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A method to estimate the remaining useful lifetime of a two-jaw parallel gripper based on experimental failure threshold data

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Abstract

Parallel grippers offer multiple applications thanks to their flexibility. Their application field ranges from aerospace and automotive to medicine and communication technologies. However, the application of grippers has the problem of exhibition wear and errors during the execution of their operation. This affects the performance of the gripper. In this context, the remaining useful life (RUL) defines the remaining lifespan until failure for an asset at a particular time of operation occurs. The exact lifespan of an asset is uncertain, thus the RUL model and estimation must be derived from available sources of information. This paper presents a method for the estimation of the RUL for a two-jaw parallel gripper. After the introduction to the topic, an overview of existing literature and RUL methods are presented. Subsequently, the method for estimating the RUL of grippers is explained. Finally, the results are summarized and discussed before the outlook and further challenges are presented.

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Keywords: Prognostics and Health Management; RUL Estimation; Remaining Useful Lifetime

1. Introduction

Mechanical grippers are responsible for repetitive processes to support manufacturing or production work cells. Repetitive processes are executed hundreds of times per day. In case of unexpected downtime or out-of-specification action, where a recalibration becomes necessary, this directly impacts on the quality of the products and the efficiency of the production processes. Therefore, to ensure consistent quality, avoid production downtime, and prevent hazards and safety risks at downstream processes, information on maintenance usage is of importance. This information is typically provided by original equipment manufacturers in static intervals, where the RUL is indicative of the

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maintenance requirements in any given state. This provides a basis for short- and long-term decisions about the maintenance or repair strategy. The RUL also supports the scheduling of future actions to avoid catastrophic events and thus, supports extending the life cycle. The presented research aims to gain information about the wear behavior of the investigated two-jaw parallel gripper via experimental data. The study sought to address three key objectives: 1) Present and classify applications based on existing literature, 2) Identify a health indicator to measure wear behavior and 3) Identify failure modes and associated failure thresholds. The motivation of this research is to present a developed method for RUL estimation of a two-jaw parallel gripper by using experimental data. Okoh et al. [1] define the RUL as „the time remaining for a component to perform its functional capabilities before failure“, although the definition of the useful life depends on the operating characteristics and their manufacturing background [2]. The concept of the RUL is used in statistics literature and operational research [3]. More application areas are found in econometrics, material science, and biostatistics [3].The research paper contains four chapters. Chapter one presents the problem statement, the research objectives, and motivation. Chapter two contains a classification of existing approaches to RUL estimation as well as examples of applications. Chapter two concludes with an explanation of the importance of deep learning applications in the context of PHM. In chapter three the RUL method is presented and explained in more detail. The experimental setup and the exploratory data analysis are also presented. Chapter four summarizes and presents further challenges.

2. Classification of RUL estimation approaches

The emerging importance of RUL estimation is evident from the recent work of scholars, such as Ahmadzadeh and Lundberg [2], Si et al. [3], Cho and Parlar [4], Dragomir et al. [5], and Peng et al. [6]. The classification of the according models divides into four approaches: physical-model based, data-driven based, experimental-based, and hybrid-model based approaches [2], [7]. In the following subsections the models are briefly explained.

2.1. Physical-model based approach

According to Skima et al. [8], the physical-model-based approach deals with the estimation of the RUL by using mathematical or physical models to describe the physics of the component and the degradation phenomena. The physical-model based approach builds upon a detailed understanding of the gripper's physics [2]. As the models calculate mathematical parameters, which describe the developmental functioning of formation and expression (so-called functional mapping), this approach presents results with higher accuracy than the data-driven approach. The initialization for a physical model is the formulation according to physical equations. With regards to the expected aim of the model, appropriate variables are considered. The equations are then solved using numerical methods. The problem with this model variant is its accurate and precise application to the real world. Engel et al. [9] state several practical concerns about the accuracy, precision, and confidence of these estimation results. These issues are limiting the usability of physical-model based methodologies. In contrast, successful applications are presented in Oppenheimer and Loparo [10], as a physical model is developed to estimate machine conditions, in combination with fault strength-to-life models based on crack growth law [2], [10]. Benmoussa and Djeziri [11] presented an application for the RUL prediction of gears with a fatigue tooth crack build upon a gear meshing stiffness identification model. Further, Watson et al. [12] proposed a physical model-based approach to estimate the RUL of a dynamic high-power dry clutch system by using a wear prediction model.

2.2. Experimental-based approach

By performing experiments, the knowledge about the lifetime of components improves. This approach has been a widely used method since the mechanization of industry [2]. Heuristic, probabilistic and stochastic tools are considered to describe the degradation phenomenon and the component life cycle. The input variables are constructed by data and the knowledge accumulated by experience [13]. Redtenbacher [14] was among the first to recognize this. Zhou et al. [15] proposed a method for light-emitting diode driver degradation of critical components, through their performance parameters. Sutrisno et al. [16] selected experimental data from multiple ball bearings measures. The data set consists of training and testing data for a constructed algorithm. A predicting algorithm linked to the data from the training bearings to estimate the RUL of the test bearings is presented. Chen et al. [17] used experimental data from a helicopter gearbox with a carrier plate crack to assess the health state of the Adaptive neuro-fuzzy inference system (ANFIS) predictor. Medjaher et al. [18] used data from an accelerated experiment of bearings to verify a method combining the physical-model based and data-driven based approaches.

2.3. Data-driven approach

Data-driven prognostics uses sensor data in models to describe the degradation behavior [18]. This approach is useful when a large quantity of data needs to be fitted into logical information about the RUL. Within this approach, the accuracy of the RUL estimation depends on the quantity and quality of the input data [2]. They are based on statistical and learning techniques, such as numerical algorithms and algorithms from the machine learning and data mining domain. Other, more advanced algorithms include Neural networks (NN), Decision trees (DT), and Support vector machines (SVM) [2]. Shifat et al. [19] presented a data-driven RUL estimation framework for brushless direct current motors. Fault characteristics of motor current and generator power are combined using a Kalman filter to estimate the RUL. Natarajan et al. [20] used the Bayesian inference of Linear Regression to estimate the RUL of lead-acid batteries.

2.4. Hybrid-model based approaches

In general, hybrid prognostic approaches benefit from combining other approaches to overcome the individual approaches' drawbacks. For example, Hansen et al. [21] presented an approach, which combines sensor-based information and model-based information. Results obtained from this approach are claimed to be more reliable and accurate [7], [22]. Wang et al. [23] proposed a hybrid model by using the vibration data of rolling element bearings to predict their RUL. A data-driven model such as the relevance vector machine regression and the Fréchet distance is applied to further improve the accuracy and convergence by obtaining experimental results. Galar et al. [24] used a hybrid approach to estimate the RUL for a railway system by using the data from rolling stock and data from the trackside to develop the physics of failure as well as support vector machines (SVM).

2.5. Failure Mode and Effect Analysis in RUL estimation approaches

A Failure Mode and Effect Analysis (FMEA) represents a system and risk analysis with the goal of optimization through error prevention for a product or process to be developed. Furthermore, it offers the possibility to build up a knowledge repository for failure types and corresponding protective measures. The first mention of FMEA was in the 1980s US Armed Forces Military Procedures document MIL-P-1629A [25]. In the context of RUL estimation, FMEA supports the identification of different failure types, where the non-useful lifetime has reached. Utah and Jung [26] identified solenoid-operated valve (SOV) fault conditions based on an FMEA and estimated the RUL using a deep neural network (DNN). Christian et al. [27] presented a model for failure prediction and RUL estimation of an anode voltage regulator system at an ion implantation accelerator. An FMEA was conducted to identify five failure modes. Failure data is then simulated and evaluated using a Random Forest Classifier (RFC) and Hidden Makarov Model (HMM).

2.6. Deep learning in RUL estimation approaches

Deep learning (DL) has attracted strong interest in Prognostics and Health Management (PHM) applications, due to its high processing power, automated feature learning capability, and problem-solving ability [28]. Several publications concur that models using DL approaches perform more accurately than those without any DL integration [29–31]. The potential, challenges, and future directions for DL in PHM have been published by Fink et al. [32]. Reviews of deep learning applications in PHM have been provided by Wang et al. [33], Zhang et al. [28], and Zhang et al. [34]. With the main interest in estimating the RUL, the implementation of DL supports the ability to process massive amounts of condition monitoring data automatically [28]. Furthermore, DL provides the ability to automatically extract useful features from high-dimensional, heterogeneous data sources [28]. DL also has the ability to learn functional and temporal relationships between and within the time series of condition monitoring signals [28]. The most widely used DL architectures in the PHM domain are considered the restricted Boltzmann machine (RBM), auto-encoder (AE), convolutional neural network (CNN), and recurrent neural network (RNN) [28].

3. Proposed RUL method

The proposed method investigates the two-jaw parallel gripper model 2F-85 from ROBOTIQ. The gripper has a single actuator and is under-actuated. Further specifications are the maximum stroke of 85 mm, a maximum gripping force of 230 N, and a maximum payload of 5 kg. An overview of the gripper structure is shown in figure 1.

Fig. 1. Investigated gripper [32]

The gripper has two fingers, where each of the fingers has two joints (two phalanxes per finger). The gripper fingers are able to engage in five points of contact with an object [35]. The two fingers of the gripper set the system boundary, since these are involved in the gripping action of the process the gripper performs. The proposed RUL estimation method is shown in figure 2. The hybrid method is based on the experimental-based and data-driven approach. Skima et al. [8] have developed a hybrid method in which grippers at microelectromechanical (MEMS) system-level have been investigated for degradation. This hybrid method mathematically calculates the nominal behavior of the gripper and derives the degradation from it. Based on this method, the proposed method has been developed. The continuous reference to the pre-experiment and experiment distinguishes the proposed method. The following subsections provide a detail explanation based on an experimental setup.

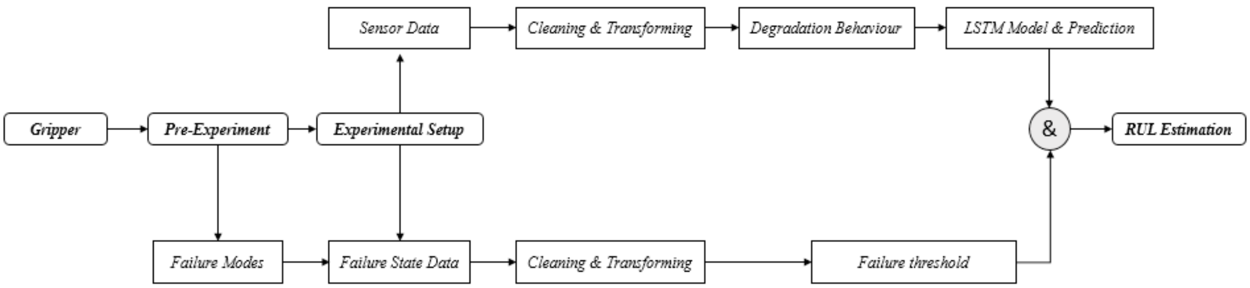

Fig. 2. Proposed method for the RUL estimation of parallel gripper

3.1. Pre-experiment

The pre-experiment determines the possible failure modes (FM) for the gripper. In this case, a failure mode and effects analysis (FMEA) identifies the different FM for a sampling process (Appendix A). The FM and their effects are summarized in table 1.

Table 1. FMEA excerpt.

Nomenclature Failure Mode	System Function	Potential Failure Mode

F1	Open Gripper	Delayed movement of gripper fingers
F2	Open Gripper	Stunted movement of gripper fingers
F3	Open Gripper	No movement of gripper fingers
F4	Close Gripper	Delayed movement of gripper fingers
F5	Close Gripper	Stunted movement of gripper fingers
F6	Close Gripper	No movement of gripper fingers

Table 1 shows that the potential FM identified are delayed, stunted or no movement of the gripper fingers. The FMEA excludes alignment and movement of the gripper unit. The following approach delimits the RUL determination by selecting the failure modes *F3* and *F4*.

3.2. Experimental setup

Within the experimental setup, the gripper executes a predefined process repeatedly. The opening as well as the closing of the gripper finger, while maintaining the gripper and robot position, is defined as the experimental process. Such a simplified process is intended to ensure repeatability. The experiment collects data, which is used to represent the degradation behavior of the gripper. Various measurements can give an indication about the degradation behavior. Possible suggestions are force measurements, which are taken at a prescribed frequency during the predefined process. Significant deviation over the time indicates degradation behavior. Furthermore, there is the possibility of distance measurements, which measure the distance between the two fingers at a given frequency. Deviation from the specification data, indicates degradation behavior. A last suggestion is time measurement, where the duration of the process execution is measured. Here, the decrease in gripper movement speed is investigated. The considered measuring approach is strongly depending on the investigated use case. In the experimental setup, the applied force on a load cell is taken as a first degradation indication. The experimental setup is shown in figure 3.

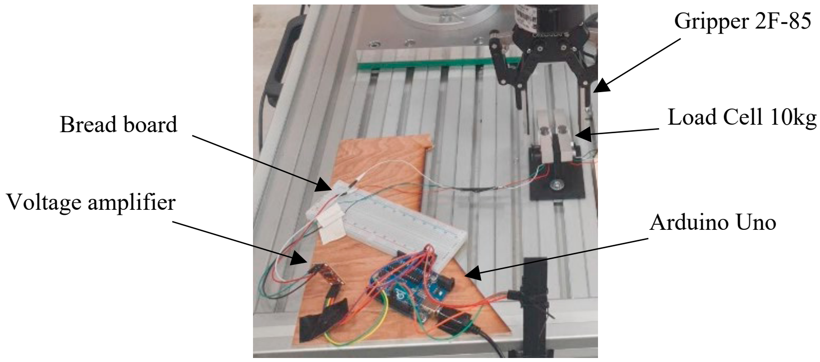

Fig. 3. Experimental setup for initial force measurement

3.3. Sensor data collection

Raw sensor data is collected from the load cell, which is recorded during the process iterations. The measured feature is acquired by saving the sensor readings into a comma delimited (CSV) file with the according timestamp. The process is done by a function in the Arduino IDE, which reads the saved sensor data, and inserts the data into a CSV file. The data cleaning takes place by detecting and handling missing values as well as outliers with the python pandas library. This results in a dataset, which represents the natural force degradation of the gripper. After the data cleaning, the data is transformed into a health indicator. To gain evidence about the force degradation in this use case, the mean value for the first 100 and last 100 measurements is calculated. The considered dataset provides 105890 raw load cell measurements. Initial data exploration is provided in figure 4.

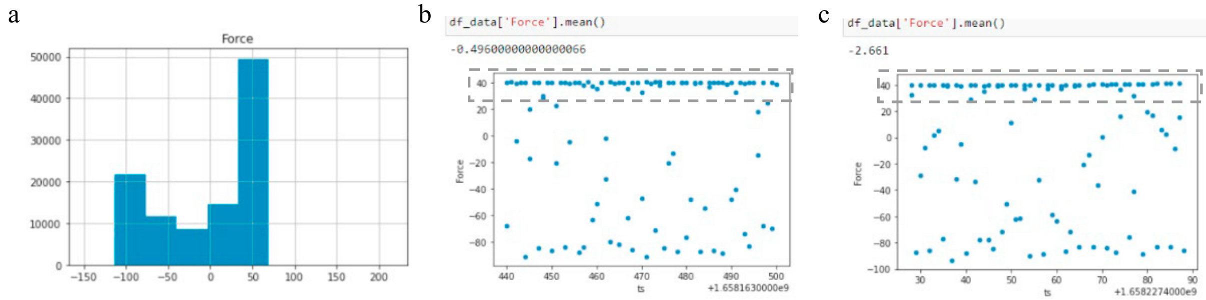

Fig. 4. (a) Force measurement distribution; (b) Mean-value and scatter plot for first 100 recordings; (c) Mean-value and scatter plot for last 100 recordings

The initial data exploration shows that the data set is unimodal distributed. The skewness of the data is described by the equation (1). For the examined data set, the skewness results 2.6. A positive skewness far from 0 indicates an asymmetric and right-skewed distribution.

$$v(X) = \frac{n}{(n-1)(n-2)} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}}{s}\right)^3 \tag{1}$$

Comparing the scatter plots of the two samples, it is seen that within the last 100 measurements, less data points reach or exceed the peak of 40 as in the first 100 measurements. The visual observation is recognized in the mean value of the samples. The mean for the first 100 measurements is -0.496 and for the last 100 measurements -2.661.

3.4. Failure state data

The gripper executes the default process and is then manually set to the Failure Modes *F3* and *F4,* see Fig. 5. In this state, the load cell continues to collect data, which describes the unhealthy stages. Based on the failure state data, the mean values for each stage are calculated, see Fig. 6. Each failure mode dataset consists of 200 recordings.

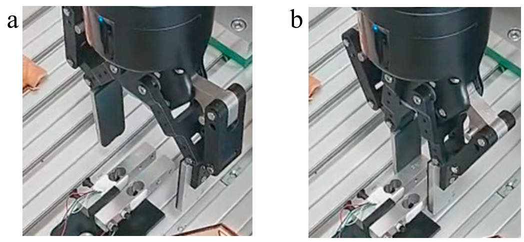

Fig. 5. (a) F3 Mode; (b) F4 Mode

To create a basis for comparison, the recordings are transformed into the mean values. The last 100 recordings are transformed into the health indicator. *F3* results in a mean of -5.7069 and for *F4* a mean of 586.458.

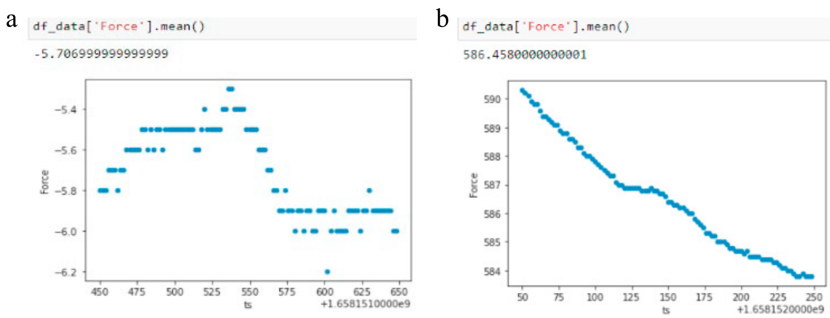

Fig. 6. (a) last 100 mean-value and scatter plot of *F3*; (b) last 100 mean-value and scatter plot of *F4*

3.5. LSTM model and prediction

The correct use of deep learning models improves the performance of RUL estimation (section 2.5). The use case concerns sensor data, which is time-sequenced with long time range dependencies. A Recurrent Neural Network (RNN) or Hidden Markov Model (HMM) can be used for RUL estimation with these data structures. However, both models present weaknesses, in cases of long periods of time series data being modelled [36]. In the use case given here, a Long Short-Term Memory (LSTM) network is appropriate since previous sequential data is used to predict the long-term degradation. Refer to Zheng et al. [37] for an in-depth explanation of the usage of LSTM networks in RUL estimation.

3.6. Failure threshold

The failure threshold (FT) delimits the states of *useful* and *not useful* from each other. If the health indicator exceeds the threshold, corrective action must be taken on the gripper. The level at which the FT is determined in three different ways. The method of determination is used depends on what data is available. Either the lifetime data, run-to-failure data or threshold data is used. Lifetime data reflects the entire life cycle of the system under study. To estimate the RUL with lifetime data, proportional hazard models and probability distributions of component failure are used. Run-to-failure data is historical data gained from systems with similar degradation behavior. For RUL estimation, similarity models such as regression or classification similarity learning is applied to the investigated system. Threshold data are prescribed values, which indicates the boundary before failure occurs. Time series models of condition indicators such as pressure, force or temperature are used to predict the point, where the condition indicator exceeds the threshold.

3.7. RUL estimation approach

The RUL estimation is obtained by the difference between the timestamp at the current system health and the timestamp of the system health when exceeding the threshold, see Fig. 7. In the presented use case, the lower threshold is set to -5 and the upper threshold is set to 550. Since it is assumed that the applied force is decreasing over time, the lower threshold needs to be considered for further research.

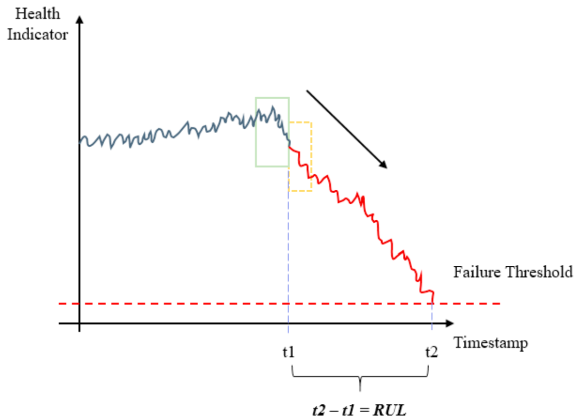

Fig. 7. RUL estimation approach with health indicator

4. Conclusion and Discussion

In this paper, a method to estimate the RUL for a two-jaw parallel gripper has been presented based on experimental failure threshold data. The results of the study presented are in line with the research objectives. We have presented numerous examples of RUL estimation on industrial applications in the second chapter. As a health indicator, we have found that the arithmetic mean can be considered to stably record a change in wear behavior. Using FMEA analysis, we identified six failure modes. What influences the results of the study are factors such as the selection of the gripper as well as the selection of the measurement method and the experimental setup. Compared to other studies, data acquisition in particular is a debatable issue. As presented in the research work of Christian et al. [27], data acquisition can also be done with simulated data such as via MATLAB. Other research work relies on publicly available datasets from industrial applications. This can achieve high resource savings. The advantage of an own experimental setup is the high level of control. Furthermore, the resulting conclusions are very specific.

5. Further Challenges and Outlook

As the discipline of RUL estimation is still evolving, there is a lack of success stories from lab experiments to real environment applications. Further challenges based on the proposed research are addressed as follows:

(1) The data used are sufficient to derive initial indications. However, the realism of RUL estimation is improved with longer measurement series and the fusion of multiple sensor data to one or more health indicators. This is stated in numerous literature [18–21].

(2) It is necessary to manage the uncertainty generated by the influence of external environmental variables and future work conditions such as process speed or future load profile. This impacts the RUL estimation since the external environment influences the condition monitoring variables and the degradation behavior. Furthermore, the operators in the work cells can extend the RUL by regulating these factors. Quantification of the uncertainty will help the RUL estimation and provide suggestions to operators.

(3) The third challenge is the verification and validation of the RUL estimation result. Theoretical estimation algorithms developed must be verified and validated first in a high-fidelity environment before practical applications. However, how to build such an environment is a puzzle for every related researcher at all times.

(4) The last challenge is how to realize accurate onboard RUL estimation. Plenty of RUL estimation approaches are intensive computation and require sufficient computing resources. It is a great challenge to reduce the computation of estimation algorithms on the premise of ensuring the accuracy and the confidence of results.

More research work should focus on accelerating the progress of real-world application studies. In recent years, the progress of RUL estimation models increased, but there is still a lot of potentials.

Appendix A. FMEA Sheet

Process or Product Name:	ROBOTIQ 2F-85			
Responsible:	Serkan Mert			
System function	**Potential Failure Mode**	**Potential Failure Effects**	**How Severe to Customer**	**Potential Causes**
Open Gripper	Delayed movement: The gripper fingers are moving in delayed sequences	The process is executed uncleanly. The positioning of the fingers is not on time and thus consequential errors might occur.	The process flows are disturbed by the errors. As a result, maintenance work may occur, which worsens the efficiency of the production line. In addition, damage to the part can occur, which must be evaluated as scrap. RPN Factor = 5	Degradation of the phalanxes joints. Electrical actuator failing in communicating position signal properly.
Open Gripper	Stunted movement: The gripper fingers stop and start moving in one or several stages of the process execution.	The process is not executed on time. Subsequent errors might occur and the process is not executed successfully.	The process flows are disturbed by the errors. As a result, maintenance work may occur, which worsens the efficiency of the production line. In addition, damage to the part can occur, which must be evaluated as scrap. RPN Factor = 5	Phalanxes joints are not able to move due to blocking substances. Electrical actuator does not reveice power supply properly. Loose contact on wiring.
Open Gripper	No movement: The gripper fingers stop moving totally.	The process is interrupted and thus consequential errors occur quickly.	The process flows are disturbed by the errors. As a result, maintenance work may occur, which worsens the efficiency of the production line. In addition, damage to the part can occur, which must be evaluated as scrap. RPN Factor = 5	Phalanxes joints are not able to move due to blocking substances or degradation. Electrical actuator does not reveice power supply. Missing contact on wiring. Robot is not on power supply.
Close gripper	Delayed movement: The gripper fingers are moving in delayed sequences	The process is executed uncleanly. The positioning of the fingers is not on time and thus consequential errors might occur.	The process flows are disturbed by the errors. As a result, maintenance work may occur, which worsens the efficiency of the production line. In addition, damage to the part can occur, which must be evaluated as scrap. RPN Factor = 5	Degradation of the phalanxes joints. Electrical actuator failing in communicating position signal properly.
Close gripper	Stunted movement: The gripper fingers stop and start moving in one or several stages of the process execution.	The process is not executed on time. Subsequent errors might occur and the process is not executed successfully.	The process flows are disturbed by the errors. As a result, maintenance work may occur, which worsens the efficiency of the production line. In addition, damage to the part can occur, which must be evaluated as scrap. RPN Factor = 5	Phalanxes joints are not able to move due to blocking substances. Electrical actuator does not reveice power supply properly. Loose contact on wiring.
Close gripper	No movement: The gripper fingers stop moving totally.	The process is interrupted and thus consequential errors occur quickly.	The process flows are disturbed by the errors. As a result, maintenance work may occur, which worsens the efficiency of the production line. In addition, damage to the part can occur, which must be evaluated as scrap. RPN Factor = 5	Phalanxes joints are not able to move due to blocking substances or degradation. Electrical actuator does not reveice power supply. Missing contact on wiring. Robot is not on power supply.

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