

Automated anomalies detection in the work of industrial robots

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Abstract. This article describes the results of the anomalies automated detection algorithm development in the operation of industrial robots. The development of robotic systems, in particular, industrial robots, and software for them is ahead of the tracking and managing technologies development. The operation of the digital production system involves the generation of a large amount of various data characterizing the state of both the specific equipment and the industrial system as a whole. Such a system produces a sufficient amount of data to develop machine learning models to analyse this data to solve problems such as forecasting and modelling. As part of the study, an experiment was conducted based on the equipment of the laboratory of industrial robots of Tomsk Polytechnic University. In the course of the research, the industrial manipulator moved loads belonging to different classes by weight. An algorithm was developed for the automated analysis of the values of the parameters of the consumed current and the position of the manipulator.

1. Introduction

In connection with the intensive development of information technologies and the onset of the 4th industrial revolution [1,2], the number of robotic industries is steadily increasing. The production and use of robots are also growing. At the same time, the direction of maintenance and management of digital production is developing [3]. Most robotic systems need human presence, as they need to be fine-tuned, timely serviced, and monitored [4,5]. One of the areas of work to eliminate unexpected failures is preventive maintenance. These works are carried out according to the equipment maintenance regulations, which are being developed by the enterprise. The regulation is based on a variety of factors. One of the factors is the cost of the product life cycle, assessment of the condition of the equipment, and recommendations for maintenance from equipment manufacturers.

Modern digital production environments generate massive datasets from the many areas and sources involved. Data sources may include sensors, optical sensors, drive controllers, tracking cameras, and other similar equipment. These ever-increasing amounts of data contain useful knowledge and information that can improve the performance of the entire production process, due to their subsequent analysis. For example, this knowledge is a valuable asset to support decision-making in various areas, especially in the field of equipment monitoring and maintenance.

There are several approaches to the maintenance of industrial equipment – reactive, proactive, preventive, and prognostic. The main difference of the reactive approach is the production of repairs after an equipment failure. For the formation of the maintenance rules with the prediction of the operation mode is the more suitable prognostic approach. The implementation of proactive maintenance allows to predict and manage equipment failures before they occur. This approach, based on data analysis, is implemented to form a maintenance plan for robotic systems [6]. Data analysis is



carried out on a large amount of historical data of equipment operation using statistical and machine learning methods [7,8]. The software architecture for data collection and analysis includes five main modules: collection, transmission, storage, analysis, and visualization [9,10]. The relevance of this work is to develop an approach to managing the means of production using the methods of analyzing data on the state of industrial equipment.

Timely acquisition and processing of data allow to most effectively develop strategies for the operation, support, maintenance, and repair of fixed assets. When analyzing the software for monitoring the state of industrial equipment from leading manufacturers of robotic systems, we identify the following general functionality:

- Monitoring of current equipment parameters.
- Archiving data.
- Assessment of equipment condition.
- Remote access to equipment functions/modes.

The disadvantage of these software products is the lack of data mining tools, which made it possible to estimate the boundaries of the standard equipment operation parameters values to identify abnormal values. At the same time in these counterparts, there is an alarm function, in the event of a malfunction of the equipment or deviations from typical values. Also, disadvantages include the fact that each software product is compatible only with the equipment type for which the product was developed. Different systems of monitoring in their functions, possibly, can complement each other's work and work more efficiently. However, in practice, this approach can be implemented only with the addition of third-party software that would provide data exchange.

The primary purpose of this work is to develop software that allows to automatically detect anomalous values in the process of operation of robotic manipulators. The research component of the work is to choose the most optimal statistical method for finding abnormal values in the data array. Different statistical methods have various limitations and accuracy of determining anomalies, so it is necessary to evaluate their effectiveness in the framework of this work.

2. Automated anomalies identification in the work of industrial robot

Abnormal values in the data set can be represented as emissions, shifts, changes like the distribution, or deviations from the “seasonal” value. Equipment operation values that go beyond the norm are often the result of possible malfunctions.

We experimented based on the KUKA robotic manipulator (Figure 1) with a loading capacity of 40 kilograms. The purpose of the manipulator is the cyclical movement of cargo from point A to point B with the operation of lifting the load with the help of vacuum suction cups. Table 1 describes the load types.

Table 1. Classes of the lifted load.

Type of the load	Weight (kg)
0	0
1	2.5
2	5
3	7.5
4	10

For the experiment, a software instruction was written consisting of 6 basic commands. The list of basic robot actions:

- Rotate the robot to point A.
- Capture cargo at point A.
- Moving the load to an intermediate point.
- Moving the weight to point B.
- Unloading the robot at point B.
- Return to the intermediate position

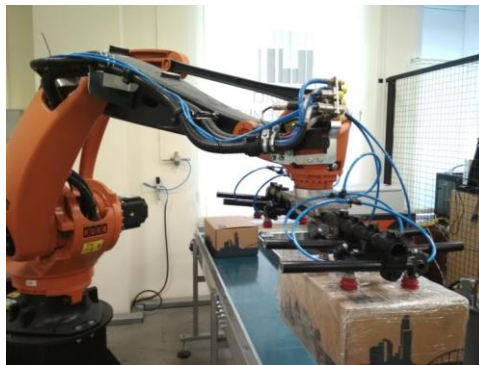


Figure 1. Industrial KUKA robot used in the experiment.

We select the following data values to analyze the anomalous values in the robot's work:

- The current value along the axes.
- The number of performed operation.
- Mass of additional load of cargo.

To understand how the current value changes over time as a whole, when operating with a certain mass of load, we calculate the average value of the currents:

$$\bar{I}_{O^k, M_x}^n = \frac{\sum_{i=O_{t_1}^k}^{O_{t_2}^k} I_{i, M_x}^n}{O_{t_2}^k - O_{t_1}^k} \quad (1)$$

where:

n – the axis number,

O^k – operation number k ,

I_{i, M_x}^n is the current value for the n axis, at time i , when the load moves M_x .

To obtain the upper and lower limit of current values when the robot is working with loads of different mass is necessary to get a list of maximum and minimum average values of current for operations:

$$\text{Max}(\bar{I}_{O_j^k, M_x}^n) \quad (2)$$

$$\text{Min}(\bar{I}_{O_j^k, M_x}^n) \quad (3)$$

where:

j – the iteration number on proceeding operation O^k with the load M_x .

Next, we need to obtain the maximum and minimum values of currents for operations with all values of the mass of the additional load:

$$\text{Max}(\text{Max}(\bar{I}_{O_j^k, M_x}^n)) \quad (4)$$

$$\text{Min}(\text{Min}(\bar{I}_{O_j^k, M_x}^n)) \quad (5)$$

This operation will allow you to build an upper and lower limit of values for all cycles of the manipulator. Figure 2 shows an example of construction for the axis №3.

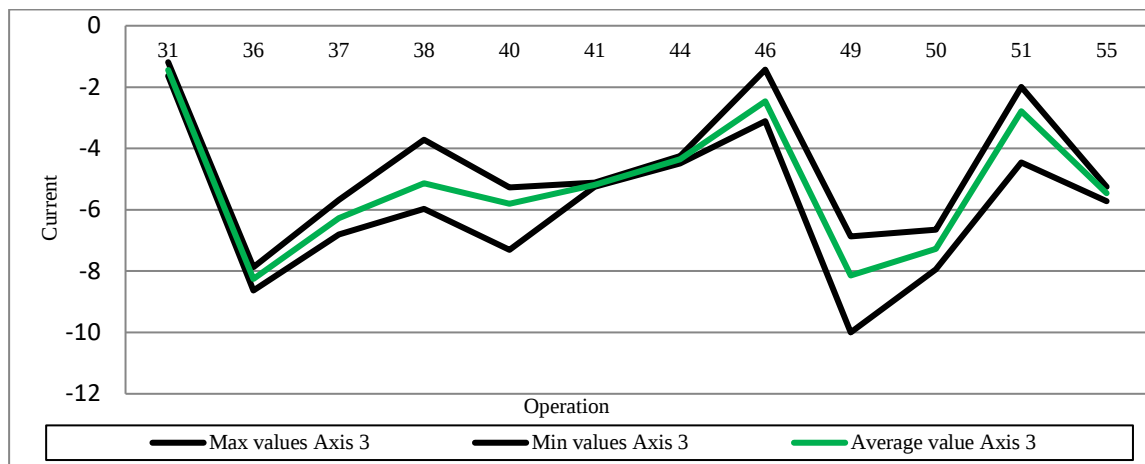


Figure 2. Maximum and minimum values of currents when operating on axis 3.

A robotic arm during an operating cycle may suddenly be exposed to external influences. For example, an unforeseen/abnormal increase in load will occur. A robot set up by an operator to work with cargo weighing 5 kilograms will suddenly accept a shipment weighing 10 kilograms. Figure 3 demonstrates how this reflected in the parameters of the equipment.

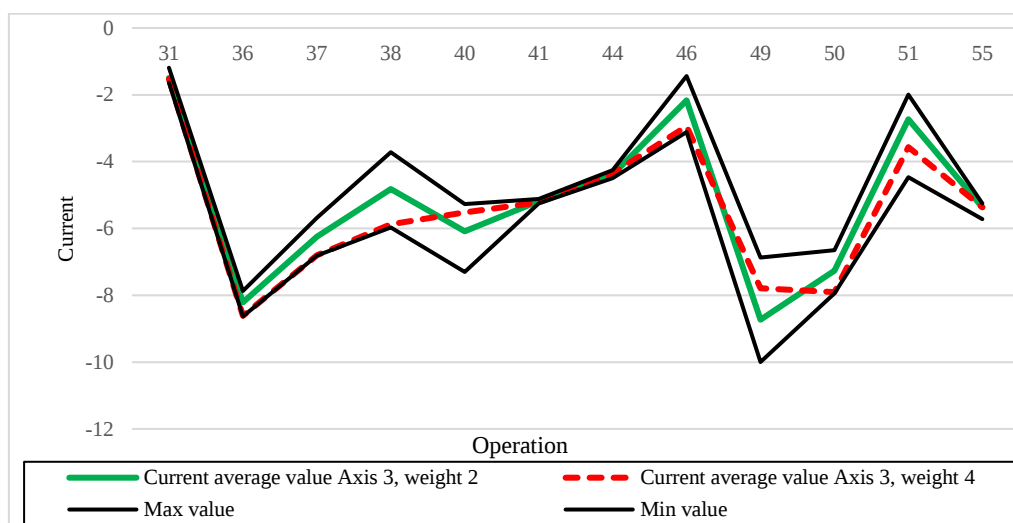


Figure 3. The values of currents when working with weights of types two and four.

The graph clearly shows the deviations in the average current parameters for operations performed with different loads. We should note that even with a massive load, the parameters do not go beyond the limits of the maximum and minimum values since these values are determined for working with all loads. Figure 4 shows a more detailed demonstration of deviations from the border of the maximum and minimum values.

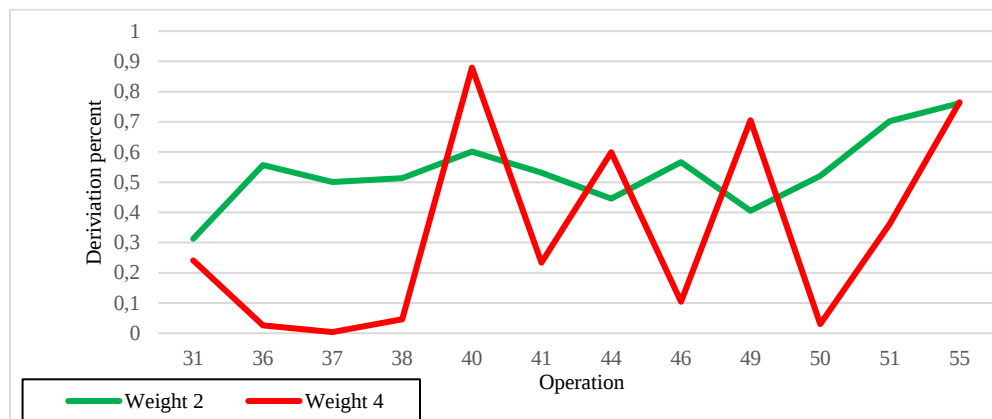


Figure 4. The percentage deviation of the average current parameters relative to the minimum values of the equipment.

An algorithm has been developed for automating operations with experimental data (Figure 5). The algorithm consists of three main stages: obtaining the boundaries of typical values during the initial setup of the equipment, calculating the permissible deviation of the equipment parameters during the operation, monitoring data during the equipment operation.

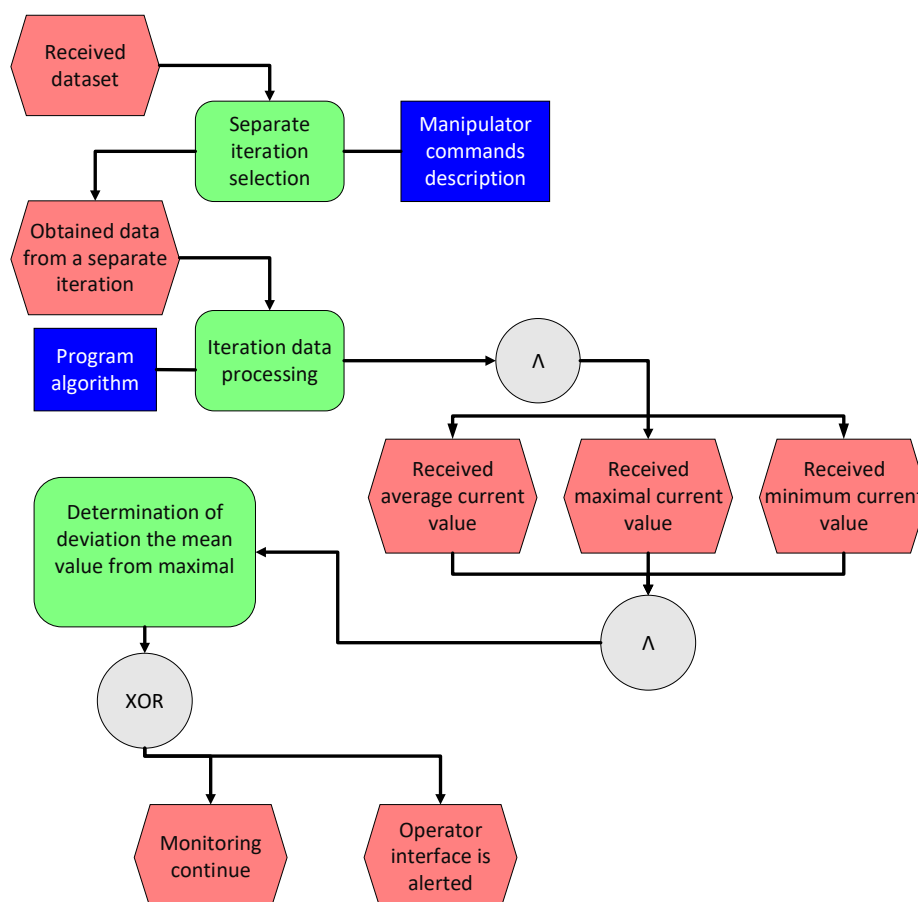


Figure 5. The eEPC diagram of the automated anomalies detection process for the industrial manipulator.

3. Summary

This paper presents an analysis of the current state and approaches to the processing of technical data used in the problem of predicting equipment maintenance, in particular, industrial robotic manipulators. Experiments were carried out on the KUKA robotic manipulator. An algorithm was developed and applied to monitor the deviations of the equipment operation parameters in different modes (under normal and excessive load).

The possibility of automated anomalies detection in the industrial robot operation based on real-time analysis of the operating parameters is demonstrated. The results obtained are intermediate in nature and will be used as the basis for the development of algorithms for diagnosing problems and predicting the state of industrial robots.

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