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Predictive Modeling of Opportunistic Maintenance Strategy in PVC Manufacturing: A Machine Learning and Simulation Approach

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Abstract

This paper investigates real-world data from a PVC manufacturing plant in Saudi Arabia to construct predictive statistical models leveraging machine learning techniques. The primary aim is to identify prevalent failures and predict their timing based on historical incidents. The study introduces the Random-Forest-Classifier algorithm to refine the dataset and enhance accuracy. Subsequently, the results are applied to simulation modeling, providing insights into proactive action and opportunistic maintenance behavior within PVC manufacturing. The motivation of the research was to reduce the sudden breakdown in the factory and provide practical recommendations to optimize maintenance practices, thereby enhancing operational efficiency. The paper concludes with a simulation model illustrating the use of opportunistic actions that support the Overall Equipment Efficiency (OEE) resulting from the predictive model's insights.

Keywords
Machine learning, Simulation, Machine failures, Maintenance strategy, Predictive model.

1. Introduction
In the rapidly evolving landscape of industries, the integration of automated processes, machine learning, and simulation has become imperative for companies and manufacturing entities. Embracing these technologies is not only a strategic move but also a necessity to stay competitive and align with the transformative Industry 4.0 trends. Programming is crucial for production lines as it enables the automation of processes, facilitates efficient control of machinery (ALRIDHA et al., 2022), and allows for the employment of advanced technologies, contributing to increased productivity and the utilization of smart operations. The process of finding the best strategy to optimize a process is critical. Simulation on the other hand plays a pivotal role in understanding the system behavior and applying different maintenance strategies within industrial settings. Combining both simulation and programming will provide

a virtual and visual representation that models a real system and analyzes the complex interplay of various components. This research will investigate areas of bottlenecks, inefficiencies, and potential areas for improvement, as this is the preliminary data for any optimization problem (Zahraee et al., 2014). Many optimization methods are available but for this research machine learning (Random-Forest-Classifier) algorithm subject to predictive analysis is conducted.

Three goals have been outlined to help clarify the aim and purpose of the research: first, analyzing the raw maintenance data from the manufacturing plant and utilizing plots to visualize it, aiming to understand patterns and identify failures and bottlenecks; second, Utilizing these statistical models and advanced analytical techniques to explore optimal methods for analyzing the data and deriving insights, with a focus on enhancing maintenance strategies, including predictive and preventive maintenance; Third, exploring and identifying the most suitable maintenance approach based on data analysis and observed patterns, aiming to optimize maintenance strategies for post-validation monitoring.

The industry partner anticipates that the paper will benefit their company by offering a different perspective on the issues raised in the case study. The ideal goal of the paper is to expose the issue—which is primarily the recurring frequency of machine failures, such as unforeseen breakdowns and corrective repairs that have a significant influence on the line's production—and to question the company's approach to problem-solving in relation to the case study.

1.1 Objectives

The research paper outlines three main objectives aimed at enhancing the efficiency and productivity of a manufacturing plant. Firstly, it aims to leverage the raw data obtained from the manufacturing plant and embedded into the machine learning algorithm to refine and clean the maintenance data. The goal is to meticulously model and analyze this data to identify bottlenecks and failures within the production line that may be hindering optimal performance. Secondly, the research emphasizes the implementation of a machine learning algorithm, specifically the Random-Forest-Classifier, to optimize the production line. By offering intelligent insights into the production process, the machine learning approach seeks to identify connections and patterns that may not be seen through traditional analysis. Thirdly, the study aims to simulate the system using a simulation model prior to and after the suggested changes are put into practice. The research seeks to assess the expected impact of the suggested changes by modeling the production line after implementing the proposed changes.

2. Literature Review

This study's methodology in predictive maintenance for PVC pipe manufacturing is greatly informed by the existing literature that integrates machine learning and simulation in industrial settings (Fan & Fan, 2015) and (Trappey et al., 2015) lay a crucial foundation by exploring reliability analysis and intelligent asset management. These insights are crucial for understanding the complexities and challenges in predictive maintenance. (Chris Coleman et al., 2017) and (Mark Haarman et al., 2017) extend this discussion to the digital transformation of supply networks, highlighting the increasing importance of integrated an intelligent system in industrial maintenance, a concept that resonates with our use of Python and Simio. The novel approach by (Wu et al., 2007) in applying neural networks to maintenance decision support systems exemplifies the potential of AI in enhancing predictive accuracy. Further, (Bousdekis et al., 2018) provide a comprehensive overview of prognostic-based decision support methods, offering a broad perspective on the advancements in the field. (Shin & Jun 2015) contribute to this dialogue by delving into the policies surrounding condition-based maintenance, while (Ahmad & Kamaruddin, 2012) offer a comprehensive view of the methodologies employed in industrial maintenance. Lastly, (Niu et al., 2010) discuss the development of optimized condition-based maintenance systems, emphasizing the need for robust and adaptive strategies in industrial environments. Together, these studies not only underline the evolving landscape of industrial maintenance but also emphasize the significance of integrating advanced technologies like machine learning and simulation for enhancing system efficiency and resilience.

3. Methods

The paper's methodology involves a straightforward process outlined in sequential steps. The first step involves collecting real-world data from a PVC manufacturing plant in Saudi Arabia. The second phase is the data collection, which comprises work order completions, machine failures, triggers for failures, and production routings along with the processing time for each machine. Moving on to the third step, a machine learning algorithm, specifically the Random-Forest-Classifier, is employed to clean and preprocess the data. In the fourth step, the algorithm is utilized to plot, optimize, and predict potential failures before they occur. This predictive analysis aids in implementing preventive maintenance measures to avoid breakdowns. Finally, the fifth step employs a simulation model to visually assess the results before and after improvements. This simulation model is then expanded to ensure optimal results, and the findings will be presented in a future publication.

4. Data Collection

The research began with an exhaustive collection of raw, real-world data sourced from a prominent PVC manufacturing company in Saudi. Over a four-year period, the dataset encompassed detailed maintenance records, repair times, reasons for failures, work order completions, and production routings. Complementary information, such as the plant layout, workforce details, operational hours, and raw PVC material composition, was also provided, forming a robust foundation for comprehensive analysis. The manufacturing company, a key industry player, faces challenges in improving Overall Equipment Efficiency (OEE) due to recurrent machine failures. In response to this operational challenge, the primary objective of this research is to propose an optimization method to mitigate machine failures and enhance OEE. The core of the proposed method involves leveraging both machine failure data and machine learning algorithms to simulate and model the outcomes of diverse maintenance strategies. In addition to advanced simulation techniques, machine learning models will be employed to analyze historical data patterns, identifying potential failure precursors, and predicting maintenance needs. The study integrates an opportunistic maintenance approach, synchronizing maintenance activities across multiple machines to proactively address potential failures. The machine learning component will play a pivotal role in refining the dataset, ensuring accuracy, and facilitating a more nuanced understanding of the system's behavior. By employing predictive modeling, the research aims to anticipate the timing of prevalent failures and identify patterns that contribute to the optimization of maintenance schedules. This proactive approach enables the system to adapt to evolving conditions, minimizing the occurrence of unexpected failures. The anticipated outcomes encompass not only a refined simulation analysis but also insights derived from machine learning models, offering a more holistic perspective on maintenance strategy optimization. The combined approach is expected to showcase an appreciable improvement in Overall Equipment Efficiency, as the integration of machine learning enhances the ability to predict and prevent machine failures. This shift from reactive to proactive maintenance is anticipated to optimize resource allocation, reduce downtime, and enhance the reliability of the PVC manufacturing process. This enhanced methodology holds significant implications for the PVC manufacturing industry by offering a comprehensive, data-driven approach to maintenance optimization. By combining real-world data, machine learning, and simulation techniques, the research provides actionable insights for industry practitioners, guiding them toward a more intelligent, efficient, and sustainable approach to addressing machine failures and improving operational resilience.

5. Results and Discussion

This study is centered on developing a method for implementing preventive maintenance by leveraging predictive statistical and machine learning models, particularly through the utilization of specific algorithms like the Random-Forest-Classifier. The primary objective of the proposed approach is to assist decision-makers in making more informed decisions when analyzing historical data on a daily basis. By harnessing the capabilities of emerging AI technologies such as machine learning and simulation, the intended outcome is to provide decision-makers with enhanced tools for strategic assessment. The integration of both machine learning and simulation techniques offers authorities a more accurate estimation of proposed strategies and their potential impact. This combined approach enables a comprehensive understanding of maintenance needs and facilitates proactive decision-making processes. In addition, a similar approach was developed by (LIU et al., 1996) his research proposes the integration of simulation studies to further enhance the analysis of production line behavior. By incorporating simulation, the study aims to explore various scenarios that may impact the performance of the production lines. These scenarios encompass diverse factors, including fluctuations in the processing times of individual machines within the production environment. Through simulation, decision-makers can assess the potential outcomes of different scenarios, enabling a comprehensive understanding of the system's dynamics and vulnerabilities. This approach empowers stakeholders to proactively address potential bottlenecks, optimize resource allocation, and refine preventive maintenance strategies based on simulated real-world conditions. By leveraging simulation studies in conjunction with machine learning techniques, the research endeavors to provide decision-makers with robust tools for strategic planning and risk management in production line operations. Ultimately, this research contributes significantly to the realm of smart factories, emphasizing the critical importance of Artificial Intelligence (AI), machine learning, and simulation. In the context of transforming conventional manufacturing facilities, into more interactive plant with smart monitoring tool that can react based on certain conditions as (Gramegna et al., 2020) illustrates very similar approach on an AI-driven digital twin research that uses innovative tool for data mining to predict the performance and production of the line for better (OEE). As (Kang et al., 2021) conducted research on employing these principles of Artificial Neural Network (ANN), The methodology of this study incorporates an Artificial Neural Network (ANN), a computational model closely mirroring the structure and functionality of neural networks found in the human brain. The intention is to devise a predictive maintenance approach for turbo engines. The proposed algorithm is specifically crafted to grasp the system's dynamic behavior over time, aiming to accurately anticipate maintenance needs and enhance operational efficiency. This research uses Random-Forest-Classification because of its popularity in the field of prediction models and machine learning, as (Speiser et al., 2019) conducted extensive research on Random-Forest-Classification, delving into various approaches for selecting different variables. The objective was to meticulously explore and analyze multiple strategies in the optimal approach tailored to the specific requirements of the desired application. Therefore, the Random-Forest-Classifier seen flowchart in (Figure 1) was incorporated. The algorithm is known for its high accuracy in prediction, as it predicted the failure rate and the maintenance work needed for each machine. The results are then incorporated in the simulation software Simio for a comparative analysis. The primary aim of the study is to mitigate maintenance arising from breakdowns, corrective repairs, and miscellaneous issues by replacing them with preventive maintenance. This shift is expected to significantly reduce downtime. The simulation model, illustrated in Figure 5, simulates the opportunistic strategy behavior, that portrays the enhanced system behavior driven by predictive analysis from the Random-Forest-Classifier. The results indicate the efficacy of automated maintenance, where the enhanced model assimilates data from the algorithm and opportunistically schedules maintenance for multiple machines as their failure rates approach critical thresholds. This simulation model employs probability and variation to accurately depict real system behavior and intelligently alerts operators to impending maintenance requirements prior to breakdowns. Ultimately, a similar methodology could be implemented in real manufacturing plants, incorporating sensors and other technologies to enhance operational efficiency and minimize downtime.

5.1 Numerical Results

Table 1. The number of machines failures and the predicted improvements

Total hours of operation = 17520		
Machine	Failures	Predicted improvements
1. Mixing Area	21	20.79
2. Extruder	103	86.52
3. Die	143	115.83
4. Vacuum Tanks	55	49.5
5. Spray Tanks	17	16.15
6. Puller	12	11.88
7. Cutter	47	40.42
8. Socketing	101	84.84
Total failures	499	425.93

Table 2. The number of work maintenance and the predicted improvements.

Total hours of operation = 17520		
Maintenance Type	Work Maintenance	Anticipated improvements
1. Breakdowns	55	44
2. Corrective Repair	193	144.75
3. Miscellaneous	47	41.36
4. General/PR	40	36.4
5. Maintenance Service	66	55.44
6. Preventive Maintenance	8	7.92
7. MCO/Heat up	90	76.5
Total work maintenance	499	406.37

Classifying the number of failures or work maintenance, as demonstrated in Table 1, constitutes a critical step in validating the proposed algorithm comparing to the improved results based on the maintenance strategy proposed. It enables the study to concentrate efforts on reducing the highest number of failures based on machine types. This classification process serves as a pivotal foundation for assessing the algorithm's effectiveness and directing strategic interventions aimed at minimizing downtime and enhancing overall operational efficiency. This goes along with analyzing the numerical results presented in Table 2, which details the number of maintenance types performed on the machines and their predicted improvements, which is equally pivotal for validating the proposed algorithm. This data allows for a comprehensive evaluation of the algorithm's efficacy in addressing specific maintenance needs associated with various machine types. Focused attention on the numerical breakdown of maintenance types is essential for refining strategies that aim to optimize work maintenance type on the machine and propose preventive maintenance over breakdowns and corrective work.

$$Predicted\ failure\ equation = \frac{\#\ Failures\ x\ (Predicted\ time\ in\ hours)}{Total\ hours\ of\ operation}$$

Equation 1.

Equation 1 outlines a predictive mathematical model predicated on a 2-year period (2022-2023), subject to 17,520 hours, which constitutes the total hours of operation in the denominator of equation 1. The count of failures is derived from the maintenance data of the production line illustrated in Figure 1. This predictive equation can be effectively utilized to input the number of desired days for any machine in the production line (see Figure 1) to ascertain the virtual day on which the machine will likely fail. Subsequently, this data was input into the proposed machine learning algorithm, the Random-Forest-Classifier, to enhance the accuracy of the results.

5.2 Graphical Results

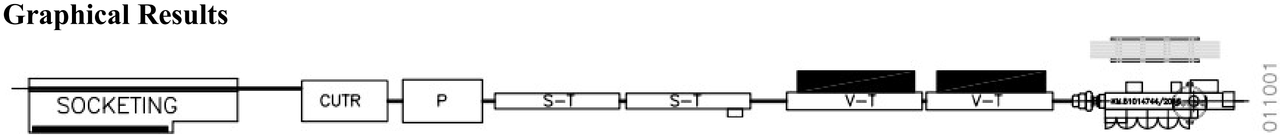

Figure 1. The schematic of the production line

Figure 1 illustrates the sequential manufacturing line at the PVC plant. The process commences with the mixing of PVC resin compound. Subsequently, the compound is vertically fed into the extrusion machine, depicted in the diagram from right to left. With appropriate heating and speed, the compound is directed to the extrusion die, where it is shaped into the desired pipe size. It then proceeds to two vacuum tanks to eliminate any residue from the air, followed by passage through two spray tanks. The pipe is then pulled by a puller, which operates at its own speed, before being directed to the cutter for precision cutting to the desired length. Finally, the pipe is routed to the socketing station to attain the desired socketing type.

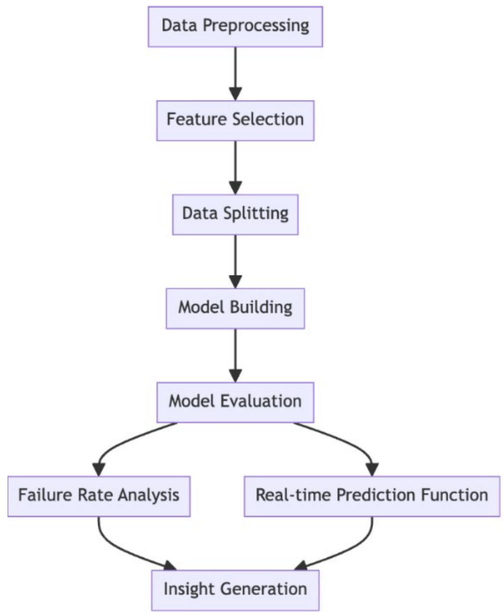

Figure 2. Predictive modeling flowchart

Figure 2 outlines the sequential steps involved in harnessing the power of the Random-Forest-Classifier, facilitating the process of failure prediction and insight extraction. A simplified step-by-step flowchart illustrates the journey from data preprocessing to insightful analysis. Initially, the data undergoes meticulous preparation, ensuring its readiness for comprehensive analysis. Subsequently, emphasis is placed on selecting only the most crucial components of the data. The dataset is then partitioned into distinct groups for both training and testing the model, a pivotal precursor to the selection of the Random-Forest-Classifier aimed at maximizing accuracy. Following model selection, rigorous testing ensues to evaluate its efficacy and performance. Ultimately, the model is deployed for real-time predictions, offering invaluable insights into significant trends and patterns. These insights serve as a cornerstone for informed decision-making, driving proactive measures and optimizing operational outcomes.

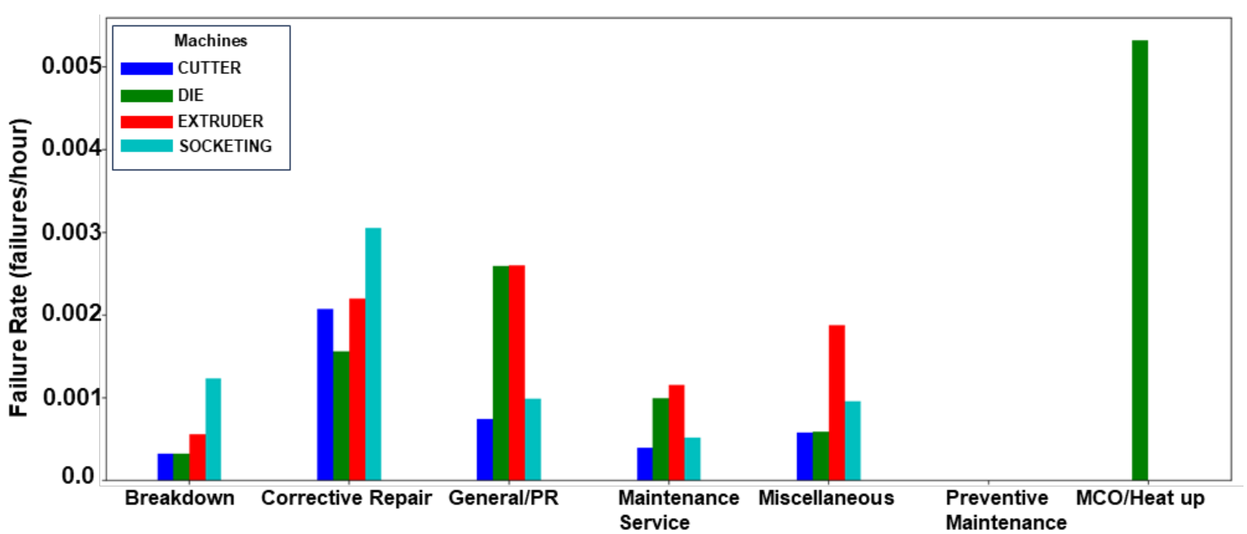

Figure 3. The predictive failure rate (failures/hour) across main machines

Figure 3 illustrates the predictive failure rate results specifically for the primary machines within the production line. The Random-Forest-Classifier exhibits intelligent selection, focusing solely on machines with the highest occurrences of failures. The plot provides a breakdown of failure rates per hour across various types of work maintenance, including breakdown, corrective repair, general/pr based on manufacturer guidance, maintenance service, preventive maintenance, and Mold Changeover/Heat Up (MCO)/Heat Up. The primary objective of this predictive algorithm is to accurately anticipate when breakdowns, corrective repairs, or other faults are likely to occur and preemptively replace them with preventive maintenance measures. Additionally, the algorithm aims to identify instances where one or more failures are expected to occur in close succession, prompting the implementation of opportunistic maintenance for multiple machines. This strategic approach aims to minimize downtime by avoiding the need to halt the production line, considering the inherent delay of 6-8 hours each time the line is restarted. Through Figure 4's detailed depiction of failure rates and maintenance types, the algorithm empowers decision-makers with critical insights into the timing and nature of potential failures. By proactively addressing maintenance needs and optimizing operational efficiency, organizations can mitigate disruptions and enhance productivity within the production environment.

5.3 Proposed Improvements

One method to enhance the efficacy of maintenance data involves thorough analysis, where prevalent issues are accurately identified and recorded. Subsequently, leveraging the Random-Forest-Classifier, the data undergoes optimization to predict the most efficient maintenance strategies, as depicted in Figure 4. This proactive approach enables the simultaneous implementation of preventive and opportunistic maintenance measures. Furthermore, a similar methodology is employed to streamline and reduce the number of maintenance tasks. By harnessing analytical insights and predictive capabilities, redundant or unnecessary maintenance activities are identified and eliminated. This systematic approach not only enhances the overall efficiency of maintenance operations but also minimizes disruptions and maximizes resource utilization within the maintenance framework.

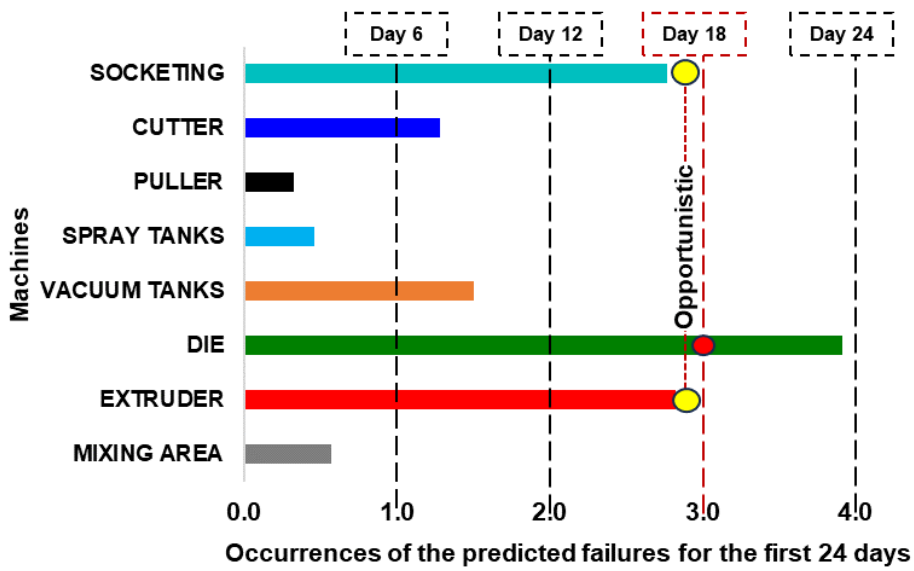

Figure 4. The opportunistic maintenance approach.

Figure 5 illuminates the opportunistic maintenance approach along with an illustrative example of its logic. As depicted, the predicted failure suggests that a third failure is imminent on day 18, specifically targeting the extrusion die machine. Coincidentally, the extrusion machine and the socketing machine are anticipated to fail shortly thereafter, mere hours following the extrusion die machine's failure. In response to this predictive insight, opportunistic maintenance is swiftly executed to mitigate the cumulative downtime across the production line. By preemptively addressing the maintenance needs of multiple machines during a synchronized failure event, operational disruptions are minimized, and overall maintenance efficiency is maximized. Opportunistic maintenance represents a proactive strategy aimed at capitalizing on predictive analytics to optimize maintenance schedules and resource allocation. By leveraging predictive models and real-time data, organizations can strategically intervene to preemptively address maintenance needs and maintain seamless operational continuity. This proactive approach not only minimizes downtime but also enhances overall productivity and operational resilience within the production environment. In order to validate the effectiveness of the opportunistic approach the results were implemented into a simulation model in Simio as shown in Figure 5.

5.4 Validation

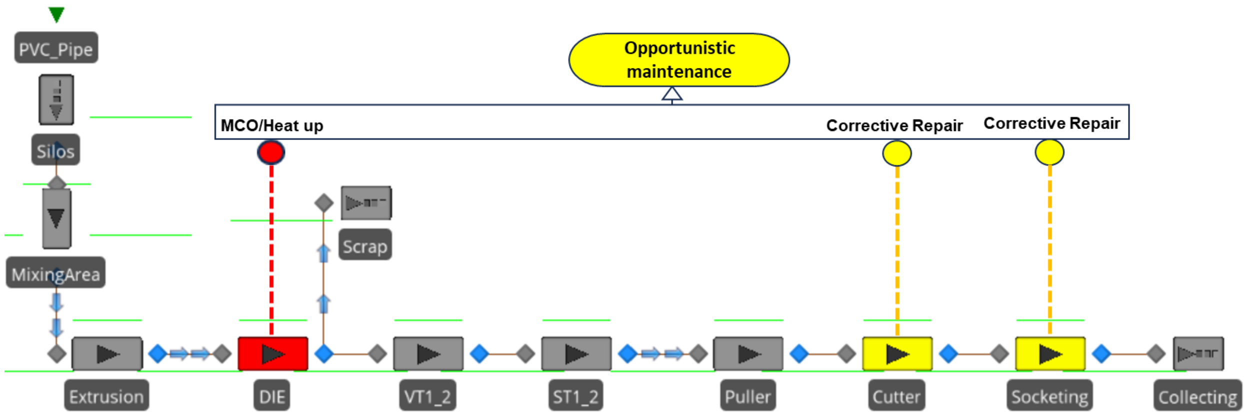

Figure 5. The simulation model for opportunistic maintenance

The opportunistic maintenance logic is embedded into the simulation model as follow:

{If production line $(\coprod_{i=2}^{n}) = F_i = 1$
Check if $\vee_{i=2}^{n}(\, 0.1 \ \leq |T_1 - T_i| \leq 24)$ #hours
Then do stop the line
And do maintenance for all.
Otherwise set to false}.

Figure 6. Opportunistic maintenance logic

Figure 6. illustrates the logic of the opportunistic maintenance approach it starts with the production line $(\coprod_{i}^{n})$ and start when it detects the first failure $(\vee_{i=1}^{n})$, then check $(\vee_{i=2}^{n})$ if there are 2 or more failures at the instance of the first failure $F_i = 1$in the production line $(\coprod_{i}^{n})$ Then check if $\vee_{i=2}^{n}(\, 0.1 \ \leq |T_1 - T_i| \ \leq 24)$ in hours, If the difference between the first failure and the predicted failure of the other $Machine_n$ is between 0.1 and 24 hours then do opportunistic maintenance. Otherwise set to false. The simulation model provides a visual representation of the proposed maintenance approach, offering insights into its implementation and effectiveness. By utilizing simulation techniques, the primary objective is to validate the efficiency and reliability of the opportunistic maintenance method. Simulation serves as a powerful tool for assessing the real-world applicability and impact of maintenance strategies within a controlled virtual environment. It allows for the testing of various scenarios and the observation of potential outcomes without disrupting actual operations. Through simulation, decision-makers can gain valuable insights into the performance of the opportunistic maintenance approach under different conditions and scenarios. Furthermore, simulation enables the identification of potential bottlenecks, optimization opportunities, and areas for improvement within the maintenance process. It facilitates informed decision-making by providing stakeholders with a comprehensive understanding of the implications and consequences of adopting specific maintenance strategies.

Table 3. Validation results for the statistical and machine learning models

Validation results			
	Failure rate (Failures/hour)		
Machine	Statistical model	ML model	Accuracy %
Mixing Area	0.0012	0.0013	8%
Extruder	0.00588	0.0071	21%
Die	0.00816	0.0101	24%
Vacuum Tanks	0.00314	0.0035	11%
Spray Tanks	0.00097	0.001	3%
Puller	0.00068	0.00074	8%

$$Accuracy\ \% = \left|\frac{Acc_{statistical} - Acc_{ML}}{Acc_{Statistical}}\right| x100$$

Equation 2.

Equation 2 outlines the accuracy variance between the statistical model outcomes and the machine learning results concerning the failure rate (failures per hour) across all machines. Table 3 presents the validation findings, where the statistical data originates from two years of historical data. The failure rate is extracted based on the prevailing behavior of the current system. In contrast, the machine learning algorithm, specifically the Random-Forest-Classifier, is employed to refine predictions using data aimed at optimizing the opportunistic maintenance strategy, as explained in Figure 6. Despite encountering higher failure rates in the extruder, die, cutter, and socketing machines due to insufficient input data, the algorithm demonstrates remarkable accuracy. The Random-Forest-Classifier 's precision serves to preempt sudden breakdowns or corrective repairs by facilitating the proactive implementation of preventive maintenance. This strategic approach significantly reduces downtime, ultimately enhancing operational efficiency and productivity. Through its predictive capabilities, the algorithm contributes to fostering a proactive maintenance culture, mitigating disruptions, and optimizing overall system performance.

6. Conclusion

In conclusion, this study pioneers a methodology that combines machine learning, particularly the Random-Forest-Classifier, with advanced statistical analysis to effectively preprocess data and identify system failures and bottlenecks. This methodology was then verified with a simulation model to carefully examine the strategy's performance over time. The research introduces opportunistic maintenance which was carefully implemented in the simulation model utilizing Simio a very high-resolution software with more than a hundred replications, Further results will be explored in future publications. This strategy primarily aims to reduce corrective repairs and breakdown-induced maintenance tasks, thus enhancing operational efficiency and resilience against disruptions. This approach underscores the transformative potential of merging machine learning and statistical analysis in industrial contexts, offering innovative methodologies for maintenance optimization.

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Biographies

Mazen Kiki As a Ph.D. candidate at the University of Akron, I specialized in cutting-edge research at the intersection of additive manufacturing, smart materials, and sensor technologies. My expertise encompasses three years of immersive experience in 3D printing technologies and techniques, particularly focused on the development of conformal sensors for robotic applications and innovative sensor solutions for tire applications under the Center for Tire Research (CenTiRe).My academic journey includes a notable publication on the creation of a 3D-printed conformal sensor for a robotic fingertip, showcasing my dedication to advancing the field of robotics through interdisciplinary research. My proficiency extends beyond traditional academic realms; I have served as a Teaching Assistant for a dynamic engineering course, imparting knowledge and fostering a dynamic learning environment. In the realm of practical engineering, I played a pivotal role in designing a motor for a gyroplane, emphasizing my versatility in combining theoretical knowledge with hands-on experience. This project involved 3D modeling of components and utilizing a lathe machine to produce assisted parts, contributing to the realization of a gyroplane with improved take-off capabilities. Currently, my focus lies on engineering simulation and predictive studies aimed at enhancing the efficiency of diverse production lines, aligning with the transformative principles of Industry 4.0. My commitment to innovation and research-driven solutions underscores my dedication to contributing valuable insights to the evolving landscape of advanced manufacturing.

Ismail Hamieh Academically established with a Doctor of Philosophy (Ph.D.) in Electrical and Computer Engineering from the University of Windsor, his research focused on developing a filtering algorithm for road surface detection using LiDAR point cloud data. He also holds a master's degree in electrical engineering from the University of Michigan, with a specialization in digital controls. His professional qualifications are further enhanced by certifications such as Design for Six Sigma Master Black Belt and Certified SAFe® 5 Agilist, alongside skills in system and software architecture, autonomous vehicles, smart city planning, land mobility, and comprehensive engineering management. Currently leading innovative projects in autonomous urban mobility as an Autonomy Driving Manager, he is at the forefront of integrating autonomous vehicle technologies and smart city concepts to revolutionize land mobility. His areas of expertise include system architecture, software architecture, and the integration of advanced technological frameworks. Before his current role, he had an extensive tenure at General Motors, where his roles were centered around the development of autonomous driving technologies and advanced sensing systems. His responsibilities included pioneering safety initiatives, advancing automated driving technologies, and contributing to the development of cutting-edge technologies in the realm of active safety and automated driving, which was instrumental in shaping his expertise in automotive engineering, particularly in the autonomous vehicles sector.

Shengyong Wang is an Associate Professor in the Department of Mechanical Engineering at the University of Akron (UA). He is the Program Director of Aerospace Systems Engineering program at UA. Prior to joining the faculty of UA, Dr. Wang worked as a Research Assistant Professor in the Department of Systems Science & Industrial Engineering at the State University of New York at Binghamton for three years. His research has been funded by NASA, FAA, New York State Senate, Lake Health System, Summa Health System, Akron General Medical Center, Virtua Health, United Health Services, M.K. Morse Company, Continental Automotive Electronics, and Vascor. He is a senior member of IISE and ASQ, and a member of IEEE, ASEM, and INFORMS. And he holds a Six Sigma black belt certification from ASQ.