Fusion Engineering and Design 153 (2020) 111506

Contents lists available at ScienceDirect

Fusion Engineering and Design

journal homepage: www.elsevier.com/locate/fusengdes

A taxonomy approach to failure mode analysis for use in predictive condition monitoring

L. Pangione*, R. Skilton, R. Powell

RACE, Culham Science Centre, Abingdon OX14 3PF, United Kingdom

ARTICLE INFO

Keywords:
Fault taxonomy
Condition monitoring
Dirichlet process Gaussian mixture model

ABSTRACT

An extensive knowledge of a system's failures is crucial for identifying areas where the reliability of the system can benefit from improvements, as well as informing the design of new systems. Moreover, relationships between faults and failures can be used to enhance the maintenance of the system.

In this paper we present a taxonomy of failure modes of the Joint European Torus (JET) Remote Handling System (RHS). This system is used during maintenance and enhancements of in-vessel systems, and consists of two transporters (articulated booms) and a two-armed manipulator, along with a number of supporting systems. In this work we first present a failure taxonomy suitable for our specific system, and then we use a clustering approach to introduce example failure modes into the taxonomy. The presented failures have been collected during commissioning and operations over a period of over 5 years. Cataloged failures are extracted from the logs produced by the control system and from the daily log books recorded by the system operator.

1. Introduction

The Joint European Torus (JET) Remote Handling System (RHS) performs maintenance and improvement activities of the tokamak vessel structure [1]. It consists of two independent transporter systems, called Octant 5 boom and Octant 1 boom. Each boom has attached at its extremity a boom end-effector. In most applications Octant 1 boom carries the task module trolley, while Octant 5 boom carries MASCOT, a two-armed master-slave manipulator [2]. JET RHS is deployed into the JET torus hall in between physics campaigns for interventions, and has been operating successfully during last the two decades.

In remote operations the reliability of equipment is of paramount importance, hence there is a need to monitor the condition of the plant throughout the maintenance process. A Condition Monitoring System (CMS) facilitates a change from maintenance as a planned process, executed at regular and fixed periods of time, to a predicted process, executed according to the components needs. Moreover, CMS will be able to inform the RHS operators of a possible imminent failure during operations to allow them to place the system in a safe position.

In this work we apply statistical methods, such as K-means and the Dirichlet Process Gaussian Mixture Model (DPGMM) to different JET RHS historic data to investigate failures occurrence during all years of operations, with respect of data availability.

This paper is organized as follows. In Section 2 we introduce a taxonomy model suitable for our investigation. In the third section we give a description of our data. In the fourth section we describe how two different sources of data were classified, with particular emphasis on identifying position error using DPGMM. In the last section we summarize the work and describe future works.

2. Taxonomy

According to [3] and [4] a failure is defined as *"a deviation from the specified service as seen by the client"*. An error is *"a state within the system which can lead to a failure"*. A fault is *"anything which could cause the system to enter an error state"*. In other words, a fault is necessary but not sufficient for the system to be in an error state; an error state is necessary but not sufficient for the system to have failed.

Different types of taxonomy models have been already presented in literature, from a very general purpose, such as the one presented in [3] and [4], to more specific one presented in [5]. We adopted the taxonomy model proposed by [3] and [4] in which we consider only failures generated by physical components faults. Our taxonomy model is presented in Fig. 1.

It is interesting to note that while JET RHS control systems are able to identify failures, they do not give to the RHS operators or maintainers an indication of the causes of the failures. An error in a joint position reported by the control systems could have been caused by

* Corresponding author.
E-mail address: luigi.pangione@ukaea.uk (L. Pangione).

https://doi.org/10.1016/j.fusengdes.2020.111506
Received 20 September 2019; Received in revised form 22 January 2020; Accepted 23 January 2020
Available online 30 January 2020

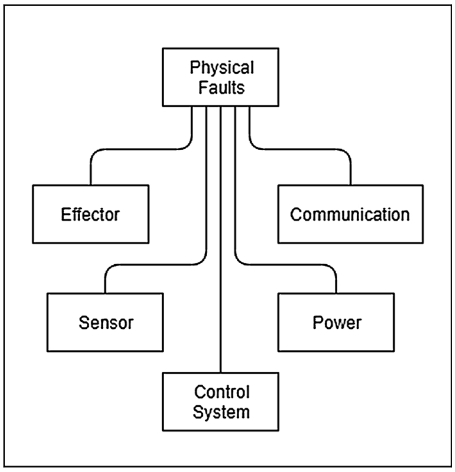

Fig. 1. Our proposed taxonomy model.

several reasons, for example, a move request that is too fast, a structure or another component preventing the movement or a genuine hardware failure.

The aim of our work is to provide a taxonomy model that can lead to a better identification of faults for common failures.

It will become clear in Section 3, how different data sources report failures in different, not congruent, ways. Failure taxonomy techniques presented in Section 4 are aimed to make a preliminary investigation on how to use available data in order to correctly identify and classify physical failures using the proposed taxonomy model.

3. Data sources

During JET RH operations data are collected from different sources. Each data source is independent from the others and has its own purpose. JET RH data sources are:

1 Data Acquisition System (DAS data). High frequency (1 kHz) control system data. They are numerical values obtained directly from sensors and actuators. Because of the vast amount of archiving space required they are stored only for failure investigations.
2 Low frequency control system data collectors (LFCS system data). They contain only a subset of the sensor and of the actuator measurements collected continuously at low frequency ($\sim$30 Hz). They are always available during operations and they are stored at the end of each day of operation. Since they are recorded at low frequency, they may not contain fast events recorded by control system.
3 Control system logs (HMI logs). These are text logs generated by each control system. They contain all information sent from the control system to the operator's graphical interface. They include all failures flagged by the control system and also contain all the commands sent by the operator to the control system.
4 Operator log. This is a log handwritten by operators during the shift. They are in form of scanned handwritten document. These logs have been recorded since the beginning and a change in how they are implemented is impractical at the current stage. Operator's comments are a valuable source of information about failures, but they depend on the personality of the operator.
5 RH issue repository. The RH repository contains a record of discussion internal to RH control system group. It is in plain English with support of pictures.

Recorded data are in form of numbers, text sentences or a mixture of the two. Data sources collect data at very different rates, moreover while the control system data acquisition rate is constant, operators collect data asynchronously. That makes it difficult to link recorded events only relying on timestamps, since timestamps do not always agree or exist. Moreover, there is not always a one to one relationship among events. For example, a failure recorded in the operator log will not be necessary recorded at the same time in the control system log. Conversely, multiple failures recorded in the control system log, can appear as one failure in the operator log.

The ideal solution would be to use all the suitable data sources needed to identify and classify each failure. It is important to note that not all the sources contain information about each failure. Moreover, identifying the optimal combination of data sources is not trivial.

During the past, not all the data sources were available at the same time. Fig. 2 shows the overall data availability. It can be seen that logs are available for almost all the time, while numerical data (LFCS and DAS data) availability is limited to approximately the last two years.

4. Failures taxonomy

To find the exact causal relationship using all the above data is impractical due to the amount of data and to the uncertainties. To overcome this problem, a first classification of the different, but not all data sources has been applied: control system logs and low frequency control system data (LFCS system).

Since control system logs contain data mainly in the form of automated text, it has been possible to consider its *"bag of words"* representation and to apply K-means techniques to group entries into clusters. K-means techniques is a set of general-purpose clustering techniques in which samples are grouped into a number K of not overlapping clusters by minimizing the distance of each sample by the cluster mean. [6].

LFCS data are numerical values, and the Dirichlet Process Gaussian Mixture Model (DPGMM) technique has been applied to identify failures directly from sensor data. In the DPGMM techniques samples are modelled as a superposition of multiple Gaussian distributions. The Dirichlet Process avoids, in practice, the need to calculate beforehand the number of Gaussians required to model the data [6].

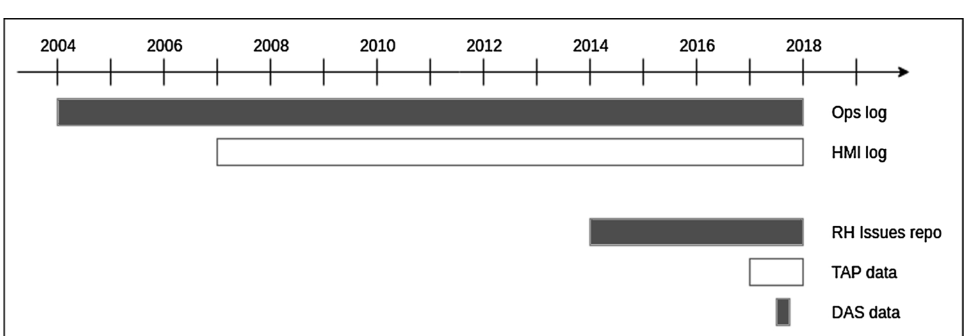

Fig. 2. JET RH data availability over time.

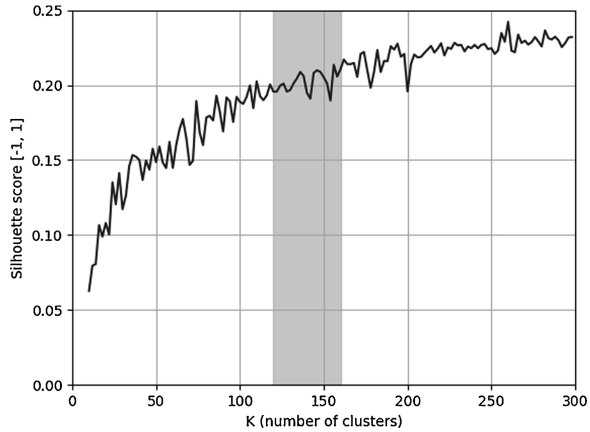

Fig. 3. Octant 1 boom control system logs silhouette score as function of number of clusters.

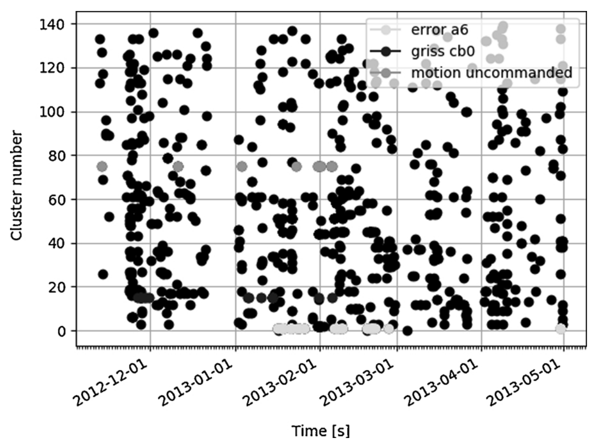

Fig. 4. Clustered Octant 1 boom control system logs represented as function of time.

4.1. Control system logs clustering

By clustering control system logs, it is possible to transform text entries into time series. Similar entries will be associated with the same cluster and so can be represented by the cluster number value.

Before applying the K-means technique uninformative words, such as conjunctions and pronouns, must be removed from the entries.

The number of clusters is chosen using the silhouette score. The silhouette score is the average of the silhouette score of each sample. For each sample i, the silhouette score is calculated as:

$$s(i) = b(i)\ a(i)\ /\ max\ \{a(i),\ b(i)\}$$

Where *a(i)* is the mean of the distances between the element *i* and all the elements inside the cluster it is assigned to, while *b(i)* is the mean of distances between the element *i* and all the elements of the nearest cluster [7].

In Fig. 3 the silhouette score is shown as a function of the number of clusters. It is possible to see that it increases rapidly up to 120 clusters, while increasing the number of clusters over 160 is not as effective. This gives us an estimation of the number of clusters between 120 and 160.

Once the number of clusters has been decided, the actual clustering action can be executed.

Fig. 4 shows control system logs of Octant 1 boom clustered entries as function of time. As example, three identified clusters *"error a6"*, *"gross cb0"* and *"motion uncommanded"* have been highlighted.

4.2. Low frequency control system (LFCS) data classification

The aim of the work presented in this subsection is to use a statistical method to identify failure occurrences from LFCS data. DPGMM is used to represent the health status of each joint. When the model is applied to a new set of data, any data with a low probability of being in any of the Gaussians, implies a low probability of being healthy and therefore likely to indicate a failure. This makes use of the DPGMM as a solution of a one-class problem. This can be very convenient as the subdomains identified by the DPGMM can be used to subdivide the data space (joint positions, joint position errors and voltage applied to the

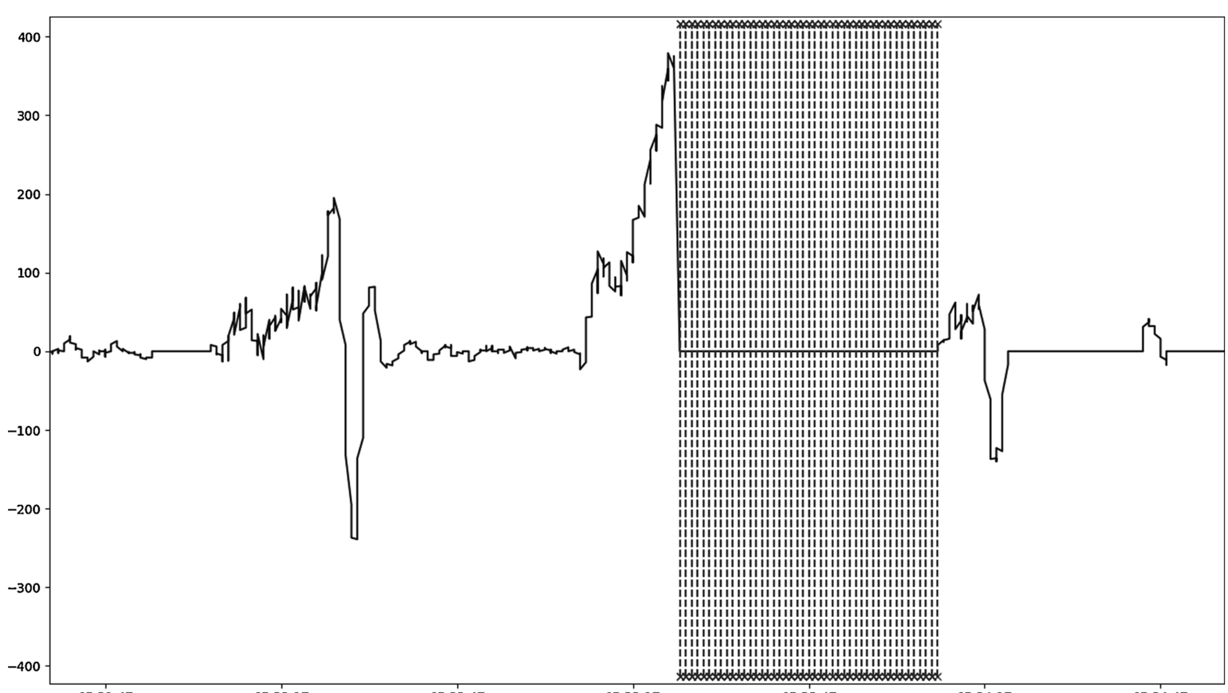

Fig. 5. Example of position error failure raised by the boom control system. The solid line represents position error as a function of time, while vertical dashed lines represent the time when a *"gross error"* failure is identified.

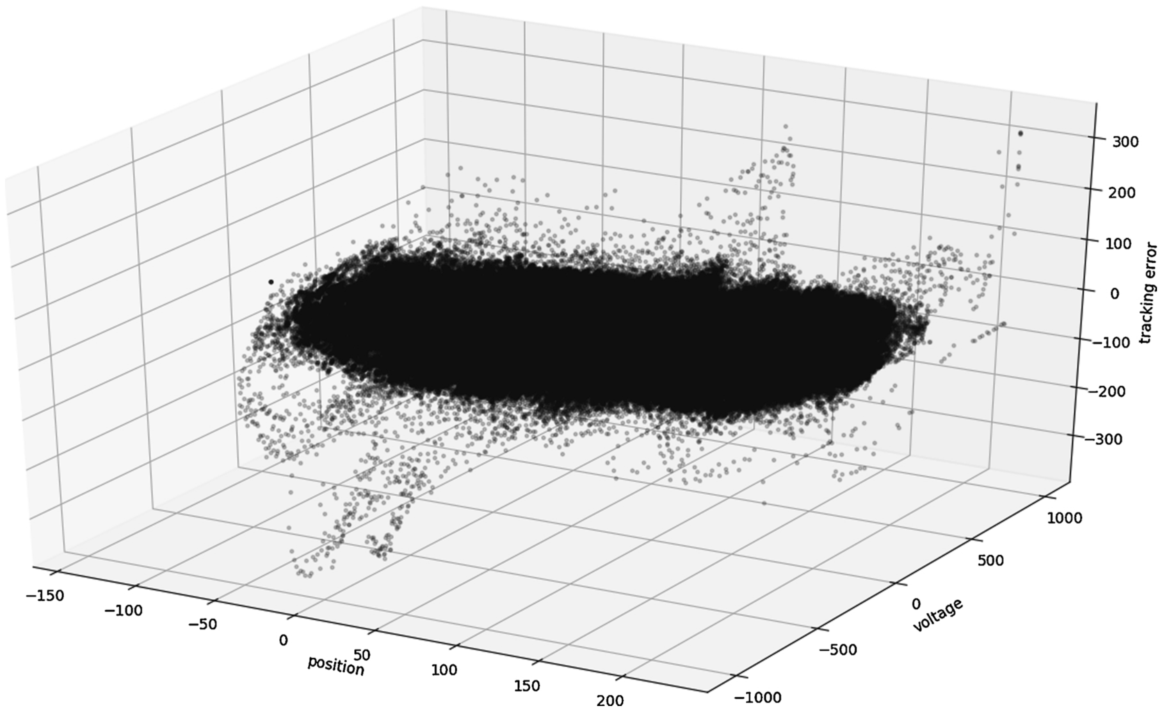

Fig. 6. Healthy data as function of joint position, joint motor applied voltage and joint position error.

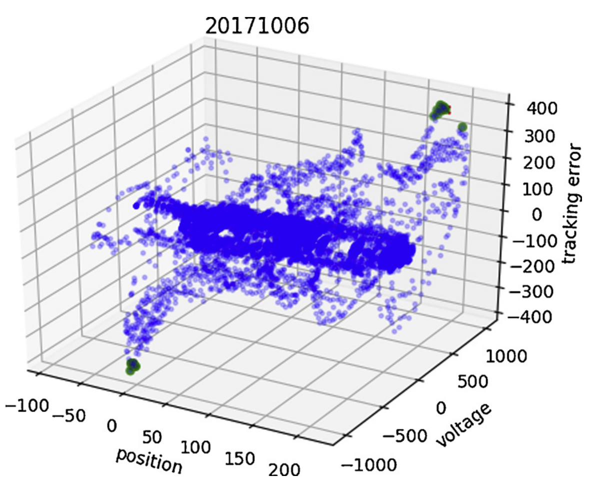

Fig. 7. Data containing *"gross error"* failures as function of joint position, joint motor applied voltage and joint position error (blue dots). Gross errors identified by DPGMM are represented with green dots. Gross errors identified by the control system are represented with red crosses.

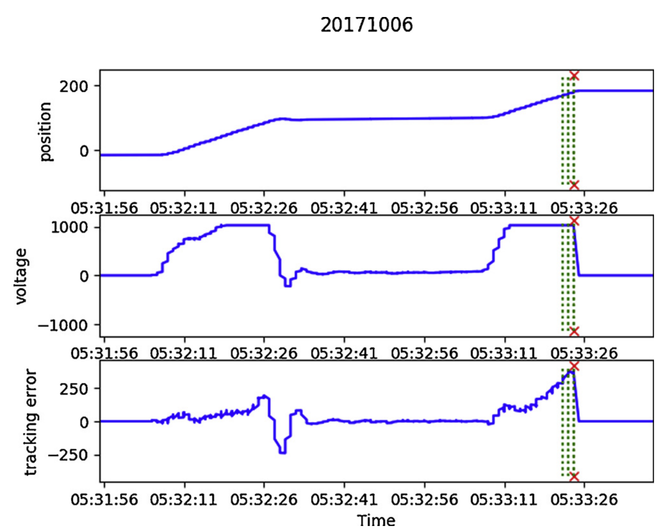

Fig. 8. Joint position, joint motor applied voltage and joint position error as function of time. Gross errors identified by DPGMM are represented with green vertical line. Gross errors identified by the control system are represented with red crosses.

joint motor). In future works this sub-divisions could be used to identify routines [8] and statistics about failures. The actual value of the threshold that separates healthy data from failures is determined by measuring the *precision*, *recall* and *F1 score* using failures recorded by the control system as ground truth. *Precision* is defined as the ratio between the failure correctly identified and all the failures identified by the model. *Recall* is defined as the ratio between the failures correctly identified by the model and failures actually occurred. The *F1 score* is defined as *2*(Recall * Precision) / (Recall + Precision)* and represents a weighted average of *recall* and *precision*. Tuning the parameters of the model, i.e. find the number of clusters and probability threshold to discriminate failures, has been performed by observing the values of *F1 score* and *Precision* as the cluster numbers and probability threshold have been changed. Values have been chosen in order to maximizing both *F1 score* and *Precision*. It is important to observe that the measure of the *F1 score* is not sufficient as in our case we prefer to have lower values of *F1 score* in order to favor higher values of *precision*.

Data provided by the LFCS system are not suitable for clustering directly. In this case the definitions of the failures as they are expressed by the control system data, are not correct from clustering point of view. As an example, a failure (internally called *"gross error"*) is signaled whenever the measurement of the position error exceeds a fixed and predefined value. When this failure occurs, the control system flags it to the RH operator and, at the same time, stops the current move by resetting the position error. The reset is done by artificially setting the target position equal to the current position. As a side effect both the position error and driving voltage recorded by the LFCS system is zeroed when this failure occurs. Moreover, the control system remains in this state until the operator manually resets the state. This situation creates confusion in between *"gross error"* and a position perfectly

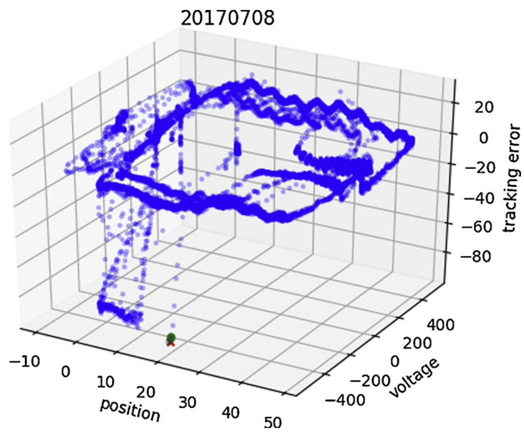

Fig. 9. Data containing gross error failures as function of joint position, joint motor applied voltage and joint position error (blue dots). Gross errors identified by DPGMM are represented with green dots. Gross errors identified by the control system are represented with red crosses.

controlled. Fig. 5 shows an example of this behavior. The solid line represents the position error, while vertical dashed lines represent the time when a *"gross error"* failure is identified by the control system. It is possible to see that when the position error is close to the threshold, in this case 400, the value drops to zero and the *"gross error"* failure is raised and maintained for many samples.

This situation can be mis-interpreted as a joint ready to operate since both position error and driving voltage have exactly the zero value. To overcome this problem the definition of the *"gross error"* event has been changed by considering it as a failure event in only one sample, i.e. the sample before the one flagged by the control system. Using this modification, the failure events are still in the data set but are correctly differentiated from the state in which the system is ready to operate.

Data have been gathered with the above modification in place. Fig. 6 shows healthy data from the joint CB0. A single data point represents the triple: joint position, joint position error and voltage applied to the joint motor.

Once the model is fitted with a DPGMM with a sufficient number of clusters and the threshold discriminating the healthy data from failures has been determined, it is possible to apply the model to data containing failures. Fig. 7 shows the reported joint data for an operational day. Each data sample is represented by a blue dot, while failures estimated by the DPGMM are represented by a green dot. The revised definition of *"gross error"* is also reported in the figure as red crosses.

Fig. 8 shows the joint position, applied motor voltage and joint position error as function of time. Dashed green vertical lines represent *"gross error"* identified by DPGMM, while red crosses represent the time when revised version of *"gross error"* is reported by control system. It is possible to observe that the DPGMM identifies 3 consecutive occurrences of "gross error" at about time 05:33:26. First two occurrences are false positive while the last one is correct. Therefore, in this example, a single true positive event has been accompanied by two false positive events hence a low value of F1 score.

In Figs. 9 and 10 a similar example from a different day of operations is shown. Also, in this case the DPGMM correctly identifies the *"gross error"* but also produces a false positive.

5. Summary

In this work we presented a first analysis of JET RH failures that occurred during remote handling operations. Firstly, we proposed a taxonomy model for classification purposes that could be used once all data sources will be analyzed. Then we apply statistical methods (K-means and Dirichlet Process Gaussian Model Mixture) to the two biggest class of data currently available.

Successful results for both techniques have been produced. In particular, machine generated control system logs have been converted into time series. Moreover, a model to identify failures using statistical methods, has been produced for low frequency control system data.

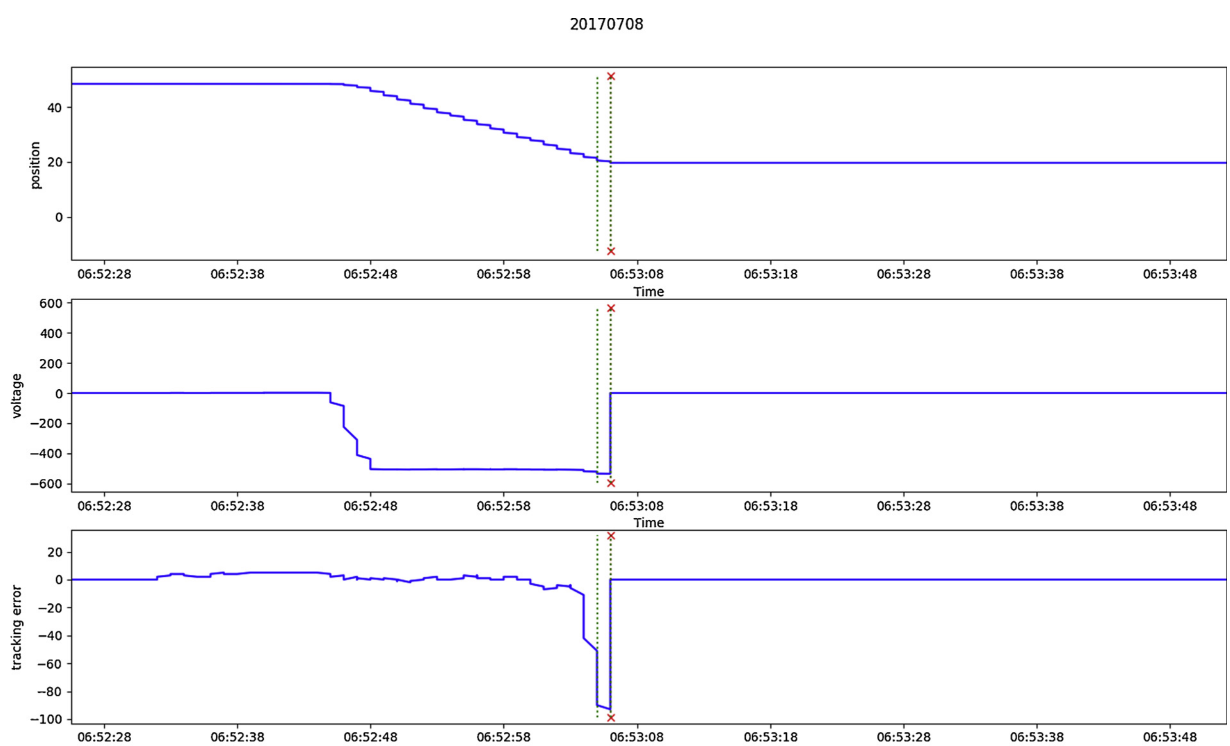

Fig. 10. Joint position, joint motor applied voltage and joint position error as function of time. Gross errors identified by DPGMM are represented with green vertical line. Gross errors identified by the control system are represented with red crosses.

More work is indeed needed to exploit all the remaining data sources and be able to correlate in time orderly manner.

Particular attention will be put on acquisition of new data specifically for training models for the condition monitoring system. Moreover, an effort will be made in order to make machine readable the handwritten operator logs. As already mention in Section 3, these logs have not been originally designed for machine learning techniques. Being able to make them machine readable will enable understanding their information content.

Future works will provide more information for the design and the development of the condition monitoring system.

CRediT authorship contribution statement

L. Pangione: Conceptualization, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **R. Skilton:** Conceptualization, Validation, Formal analysis, Investigation, Writing - review & editing, Supervision. **R. Powell:** Conceptualization, Validation, Formal analysis, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] B. Haist, D. Hamilton, A Rational Approach to Remote Handling Equipment Control System Design, (2001) United Kingdom: N. p., Web.
[2] G. Preece, Development of the MASCOT Telemanipulator Control System Development of the MASCOT Telemanipulator Control System, (2001).
[3] J.C. Laprie, Dependable computing and fault tolerance: concepts and terminology, Twenty-Fifth International Symposium on Fault-Tolerant Computing (1995).
[4] J. Carlson, R.R. Murphy, How UGVs physically fail in the field, IEEE Trans. Robot. 21 (3) (2005) 423–437.
[5] Gerald Steinbauer, A Survey about Faults of Robots Used in RoboCup, (2013), https://doi.org/10.1007/978-3-642-39250-4_31.
[6] Bishop, Pattern Recognition and Machine Learning, (2006).
[7] Peter J. Rousseeuw, Silhouettes: a graphical aid to the interpretation and validation of cluster analysis, Comput. Appl. Math. 20 (1987) 53–65.
[8] Sun, Nonparametric discovery of human routines from sensor data, IEEE International Conference on Pervasive Computing and Communications (2014) 978-1-4799-3445-4.