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Exploring Effective Approaches To Minimize Downtime In Final Assembly Line Of Braking Systems

Sriram Madhav[1], Mahantesh M Math[2*], Rajeswara Rao K V S[3], Shivaraj B. W[4], , Prapul Chandra A C[5]

[1]PG Student Department of Mechanical Engineering, R.V. College of Engineering, Bangalore-560059, Karnataka, India

[2,4,5]Assistant professor Department of Mechanical Engineering, R.V. College of Engineering, Bangalore-560059, Karnataka, India

[3]Professor, Department of Industrial Engineering and Management, RV College of Engineering, Bengaluru-560059, Karnataka, India.

***Corresponding author:** Dr Mahantesh M Math, mahanteshm@rvce.edu.in

Abstract

The global automotive manufacturing industry's growth in downtime reductio is substantial, valued at $3272.6 billion USD with a 3.01% growth rate.This growth in downtime reduction underscores the industry's commitment to enhancing efficiency, quality, and overall productivity across its diverse range of operations. Downtime in the braking system assembly line can lead to utilization loss or technical availability loss. In this context, many proactive maintenance strategies are explored but there's limited focus on addressing error-prone machines and utilizing Machine Learning for predicting downtime. The objective is to prioritize downtime reduction through error analysis, critical machine identification, and implementing ML-based solutions.

This comprehensive research delved into the significance of minimizing downtime in the braking system final assembly line through meticulous data analysis, visualization techniques and targeted interventions and then identified key issues and achieved tangible improvements in operational efficiency. The analysis revealed significant findings and then employed the Pareto Principle to identify top downtime machines, illustrating their distribution through a Pareto chart of machine defects. Furthermore, Exceptions and Problem Areas were identified utilizing statistical process controls, offering insights into critical error contributors. Notably, a comprehensive exploration of the most prominent downtime machine was undertaken, evidenced by LCL and UCL charts and a Fishbone Diagram detailing causal relationships. The research leverages real-world data involving dates, machine names, and downtime durations to develop a predictive model that aids in proactively managing production disruptions.

The application of RPN calculations before and after error correction demonstrated a substantial reduction from of 432 to 75, validating the efficacy of the corrective actions. The real time data was used to build a model that can predict when production machines downtime might happen. This helps us be prepared and manage any possible disruptions in production.The outcome of the project highlights the intrinsic link between downtime reduction and assembly line efficiency, emphasizing the importance of data-driven interventions. This culminated in the resolution of key issues, illustrated by the mitigation of the PCBA Pressin machine and LVDT sensor errors, yielding tangible reductions in downtime and notable productivity improvements. In this direction, exploring Ai driven predictive maintenance holds immense potential for advancing downtime reduction strategies. Leveraging AI algorithms to analyse live data streams from machinery and sensors can enable the detection of patterns indicating imminent failures and can pre-emptively prevent downtime.

Keywords: Line balancing, Machine Learning, Statistical Analysis, Production line, Production improvement, Efficiency

1. **INTRODUCTION**

The contemporary automotive industry places utmost importance on safety and operational efficiency, casting the final assembly phase of braking systems in a pivotal role with a market value of $3272.6 USD and a growth rate of 3.01%. Instances of prolonged downtime during this critical stage can trigger production bottlenecks, amplified expenses, and potential compromises in quality. This comprehensive analysis delves into the imperatives of curtailing downtime, its ripple effects within the global automotive landscape, and the far-reaching implications for society.

The Automotive industry remains a driving force in the global economy, consistently demonstrating growth even amidst broader economic fluctuations. This sector's steady expansion, as indicated by data provided by the International Organization of Motor Vehicle Manufacturers (OICA), underscores its resilience. While innovation and quality are the cornerstones of the automotive industry, the automotive system sector is underpinned by three vital pillars: Competitiveness, Delivery, and Quality.

The research focuses on a global company within the automotive system development and manufacturing industry, specializing in braking systems. The motivation behind this endeavour is multifaceted, driven by considerations spanning Market, Industry, and Societal dimensions. The core objective is to significantly reduce downtime within the braking system assembly line through statistical methodologies, ultimately bolstering the Risk Priority Number (RPN) through effective corrective actions.

[1], [2], and [3] underscore the importance of data-driven approaches in identifying patterns and anomalies that may lead to downtime. These sources advocate for the utilization of real time data streams from sensors and machines to predict and prevent failures. By employing advanced analytics and machine learning algorithms, manufacturers can gain insights into equipment health and performance. Implementing proactive maintenance strategies based on predictive analytics can lead to timely interventions and the prevention of unexpected breakdowns. This not only reduces downtime but also ensures that maintenance activities are scheduled efficiently, optimizing the utilization of resources. In the context of the research paper at hand, titled "Analysis and Improvement of an Assembly Line in Automotive Industry" [1],a significant literature gap emerges within the intersection of automotive manufacturing, downtime reduction, and assembly line optimization. While existing literature has explored various aspects of automotive manufacturing and assembly line improvements, a comprehensive investigation into the precise methodologies and strategies for reducing downtime within braking system assembly lines remains notably underrepresented.

[4], [5], [6], [7], [8], [9], and [25] address the significance of reliable automotive components, particularly in braking systems. As braking systems are critical for vehicle safety, understanding their working principles, specifications, and control mechanisms is essential to prevent failures and subsequent downtime. Integrating advanced technologies like Anti-Lock Braking Systems (ABS) effectively can enhance vehicle safety while reducing the risk of malfunctions.A significant portion of the literature focuses on optimizing assembly line processes to minimize idle time and bottlenecks. [11] investigates strategies to enhance productivity in assembly lines through effective line balancing techniques. [12] delves into optimizing machine efficiency and workforce utilization in the context of production lines. [13] focuses on addressing challenges related to sequence dependent setup times to achieve better task scheduling. [14] highlights problems and methods associated with generalized assembly line balancing providing a comprehensive overview. [15] propose problem definitions and effective solutions for assembly line balancing with variable parallel workplaces. [16] introduces a versatile algorithm for addressing assembly line balancing challenges.

[17] categorizes different types of assembly line balancing problems to guide effective problem solving approaches. [18] explores various assembly line balancing models and discusses their appropriate applications.

[19] focuses on software development for addressing assembly line balancing challenges in the manufacturing industry. [20] explores assembly line balancing using simulation techniques with a case study in the garment manufacturing sector. These references collectively contribute to the understanding and enhancement of assembly line processes, highlighting the importance of balanced and optimized production lines for improved efficiency and reduced downtimes. These sources recognize that balanced and optimized production lines lead to smoother workflows and reduced downtimes. By distributing tasks evenly and strategically among workstations, manufacturers can prevent overburdened stations and streamline production processes.[21], [24], [28], and [29] emphasize the role of lean manufacturing principles in evaluating and improving manufacturing systems. Lean practices prioritize the elimination of waste, including excessive downtime, by optimizing processes and resource utilization. Metrics such as Overall Equipment Effectiveness (OEE) and Operational
Availability are utilized to quantify production line efficiency and identify areas for improvement. These metrics enable manufacturers to measure the impact of downtime reduction efforts and track progress over time.Certain references, including [26] and [30], delve into automotive industry-specific optimizations. Automotive assembly lines require tailored strategies to minimize downtime and optimize production. By standardizing and optimizing components production lines, manufacturers can achieve better synchronization and coordination among processes.Bhargava et al.

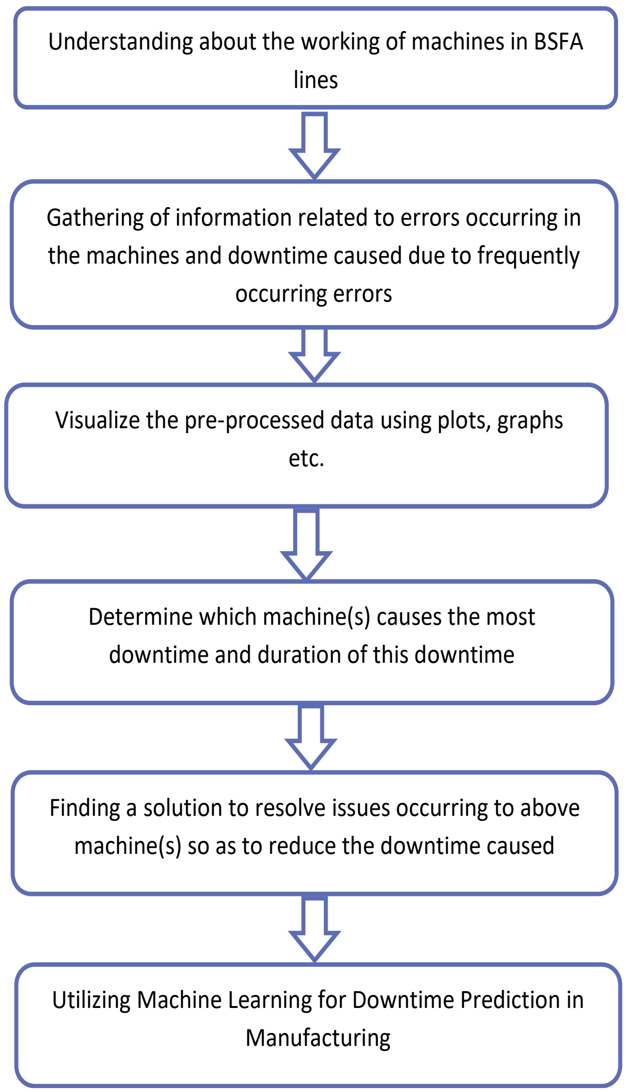
[39] explored the J48 algorithm's effectiveness for data mining, while Freund and Mason [40] introduced the alternating decision tree learning algorithm. Pandey and Sharma [41] focused on student performance analysis and prediction utilizing a decision tree approach, while Priyama et al. [42] conducted a comparative analysis of decision tree classification algorithms. Additionally, studies by Banu [45], Jayakameswaraiah and Ramakrishna [46], and others [47-50] extended the exploration of decision tree models across diverse domains, such as healthcare diagnosis and optimization of classification schemes.In concise, the literature review reveals a multifaceted approach to downtime reduction in the manufacturing industry. Strategies such as data-driven

predictive maintenance, assembly line balancing, lean manufacturing principles, industry-specific optimizations, and the integration of reliable automotive components all contribute to minimizing disruptions and improving productivity. Manufacturers can benefit from a holistic understanding of these strategies and tailor their implementations to achieve enhanced operational efficiency and sustained competitiveness.

The extensive literature survey spanning references [1-50] highlights a prevalent research landscape where proactive maintenance strategies have received considerable attention. However, a noticeable research gap emerges, as there is limited or virtually no exploration of addressing the machine responsible for the highest number of errors, despite its critical role in assembly line downtime. Furthermore, the potential of incorporating Machine Learning algorithms to predict and preempt downtime occurrences remains largely unexplored. This gap signifies a unique avenue for investigation, where efforts can be directed towards not only identifying the most error-prone machine but also harnessing predictive analytics to enhance the efficiency and reliability of the assembly line by minimizing unexpected downtime instances. Moreover, the existing body of literature does not adequately encompass the amalgamation of statistical methods and corrective actions aimed at effectively reducing downtime in the automotive braking system assembly lines. While certain studies have investigated statistical techniques in manufacturing contexts, their application to the intricate domain of braking system assembly lines is notably lacking.

2. METHODOLOGY

In the realm of BSFA line operations, our approach encompasses a multifaceted strategy. Firstly, we delve into comprehending the inner workings of the machines within these lines, aiming for a profound understanding. Concurrently, we harness the power of data visualization, employing various plots and graphs to gain insights from pre-processed data, thereby illuminating trends and patterns. Furthermore, our focus sharpens on the meticulous gathering of information, particularly pertaining to errors that frequently disrupt operations, thereby leading to downtime. Subsequently, we embark on a mission to pinpoint the root causes of these disruptions, identifying which specific machine or machines contribute most significantly to downtime and quantifying the duration of these interruptions. Armed with this knowledge, our quest is to engineer solutions that target these troublesome machines, aiming to curtail downtime effectively. Lastly, we explore the realm of Machine Learning, specifically employing a Decision Tree approach, to predict downtime in advance and proactively mitigate its impact on BSFA line operations.



2.1 Understanding about the working of machine in BSFA lines

The final assembly of the braking system is a critical process that ensures the safety and reliability of any vehicle. Any errors during this process can result in significant downtime, which can cause delays, increase costs, and negatively impact customer satisfaction. Therefore, it is essential to focus on reducing downtime by minimizing errors in the final assembly of the braking system.One of the primary reasons for errors during the final assembly process is the complexity of the braking system. The braking system is composed of several components, each of which must be assembled correctly for the system to function effectively. Additionally, the braking system must meet specific safety standards, making it challenging to ensure that every component is correctly installed and functioning correctly. To overcome this complexity, manufacturers can implement strategies to reduce errors and minimize downtime.

The BSFA Line comprises 21 machines, each serving a vital role in the intricate process of producing electronic control units (ECUs). These machines encompass a wide array of functions, ranging from the initial steps of sealing and curing the ECU housing to the final stages of testing and packaging. Beginning with the HU Seal Dispensing and HU Oven, the process commences with the application and curing of HU sealant to prevent leakage. DMC & Connector Sealing machines follow, contributing to tracking and sealing connectors effectively. The DMC and UV Curing machines employ UV rays to cure parts, while the Flowtest Machine assesses airflow in the membrane. Subsequently, the assembly phase commences with Damping Ball Assembly and Coil Assembly, where operators provide cushioning and manually assemble coils. Coil Pressing machines then ensure precise coil placement within the housing, followed by Taifun Cleaning to maintain cleanliness. Spring Assembly machines insert springs, and AOI Housing machines meticulously check spring presence, pin height, and straightness. PCBA Pressing machines insert the PCB assembly, and AOI Pin Height checks pin height uniformity. Laser Welding machines secure the lid to the housing, and HT Oven heats the ECU for high-temperature testing. HT Test machines assess the ECU's functionality, and Cooling Stations bring it back to room temperature. O-Ring Assembly adds O-rings to motor contact pins, and Leak Test machines ensure there are no leaks. Finally, the Packing Station marks the conclusion, placing ECUs into bins as per standard procedures.

This diverse array of machines showcases the complexity and precision required in ECU manufacturing, with each step playing a crucial role in ensuring the quality and reliability of the final product. The seamless coordination of these 21 machines is essential to delivering high-performance electronic control units that meet stringent industry standards and customer expectations.

2.2Visualize the pre-processed date with plots, graph etc

Gathered data on the number of errors and downtime in minutes for previous months in order to have an idea about the trend of downtime caused by machines.

By referring to Fig 2, we collected historical data encompassing the frequency of errors and downtime durations in previous months. This approach aims to discern the downtime trend resulting from machine-related factors.

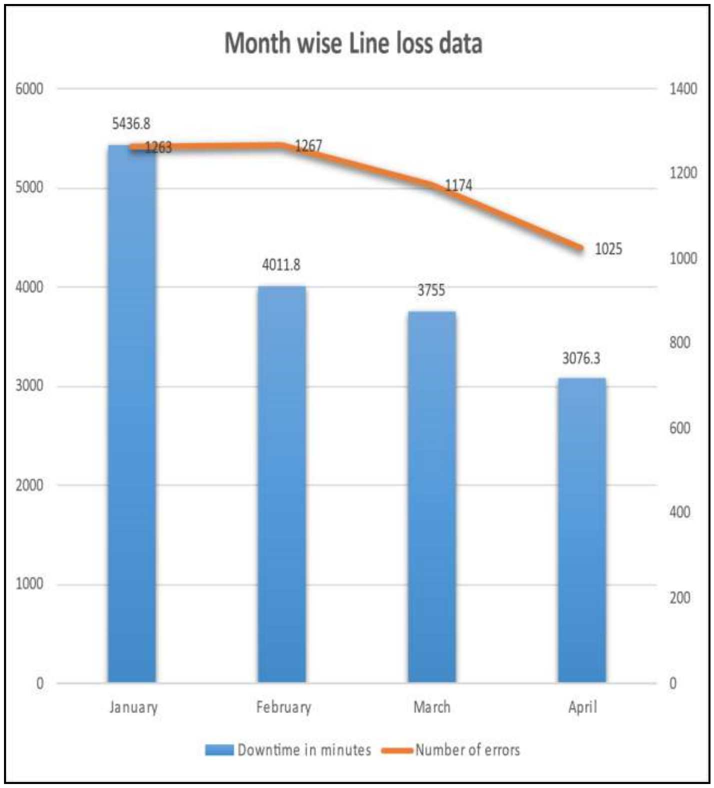


Fig 2 Month wise Line loss Data

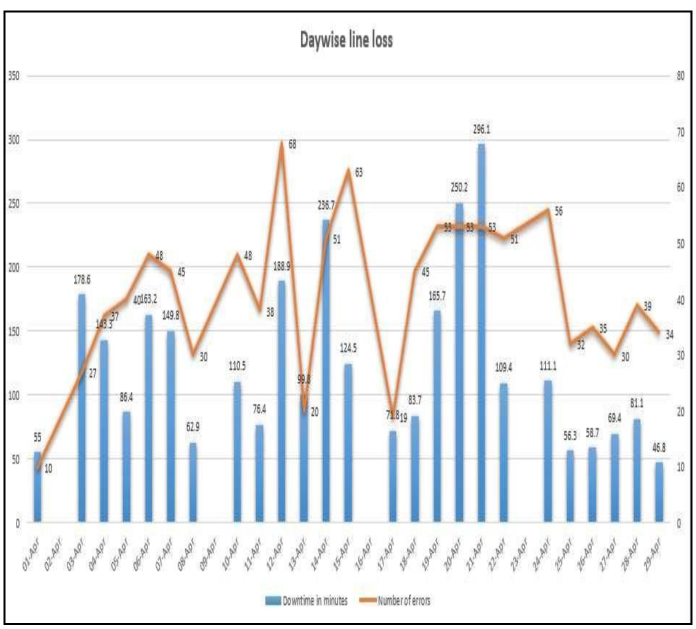


Fig 3 Day wise Line loss Data

From Fig 3, we conducted a meticulous daily examination of error occurrences and the resulting downtimes. These observations are translated into visual representations, allowing for a comprehensive understanding of the patterns in errors and associated downtimes on a daily basis.

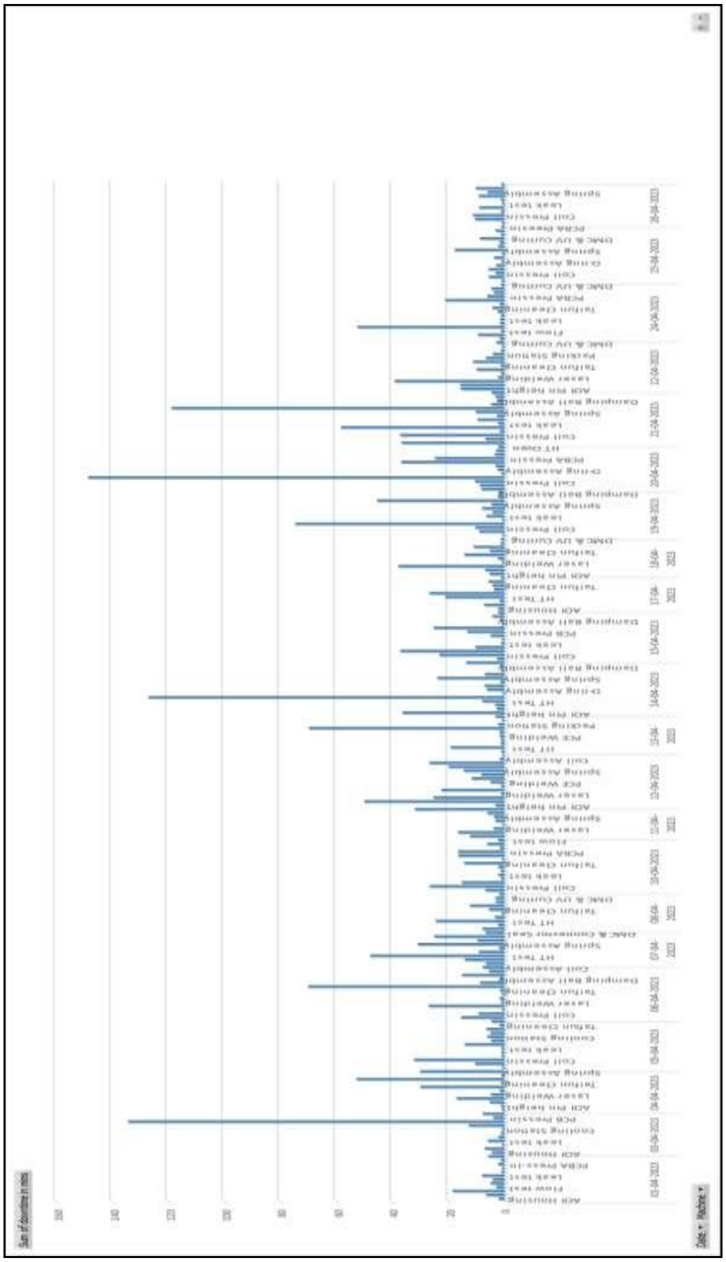


Fig 4 Day wise Line loss Data – Machine wise

With reference to Fig 4, we meticulously recorded the daily losses incurred by each machine and transform this data into graphical representations. This process facilitates a visual depiction of the daily machine-specific losses, aiding in the identification of trends and variations in the downtime patterns across different machines.

2.3 Gathering of information related to errors occurring in the machines and downtime caused due to frequently occurring errors

Figures 5 and 6 serve as invaluable tools for gaining deep insights into the intricacies of machine-related downtime within the assembly line. In Figure 5, we present a clear and concise breakdown of the percentage contribution of each individual machine to the overall machine loss. This detailed analysis not only pinpoints the specific machines that significantly impact production interruptions but also highlights the distribution of downtime across the assembly line. Such granularity is crucial for identifying critical sources of downtime and laying the foundation for targeted improvement efforts.

Figure 6 takes this analysis a step further by providing a visual representation of the consolidation of machine-related downtime. Visualizing the data in this manner offers a holistic perspective on the patterns and trends in downtime, making it easier for stakeholders to grasp the overall landscape of disruptions. This visual approach enhances our ability to identify clusters of machines that may be susceptible to similar issues or those that consistently operate at peak efficiency. As a result, these figures empower decision-makers with the knowledge needed to implement effective strategies for minimizing downtime, optimizing production processes, and ultimately enhancing the assembly line's overall performance and reliability.

Machine	0-2 mins	2-5 mins	5-10 mins	>10 mins	Total	Machine Contribution	%contribution in machine loss
HU Seal Dispensing	1	0	0	0	1	0.189	0.02
HU Oven	0	0	0	0	0	0.000	0.00
DMC and connector sealin	4	1	2	0	7	1.323	0.14
DMC and UV Curing	9	10	3	1	23	4.348	0.46
PCE welding	25	8	3	1	37	6.994	0.74
Flow test	5	2	0	0	7	1.323	0.14
Damping ball Assembly	14	2	2	1	19	3.592	0.38
Coil Assembly	5	0	1	0	6	1.134	0.12
Coil Pressin	36	19	13	6	74	13.989	1.48
Taifun Cleaning	7	8	3	2	20	3.781	0.40
Spring Assembly	28	27	8	7	70	13.233	1.40
AOI Housing	9	1	1	1	12	2.268	0.24
PCBA Pressin	33	1	3	9	46	8.696	0.92
AOI pin height	17	12	11	3	43	8.129	0.86
Laser Welding 1 & 2	28	6	2	4	40	7.561	0.80
HT Oven	1	1	0	0	2	0.378	0.04
HT Test	16	11	9	19	55	10.397	1.10
Cooling Station	4	0	3	0	7	1.323	0.14
O-ring Assembly	10	2	1	2	15	2.836	0.30
Leak Test	23	7	0	1	31	5.860	0.62
Packing Station	8	5	1	0	14	2.647	0.28

Fig 5 Percentage Contribution in Machine Loss

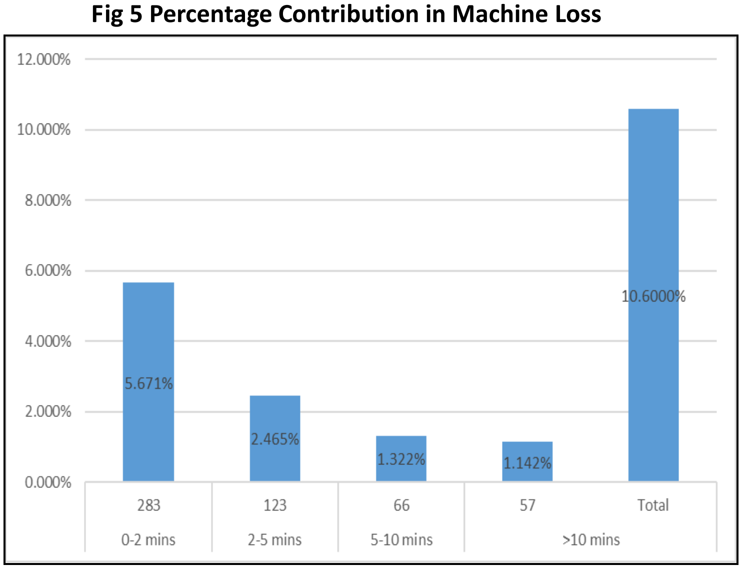


Fig 6 Consolidated % contribution according to time taken

2.4 Determine which machine(s) causes the most downtime and duration of this downtime

Statistical Analysis

Pareto Principle

- The Pareto Principle, also known as the 80/20 rule, can be applied to identify the vital few causes of downtime in the braking system final assembly line. According to this principle, approximately 80% of the downtime is caused by 20% of the underlying factors.
- By analyzing and prioritizing these vital few causes, such as equipment failures, material shortages, or process inefficiencies, manufacturers can focus their efforts on the most significant contributors to downtime.
- This allows them to allocate resources effectively, implement targeted improvements, and achieve substantial reductions in downtime, thereby enhancing overall productivity and efficiency in the assembly line

Table 1 Top Downtime Machines Identified using Pareto Principle

PCE Welding	11	HERRMANN ULTRAPLAST DIGIT	8	1301
Damping Ball Assem	3	EXTRA DAMPING BALL MOUNTED	8	1309
Laser welding	25	SAFETY --- INTE	8	1317
PCBA Pressin	13	LINE TAKEN BY MAINTENANCE	8	1325
Leak Test	10	MES_DDLV ERROR	8	1333
Spring Assembly	6	AIRFLOW OVERLOAD	8	1341
PCBA Pressin	16	K011A2-K02 _131B	7	1348
Laser Welding	3	BUBBLE MARK ON	7	1355
PCBA Pressin	1	PROGRAM LOADING ISSUE	7	1362
DMC & UV Curring	19	LASER MARKING: DISPENSER ERROR	7	1369
AOI Housing	6	LINE TAKEN BY MAINTENANCE	7	1376
PCBA Pressin	3	A051A6 _101B3	6	1382
Laser Welding	13	HUPO NOT IN POS	6	1388
PCBA Pressin	4	000K721E _201B204B TEST C	6	1394
Leak Test	9	MANUAL LEAK TESTER DOWN END	6	1400
DMC & UV Curring	21	MATERIAL LEK	6	1406
PCBA Pressin	9	DIGIFORCE NOK P	6	1412
Leak Test	12	SCANNED CODE HAS WRONG LENGTH	6	1418
DMC & Connector Se	2	OTHERS	5	1423
DMC & UV Curring	6	000K112C _10	5	1428
Coil Pressin	32	UNLOCK CYL MOVED IN/OUT	5	1433
Coil Pressin	33	VERTICAL UNIT IN UPPER/LOWER POSITION	5	1438
PCBA Pressin	39	PCBA PRESS IN NOK	5	1443
Laser Welding	18	MES VMDT ERROR	5	1448
Laser Welding	32	SOFTWARE_CONTUR	5	1453
HT Test	10	CODE IS NOT READABLE	5	1458
PCBA Pressin	6	UNLOADING GRIPCB	5	1463
O-Ring Assembly	1	PART NOT FOR STATION	5	1468
Coil Pressin	31	THE HEIDEHEIN COMPENSATE VALUE IS NOT RIGHT	5	1473
PCE Welding	15	NOK- DAE NOT IN C	4	1477
Damping ball assemb	15	STA50A DAMPING ELEMENT LOW	4	1481
Coil Assembly	10	OTHERS	4	1485

Table 1 showcases the outcome of applying the Pareto Principle to pinpoint the key contributors to downtime. This image displays the top downtime machines, which were identified by analyzing data and categorizing the vital few causes. By leveraging this visual insight, we can readily grasp the critical machines that demand immediate attention and allocate resources for targeted improvements. This representation not only facilitates effective decision-making but also aids in fostering a proactive approach to maintenance and optimization within the assembly line.

PARETO CHART - MACHINE DEFECTS

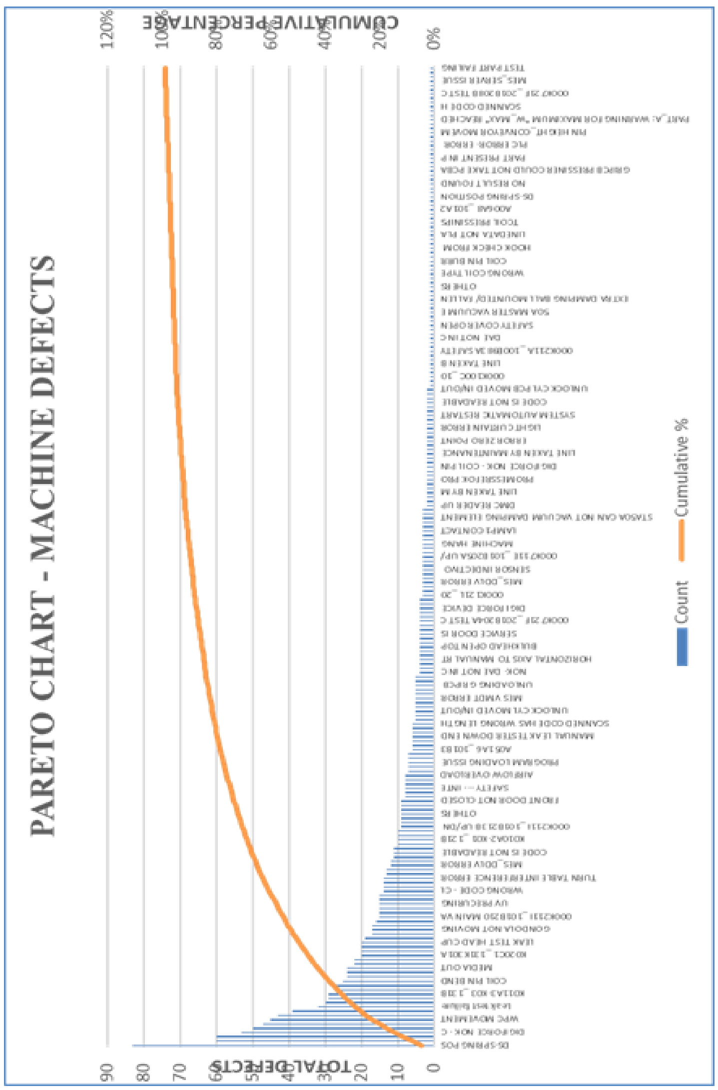


Fig 8 Pareto Chart of Machine Defects

The Pareto chart analysis shows the most significant downtime causes in descending order of frequency. By addressing the top few causes, we can potentially reduce a substantial portion of the downtime. Focusing on these critical issues will lead to more efficient allocation of resources and efforts, ultimately leading to a significant reduction in overall downtime and improved productivity in the process.

Error No	Defect Description	Count	Cumulative
10	DS-SPRING POS	83	83
12	HT-TEST PART FAILING	60	143
14	WORK PIECE CARRRIER ERROR	60	203
2	DIGIFORCE NOK - C	53	256
16	ESD-SPRING NOT ARRIVED ON PART	50	306
5	COIL LIFTED	47	353
1	WPC MOVEMENT	45	398
10	NO RESULT FOUND	43	441
11	FAULT CCS RESET	39	480
6	LEAK TEST FAILURE	32	512
4	CONVEYOR MOVEMENT ERROR	30	542
10	HANG	29	571
17	K011A3-K03 _131B	29	600

Table 2 Defects causing most downtime

Statistical Process Control (LCL& UCL)

- The Lower Control Limit (LCL) and Upper Control Limit (UCL) are statistical boundaries used in Statistical Process Control (SPC) to identify abnormal variations in a process.
- The LCL represents the lower boundary below which data points are considered unusual or abnormal. When data points fall below the LCL, it suggests that the process is experiencing some form of issue or variation that is affecting its performance negatively.
- On the other hand, the UCL represents the upper boundary above which data points are considered unusual or abnormal. Data points exceeding the UCL indicate that the process is performing

at a higher level than expected or experiencing some form of variation that is potentially impacting its performance positively.

- When monitoring a process, any data points falling outside the control limits (either above the UCL or below the LCL) indicate the presence of special cause variation or assignable causes. These data points signal that the process is operating in an unpredictable or out-of-control manner and require investigation and corrective action to address the underlying issues.

Table 3 Exceptions and Problem Areas by LCL and UCL Analysis

12-06-2023	PCBA Pressin	DIGIFORCE NOK - C	1	19.52	118.9358256	-79.89431613
13-06-2023	PCBA Pressin	DIGIFORCE NOK - C	8	19.52	118.9358256	-79.89431613
14-06-2023	PCBA Pressin	DIGIFORCE NOK - C	35.9	19.52	118.9358256	-79.89431613
15-06-2023	PCBA Pressin	DIGIFORCE NOK - C	15.1	19.52	118.9358256	-79.89431613
17-06-2023	PCBA Pressin	DIGIFORCE NOK - C	2	19.52	118.9358256	-79.89431613
19-06-2023	PCBA Pressin	DIGIFORCE NOK - C	5.7	19.52	118.9358256	-79.89431613
02-06-2023	PCBA Pressin	DIGIFORCE NOK - COIL PIN	1	0.65	1.7	-0.4
03-06-2023	PCBA Pressin	DIGIFORCE NOK - COIL PIN	0.3	0.65	1.7	-0.4
24-04-2023	PCBA Pressin	DIGIFORCE NOK P	0.3	1.45	4.017586415	-1.117586415
25-04-2023	PCBA Pressin	DIGIFORCE NOK P	0.3	1.45	4.017586415	-1.117586415
27-04-2023	PCBA Pressin	DIGIFORCE NOK P	1.5	1.45	4.017586415	-1.117586415
12-05-2023	PCBA Pressin	DIGIFORCE NOK P	2	1.45	4.017586415	-1.117586415
15-05-2023	PCBA Pressin	DIGIFORCE NOK P	2.3	1.45	4.017586415	-1.117586415
25-05-2023	PCBA Pressin	DIGIFORCE NOK P	2.3	1.45	4.017586415	-1.117586415
03-06-2023	PCBA Pressin	DIGIFORCE NOK PSEUDO FAILURE	7.5	7.50	7.5	7.5
07-04-2023	PCBA Pressin	ENGAGE CYL FORCE PICK UP MOVED UP	1	1.25	2	0.5
07-04-2023	PCBA Pressin	ENGAGE CYL FORCE PICK UP MOVED UP	1.5	1.25	2	0.5
05-04-2023	PCBA Pressin	GRIPCB PRESSINER	1	6.10	47.88527728	-35.69527728
06-04-2023	PCBA Pressin	GRIPCB PRESSINER	66	6.10	47.88527728	-35.69527728
11-04-2023	PCBA Pressin	GRIPCB PRESSINER	4	6.10	47.88527728	-35.69527728
19-04-2023	PCBA Pressin	GRIPCB PRESSINER	2	6.10	47.88527728	-35.69527728
21-04-2023	PCBA Pressin	GRIPCB PRESSINER	1	6.10	47.88527728	-35.69527728
26-04-2023	PCBA Pressin	GRIPCB PRESSINER	6.2	6.10	47.88527728	-35.69527728
27-04-2023	PCBA Pressin	GRIPCB PRESSINER	7	6.10	47.88527728	-35.69527728
28-04-2023	PCBA Pressin	GRIPCB PRESSINER	3	6.10	47.88527728	-35.69527728
04-05-2023	PCBA Pressin	GRIPCB PRESSINER	0.7	6.10	47.88527728	-35.69527728
05-05-2023	PCBA Pressin	GRIPCB PRESSINER	6.5	6.10	47.88527728	-35.69527728
09-05-2023	PCBA Pressin	GRIPCB PRESSINER	4.5	6.10	47.88527728	-35.69527728
16-05-2023	PCBA Pressin	GRIPCB PRESSINER	1	6.10	47.88527728	-35.69527728
16-05-2023	PCBA Pressin	GRIPCB PRESSINER	1.5	6.10	47.88527728	-35.69527728
17-05-2023	PCBA Pressin	GRIPCB PRESSINER	1	6.10	47.88527728	-35.69527728
17-05-2023	PCBA Pressin	GRIPCB PRESSINER	3	6.10	47.88527728	-35.69527728
29-05-2023	PCBA Pressin	GRIPCB PRESSINER	1	6.10	47.88527728	-35.69527728
11-06-2023	PCBA Pressin	GRIPCB PRESSINER	8	6.10	47.88527728	-35.69527728
12-06-2023	PCBA Pressin	GRIPCB PRESSINER	2.5	6.10	47.88527728	-35.69527728

The LCL and UCL analysis revealed an abnormal pattern in the case of LVDT Sensor defect compared to other defects. This indicates that the LVDT sensor defect plays a significant role in the downtime. As the sensor's performance has a pronounced impact on product quality and downtime, it is crucial to conduct a comprehensive analysis of the LVDT sensor.

Downtime by LVDT sensor	Mean	UCL	LCL
1	17.67	158.0141	-122.674
4.4	17.67	158.0141	-122.674
1.6	17.67	158.0141	-122.674
0.5	17.67	158.0141	-122.674
3.8	17.67	158.0141	-122.674
0.8	17.67	158.0141	-122.674
3.2	17.67	158.0141	-122.674
0.3	17.67	158.0141	-122.674
165.4	17.67	158.0141	-122.674
9.3	17.67	158.0141	-122.674
4.1	17.67	158.0141	-122.674

Table 4 Downtime Caused due to LVDT Error

Further investigation will help identify the root causes of the deviation and implement targeted corrective actions to improve the sensor's accuracy and stability. This analysis will ultimately enhance the overall process performance and ensure consistent and reliable production results.

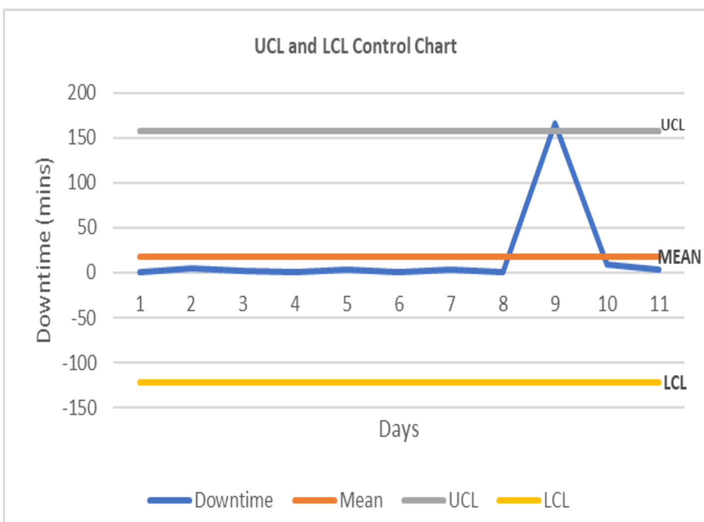


Fig 9 Problem Area Identified by LCL and UCL Analysis – LVDT Sensor Error from PCBA Pressin Machine

Fig 9 illustrates the pivotal findings extracted from the Lower Control Limit (LCL) and Upper Control Limit (UCL) analysis, shedding light on a notable problem area within the assembly line. This chart serves as a graphic testament to the power of data-driven insights, offering a tangible depiction of the deviation detected in the LVDT sensor, a crucial component of the PCBA pressin machine. The chart's placement within the report underscores its significance, presenting a concise yet impactful narrative of how the LCL and UCL analysis has identified the LVDT sensor error as a focal point for investigation and improvement. As a pivotal point of reference, this chart encapsulates the essence of the anomaly, setting the stage for the subsequent analysis and strategies that seek to address this pivotal concern and optimize the assembly line's performance.

Downtime caused by LVDT sensor error (in ms)	Mean	UCL	LCL
1	17.67	158.0141	-122.674
4.4	17.67	158.0141	-122.674
1.6	17.67	158.0141	-122.674
0.5	17.67	158.0141	-122.674
3.8	17.67	158.0141	-122.674
0.8	17.67	158.0141	-122.674
3.2	17.67	158.0141	-122.674
0.3	17.67	158.0141	-122.674
165.4	17.67	158.0141	-122.674
9.3	17.67	158.0141	-122.674
4.1	17.67	158.0141	-122.674

Fig 10 Highlighting the main downtime caused due to LVDT sensor

In Fig 10, a detailed breakdown emerges, showcasing the direct impact of the LVDT sensor error on the assembly line's operational efficiency. This figure not only enumerates the instances of downtime, meticulously quantified in milliseconds, but also unveils key statistical indicators that provide crucial context. The Mean value serves as a central reference point, encapsulating the average downtime caused by the LVDT sensor error. Complementing this, the Upper Control Limit (UCL) and Lower Control Limit (LCL) derived values establish the boundaries within which the variations in downtime are expected to operate. This encapsulation of data within the defined control limits underscores the meticulous approach taken to assess the error's significance. The figure thus emerges as a dynamic snapshot that bridges the gap between raw data and actionable insights. By presenting a comprehensive view of both the magnitude of downtime and its statistical dimensions, Fig 10 not only underscores the immediate consequences of the

LVDT sensor error but also lays the groundwork for targeted interventions and improvements that aim to rectify the anomaly and optimize the assembly line's overall performance.

2.5 Finding a solution to resolve issues occurring to above machine(s) so as to reduce the downtime caused

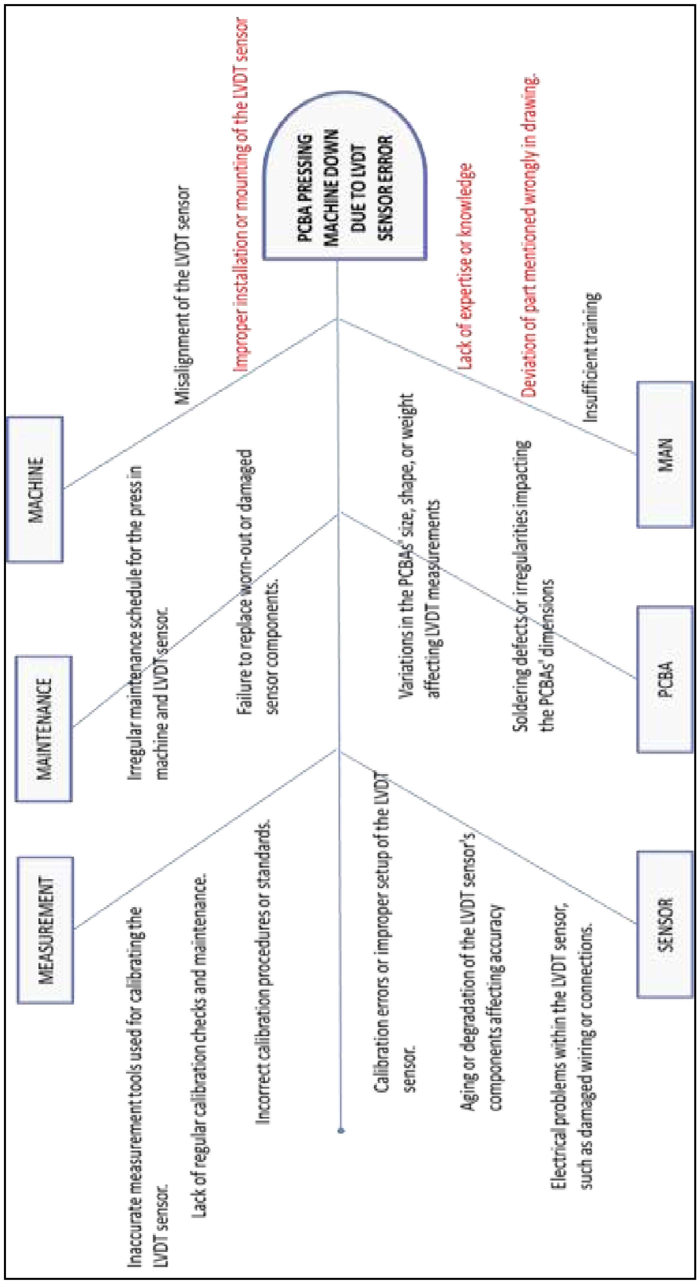


Fig 11 Fishbone Diagram of Cause And Effect Of Downtime Of PCBA Pressing Machine Due to LVDT Sensor Error

Fig 11 unveils a potent visual representation in the form of a Fishbone Diagram, meticulously dissecting the intricate cause and-effect relationships that underlie the downtime of the PCBA pressing machine attributed to the LVDT sensor error. This diagram serves as an insightful roadmap, leading stakeholders on a journey to unearth the root causes that contribute to this specific challenge.

RPN

Risk Priority Number (RPN) is a quantitative method used in risk assessment and prioritization to identify and prioritize potential risks based on their severity, occurrence, and detectability. The RPN is calculated by multiplying the Severity, Occurrence, and Detection scores of a risk. The formula for calculating RPN is as follows:

RPN = Severity (S) × Occurrence (O) × Detection (D)

Each factor is usually rated on a scale from 1 to 10, with 1 being the lowest impact or probability, and 10 being the highest. A higher RPN indicates a higher priority risk that requires more attention and mitigation efforts.

RPN Before Corrective Action

RPN = 8 * 9 *6 = 432

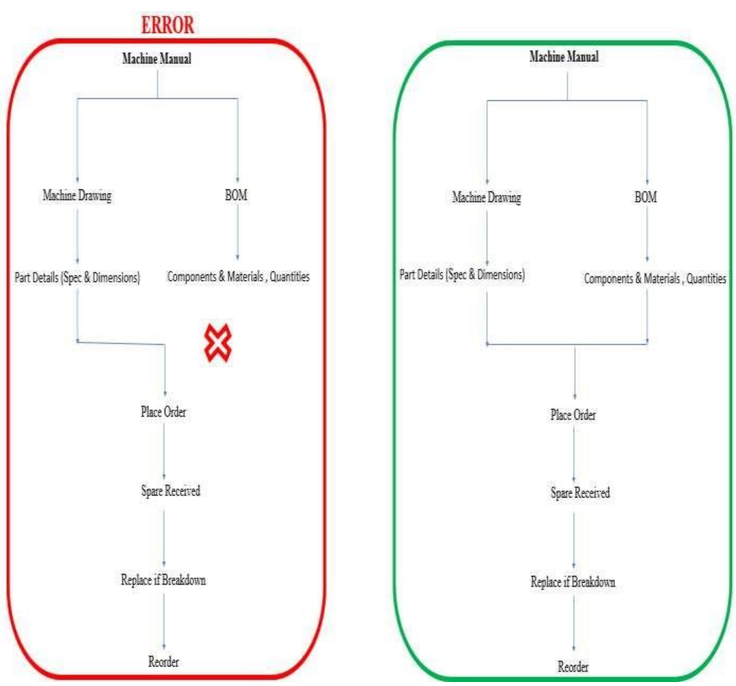


Fig 12 Root Cause Analysis for LVDT Sensor Error

Corrective Actions

- Physical Verification of Machine along with part drawing and Bill Of Materials (BOM)
- Any BOM Change or Drawing Change needs to be taken care before MAE dispatch
- Implement a robust document control system to manage part drawings, BOMs, and any changes effectively. Ensure that all revisions are properly documented and communicated to relevant stakeholders.
- Ensure that all operators are properly trained and certified to operate the machine to prevent errors and mishandling.
- Establish a preventive maintenance program that includes routine inspections, cleaning, and servicing to prevent unexpected breakdowns and prolong the machine's lifespan.

RPN After Corrective Action

RPN = 3 * 5 * 5 = 75

2.6 Utilizing Machine Learning for Downtime Prediction in Manufacturing: A Decision Tree Approach

In the realm of modern manufacturing, downtime is a significant concern, impacting productivity, efficiency, and overall profitability. The ability to predict and prevent machine downtime has become increasingly crucial. This project presents a comprehensive study on the application of machine learning, specifically the Decision Tree algorithm, to predict machine downtime in a manufacturing setting. The research leverages real-world data involving dates, machine names, and downtime durations to develop a predictive model that aids in proactively managing production disruptions.

The research methodology involves several key steps:

1.Data Collection: Gathered historical data for the past 2.5 (April – June Mid) months that includes the following columns:

- Date: The date when the downtime occurred was recorded.
- Machine Name: The name of the machine for which error occurred
- Error: Error code
- Downtime: The duration of downtime in minutes

2. Feature Extraction: From the raw data, derived relevant features that could potentially influence the occurrence of an error and downtime. These features include:

- Converting the downtime values to integer
- Error: Added the count of specific errors occurred on a day in a machine.

2. Data Transformation: Transform categorical variables like “Date" and “Machine Name" into numerical format using techniques like LabelEncoder.

3. Data Splitting: Split the data into a training set and a testing set. Used 85% of random picked data for training and the remaining 15% data for testing. Model Training and Validation: The dataset was split into training and testing subsets. The Decision Tree model was trained on the training subset and evaluated on the testing subset using appropriate performance metrics, such as accuracy, precision, recall, and F1-score.

Modeling

Decision Tree Algorithm: Trained the model using the training dataset. The binary outcome variable will be whether a machine will be down (1 for down, 0 for machine in running condition), and the predictor variables will include the derived features.

Python Program

```
from google.colab

import files %matplotlib inline

 import numpy

import io from pandas

import read_excel

 import matplotlib.pyplot as plt from matplotlib.pyplot import

pie, axis, show

 import pandas as pd from pandas.plotting

 import scatter_matrix from numpy

 import array from numpy

import argmax from sklearn.compose
```

```
 import make_column_transformer from sklearn.preprocessing

import RobustScaler from sklearn.preprocessing

 import LabelEncoder from sklearn.preprocessing

import OneHotEncoder from sklearn.model_selection

 import train_test_split from sklearn

import svm from sklearn.neural_network

import MLPClassifier from sklearn

import tree from sklearn.linear_model

import LogisticRegression from   sklearn.linear_model

import LogisticRegressionCV from sklearn.svm

 import SVR from sklearn.svm

 import NuSVR from sklearn.preprocessing

import StandardScaler from sklearn.svm

import SVC from sklearn.svm

 import NuSVC from sklearn

import linear_model from sklearn.linear_model

import SGDClassifier from sklearn.pipeline

 import make_pipeline from sklearn.metrics

import accuracy_score from sklearn.metrics

import confusion_matrix from sklearn.metrics

import classification_report

 import warnings warnings.filterwarnings('ignore')

uploaded = files.upload() df = read_excel('DowntimeData.xlsx')

df = df.drop(

['Unnamed: 4','Unnamed: 5','Unnamed: 6','Unnamed: 7'],axis=1)

print(df)
```

```
print(df["Date"].value_counts()) print('\n',
df["Machine"].value_counts()) print('\n', df["Downtime in
mins"].value_counts())

categorical = [var for var in df.columns if df[var].dtype=='O']
print('There are {} categorical
variables\n'.format(len(categorical)))

print('The categorical variables are :', categorical) numerical =
[var for var in df.columns if df[var].dtype!='O'] print('There are {}
numerical variables\n'.format(len(numerical))) print('The
numerical variables are :', numerical)

print(df.head()) label_encoder = LabelEncoder() df['Machine'] =
label_encoder.fit_transform(array(df['Machine'])) df['Date'] =
df['Date'].values.astype("float64") print(df['Date']) print(df)
X = df.drop(['Error'], axis=1) y = df['Downtime in mins']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.15, random_state = 42) print(X_train.shape, X_test.shape)
print(X_train, X_test) dct = tree.DecisionTreeClassifier()
dct.fit(X_train, y_train) y_pred = dct.predict(X_test)
print('Model accuracy score: {0:0.4f}'.
format(accuracy_score(y_test, y_pred))) y_pred_train =
dct.predict(X_train) print('Training-set accuracy score:
{0:0.4f}'. format(accuracy_score(y_train, y_pred_train)))
print('Training set score: {:.4f}'.format(dct.score(X_train,
```

```
y_train))) print('Test set score:

{:.4f}'.format(dct.score(X_test, y_test))) cm =

confusion_matrix(y_test, y_pred)



cm_df = pd.DataFrame(cm)

print(classification_report(y_test, y_pred))

print('***************************************')
```

The code begins with importing necessary libraries and modules. These include libraries for data manipulation (NumPy, pandas), data visualization (matplotlib), machine learning algorithms (scikit-learn), and warnings handling. The code uploads the Excel file 'DowntimeData.xlsx' using the files.upload() function and reads its content into a pandas DataFrame named df. Label Encoding is applied to the "Machine" column to convert categorical values into numerical labels. Additionally, the "Date" column is converted to float64 data type. The updated DataFrame is printed to show the changes. Features (X) and the target variable (y) are separated. The dataset is split into training and testing sets using the train_test_split() function. An instance of DecisionTreeClassifier (dct) is created. The model is trained on the training data using the fit() method. Predictions are made on the testing set using predict(). The confusion matrix is computed and converted to a DataFrame (cm_df) for better visualization. The classification_report()function generates a detailed classification report including precision, recall, F1-score, and support metrics for each class. This Python code demonstrates the complete process of preprocessing data, training a Decision Tree Classifier, evaluating the model's performance, and providing valuable insights for downtime prediction in manufacturing processes.The results of the predictive model were promising. The Decision Tree algorithm exhibited a high accuracy rate in predicting machine downtime. Precision, recall, and F1-score metrics further indicated the model's effectiveness in distinguishing between downtime and normal operational periods. This suggests that the model can reliably identify situations where machine downtime is likely to occur.

OUTPUT

```
Model accuracy score: 0.9593
Training-set accuracy score: 1.0000
Training set score: 1.0000
Test set score: 0.9593
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        96
           2       1.00      1.00      1.00        60
           3       1.00      1.00      1.00        26
           4       1.00      1.00      1.00        11
           5       1.00      1.00      1.00        14
           6       1.00      1.00      1.00        14
           7       1.00      1.00      1.00         6
           8       1.00      1.00      1.00         8
           9       1.00      1.00      1.00         5
          10       1.00      1.00      1.00         5
          11       1.00      1.00      1.00         5
          12       1.00      1.00      1.00         1
          13       1.00      1.00      1.00         1
          14       1.00      1.00      1.00         1
          15       1.00      1.00      1.00         2
          16       1.00      1.00      1.00         1
          18       1.00      1.00      1.00         1
          20       0.00      0.00      0.00         0
          21       0.00      0.00      0.00         2
          23       0.00      0.00      0.00         2
          24       0.00      0.00      0.00         1
          25       1.00      1.00      1.00         1
          26       1.00      1.00      1.00         1
          42       0.00      0.00      0.00         0
          44       0.00      0.00      0.00         1
          62       0.00      0.00      0.00         0
          65       0.00      0.00      0.00         1
          66       0.00      0.00      0.00         0
          71       0.00      0.00      0.00         1
          78       0.00      0.00      0.00         0
         117       0.00      0.00      0.00         0
         134       0.00      0.00      0.00         1
         149       0.00      0.00      0.00         1
         251       0.00      0.00      0.00         1
         301       0.00      0.00      0.00         0

    accuracy                           0.96       270
   macro avg       0.54      0.54      0.54       270
weighted avg       0.96      0.96      0.96       270

****************************************************************
```

3. RESULTS AND DISCUSSIONS

The primary focus of this research is to address the challenge of downtime reduction in the braking system's final assembly line within the context of the automotive industry. The study emphasizes the importance of continuous improvement and process optimization to enhance global competitiveness and technological innovation.

The study starts by acknowledging the competitive nature of the automotive manufacturing sector, particularly in the Anti-lock Braking System (ABS) domain. It highlights the significance of fostering a culture of perpetual enhancement, both economically and technologically. By pursuing process optimization, increased efficiency, and waste reduction, organizations can not only enhance their economic standing but also bolster their technological advancements.

The specific problem tackled in the research revolves around downtime occurring in the braking system's final assembly line. The study identifies that frequent errors lead to utilization loss or technical availability loss, impacting the overall efficiency of the assembly line. The objective is to understand these errors, their root causes, and subsequently devise effective solutions to minimize downtime and enhance productivity.

To address this objective, the study undertakes a comprehensive methodology, starting with data collection and analysis. Various visualization tools such as plots and graphs are employed to analyze the trend of downtime caused by machines. Day-wise and machine-wise analysis is conducted to delve into the nuances of downtime occurrences.

Through statistical analysis techniques, the study identifies key machines causing significant downtime. The Pareto Principle, known as the 80/20 rule, is applied to prioritize the vital few causes of downtime. This allows for targeted efforts towards mitigating the most significant contributors to downtime. By focusing on these high-impact factors, manufacturers can effectively allocate resources and reduce overall downtime.

Additionally, the study employs Statistical Process Control (SPC) tools, particularly the Lower Control Limit (LCL) and Upper Control Limit (UCL) analysis, to identify abnormal variations in the process. This analysis identifies exceptions and problem areas, highlighting specific aspects that require attention and corrective action.

A significant focus of the study is on the LVDT Sensor error, a recurring issue causing downtime in the PCBA Pressing machine. The study provides a detailed breakdown of the downtime caused by this error and presents a fishbone diagram to visually represent the cause and effect relationship. The study then outlines corrective actions to address this issue, including physical verification of the machine, implementing a robust document control system, ensuring operator training, and establishing a preventive maintenance program.

The outcomes of these efforts are reflected in the reduction of the Risk Priority Number (RPN), a quantitative measure of risk assessment. The RPN before corrective action was calculated to be 432,which is significantly reduced to 75 after the implementation of corrective actions. This reduction signifies the success of the targeted interventions in mitigating risks and improving the operational framework.

The research leveraged real-world data involving dates, machine names, and downtime durations to develop a predictive model that aids in proactively managing production disruptions.

Focus of Research	Downtime Reduction in Braking System's Final Assembly Line
Importance	Enhancing Global Competitiveness and Technological Innovation
Industry Context	Automotive Manufacturing Sector, particularly ABS domain
Key Emphasis	Continuous Improvement, Process Optimization, Efficiency
Specific Problem	Frequent Errors Leading to Utilization Loss and Inefficiency
Methodology	Data Collection, Analysis, Visualization, Statistical Analysis
Tools Used	Plots, Graphs, Pareto Principle, Statistical Process Control
Focus Area	LVDT Sensor Error in PCBA Pressing Machine
Corrective Actions	Machine Verification, Document Control, Operator Training, Preventive Maintenance
Outcome	Reduction in Risk Priority Number (RPN) from 432 to 75
Data Utilization	Leveraging Real-World Data for Predictive Model Development
Achievements	Tangible Downtime Reduction, Enhanced Productivity
Contribution to Industry	Optimization of Automotive Assembly Line Processes

Table 5 Summary of Research Focus and Key Findings

In essence, the research successfully identifies and addresses the challenge of downtime reduction in the braking system's final assembly line. By employing a systematic methodology, including statistical analysis and targeted corrective actions, ML based solutions, the study achieves a tangible reduction in downtime, thereby enhancing overall productivity and efficiency within the automotive system sector. The research serves as a valuable contribution to the optimization of assembly line processes in the automotive industry.

4. CONCLUSION AND FUTURE SCOPE

In this research paper, our primary objectives revolved around recognizing the criticality of minimizing downtime in the braking system final assembly line, compiling a thorough dataset of errors and corresponding downtimes, employing data visualization techniques, utilizing Pareto analysis and LCL UCL statistical analysis to pinpoint prominent sources of downtime, and, most importantly, devising practical solutions to curtail machine-specific downtimes and enhance overall productivity.

The journey through this project has underscored the pivotal role that reducing downtime plays in optimizing the efficiency and effectiveness of the braking system final assembly line. Through meticulous data collection, we gained an in-depth comprehension of errors and their associated downtimes, thus establishing a solid foundation for targeted interventions.

The application of diverse data visualization tools allowed us to extract meaningful insights from the collected data, making trends and patterns readily understandable. The strategic use of Pareto analysis and LCL UCL statistical analysis effectively illuminated the specific machines responsible for a significant portion of the downtime, thereby guiding our focus toward the most impactful contributors.

The culmination of our efforts resulted in the identification and resolution of key issues affecting productivity. Notably, the PCBA Pressin machine error emerged as a notable source of downtime, and the LVDT sensor error emerged as a major disruptor. By replacing the 10 mm LVDT sensor with a more appropriate 25 mm specification, we effectively addressed the problem, resulting in a tangible reduction in downtime and an enhancement in productivity.The research leverages real-world data involving dates, machine names, and downtime durations to develop a predictive model that aids in proactively managing production disruptions.

In closing, this paper serves as a testament to the symbiotic relationship between downtime reduction and operational efficiency within the complex context of the braking system final assembly line. Our meticulous analysis and targeted interventions have illuminated a path toward sustained improvement, underscoring the potential for data-driven strategies to enhance manufacturing processes. As industry dynamics continue to evolve, the insights gleaned and solutions implemented through this project will remain invaluable tools for achieving operational excellence and maintaining a competitive edge.

In the realm of future project scope, the integration of Ai powered predictive maintenance emerges as a pivotal advancement. This entails the implementation of sophisticated AI algorithms for real-time monitoring and immediate alerts pertaining to machine health within the manufacturing process. By harnessing the power of artificial intelligence, this forward looking approach can continuously scrutinize data streams from the machinery, swiftly identifying anomalies or discerning patterns that might signify impending failures. When such deviations are detected, the system can automatically generate alerts, promptly notifying maintenance teams. This proactive intervention capability not only minimizes downtime but also optimizes resource allocation by ensuring that maintenance efforts are directed precisely where and when they are needed, ultimately enhancing operational efficiency and productivity in the manufacturing sector.

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