operating in different conditions. This is where response surface approaches can be helpful as they can model the response behaviour in the defined experimental region, but effectiveness will depend on the factors chosen and the range of factors explored. Another restriction is that an optimum control system be required may not be representative of the range of variation found in normal production. Disturbances, deterioration of equipment, and material differences in real manufacturing environments can change the process behaviour over time. This establishes a requirement for analytical methods that are not only able to find optimal runs but also identify variations from the run behaviour.

As more production data becomes available, it is possible to identify such deviations and link process monitoring to quality assurance. Anomaly detection in high-throughput manufacturing systems can be facilitated by machine learning-based process mining as suggested by Roy and

Hasan [8], which uses process data to detect patterns that are correlated with abnormal or potentially problematic process behaviour. This view of quality management moves beyond the traditional inspection post-production approach and focuses on identifying abnormal process behaviour at an earlier stage. However, the fact that there is an anomaly does not mean that the anomaly will lead to a defective product, as the anomaly could be due to a legitimate change in production conditions and not a production defect. Hence, machine learning systems need the right background information of the process and relevant quality metrics, as well as the ability to differentiate between anomalies and normal process variations. The strong connection between quality and efficiency is also highlighted by Ullah et al. [9], who pointed out that simulation, line balancing, and optimization tools can be used to enhance manufacturing performance. While optimizing the production flow can lead to fewer bottlenecks and imbalanced workloads, it may also simply shift the variability to another point in the production system if the production of flow is optimized without considering the consequences for quality. However, simulated performance can differ from actual production when assumptions are inadequate representations of actual operational disturbances, making simulation-based analysis valuable as an alternative configuration can be analyzed before it is implemented. The problems raised suggest that manufacturing quality management should be an integration between process optimization, issues of anomalies, and the behaviour of the production system, and should not rely on any single analytical technique.

The variability of the process also affects the reliability and economic efficiency of quality control. If interpreted within the framework of Rogalewicz et al. [10], minimizing the variability in the process can help to ensure more stable production and fewer resources for quality control processes. The cost associated with quality management is important and is not only based on the quality of the product produced, but also based on the quality of the inspection process, rework, monitoring, and corrective actions that are needed if the behaviour of the process is not steady. Minimizing variability can thus help to increase uniformity and may help to lower the severity of downstream quality control measures. Variability, however, does not always have to be a bad thing, as some variation can be expected in the manufacturing process and may not significantly affect the critical product properties. If variation is eliminated, then there may be a significant cost associated with the operation that results in no commensurate gain in quality. This is especially significant because optimization efforts should concentrate on variations that materially impact manufacturing outcomes, which is why it is of critical importance to identify the influential process factors. Analytical results coming from response surface modelling, machine learning anomaly detection, and simulation suggest that process quality can be studied at a variety of levels: from the relationship between the processes' factors to process deviations in the production behaviour, to system-level inefficiencies. This presents a methodological requirement to distinguish influential variation from ordinary fluctuation and to relate the statistical patterns to measurable quality outcomes instead of viewing all the deviations observed as manufacturing problems, when applying it to data-driven process optimization.

C. Data-Driven Process Optimization and Defect Reduction

Increasingly, data-driven process optimization becomes about recognizing conditions that lead to losses in quality and inefficiencies in the production process. Process quality should be optimized in conjunction with equipment condition, which has been studied by Sadraoui et al. [11] in the combined optimization of the quality process control and preventive maintenance. It is important that this approach is taken because even if there are no nominal changes to the parameters of the process, equipment degradation can eventually cause process behavior to change, increasing the likelihood of defects. But scheduling maintenance without considering equipment conditions could lead to sub-optimal maintenance decisions, and reactive maintenance might allow deterioration to impact product quality prior to the time of maintenance. This can be overcome using a data-driven approach, which is able to link process information to maintenance indicators and quality outcomes. The problem is not just the

gathering of more production data but determining variables that offer some real evidence of process deterioration.

If there are important process characteristics that cannot be continuously measured using a standard physical sensor, the other means of supporting optimization is soft sensing. Soft sensors, as described by Jiang et al. [12], are developed based on available process measurements and computational models to estimate variables that are hard to measure and enable monitoring, control, and optimization of the industrial processes. This is especially significant when quality characteristics need to be tested in the laboratory or are not inspected until after the product has been manufactured. The information created during the estimation of the process could enable corrective actions to be taken earlier, thus minimizing the length of time that abnormal conditions are not detected. However, the ability of the soft sensors is affected by the stability of the relationships between the measured variables and the variable being estimated. The reliability of the model and the accuracy of the estimated values may be reduced due to changes in raw materials, equipment condition or operating regime. Therefore, soft sensing is not to be used as a substitute for direct quality measurement. It becomes more useful when there is ongoing validation of the value of the estimated information with available quality observations and the information is part of a wider process monitoring system.

With the shift towards smart factories, the amount and type of information for the optimization of processes increases even more. Khang et al. [13] present the idea of adopting robotics and IoT technologies in the context of Industry 4.0 manufacturing, and the implementation of connected production systems could enable more automated and responsive manufacturing processes. This integration can give detailed information about machine activity, production cycles and process conditions and will allow opportunities to identify operational patterns which may result in inefficiency or defects. Connectivity does not, however, mean good optimization as there can be a lot of data, which is not homogeneous, and can add to the complexity of the analysis. The data produced by robots, sensors, and other production devices needs to be synchronized and understood in terms of the manufacturing process. If not, optimization models can find correlations that may not be of much use in reality. As such, when implementing IoT and robotics, it is important to pay attention to the quality of the data, temporal consistency, and the correlation between the process conditions as observed and the production's measurable results.

One of the big analytical challenges is from detecting abnormal conditions to minimizing actual defects. Whilst data-driven models have the ability to show unusual observations, estimate unobservable process states, and discover relationships between equipment behaviour and quality performance, they do not necessarily indicate which process changes will lead to desired improvement. In preventive maintenance analysis, prediction has to be linked to an actionable maintenance intervention; connected manufacturing systems offer the infrastructure to continuously collect data, and soft sensors show the need for reliable process estimation. How these analytical components are mapped to decisions in the process thus determines the effectiveness of optimization. Process analysis for exploratory purposes needs some special emphasis on the distribution and interaction of the process variables, identification of influential variables, and finding conditions that lead to undesirable outcomes. This facilitates the identification of systematic causes of manufacturing failure from regular manufacturing variation and makes better-informed decisions.

D. Literature Gap

Previous studies have shown that a data-driven or machine-learning-based methodology is valuable in manufacturing; however, exploratory frameworks that systematically link manufacturing process parameters with quality outcomes and apply these relationships to support practical process optimization and decision-making are still needed.

Method

A. Research Design

This study has used a quantitative, data-driven, exploratory research design to investigate manufacturing process variation, quality performance, and defect patterns in resistance spot welding. The research involves structured experimental data with measured quality outcomes, process parameters, and characteristics of the materials. The methodology is oriented to finding relations between manufacturing conditions and quality performance instead of creating a completely automatic predictive production system. Exploratory analysis is employed to check how the important process parameters are distributed and varied, to investigate the relationships with the PullTest and NuggetDiameter process parameters, and to analyze the quality categories: Good, Bad, and Explode. The study further relies on these patterns to highlight the key factors of the process and form a framework for process optimization and decision-making using data. This design is suitable since it allows the system of manufacturing conditions to be evaluated systematically by measurable process and quality variables.

B. Data Source and Dataset Description

The dataset “Resistance Spot Welding Insights: A Dataset Integrating Process Parameters, Infrared, and Surface Imaging” from Mendeley Data is used in this study. This dataset consists of observations of resistance spot welding and has 4,186 rows and 13 columns [14]. The variables are Pressure, Welding Time, Angle, Force, Current, Thickness A, Thickness B, Material, PullTest, NuggetDiameter, Category, Sample ID, and Comments. Process variables are the operating conditions during welding, and thickness and material variables give information about the welded components. PullTest and NuggetDiameter are measured aspects of weld quality, while Category offers quality measurements like Good, Bad, and Explode [14]. The dataset is thus a decent foundation for studying process variation, inconsistencies in quality, patterns of defects, and links among operating conditions and manufacturing results.

C. Data Preparation and Cleaning

Exploratory analysis was performed after data preparation to ensure the data is structured correctly for statistical analysis and visualization. The data set was imported into the computer program R, and the variable names, variable types, observations, and numerical ranges were checked. You can find all the information for the main process, material, quality, and category variables, and many comments have no information in them. Records were also checked for duplication, and there were no complete duplicate observations. Values of numerical variables were checked for unusual values and/or values that may not have been physical, especially on process measurements such as Force and Current, where coded values like negative values were found. These observations were not taken for granted as meaningful physical operating conditions when interpreted but were rather taken into account. Categorical variables were kept as categorical to allow for analysis of the three quality categories Good, Bad, and Explode. This preparation gave rise to a homogeneous data set to be examined in the following exploratory analysis.

D. Exploratory Data Analysis

The exploratory data analysis was conducted in R to gain insight into the distribution, variation, and association of manufacturing process and quality variables. The analysis began by looking at the descriptive characteristics of the variables of Pressure, Welding Time, Angle, Force and Current, so as to determine whether there were any differences in their ranges and level of variation. The quality variables, viz. PullTest and NuggetDiameter were then studied to understand the variation in the welding performance. The distribution of Good, Bad, and Explode ratings was examined in the Category variable, and the distribution of the various

quality outcomes was identified. The relationships between selected process parameters and quality measures were also investigated to see if there was any correlation between the changes in the process parameters and the changes in the manufacturing performance. The EDA stage was nonconfirmatory and was designed to uncover significant trends that could aid in the identification of key process parameters and optimization of the process.

E. Visualization and Analytical Techniques

For visualization and analysis of the data, R was used as the main analytical environment. Various visualization methods were chosen depending on the research questions and variables being analyzed. The variation and spread of the important manufacturing process parameters such as Pressure, Welding Time, Force and Current have been examined by boxplots. To explore the relationships between selected process parameters and quality parameters like PullTest and NuggetDiameter, scatter plots were utilized. Selected process conditions were analysed using grouped and stacked bar charts. The relationship between numerical process, material, and quality variables was analyzed by a correlation heatmap to find parameters with possibly higher correlation values to manufacturing performance. Descriptive statistics, distributions, correlations, and comparisons were studied visually together, not one by itself. This combination has been used as a sort of exploratory basis in understanding process behavior and in providing a data basis for manufacturing decisions.

F. Identification of Critical Process Factors

Factors that are critical for making a product were identified by studying the relationship between each manufacturing parameter and the quality outcomes and defect patterns. The material thickness variables and quality measures such as PullTest and NuggetDiameter were taken into consideration along with the Process variables such as Pressure, Welding Time, Angle, Force, and Current. Visual relationships and correlation relationships were analyzed together for the purpose of determining the comparatively meaningful relationships between the weldability parameters and weldability performance. The distribution of Good, Bad, and Explode categories across process conditions was also taken into account as a parameter can be important both because of its relationship with a continuous quality measure and because of its relationship with undesirable quality outcomes. Thus, the following factors were deemed to be of critical importance because they exhibited significant differences, associations with quality indicators, or trends of differences among the different quality categories. This approach facilitates identification based on evidence of the process conditions that need to be paid more attention during manufacturing control and optimization.

G. Data-Driven Process Optimization Framework

The results of the exploratory study were used to develop a data-driven process optimization framework that links the process conditions, quality assessment, critical factors identification, and manufacturing decision-making. The framework starts with gathering and preparing process and quality data before moving into exploratory analysis to uncover variation and quality patterns. The relationship between the process parameters and quality results is then analyzed, and process parameters that are critical and favorable operating conditions are determined. The patterns identified can then be used to inform process adjustments to ensure acceptable welding quality and minimize undesirable outcomes. Optimization in this study is defined as finding data-based operating conditions, and not as running an automatic optimization algorithm. The framework thus offers a logical progression from manufacturing data to understanding and informed decision-making. It can assist with better process stability, quality management, production reliability, and future development of more sophisticated predictive models or optimization models.

H. Limitations and Ethical Consideration

There are some limitations to be considered in the interpretation of the results of the study. The data set is for resistance spot welding conditions, and the results may not necessarily apply to other manufacturing processes, materials or production environments. The data set includes process and quality variables, but not direct measures of production throughput, downtime, labour, energy or material waste, which makes it difficult to directly assess overall production efficiency and reduction of waste. The analysis focuses on recognizing associations and is therefore considered exploratory and does not provide evidence of the causal relationships between process parameters and quality outcomes. Also note that odd-coded numbers also should be interpreted with caution and should not be interpreted as physical measures alone. At an ethical level, the analysis needs to preserve the integrity of the data, not draw unsupported conclusions, and be clear about any conclusions made about process improvement. A future automated decision-support system should have proper human oversight in suggesting any changes in the manufacturing process.

Conceptual Framework

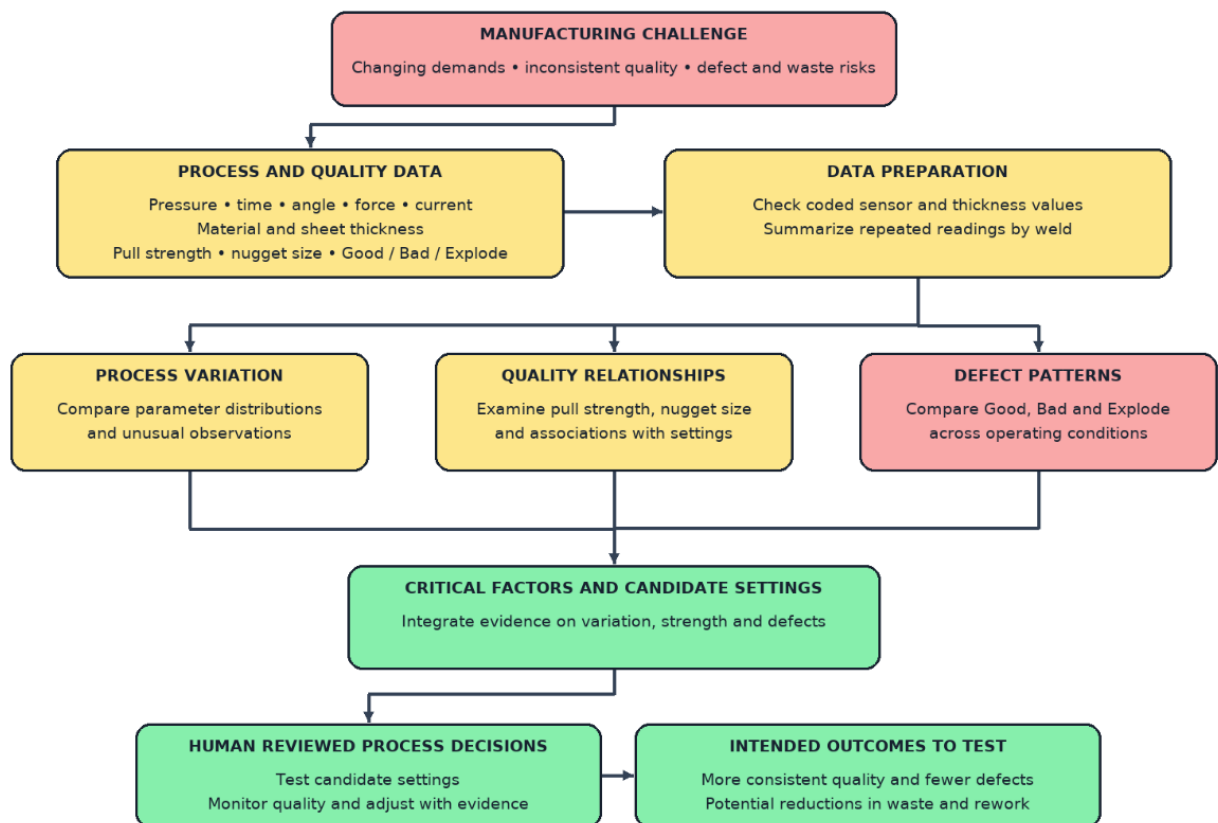


Figure 1. Conceptual Framework Diagram

(Source: Created by learner)

Dataset Overview

A. Screenshot of Dataset

(Source Link: <https://data.mendeley.com/datasets/rwh8kjzdc/2>)

B. Dataset Overview

The dataset consists of 4187 experimental data pairs of process parameters and weld quality for resistance spot welding (RSW) of AISI 1010 carbon steel. Pressure (35-95 PSI), welding time (200-1500 ms), electrode angle, force, current, sheet thickness, pull-test strength, nugget diameter, and weld category are all key variables [14]. Category is the target variable, which indicates whether the weld is Good, Bad, or Exploded. Longer welding times (1000-1500 ms) are generally associated with stronger welds and larger nugget diameters (about 3.5-4.7 mm), and shorter welding times (200 ms) tend to generate mostly Bad welds with higher pull-test strengths (around 3,000-5,800 N) [14]. The data can be used for predictive modeling, quality classification, process optimization, and manufacturing analytics.

Results

A. Variation in Key Manufacturing Process Parameters

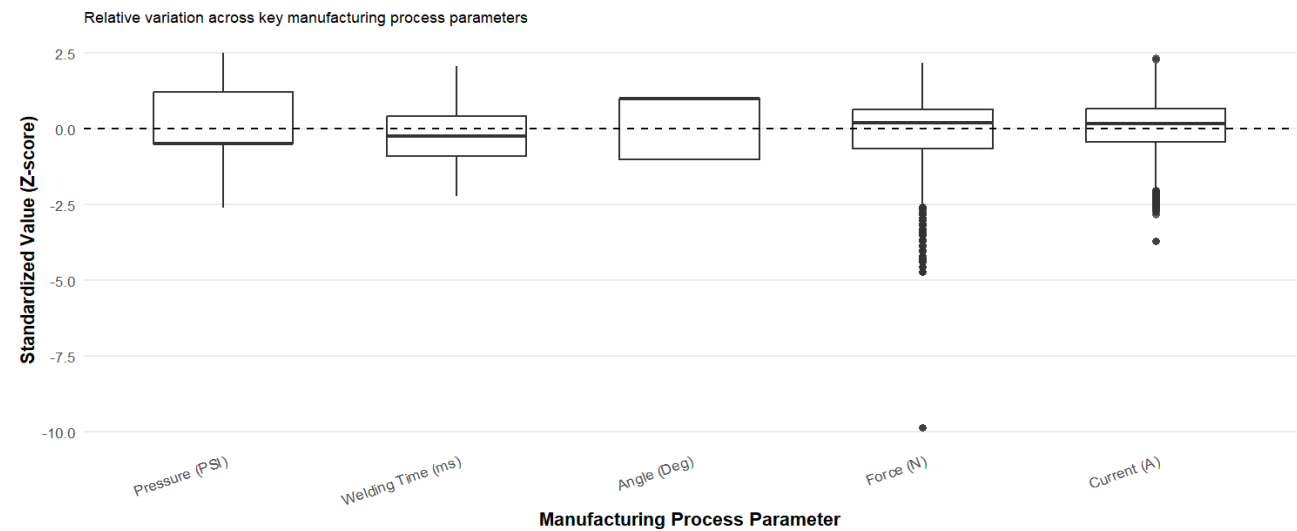


Figure 2. Distribution of Resistance Spot Welding Process

(Source: Created by learner)

The box plots indicate that there is variation in pressure, welding time, angle, force, and current among the observed welding runs. Angle and pressure are distinct settings, and force and current have unusually low readings that could warrant checking before interpretation. This variation looks for parameters that need to be monitored consistently if the production requirements change. While standardized values help you compare welds from different units, it is important to remember that no value can be used to determine which settings will reliably yield high-quality welds or minimize waste.

B. Relationship Between Manufacturing Process Parameters and Quality Performance

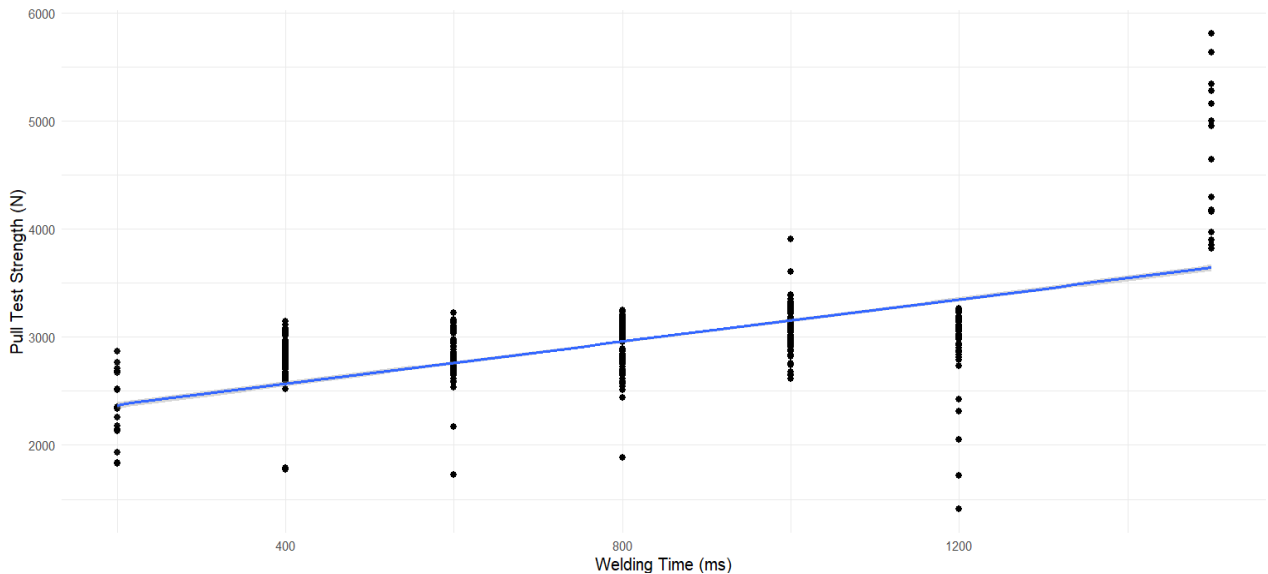


Figure 3. Relationship Between Welding Time and Pull Test Strength

(Source: Created by learner)

As illustrated in the trend line, the pull test strength tends to increase with the welding time. The results at the longest duration, however, show a wide range, with some longer welds being of low strength. The plot thus indicates that time has an effect on the performance, but does not indicate that longer welding time always equates to higher quality. Strength comparisons at matched material thickness, angle, and pressure must be made as a prerequisite for choosing an operating time used for defects and rework reduction.

C. Manufacturing Quality and Defect Patterns Across Process Conditions

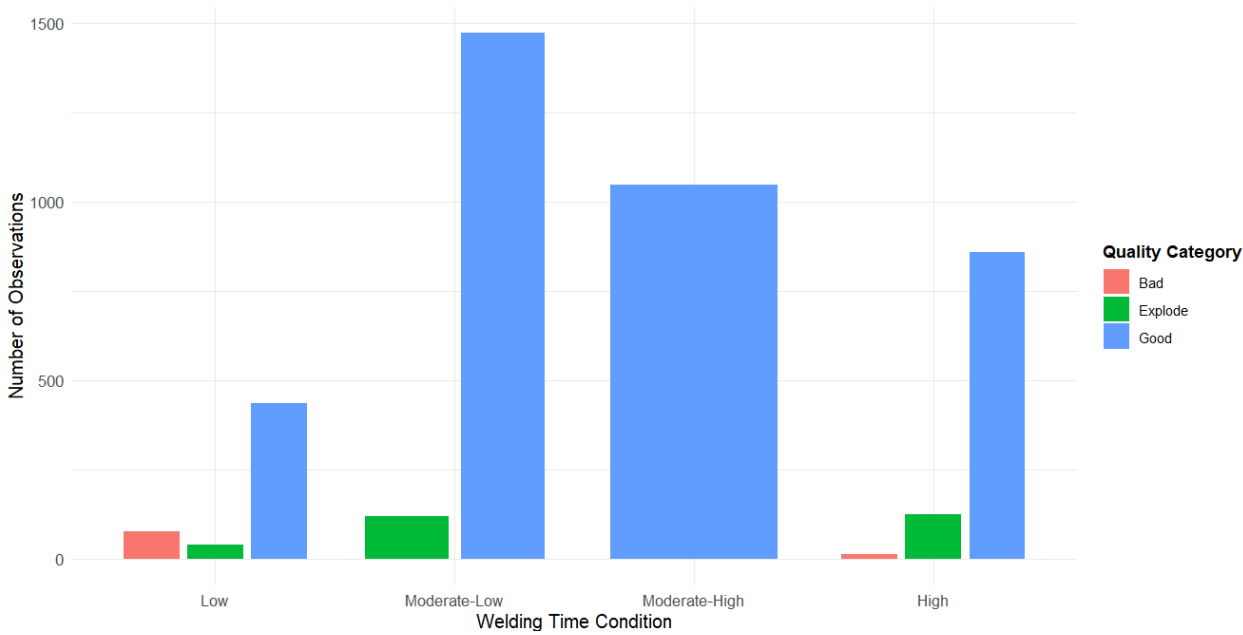


Figure 4. Manufacturing Quality Categories Across Welding Time Conditions

(Source: Created by learner)

The grouped bars indicate that more observations show bad results at low welding times, and all of the ‘moderate-high’ observations are good. However, extending time does not imply acceptable quality, as there are some other time groups with exploded observations, such as the high group. The heights of bars should NOT be interpreted as defect rates [1] since the bars are counting repeated measurements and NOT separate welds. Weld level comparisons can be done carefully to find settings that can lower rejects and material waste.

D. Critical Process Factors for Data-Driven Optimization

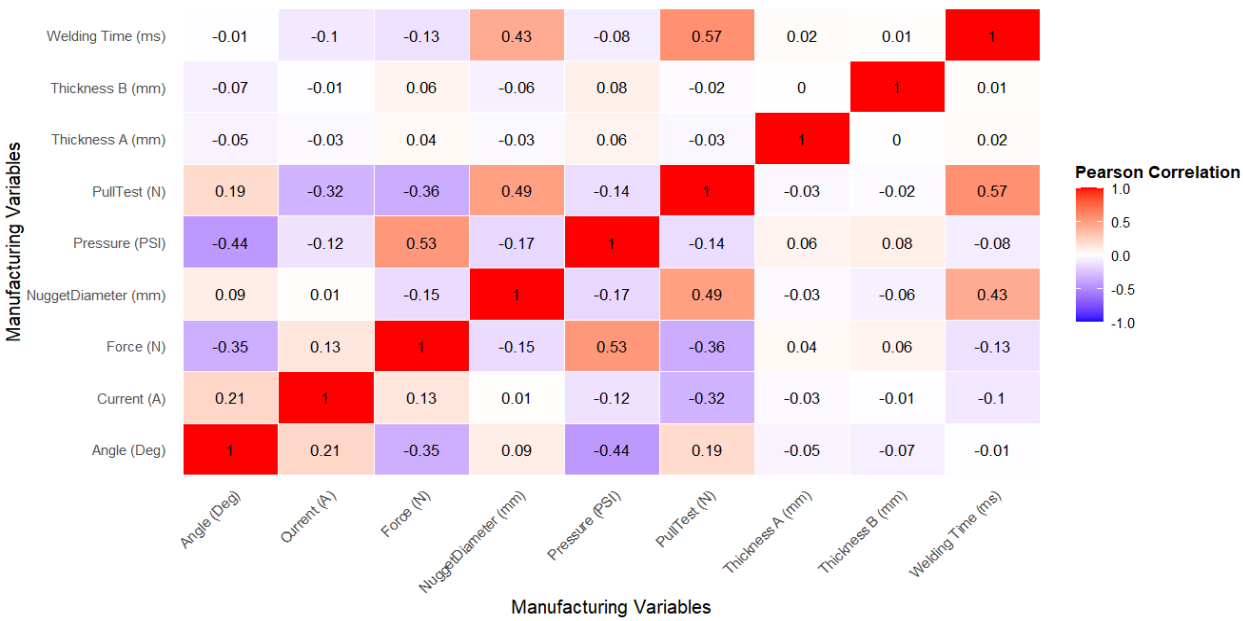


Figure 5. Correlation Structure of Manufacturing Process

(Source: Created by learner)

Welding time is positively related to pull strength (0.57), to nugget diameter (0.43), and to the relationship between nugget diameter and strength (0.49). Some of the quality measures are negatively associated with force and pressure. The values shown represent plotted data and do not represent independent effects as the settings of the processes are changing together. The current strength association is negative, and thickness correlations are very close to zero; both of these should be checked for recording errors and repeated measurements. Optimized operating conditions must be defined by means of controlled comparisons to ensure consistency and minimize scrap.

Discussion

The four visualizations address the first research objective by revealing which recorded welding conditions vary and illustrating how the quality of welds varies between the conditions. The standardized distributions provide references for the pressure, time, angle, force, and current values to be monitored during varying production demands. The strength plot and quality bars indicate that, particularly, welding time is important, because the shorter the weld, the lower the performance results, and the group with a welding time of 1000 milliseconds demonstrates comparatively good results. Out of the provided data, 4186 signal measurements correspond to 495 welds, and there are 101 welds at 1000 milliseconds that are marked as good. The highest bars therefore represent units of repetition, not production. This comparison has been extended with a correlation plot where time and nugget diameter are correlated with the strength as a measure that can be measured for process assessment and not only based on operator judgment.

The second one is to optimize conditions, but the numbers apply to a candidate and not to an optimum. The 1000 millisecond appears to be a good setting, as its quality group has no known defects, and pull results are generally good. However, the differences were not due to time, pressure, angle, force, and current being varied independently in each setting, and other changes may account for the differences. The negative current strength association in the raw matrix cannot be considered a current effect on strength and should not be used to make a causal estimate. The additional suspicious sensor reading and thickness readings only reinforce the need to clean and reanalyze the sensor thickness prior to setting targets. The data are not directly related to the skill level of the workers, the amount of waste, the production cost, or the throughput. The four figures are not the only ones who are responsible for the improvements in these business outcomes; these are business outcomes that motivate the research.

Future Work

Future work needs to be first to address invalid sensor values and inconsistent thickness entries, and then to summarize each weld as a single observation. An experimental balanced design should systematically change the welding parameters of welding time, welding pressure, welding angle, welding current, and welding force, while maintaining the thickness of the materials as stable as possible and other factors. The trials would be repeated several times on machines, operators, shifts, and production batches to determine if positive settings continue to be effective with varying needs. Pull strength, nugget diameter, defect rates, and clear acceptance limits (not a single one) should be used to determine quality. The anticipated benefits of being more efficient, sustainable, and more profitable should be measured by researchers by also recording cycle time, electrical energy, scrap amount, rework hours, and production cost. Operator training and adherence to new procedures can be directly quantified rather than the results of the weld. Models developed with cleaned welds should be tested on future production and on different facilities. Hence, potential clinical trials could be performed to see how the candidate settings relate to current practice, and to demonstrate that quality improvements would be maintained without increasing the risk of explosions or use of resources over multiple future production runs.

Conclusion

In this paper, the authors studied the use of manufacturing data to improve consistency in quality when production needs vary. Based on the research into digital manufacturing and process control, it used exploratory analysis on the record of the resistance spot welding to make a link between operating conditions and weld performance. The study highlights process parameters that require further monitoring and suggests a practical framework that flows from a reliable preparation of data to a quality evaluation to a set of decision criteria for potential settings. In this way, it further contributes to both goals by outlining which factors need to be studied and where the next optimizations might start. The analysis does not, however, establish cause-and-effect for the ability to make better welds; it simply identifies correlations. The available records also do not capture the skills of the workforce, the production efficiency, the material wastes, or the financial results. So statements of overall business or environmental benefit need to be backed up with more evidence. The use of candidate settings and responsible decision-making in changing manufacturing environments is possible through future controlled trials and monitoring.

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