The Requirements for Predictive Maintenance Strategy and the Data Required for Successful Implementation, for the case of Nutrunners

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Abstract

With the rise of Industry 4.0 and the implementation of "smart machines" new opportunities have opened to optimize the utilization of all data gathered from machines in an automotive manufacturing environment. The most prevalent model found in predictive maintenance is data-driven and based on statistical process control, pattern recognition or machine learning algorithms. A big obstacle faced by maintenance staff is understanding the data retrieved from the machines as the volume is often overwhelming and needs to be processed to be fully useful. Hence, this paper identifies the requirements for a successful implementation of predictive maintenance specifically for the use case of bolted connections using electronically controlled nutrunners in a modern, high-volume manufacturing environment.

Keywords
Predictive maintenance, Internet, Industry 4.0, Manufacturing, Big data

1. Introduction

The automotive industry is one of the world's largest industries by revenue. According to the International Organization of Motor Vehicle Manufacturers, the industry saw an increase of 54 million cars produced in 1997 to a peak of 97 million in 2017. One major concern for the automotive industry is the safety and compliance to standards. In extreme cases, non-compliance to international and local standards can lead to a complete product recall. The ISO 26262 standard is considered to be best practice for achieving automotive functional safety (ISO 26262-10 2012).

Non-permanent bolting connection quality is one of the critical compliance considerations for international standards. These connections are generally classified critical when they pose an immediate danger to the driver of the car if the connection fails. The standards require that these connections be performed with Electronically Controlled nutrunners (also known as EC-Tools) that provide reliable and accurate process control of the bolting process and simplifies manufacturing. They are expensive to implement but are a critical part of the technology systems for modern automotive manufacturing. EC-Tools come equipped with torque transducers to measure and record the applied torque during the bolting process.

All technology systems and machinery require maintenance due to operational wear and unexpected breakdowns. Recent progress in industrial practice has resulted in an evolution of maintenance management from a "necessary evil" to a competitive advantage and consequentially higher profit, product quality and technical availability of machines.

The constant increase in product complexity, international standard requirements and machine-train advancements have created new opportunities in maintenance management.

The onset of Industry 4.0 enabled improved predictive maintenance strategies as machines now have the ability to track and record operating conditions by using external and internal monitoring and sensors (Poór et al. 2019). Access to the process parameters of machinery has made it possible to better understand and predict the condition of the system, i.e., predictive maintenance.

Predictive maintenance requires proper planning, implementation, and awareness. It also requires a critical analysis and understanding of the machine-train and data retrieved during operation (Mobley 2002). This study aims to understand the scope of a modular predictive maintenance framework specifically for EC-tools. The modular approach is significant as this study represents the initial investigation into the feasibility of predictive maintenance for the manufacturing plant. Further, it explores the potential for return on investment for future implementation.

The success of the implementation is measured through the technical availability of the EC-Tools system, product quality and the utilization of maintenance resources. This includes time spent on maintenance and costs of the spare parts used. Further, as validation for the study, the Overall Equipment Effectiveness (OEE) is used to track the influence on the system. This factor is dependent on the cycle time, total time, and the quality of the product.

1.1 Objectives

The aim of the study is to investigate the feasibility of using process parameters for a modular predictive maintenance strategy for EC-Tools. This forms part of a bigger study to develop a maintenance strategy for the automotive industry.
The following objectives are set:

1. Research the evolution of maintenance management strategies to understand the current best practice.
2. Critically analyze the nutrunner machine-train as well as the bolting curves acquired from process parameters.
3. Perform a failure analysis on common machine failures for nutrunners.
4. Identify characteristic curves for failures found during the analysis.
5. Establish feasibility of process parameters for further predictive analysis.

2. Literature Review

Maintenance refers to all actions performed with the objective to restore or retain an item to a state in which it can perform its required function (Parida and Kumar 2009). Maintenance costs account for up to 60% of operating costs for all manufacturing. This cost has increased over time as machines and technical systems became more complex and optimized for operation (Mobley 2002). The previous industrial revolutions occurred in parallel with an evolution in maintenance management strategies (Poór et al. 2019). Industry 1.0 is associated with corrective maintenance. This evolved to preventative maintenance with Industry 2.0. With Industry 3.0, a new strategy of proactive maintenance was introduced and finally, currently in Industry 4.0, the biggest shift is towards predictive maintenance.

Further, the literature review contains a section on nutrunners and bolted connections to explain important concepts used in the study.

2.1 Industry 1.0 and Corrective Maintenance

The First Industrial Revolution is most famous for the invention of the steam engine in 1765. This introduced basic industrialization with simple machinery used to perform jobs. Machines worked until they broke down and only then was the most intuitive form of maintenance applied. Corrective maintenance is emergency maintenance carried out on already failed machinery or technical systems to rectify the fault and recover the system to operating conditions. It follows the philosophy of “if it ain’t broke, don’t fix it”. This strategy worked well with simple machines that could be restored to working condition easily and without intervention from a specialist.

The modern approach to maintenance is to avoid corrective maintenance due to the high cost of downtime and reduced product quality. This maintenance strategy also leads to reduced lifespan of the machines as critical preventative asset care maintenance is often not performed. This does, however, save on overhead costs and time as it requires minimum input from the maintenance staff when the machines are running (Christer and Whitelaw 1983).

2.2 Industry 2.0 and Preventative Maintenance

The Second Industrial Revolution occurred around 1870 and is associated with electrification, as illustrated with the invention of the Ford Model T automotive assembly line. The Second Industrial Revolution resulted in more complex technical systems and a need for a better maintenance strategy, i.e., preventative maintenance. Preventative maintenance refers to a periodical inspection of machines to notice small problems and resolve these before major breakdowns develop (Butler 1996). The goal is to prevent all breakdowns from happening. Some maintenance principles developed during this period are still used in modern times.

This maintenance strategy is very costly as it requires a lot of time from maintenance staff to perform all inspections. The main objective is to increase the equipment lifespan and to minimize production losses due to technical downtime. This type of strategy can be either cycle based, time based, or condition based in the interval between inspections and actions taken to improve the machine's operating conditions (Poór et al. 2015).

2.3 Industry 3.0 and Proactive Maintenance

The start of the Third Industrial Revolution is characterized by the invention of the Programmable Logic Controller (PLC) in 1969. This was the start of real-time automation in assembly plants and led to the development of proactive maintenance – a combination of preventative and corrective maintenance that aims to increase the economic efficiency of a plant by identifying and rectifying problems before they lead to breakdowns.

The biggest shift that proactive maintenance introduced is the importance of proper machine maintenance and the support structure required. The PLC enabled plants to store process data and led to a statistical approach to machine failures (E. C. Fitch 1992).

2.4 Industry 4.0 and Predictive Maintenance

The Fourth Industrial Revolution started in the 1990's and is still ongoing (Hořánek and Basl 2018). This came about with the rise of the Internet and paved the way for predictive maintenance, the most advanced form of maintenance strategy to date. The common definition of predictive maintenance is the ability to regularly monitor actual mechanical conditions, process parameters and operating efficiencies to better manage the interval between repairs and reduce the number and cost of unscheduled outages created by machine-train failures (Ayvaz and Alpay 2021). It also refers to the increased productivity of maintenance staff, product quality and overall plant efficiency (Mobley 2002).

Predictive maintenance uses direct machine data to schedule maintenance activities on an as-needed basis. It is an improvement on preventative and proactive maintenance as it does not rely on manufacturer's data or in-plant data for maintenance intervals, but rather makes use of factual machine data. This data can be gathered from external sources such as vibration analysis and thermography but can also be process parameters from transducers or current meters. The main goal of predictive maintenance is the ability to schedule maintenance tasks at the most cost-effective time and before the machine causes down-time to the plant (Amruthnath and Gupta 2018). This can be determined by statistical process control to predict the future trend of the machine's conditions.

New opportunities to optimally use all the data gathered from machines opened with the rise of Industry 4.0 and the implementation of "smart machines". Process parameter based predictive maintenance was originally introduced by NASA to monitor and detect developing faults on main engines of shuttles (Duyar and Merrill 1992). The most prevalent model found in predictive maintenance is data-driven and based on statistical process control, pattern recognition or machine learning algorithms (Susto et al. 2014). A big obstacle faced by maintenance staff is understanding the data retrieved from the machines, as the volume is often overwhelming and needs to be processed to be fully useful. This paper sheds some light in addressing this issue.

Some important considerations for the implementation of predictive maintenance are available budget, team culture and morale, availability of data and process parameters, and technical feedback capacities of machines. This is still an evolving field and solutions for predictive maintenance will vary from plant to plant and from machine to machine. A critical analysis and audit of the current machinery is thus needed to establish which technology system can provide enough data to analyze. Predictive maintenance can be prohibitively expensive to implement due to all the hardware requirements but can lead to major cost-savings if implemented correctly (Mobley 2002).

2.5 Bolting Connections

The objective of a bolted connection is to create a non-permanent clamping force between two or more surfaces. A bolted joint presents various challenges as the joint changes in response to service and environment (Bickford 2007). Further, bolted joints' assembly process is difficult to design as the process is influenced by hundreds of variables. Some major variables include friction effects, geometry of the threads and surface, surface finishes and after bolting effects such as relaxation of the joint (Budynas 2011).

The assembly of bolted joints is further complicated because it is not feasible nor practical to measure the clamping force of the surface. Thus, to control the clamping force during fastening, the preload is determined by controlling the amount of torque to the bolt and the angle through which the bolt turns. The input work to the bolting joint can be calculated with Equation 1, using the torque (T) applied to the connection through the angle of turn (θ). The input work is transferred as potential energy stored in the joint and forms the clamping force. It should be noted that typically only 10% of the input work is translated in clamping force due to various reasons including heat loss from friction, alignment, and nut dilation (Bickford 2007).

$$W = \frac{1}{2} T\,\theta \text{..........................Equation 1}$$

Figure 1 shows a typical two-phase bolting curve of the input torque versus the angle of turn of the bolt. During the Rundown phase, the bolt has not yet contacted the mating surface and the torque required is due to the friction in the threads. Point A on Figure 1 is defined as the maximum torque reading during rundown and, if a sudden spike in this value is measured, it can indicate misalignment. The Alignment phase indicates mating between the two surfaces has taken place. The curved radius of this phase is non-linear and is influenced mainly by the stiffness of the joint. This is the start of preload build-up in the connection. Point B on Figure 1 indicates the seating-torque and is the point where the curve becomes linear. The clamping phase is linear and should remain consistent over identical bolting connections. The gradient of the curve is given by Equation 2 and represents a linear relationship between the pitch of the thread, friction coefficients of the bolt (KB) and joint members (KJ). The curve remains linear until Point C where one of the mating surfaces starts to yield and failure in the connection occurs. Post-yield the bolt elastically deforms until ultimately failure occurs and it breaks off. The area under the curve of Figure 1 can also be used to calculate the input energy.

$$Slope = \left(\frac{K_B\,K_J}{K_B+K_J}\right)\frac{P}{360} \text{.................Equation 2}$$

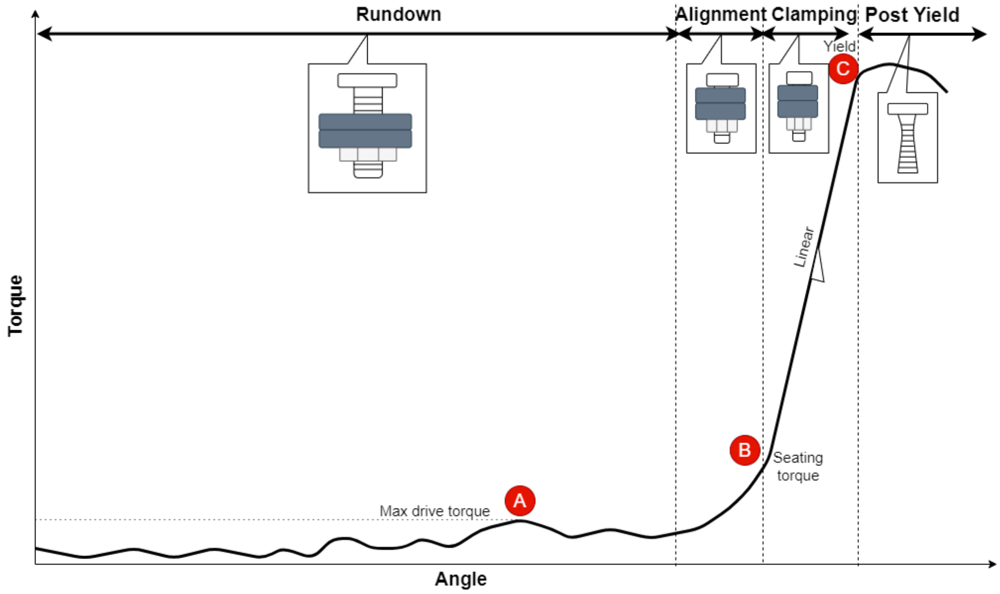

Figure 1. Typical bolting curve for two-phase tightening**.**

2.6 Electronically Controlled Nutrunners

Modern automotive manufacturing requires processes that are accurate, highly repeatable, and reliable. This sector also needs to comply to international regulations and standards which differ from country to country. In order to ensure strict compliance, all critical bolts and nuts on automotive systems are secured using EC-Tools. These tools are equipped with torque transducers to reliably achieve user-defined torque requirements of bolting connections. The transducers are also capable of sending process parameters to the controller for each bolting connection. A typical EC-Tool, as can be seen in Figure 2, consists of a motor, gearbox, torque transducer and output drive. The tool is controlled by a controller which is reporting to an operating system (in most cases the plant PLC). All process parameters are typically sent to the controller and stored on the PLC. Certain EC-Tools also have an added redundancy transducer that measures the current usage of the motor.

This paper identifies the requirements for a successful implementation of predictive maintenance specifically for the use-case of bolted connections using electronically controlled nutrunners in a modern, high-volume manufacturing environment.

3. Methods

This section outlines the proposed experimental setup as well as identifying the specific scope within the system. Furthermore, a control strategy for the system is given as an initial step in understanding the process parameters. These control strategies are also needed to maintain system reliability throughout the implementation.

3.1 Proposed experimental setup

Figure 2 shows the proposed experimental setup for the predictive maintenance framework feasibility study. The study is limited to nutrunners to reduce the scope and complexity. The controller and PLC are purely electrical, and the failure mode is run-to-failure. A predictive model is therefore not applicable. The manipulator is purely mechanical, and it cannot send process feedback. It is standard practice for modern nutrunners to include a transducer, gearbox, and DC-brushless motor. The transducer has the capability to measure torque and angle. Certain manufactures also include current redundancy features.

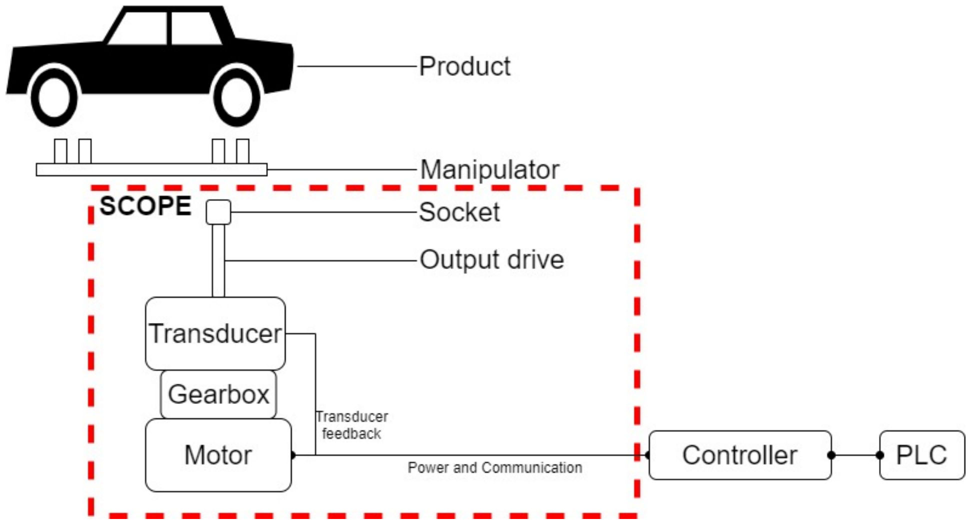

Figure 2. Proposed experimental setup for the feasibility study.

With reference to Figure 2, only the nutrunner (including socket, output drive, transducer, gearbox, and motor) is included in the scope for this project. The manipulator is mechanical and is not wired to give feedback. The PLC is the leading (master) controller and is responsible for sending the needed application to the controller. It also serves as a convenient interface between the user and the tool for setting process parameters and viewing results. The controller is the "intelligence" of the nutrunner and implements the control system. Further, the controller stores all the bolting results and powers the nutrunner. The nutrunner consists of a DC-brushless motor, gearbox, transducer, output drive and socket. All the measurements are done by the transducer and the data is sent back to the controller for processing via the transducer feedback cable.

The nutrunners are mounted on a manipulator to minimize human intervention. The manipulator is moved via pneumatics towards the product on request from the PLC. This method is chosen as it eliminates human influences during processes such as differences in pressure on the nutrunners and added vibrations to the joints.

3.2 Control Strategies with torque and angle

One requirement for successful implementation of a predictive maintenance strategy is a critical overview and analysis of the system. This includes comprehension of the basic process values of the system and what influences them. This can be done by understanding the reasoning behind the control strategies used during the process as this explains the behavior of possible failures that could occur. It also serves as a good starting point in deciding the possible methods for predictive and statistical calculations.

3.3 Final Torque-Angle Window

The Final Torque-Angle window, as illustrated in Figure 3A, is a torque-controlled, angle-monitored target window. The nutrunner starts measuring the angle at a certain threshold torque and ensures the final torque value (controlled) is reached within a pre-defined angle range, thereby creating an acceptability window. This helps to detect failures such as thread galls and misalignment if the final torque is reached before the expected angle. It can also detect failures such as bolt softness and oversized holes in situations where the maximum angle is achieved before proper torque buildup. The torque transducer is responsible for achieving final torque and a deviation in final torque could indicate a need for re-calibration. This window is based on the snug-torque and K constant during clamping and should be constant for identical bolts. Further, a sudden change in final torque can indicate contamination of the bolted joint, such as abnormal lubrication in the hole or threads.

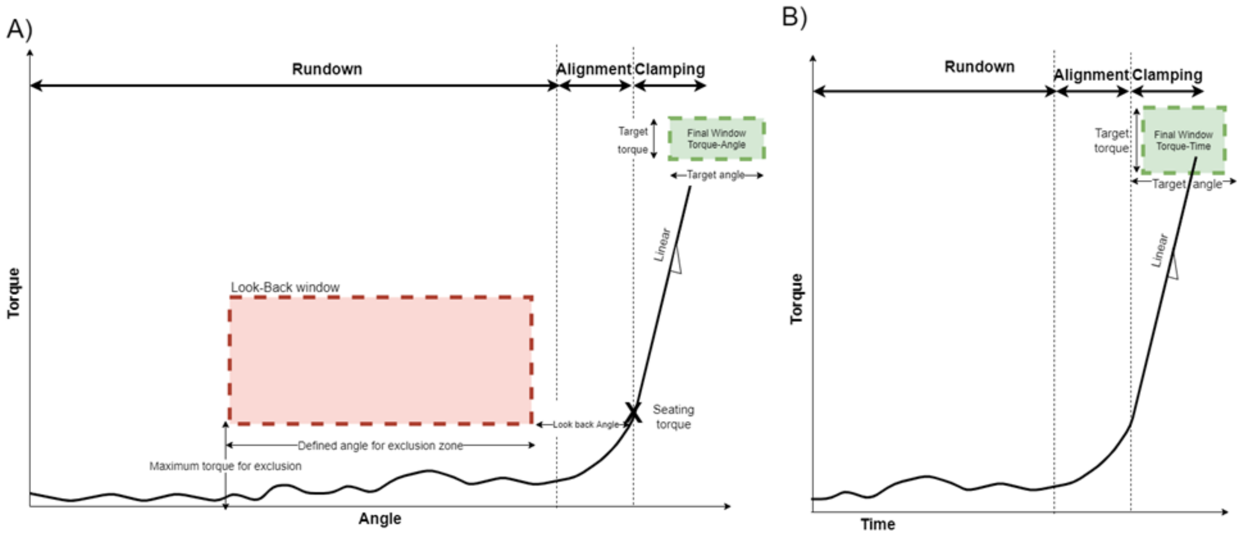

Figure 3. A) Control strategy for Torque-Angle with an exclusion look-back window on rundown phase and final target window in the clamping phase. B) Control strategy for Torque-Time diagram with only a final target window in the clamping phase.

3.4 Look-back Window

The Look-Back window, also shown in Figure 3A, is a constraint specifically used during the rundown phase. It monitors the rundown torque of the tightening as an exclusion zone looking back from the snug-torque (often 30% of the final torque value) for a defined angle. This defined angle should be enough to exclude the alignment zone as this is not linear and difficult to predict. The look-back window is especially useful in flagging failures such as cross threading and misalignment.

3.5 Final Torque-Time Window

The final Torque-Time target window is similar to the Torque-Angle target window, but it is time rather than angle monitored. The typical torque-time graph with target window can be seen in Figure 3B and is very similar to a torque-angle graph. This window is especially useful in flagging misalignment, cross-threading, and changes in the system. Further, with enough data it is used to optimize the system as it is a good way to stop the process as soon as it exceeds the expected time.

4. Data Collection

The traditional way of thinking of predictive maintenance is through vibration analysis. As technology advanced it has evolved to include many other ways of measuring process parameters. Traditional vibration analysis is not feasibly for nutrunners due to the cost involved to implement it in a manufacturing environment. Additionally, nutrunners are often handled by human operators and this would affect the measurements. For this reason, vibration analysis is excluded from the proposed framework. Instead, the proposed framework will use only data coming directly from the nutrunner transducer and controller, including torque, angle, and time process parameters.

Modern nutrunner controllers are equipped with the ability to store bolting curves. For this study the data is sent from the transducer on the nutrunner to the controller during the process. After bolting, the controller sends the raw data to a Manufacturing Service Bus (MSB) where it can be retrieved. The MSB is a cloud-based server that has the capability to store the required volume of data from all the controllers in the plant. The raw data can then be processed using software such as MATLAB. This process can be streamlined and automated if the feasibility of the initial study shows a positive outcome.

The PLC in the manufacturing plant is already set up to track downtime from equipment and record downtime based on the errors and process times. Further, systems such as System Analysis and Software Development (SAP) track spare part usage and Mean-Time-to-Repair (MTTR). This data can be used to calculate the availability, time used and costs of the system implementation.

5. Results and Discussion

The critical failure analysis of the machine-train can be classified into three main categories, namely rundown, alignment and clamping. The first reason for the categorization is due to a loss of data for connections where a failure occurred before the final conditions are met. If the connection entered an exclusion window during rundown, it does not have data for the clamping phase as the process is aborted. The separation of phases makes it possible to analyze all curves regardless of how far into the bolting process it got. The analysis and failures are matched through characteristics in the process parameters as a preliminary insight to be used for further mathematical models. This can be expanded as more failures and characteristics are identified. Another key observation is the added insight gained by comparing nutrunners on the same manipulator or performing the same bolting process.

5.1 Rundown failures

The Rundown phase for a two-phase bolting curve should remain similar in shape for identical applications. Figure 4 illustrates sample curves of typical failures encountered on a single nutrunner during the rundown phase. The jagged line of a socket slipping is shown in green while misalignment causing little to no torque buildup is also shown with a purple line. The sudden spike due to misalignment of either the manipulator or the output drive is indicated by the yellow line. In the case of the manipulator misalignment, all nutrunners on that manipulator shows this characteristic failure. Table 1 contains a summary of the main identified failures found from graph observations of the rundown phase as well as a recovery strategy. It should be noted that the failures occurring during rundown would not contain data for the other phases as the nutrunner controller stops the process in this phase if an exclusion conditional window is hit.

A further investigation will follow to create a mathematical model to predict and track trends of the rundown phase. This mathematical model should be able to track the maximum drive torque values, the distribution of values and the time taken to complete the phase. Further, grouped nutrunners on the same manipulator should be monitored for manipulator specific failures such as alignment or pneumatic pressures. Lastly, the torque value reached to exit the rundown phase could indicate a need for calibration and should also be monitored.

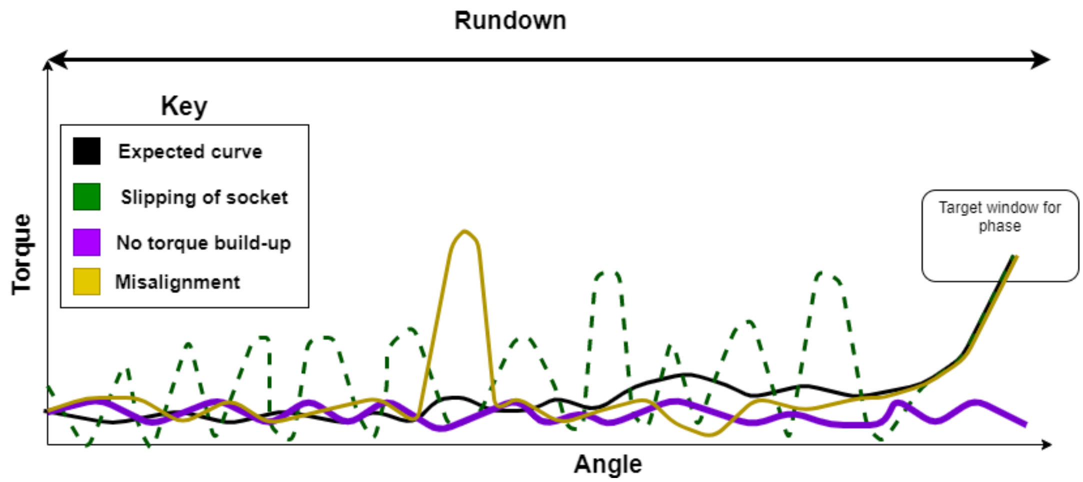

Figure 4. Illustration of example graphs for failure modes during rundown phase

Table 1. Overview of rundown phase machine failures

Possible Causes	Effected parts	Recovery	Graph	Characteristic on curve	Color on Figure 4
Socket worn	Socket	Replace socket	Torque vs Angle Torque vs Time	Jagged rundown; Lots of spikes in rundown	Green
Misalignment of manipulator	Manipulator/Robot	Correct alignment according to jig	Torque vs Angle Torque vs Time	No torque build-up; Sudden spike in rundown; Only failures of bolts done by that manipulator	Yellow
Output drive square worn	Output drive	Replace output drive	Torque vs Angle	Deviations in phase; Only one nutrunner effected	Purple
Output spring worn	Output drive	Replace output drive	Torque vs time	No torque build-up during rundown	Purple

5.2 Alignment failures

The Alignment phase is non-linear and difficult to predict. Thus, as a start, only the change in hardness of the joint is considered. This failure is shown in Figure 5 for a harder joint (yellow line) and a softer joint (blue line) than expected. This failure is not machine related but can influence the quality of the product as the properties of the bolted connection changed. Table 2 summarizes the failure for the alignment phase. An important observation is the change in angle for reaching the seating torque value as this can influence the clamping phase.

The mathematical model should be able to track the deviation in radius of the curve. Further, the snug torque values and time taken to reach could also indicate a drift in properties of the surfaces. This failure mode should not be coupled to the maintenance system as it is purely a quality discussion. It is, however, a critical change to monitor as it could lead to product recall.

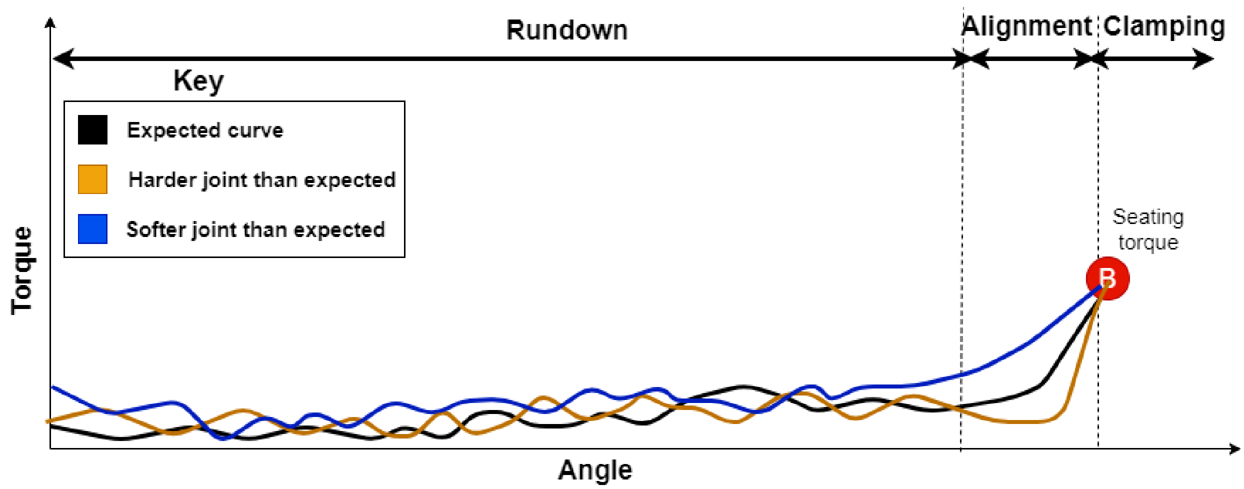

Figure 5. Illustration of failures identified for the alignment phase of two-phase bolting.

Table 2. Overview of Alignment phase machine failures

Possible Causes	**Effected parts**	**Recovery**	**Graph**	**Characteristic on curve**
Hardness of joint changed	Bolt and hole	Investigation into hardness of components	Torque vs Angle Torque vs Time	Change in snug radius

5.3 Clamping failures

The Clamping phase is the final phase in two-phase bolting and is defined by having a linear relationship caused by the friction coefficients of the surfaces. This phase is also the most important as the specified torque and angle relation needs to be met to comply with the engineering requirements of the connection. Identified failures and curve characteristics can be seen in Figure 6 and is summarized in Table 3. It should be noted that failure in the previous phases results in the nutrunners not reaching the clamping phase.

The mathematical model needed for predicting this phase has multiple requirements. Firstly, the gradient of the linear portion should remain similar throughout the same bolting conditions. A change in the gradient could indicate several changes depending on the circumstances. Secondly, the final torque values, time taken, and angle need to be monitored and modeled as this could indicate a need for calibration, alignment, or bolting failures such as cross-threading. A drift in the time could indicate a worn output spring.

Table 3. Overview of Clamping phase machine failures

Possible Causes	**Effected parts**	**Recovery**	**Graph**	**Characteristic on curve**	**Color on Figure 6**
Output spring worn	Output drive	Replace output drive	Torque vs Angle Torque vs Time	Maximum time reached before required torque.	Green
Lubrication changes to hole or thread	Bolt and hole	Rework bolted connection	Torque vs Angle Torque vs Time	Sudden failure of bolt before final torque	Yellow
Surface of joint changed	Bolt and hole	Investigation into surface of components	Torque vs Angle Torque vs time	Change in snug radius; Final torque outside defined angle	Pink and blue

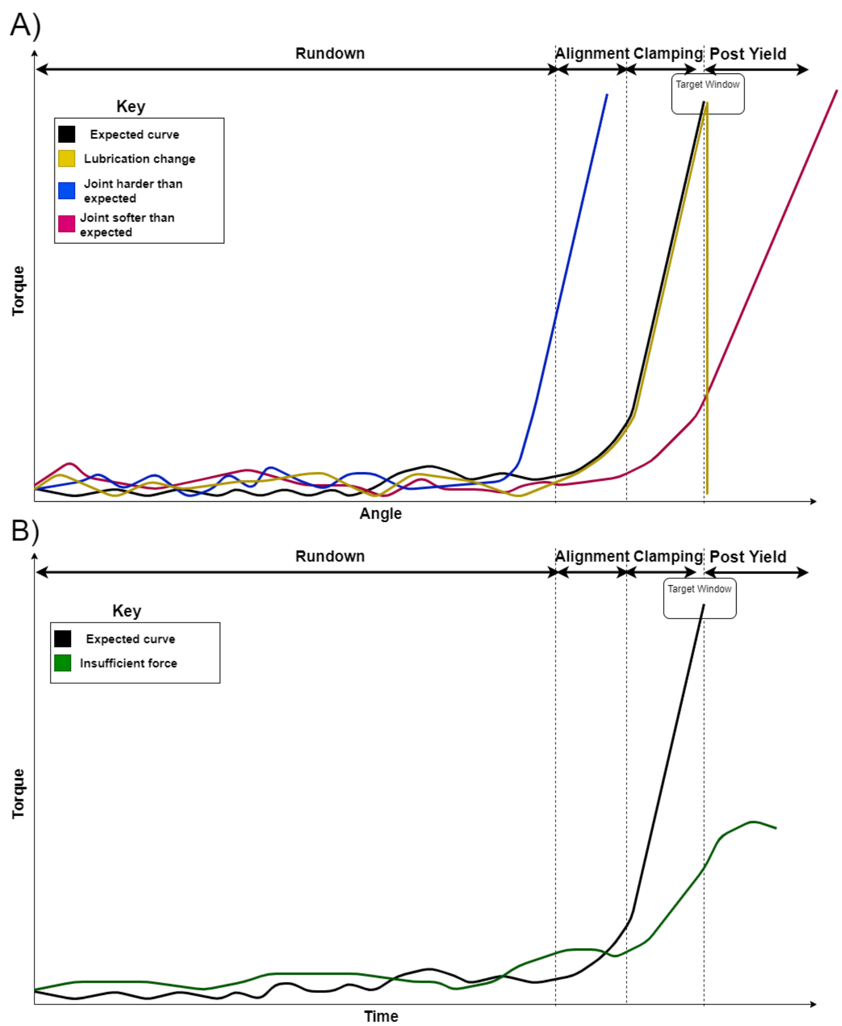

Figure 6. Illustration of failures identified for the Clamping phase of two-phase bolting.

6. Model Validation

The validation of the implementation of the feasibility study is measured with the change in spare part cost, overhead time, MTTR and overall equipment availability. The spare part cost can be tracked and compared with historical data from the SAP system. From this data, the validation of the trend of spare part cost and usage can be calculated. An increase in this trend can be expected as the new model could improve on current strategies. The SAP system is also used to track overhead time as all maintenance and restorative time is booked on the system. These costs are compared to rework and break down time to establish the total cost of the implemented model.

The current system implemented in the PLC can calculate Overall Equipment Effectiveness (OEE) using the formula in Equation 3. This formula is dependent on cycle time, units produced, quality and technical availability. The influence of cycle time and output can be seen in Equation 5. A trend in the OEE can be used to track the overall availability of the equipment. Equation 4 and 6 show the influence of technical availability, as well as quality of the product, which makes it an excellent validation tool, as this proposed prediction strategy can also be used to flag quality deviations in the bolted connections.

$$Availibility \ \times Performance \ \times Quality = OEE \text{..........Equation 3}$$

where

$$Availibility = \frac{Required\ Availibility - Downtime}{Required\ Availibility} \text{.........Equation 4}$$

$$Perfomance = \frac{Cycle\ Time \times Output}{Operating\ time} \text{......................Equation 5}$$

$$Quality = \frac{Produced - Defected}{Produced} \text{................................Equation 6}$$

The connection between equipment condition and product quality is significant and, by using the OEE, it is possible to measure the complex relationship between quality and availability. For example, the strategy may worsen availability, but improve the quality, or *vice versa*.

7. Conclusion

Maintenance management strategies have evolved in line with industrial revolutions. It started as reactive maintenance with simple machines in the first industrial revolution to current, Industry 4.0, predictive strategies with "smart machines". The paper has focused on nutrunners, since they are critical equipment in the automotive industry and are widely used to secure non-permanent bolted connections. Failure analysis on nutrunners was explored in this paper. Main failures for each bolting phase were exposed as well as their characteristics with reference to their bolting curves. The process parameters used to identify the characteristics are torque, angle, and time. The results of this study will be used in a further investigation to determine statistical control algorithms to implement and monitor a predictive maintenance strategy.

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Biography / Biographies

Emma L Bekker is a graduate mechatronics engineer currently working at Mercedes-Benz South Africa in the Technical Site Service division. She earned her BEng Mechatronic Engineering degree from Stellenbosch University, with a bursary from Mercedes-Benz granted from her second year onwards. Her final year project focused on the use of photogrammetry as a method for determining drone position. She started pursuing her MEng in Engineering Management in February 2021 at Stellenbosch University. Her research interest includes maintenance management, Industry 4.0, manufacturing, and optimization. She currently resides in East London, South Africa.

Prof Stephen Matope is currently an associate professor in the Department of Industrial Engineering, Stellenbosch University with over 16 years of lecturing industrial engineering related subjects at university level. His research interests are in advanced manufacturing covering additive manufacturing, manufacturing processes and manufacturing systems. He has so far co-authored over 70 peer-reviewed journal papers, international and national conference papers. He is a registered professional engineer with the following engineering boards: 1) Engineering Council of South Africa (ECSA), 2) South African Institute for Industrial Engineering (SAIIE), and 3) International Institute of Industrial and Systems Engineers (IISE). He is also a member of the European Network of Innovative Learning Factories (NIL) and was the first coordinators for NIL on the South African side. He was an invited Visiting Research Scientist at Chemnitz University of Technology, Germany, in 2011. He is an external examiner for five universities: three in South Africa (SA) and two in Zimbabwe (Zw). He is a registered journal article reviewer e.g., for South African Journal for Industrial Engineering and Zimbabwe Journal of Science and Technology (ZJST). He served(s) 1) as an organizing international committee member for the Competitive Manufacturing international conferences (e.g., COMA'16 and COMA'19), 2) as an international scientific committee member for the 9th Conference on Learning Factories 2019 (CLF) in Braunschweig, Germany, 3) as an international scientific committee member for the 10th Conference on Learning Factories (CLF) 2020 in Graz, Austria.