DATA-ENABLED PHM SOLUTIONS FOR ROBOT HEMMING IN AUTOMOTIVE PRODUCTION LINES

Abstract

This abstract presents data-enabled Prognostics and Health Management (PHM) solutions for Robot Hemming in Automotive Production Lines. Hemming is a critical process in automotive manufacturing that involves folding and joining sheet metal components to create a structural closure. Ensuring the quality and reliability of hemming operations is crucial for maintaining product integrity and minimizing defects in the final assembly. Simple statistical models have been the foundation of traditional methods. These simulations frequently fail to represent the intricacy of actual hemming operations. The development of data-enabled PHM solutions that take advantage of the enormous amount of data generated by robot hemming systems is now possible using data analytics and machine learning techniques. This study proposes a framework that integrates data collection, preprocessing, feature engineering, and machine learning algorithms to enable real-time monitoring, fault detection, and RUL(Remaining Useful Life) prediction for robot hemming operations. The framework utilizes sensor data, such as force measurements, position data, and process parameters, to develop predictive models that identify potential faults or anomalies in the hemming process.

Keywords: Prognostics and Health Management; Data-Enabled PHM; Data Processing; Machine learning

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I. INTRODUCTION

In the fast-paced world of automotive manufacturing, ensuring the quality and reliability of production processes is paramount. One critical operation in this industry is robot hemming, which involves folding and joining sheet metal components to create structural closures. The success of hemming operations directly impacts the integrity and durability of the final automotive product, making it a crucial area for optimization and improvement. Prognostics and Health Management (PHM) systems have historically been essential in preserving the health and functionality of sophisticated machinery and equipment. However, simple statistical models and rule-based systems have trouble capturing the complexities and unpredictability present in real-world hemming operations. Fortunately, recent advancements in data analytics and machine learning offer new opportunities for developing data-enabled PHM solutions. These solutions leverage the data generated by robot hemming systems, enabling real-time monitoring and fault detection. The benefits of data-enabled PHM solutions in robot hemming are twofold. Firstly, by providing early warnings of potential failures, these solutions enable proactive maintenance strategies, reducing downtime and minimizing costly repairs. Secondly, they facilitate process optimization by identifying factors contributing to hemming defects and allowing real-time adjustments to improve quality and efficiency. The framework proposes to collect and analyze extensive data from robot hemming operations in an automotive production line. The results would demonstrate the effectiveness of the data-enabled PHM solutions in detecting faults, predicting remaining useful life, and optimizing the hemming process.

Thus, this research highlights the potential of data-enabled PHM solutions in enhancing the reliability, efficiency, and quality of robot hemming in automotive production lines. By leveraging the power of data analytics and machine learning, manufacturers could achieve process performance and overall product quality in the automotive field. This study emphasizes the value and promise of data-enabled PHM systems for robot hemming in automobile manufacturing lines. Manufacturers can improve reliability and customer happiness by leveraging the power of data analytics and machine learning.

II. LITERATURE SURVEY

1. **[Luca Actis Grosso , Andrea De Martin , Giovanni Jacazio and Massimo Sorli]:** The presented paper focuses on Prognostics and Health Management (PHM) systems for robotic roller hemming in the automotive industry. Robotic roller hemming is a widely used solution for joining metal sheets in car doors, combining technical and aesthetic requirements. The quality of the hemming process directly impacts the final product's quality and production efficiency, making the development of a PHM system crucial to ensure continuous operation and high-quality output. The paper highlights the significance of maintenance in production systems, emphasizing its impact on productivity, product quality, and overall production costs. Traditional preventive maintenance approaches often lead to unnecessary interventions and unexpected downtime. Due to this, manufacturers seek effective PHM solutions to optimize maintenance strategies and minimize disruptions. The automotive industry, specifically the hemming process, is explored as a critical application for PHM. Roller hemming using a rolling element to bend metal sheets is particularly suitable for lightweight designs. The process is frequently performed by robotic arms, making it highly sensitive

to changes in robot performance. The motivation for developing a PHM system for robotic roller hemming lies in the need to improve maintenance practices and achieve the goals of the World Class Manufacturing (WCM) methodology. WCM aims for continuous improvement, waste elimination, zero accidents, breakdowns, and inventory. In conclusion, the paper presents a preliminary analysis of a new PHM framework for robotic roller hemming without PLC data. It emphasizes the importance of PHM in the automotive industry, particularly in hemming processes, and showcases the methodology used for developing the PHM system.

2. **[Eduardo Esquivel, Giuseppe Carbone, Marco Ceccarelli, And Juan C. Jáuregui]:** This paper focuses on the roll hemming process in the automotive industry, where a robot attaches the exterior panel to the interior panel of a door using a roller. The process offers flexibility but can result in defects such as wrinkles on the panel surface. The capacity of the robot to deform the panel depends on its pose and stiffness. This paper proposes a compensation strategy for roll hemming based on the variable stiffness of the robot and panel deformation to minimize tool deviation during the trajectory. The compensation strategy involves simulation and analysis of the trajectory. The paper presents a schematic model for the compensation strategy, where they use the position and force inputs to compute a new trajectory. The position controller receives the commands and manages the robot accordingly. The compensation strategy considers variables such as the force during the hemming process and the speed related to the wrinkling defect. The paper highlights the importance of accurately determining the force and speed variables for the model's inputs to achieve compensation. The compensation strategy aims to minimize deviations caused by the robot and panel during the hemming process. The paper also discusses the compensation model and the trajectory deviation analysis. It presents a process scheme where the robot deforms the panel's flange with the roller. They model the first three robot joints as torsional springs and model the sheet with linear springs and damping effects. The compensation strategy addresses the error between the desired and the original trajectory. The paper focus is on the experimental validation of the compensation model. The stiffness/compliance of the robot is analyzed, and the values for the joint stiffness matrix are obtained. The force and thickness of the panel are correlated using a sensor during the tool-shaping process. The model is then developed and tested, and the compensation model graphs are discussed. The stiffness/compliance of the robot is determined by evaluating two different positions while applying varying forces along the Z-axis. Overall, the paper proposes an offline compensation strategy for roll hemming in the automotive industry, emphasizing variable stiffness and trajectory correction. Experimental tests validate the proposed method demonstrating its approximation and accuracy in minimizing trajectory errors. Implementing this compensation strategy leads to product quality and accuracy in roll-hemming processes.

III. PROPOSED METHOD

The benefit of creating a PHM system for in-service machinery is that data from the field can be easily accessed, providing a consolidated input to FMECA analysis and a great asset of data to evaluate the nominal behavior of the hemming system. Nearly more importantly, having access to these data makes it possible to draw attention to usage-related practical problems that are typically overlooked in simulation-only environments, greatly increasing the confidence in the developed feature extraction method.

In order to rank the known concerns that may affect the hemming machine based on severity, frequency, and observeability criteria, an FMECA(Failure Modes, Effects and Critical)analysis is initially employed (Vachtsevanos, Lewis, Roemer, Hess, and Wu, 2006).

On top of those data, a physical model of the system is constructed, validated, and utilized to produce increasingly degraded circumstances for a few significant failure modes that describe the fault progression in accordance with a well-established, reliable physical representation that is documented in literature. This methodology has been successfully used in the aeronautic field and was deemed required due to the dearth of relevant historical data (Autin, Sochelau, Dellacasa, De Martin, Jacazio, and Vachtsevanos, 2018).

Due to the fact that the application will not involve information exchange with the PLC controlling and monitoring the behavior of the machine, considerable effort has been set aside to study the feature extraction process, to ensure the capability to correctly recognize the beginning and end of each working period and to keep track of information gathered during potential hemming process pauses.

The process of feature selection has since been carried out, paying close attention to how the feature candidates behave when potential sensor degradations are present.

As a result, procedures for defect detection have been created and evaluated using simulated data. Finally, prognosis has been obtained using two distinct approaches, whose benefits and drawbacks are discussed and contrasted. A quick summary of the used approach is shown in fig1.

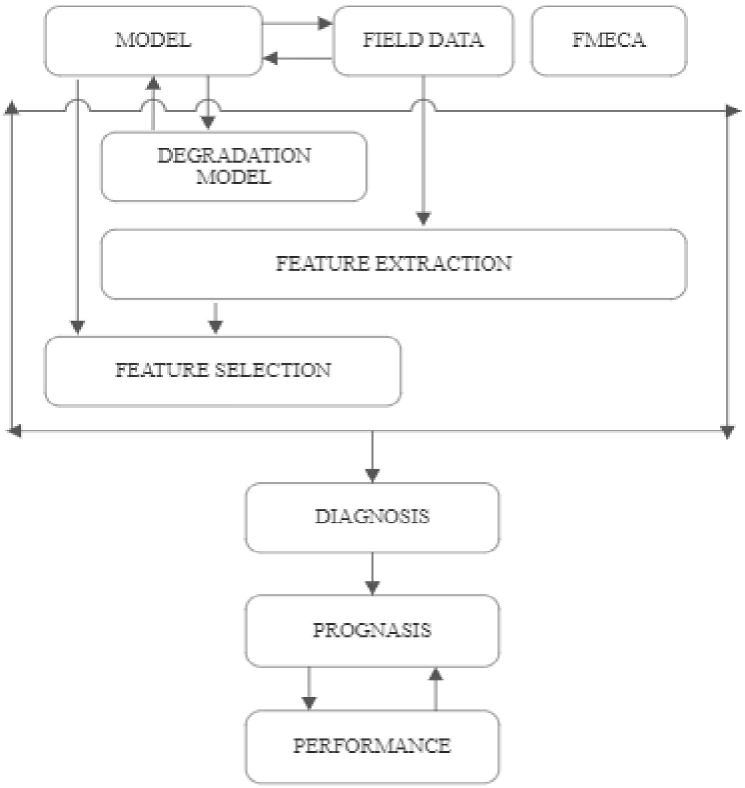

Figure 1: Methodology

The "Data-Enabled PHM Solutions for Robot Hemming in Automotive Production Lines" technique is a suggestion to use data-driven methodologies to enable Prognostics and Health Management (PHM) solutions for robot hemming in automobile production lines. PHM is the process of keeping track of, determining the cause of, and projecting the performance and health of systems or pieces of equipment in order to maximize efficiency and reduce downtime.

Hemming, which is primarily employed in the assembly of automotive body pieces, is the process of attaching sheet metal components together in the context of automotive production lines. Industrial robots with hemming tools are frequently used to carry out this process. By incorporating data-driven PHM techniques, the suggested method aims to increase the effectiveness and dependability of robot hemming operations.

The some more key steps involved in the proposed method are;

1. **Data Acquisition:**Relevant data is collected from various sources within the robot hemming system.

   This could include sensor readings from the robot, hemming tool, and other equipment, as well as process parameters, such as force, speed, and position.

2. **Data Preprocessing:** The collected data is preprocessed to remove noise, outliers, and irrelevant information. This step involves cleaning the data, handling missing values, and normalizing or standardizing the data to ensure consistency and comparability.

3. **Feature Extraction:** Relevant features are extracted from the preprocessed data. These features could capture important characteristics of the hemming process, such as force profiles, tool vibrations, or deviations in position.

4. **Condition Monitoring:** The extracted features are used to monitor the condition of the hemming process in real-time. Machine learning algorithms, such as classification or regression models, are trained using historical data to detect anomalies or deviations from normal operation. This enables the early detection of potential faults or performance issues.

5. **Fault Diagnosis:** When an anomaly is detected, the system performs fault diagnosis to identify the root cause of the issue. This could involve analyzing patterns in the data, comparing against known fault signatures, or using expert knowledge to determine the underlying problem.

6. **Prognostics and Predictive Maintenance:** Based on the detected anomalies and fault diagnosis, the proposed method enables predictive maintenance strategies. By analyzing historical data and identifying patterns leading to failures or deteriorations, the system can predict when maintenance or corrective actions should be taken to prevent unplanned downtime and optimize the robot hemming process.

G. **Decision Support:** The proposed method provides decision support to production line managers or operators. It generates actionable insights, such as recommended maintenance schedules, process adjustments, or alerts for potential issues, empowering them to make informed decisions to optimize production efficiency and minimize costs.

IV. FLOW CHART

Maintenance practices of hemming automation overflow is depicted in Fig2

Figure 2: Maintenance practices of hemming overflow

V. OPERATIONAL SCENARIO

The operational scenario that was selected involves a robotic roller hemming machine operating on an assembly line for cars. The hemming head is utilized in this instance to execute joints on the car doors. Even though most tasks are automated, the robot can only function under direct human supervision. As a result, the order in which the doors are operated is unknown at the outset and may change during production, whereas the quantity of operations required for each car can be taken for granted to be constant. The length of each working cycle can also vary greatly and is not set in stone.

One of the most frequent occurrences is that a working cycle may be interrupted due to maintenance on the robot or other components of the assembly line, or due to the required breaks the human supervisor must take during his or her shift; in these circumstances, the robot is paused and kept still in a neutral position, while sensors signals are still recorded. Given that they derive from actual in-service devices, the data on healthy systems used in this work inherently includes these issues. There are also other potential disturbances including electrical noise, small temperature changes, and abnormal operating circumstances.

The PHM system will not have access to PLC data, as specified in Section 2, to facilitate implementation on lines that are currently in operation. As a result, it won't have access to information about the robot (such as motor currents, joint position, etc.), and will instead rely solely on the signals provided by the roller-hemming head (the exerted force signal). The PHM routines have to be computationally inexpensive so they can be executed on-site without the aid of external servers or the requirement to link the robotic hemming system to a centralized hub for data mining.

Due to the reliance on a single sensor, more care must be taken in the processing of raw data and in the feature extraction, and features must be affected by potential force sensor degradations as little as possible. The PHM system will rely on the feature(s) retrieved from a single force signal to recognize a specific number of abnormal behaviors in the given scenario. Thus, fault isolation and, whenever practicable, fault detection will be the responsibility of the reasoner. After that, a prognosis is made, and the plant maintenance office or system is informed.

VI. CONCLUSION

Our solution aims to develop a data-enabled Prognostics and Health Management (PHM) system for robot hemming in automotive production lines. This method leverages data-driven approaches to monitor, diagnose, and predict the health and performance of the hemming process. By integrating real-time data acquisition, pre-processing, feature extraction, condition monitoring, fault diagnosis, and prognostics, the proposed method enhances the efficiency and reliability of robot hemming operations. This operational scenario chosen for this method is a robotic roller-hemming machine in an automotive assembly line.

Our system works under human supervision, and the order of door hemming is subject to changes during production. The duration of each working cycle can vary, and pauses may occur due to maintenance or mandatory breaks. This PHM system relies solely on the force signal from the roller-hemming head as the input sensor, without access to PLC data. The computational requirements of the PHM routines are designed to be efficient, enabling on-site implementation without external servers or central hubs.

Our idea follows a systematic approach, including data acquisition, pre-processing, feature extraction, condition monitoring, fault diagnosis, prognostics, and decision support. The Machine learning algorithms implemented in our idea used to detect anomalies and deviations from normal operation, enabling early fault detection. Fault diagnosis is thus performed to identify the root cause of issues, and predictive maintenance strategies are employed based on historical data analysis.

VII. RESULT

Our system offers several advantages in the context of robot hemming in automotive production lines. By utilizing data-driven approaches, it provides consolidated input for failure mode analysis and enhances the confidence in the feature extraction process. This method effectively detects anomalies and deviations in the hemming process, enabling early fault detection and diagnosis. This proactive approach enables predictive maintenance, preventing unplanned downtime and optimizing the robot hemming process.

The advantages of implementing this idea include improved production efficiency, minimized downtime, and cost savings through optimized maintenance schedules and process adjustments. The decision support provided by the PHM system empowers production line managers and operators to make informed decisions based on actionable insights.

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