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An Integrated Approach for Failure Diagnosis and Analysis of Industrial Systems Based on Multi-Class Multi-Output Classification: A Complex Hydraulic Application

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For complex systems, a fault of one or several components does not necessarily lead to a failure of the system, but if the failed components are not immediately replaced, they may conduct some other components to an idle state. In this work, a data-driven model with a two-step decision approach is proposed to provide a comprehensive analysis of the potential failures and their causes. In the first step, a Multi-Class Multi-Output (MCMO) classification technique is used to diagnose potential failures based on sensor signals, and, in the second step, Failure Analysis (FA) is applied to investigate the root causes of those failures. The proposed approach is applied to a multi-component Hydraulic System (HS) case study, showing the resulting effectiveness in improving system reliability, reducing downtime, and minimizing the impact of failures on system operations. The results show that MCMO classification is a promising approach for multi-component system failure diagnosis that offers several advantages over conventional methods.

Keywords: Reliability, Failure Analysis, Failure Diagnosis, Machine Learning, Classification, Industrial Systems, and Hydraulic Systems.

1. Introduction

Industrial systems are complex and failure-prone systems that require constant monitoring and maintenance to prevent downtime and ensure safety. Machine Learning (ML) and Failure Analysis (FA) are two powerful tools that can be used to diagnose system failures and establish the root cause of failures. On the one hand, ML techniques can learn from historical data to diagnose the likelihood of future failures. For instance, several automated techniques have been proposed in the literature to solve fault diagnosis issues in industrial assets (Xu and Saleh (2021)), particularly hydraulic systems (HSs). Multivariate statistics (Helwig et al. (2015)), conventional machine learning (ML) (Chawathe (2019); Lei et al. (2019); Zhao et al. (2019); Peng et al. (2020);

Wang et al. (2021)), deep learning models (Huang et al. (2021); Kim and Jeong (2020)), and early classification (Askari et al. (2022)) are among the widely used methods. These techniques are capable of dealing with various challenges in fault diagnosis, such as the non-linear nature of sensor signals, varied sampling rates, and coupling interactions between components. On the other hand, FA is a systematic approach to investigate the root cause(s) of a failure or malfunction in a system or component (Ahmed et al. (2021)). The process of FA typically involves a combination of data analysis, physical inspection, and testing to identify and isolate the cause(s) of the failure. Fault tree analysis (FTA) is one of the most common techniques within the broader field of FA that can identify the root causes of failures and help engineers develop effective mitigation strategies as one of the reliability analysis tools. Several studies propose different methods for FA and maintenance planning of industrial systems: for instance, Ferri et al. (2013) propose a methodology for maintenance planning based on system-level prognostics and FA. Tuncay and Demirel (2017) use FA to analyze failure behavior and component contributions on a coal mine's dragline for maintenance planning and cost reduction. Patil et al. (2018) present a case study showing how their approach identifies events causing failures during the warranty period in a computer numerical control (CNC) turning center. Li et al. (2021) introduce a method to determine the likelihood of uncertain events by combining expert opinions with FTA for an HS case study. Waghen and Ouali (2021) analyze faults in complex systems to capture hierarchical causality between root causes and faults using an actuator system dataset.

While FTA is a powerful tool for analyzing the causes of system failures, it has limitations when it comes to dynamic systems. In such cases, statistical FA (Lee et al. (2020); Mo et al. (2020); Ni and Yang (2021)) may be more appropriate, as they can provide a more accurate picture of the industrial system behavior contributing to failure.

The previously reported literature review shows that existing works apply either ML or FA to diagnose and analyze the system failures, based on the dataset availability and system knowledge. In particular, ML techniques are typically employed for handling large and complex industrial datasets, whereas FA is employed for analyzing the failure behavior of individual components or systems. Moreover, FA is typically based on expert knowledge and requires a thorough understanding of the system under consideration, while ML algorithms can learn patterns and behaviors from large datasets without prior knowledge of the system.

Different from the related literature, this work aims at combining the use of ML with statistical FA to define a tool able to analyze the behavior of a complex system with minimum user intervention. Indeed, we develop a hybrid model that integrates both ML and statistical FA techniques: in particular, the ML model is used to detect the states of the hydraulic components and the final state of the HS, whilst the statistical FA is used to identify the root cause of the failure. A Multi-Class Multi-Output (MCMO) classification method is thus constructed to process the sensors measurement data coming from the industrial HS and forecast not only the potential faults of the system components but also the overall state of the system and simultaneously determine the root cause of failure. MCMO model is suitable for handling complex classification problems with multiple labels. This model allows for the assignment of multiple labels to a single data point, which can be beneficial in cases where a data point belongs to more than one output or has multiple classes.

The rest of this paper is organized as follows. Section 2 presents the MCMO method to classify fault types industrial systems, used as inputs for the rule-based model for the purpose of FA. Section 3 describes a case study where the MCMO method is applied to the state of the components of the HS, and results are discussed and compared with baseline methods. Lastly, concluding remarks and outlooks for future work are presented in Section 4.

2. Methodology

In this section a two-step procedure is presented for the complex multi-component system to diagnose not only the failure of the system but also

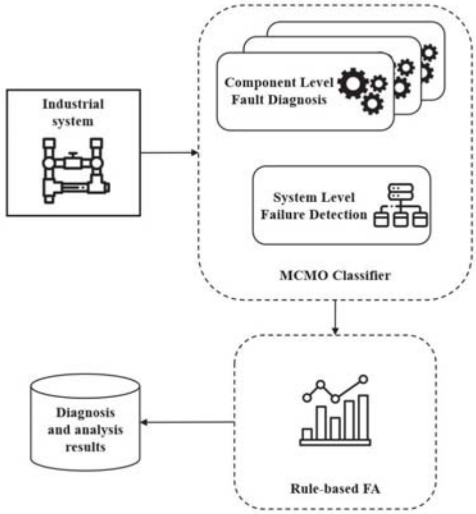

Fig. 1. Scheme of the failure diagnosis and analysis method based on MCMO classification.

the fault of each component at the same time (see Figure 1). The proposed hybrid model consisting of the MCMO classification and the rule-based system for FA is described in Algorithm 1.

2.1. *Multi-Class Multi-Output Classification*

An MCMO classification problem involves forecasting multiple target variables, where each target variable has more than two possible classes.

MCMO classification models based, for instance, on Logistic Regression (LR), K-Nearest Neighbor (KNN), Support Vector Machines (SVM), Decision Tree (DT), and Random Forest (RF) – denoted as MLR, MKNN, MSVM, MDT, and MRF, respectively – are an extension of traditional classification techniques that can handle multiple output variables simultaneously. In contrast to the corresponding single-output models LR, KNN, SVM, DT, and RF, the MCMO models can predict multiple dependent variables that are correlated with each other. In addition to labeling each basic component to its corresponding class, MCMO models can also label the entire state of the system to a specific binary class (Stable and Non-stable).

Let us consider a system with a cyclic operation, whose generic component working-cycle is represented by a set $\mathcal{X} = \left\langle \mathbf{X}^{(1)}, \mathbf{X}^{(2)}, \ldots, \mathbf{X}^{(N)} \right\rangle$ of N time-series, each being composed of T real-valued measurements $\mathbf{X}^{(i)} = \left(x_1^i, x_2^i, \ldots, x_T^i\right)$ (for each $i = 1, 2, \ldots, N$). Each time-series is classified in accordance with M labels defined in $\mathcal{C} = \{c_1, c_2, \ldots, c_M\}$: $\mathcal{Y} = \left\langle Y^{(1)}, Y^{(2)}, \ldots, Y^{(N)} \right\rangle$ denotes the labels corresponding to the time-series in $\mathcal{X}$.

The goal of the MCMO classification is to optimally classify the time-series set $\mathcal{X}$ to the class labels $\mathcal{Y}$, i.e., determining the pairing $\left(\mathbf{X}^{(i)}, Y^{(i)}\right) \in \mathbb{R}^T \times \mathcal{C}$ for each $i = 1, 2, \ldots, N$.

The proposed MCMO-based method is described in detail in steps 1-4 of Algorithm 1. The inputs to the algorithm are a set of timeseries $\mathcal{X}$ and its corresponding multi-labels $\mathcal{Y}$. The algorithm splits the dataset into training and testing sets and fits an MCMO classification model using the training set. It then uses the trained model to predict the labels $\mathcal{Y}_{pred}$ for the testing set.

Note that the reproducibility of the MCMO classification method depends on several factors, including the availability and quality of training data, the chosen model, and the specific implementation. To ensure reproducibility, it is important to have a well-defined and representative training dataset that accurately represents the variability and complexity of the problem at hand. It should include samples from all classes of each target variable to provide sufficient information for the MCMO model to learn.

2.2. *Rule-based Model for Failure Analysis*

A rule-based model is a systematic approach used to analyze the possible causes of failure in a system. The procedure starts by defining all possible failure modes M_j that could occur in the system, having identified all the potential issues that could arise and lead to the failure of the system by taking a type of fault in the components. Subsequently, the failure probability (FP) for each of the identified failure mode M_j is computed. The probability of a given failure mode M_j is $\mathbb{P}(M_j) = N_{M_j}/N$, which corresponds to the

Algorithm 1 Failure Diagnosis and Analysis based on Multi-Class Multi-Output classification

Inputs: $\mathcal{X}$, $\mathcal{Y}$

Outputs: FA results

1: Split the dataset $\mathcal{X}$, $\mathcal{Y}$ in train data $\mathcal{X}_{tra}$, $\mathcal{Y}_{tra}$ and test data $\mathcal{X}_{test}$, $\mathcal{Y}_{test}$

2: Build the MCMO model using the train data $\mathcal{X}_{tra}$, $\mathcal{Y}_{tra}$

3: Determine the classes $\mathcal{Y}_{pred}$ associated with the test data $\mathcal{X}_{test}$

4: Compute the accuracy and precision of the MCMO model comparing $\mathcal{Y}_{test}$ and $\mathcal{Y}_{pred}$

5: Define all failure modes M_j from $\mathcal{Y}_{pred}$

6: Compute the failure probability of M_j

7: Find the steady-state and transient-state of the system

8: Perform the statistical FA

ratio between the number N_{M_j} of observations and the total number N of failures in the dataset. The results of the statistical FA are used for the development of a risk management plan, with the final aim of minimizing the risk of failure and ensuring a safe and efficient operation. The statistical FA procedure is described in steps 5-8 of Algorithm 1. The algorithm calculates all possible failure mode M_j by taking the Cartesian product of the predicted labels in $\mathcal{Y}_{pred}$ and then proceeds to find the steady-state and transient state of the system, which may provide insights into the underlying causes of failure.

Note that the reliability of the mentioned approach for failure analysis depends on various factors, including the quality of data, the expertise of analysts, and the complexity of the system being analyzed. It also relies on a comprehensive database that covers a wide range of failure modes, with sufficient quantities to capture probabilities and system behavior. A more robust and comprehensive database leads to more informed and effective decision-making in the context of maintenance policies.

3. Case Study

This section applies the proposed methodology to a realistic complex HS using data from an

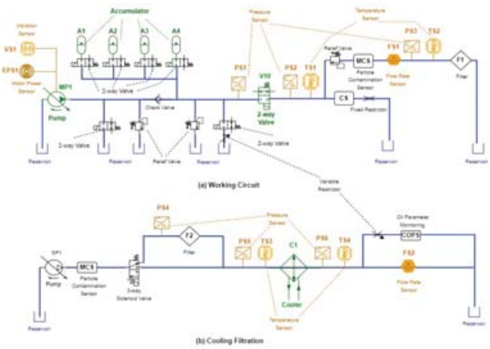

Fig. 2. Scheme of the case study HS: (a) primary working circuit and (b) secondary cooling-filtration circuit (adapted from Huang et al. (2021)).

experimental study on predictive maintenance that is available in (Dua and Graff (2017)).

3.1. *Setup of Experiments*

The HS under consideration consists of primary working and secondary cooling-filtration circuits connected via an oil tank as shown in Figure 2. The primary circuit contains a main pump, switchable accumulators, a filter, and valves, while the secondary circuit comprises a hydraulic pump, a solenoid valve, a filter, a cooler, and various sensors. The state of four main components, i.e., the cooler C_1, a two-way valve V_{10}, the main pump MP_1, and the accumulators A_1-A_4, varies dynamically, and different types of faults may occur. The monitoring system records process values for sixty seconds on the four components using data collected from 2205 working cycles under different conditions. These data are recorded in the predictive maintenance data set of the HS (Dua and Graff (2017)).

Using the sensors signals listed in Table 1 as input, the MCMO model is able to simultaneously diagnose the multi-outputs of hydraulic components and the overall state of the HS described in Table 2, making it a powerful tool for decision-making problem. In Figure 3, the state of the four hydraulic components and the overall state of the HS during the 2205 working cycles have been graphically represented, providing a comprehensive visual overview of the system's

Table 1. Description of sensors deployed in the case study HS.

Identifier	Measured quantity	Unit	Frequency
PS1-6	Pressure	Pa	100 Hz
EP1	Motor Power	W	100 Hz
FS1-2	Flow Rate	Lit/min	10 Hz
TS1-4	Temperature	$^{\circ}$C	1 Hz
VS1	Vibration	mm/s	1 Hz
CE	Cooling Efficiency	%	1 Hz
CP	Cooling Power	kW	1 Hz
SE	System Efficiency Factor	%	1 Hz

Table 2. Description of fault types for each component and overall state of the HS.

Component	Value	Fault Severity	Samples
Cooler (C1)	3%	C_1	732
	20%	C_2	732
	100%	C_3	741
Valve (V10)	73%	V_1	360
	80%	V_2	360
	90%	V_3	360
	100%	V_4	1125
Pump (MP1)	0	P_3	1221
	1	P_2	492
	2	P_1	492
Accumulators (A1-A4)	90 bar	A_1	808
	100 bar	A_2	399
	115 bar	A_3	399
	130 bar	A_4	599
HS stable flag (SF)	0	SF_2	1449
	1	SF_1	756

Note: (C_1): total failure; (C_2): reduced efficiency; (C_3): full efficiency; (V_1): total failure; (V_2): severe lag; (V_3): small lag; (V_4): optimal behavior; (P_1): severe leakage; (P_2): weak leakage; (P_3): no leakage; (A_1): total failure; (A_2): severely reduced pressure; (A_3): slightly reduced pressure; (A_4): optimal pressure; (SF_2): stable conditions; (SF_1): unstable conditions.

performance. For simplicity and dimensionality reduction, we used the average of time series $\mathcal{X}$ instead of processing the individual data points which can be useful in very specific situations. In this case, averaging the time series can help smooth out any noise or fluctuations in the data, making it easier to visualize trends or find patterns using ML algorithms. Then, to compare the performance of different classifiers, the dataset has been splitted into a training set (80%) to train the MCMO model and a testing set (20%) to evaluate the performance of the model. This split ratio is a commonly used ratio, although it may vary depending on the size of the dataset and the complexity of the problem being solved. For the sake of comparing the results achieved by the MCMO methods with those obtained by the baselines, accuracy, and precision are used to evaluate the performance of the models.

3.2. *Results Analysis and Discussion*

The results of the implementation of the proposed approaches for failure diagnosis in the HS can be evaluated in terms of accuracy and efficiency. The accuracy of the fault detection depends on the performance of the ML algorithm used for classification. Table 3 shows that the MCMO methods have better accuracy in comparison with corresponding traditional methods. Among them, the use of an ensemble of decision trees in a Multi-Class Multi-Output Random Forest (MRF) can capture the non-linear and complex relationships between the input features and the output labels of the HS. This leads to better diagnosis performance compared to models that use linear or simpler non-linear models where the accuracy and precision for the cooler, valve, pump, accumulator, and HS are respectively, 100, 97.50, 99.77, 97.73, and 98.90. The MCMO model involves multiple target variables, which can lead to high-dimensional feature spaces. Therefore, understanding the relationships between input features and multiple output variables is more complex and challenging compared to traditional single-output classification models.

To evaluate the reliability of the complex HS, an FA is required to examine all possible FM in which the system may fail. However, in this case, the scope of the analysis is limited to the four main components, namely the cooler, valve, pump, and accumulator. Various hydraulic components and environmental effects may have an impact on the overall condition of the HS even though they were not taken into account in this analysis. Thus, the inspection and evaluation of the system reliability

Table 3. Accuracy of component and system level through MCMO classification model.

Model	Cooler		Valve		Pump		Accumulator		HS	
	Accuracy	Precision	Accuracy	Precision	Accuracy	Precision	Accuracy	Precision	Accuracy	Precision
LR	99.77	99.77	71.65	77.30	98.86	98.89	61.22	58.86	92.97	84.48
KNN	99.83	99.83	84.12	84.46	97.95	98.03	94.55	94.60	92.06	87.17
SVC	99.83	99.83	48.75	36.54	95.01	95.80	57.14	65.68	92.97	84.48
DT	99.83	99.83	94.10	94.09	58.27	43.71	95.23	95.24	91.60	88.00
RF	99.83	99.83	96.37	96.37	58.27	58.27	97.73	97.73	91.83	86.62
MLR	100	100	50.79	81.79	75.96	78.58	41.95	59.38	87.30	87.27
MKNN	100	100	73.69	74.55	98.18	98.24	87.07	87.18	95.01	95.06
MSVM	53.51	55.46	46.48	25.00	54.42	33.33	36.50	25.00	68.70	50.0
MDT	100	100	94.10	94.14	99.77	99.77	95.23	95.29	97.27	97.27
MRF	**100**	**100**	**97.50**	**97.59**	**99.77**	**99.77**	**97.73**	**99.73**	**98.86**	**98.90**

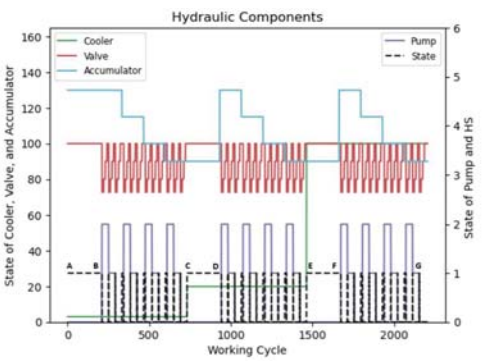

Fig. 3. Degradation of hydraulic components and stable state of hydraulic system.

are focused solely on these main components, while external factors and other components are excluded. To this aim, all possible combinations of FM are defined for the HS by taking only the four main components into consideration. These FM are then assigned to probabilities based on their likelihood of occurring. By calculating the probability of each FM, the most critical points of failure within the HS are identified, while facilitating the development of strategies to mitigate the corresponding risks. The results of this analysis can be seen in Table 4, which provides a clear picture of the system reliability and identifies areas that require improvement.

Table 4 shows that it is not uncommon for the HS to fail even when individual components such as coolers, valves, pumps, and accumulators are in optimal conditions (e.g., $C_3V_4P_3A_4$). This is due to two main reasons. First, some issues on the overall system design or configuration could occur, such as incorrect sizing or installation of components, or inadequate maintenance and monitoring of the system. Second, environmental effects or interactions and dependencies between components are not captured by the individual sensor measurements used for diagnosis. As a consequence, it is evident that the dataset related to the case study HS does not embed all failure system information. Alternatively, a thorough analysis of the system's design and operation may be conducted to identify any redundancies, backup systems, or alternative pathways that may allow the system to continue functioning despite component failures. To this aim, Tables 5 and 6 respectively present the steady-state and transient-state conditions of the HS, highlighting the stable and consistent operation of the system under normal conditions [AB], [CD], and [EF] (see Figure 3), as well as its response to changes (transient-state [BC], [DE], and [FG]). Regardless of the cooler state (i.e., it is failed or at full efficiency), the system exhibits the same behavior pattern for [BC], [DE], and [FG] (see Figure 3), thus indicating that the cooler is not a critical component. Comparing Table 4 with Tables 5 and 6, the dynamic nature of the HS's failure behavior is clearly evident, as opposed to being primarily static. Table 5 shows

Table 4. Failure probability (FP) for all failure modes (FM) of the HS.

FM	FP(%)	FM	FP(%)	FM	FP(%)	FM	FP(%)
$C_1V_4P_1A_1$	0.13	$C_1V_4P_1A_2$	0.13	$C_1V_4P_1A_3$	0.13	$C_1V_4P_1A_4$	0.13
$C_2V_4P_1A_1$	0.13	$C_2V_4P_1A_2$	0.13	$C_2V_4P_1A_3$	0.13	$C_2V_4P_1A_4$	0.13
$C_3V_4P_1A_1$	0.13	$C_3V_4P_1A_2$	0.13	$C_3V_4P_1A_3$	0.13	$C_3V_4P_1A_4$	0.13
$C_1V_4P_2A_1$	0.13	$C_1V_4P_2A_2$	0.13	$C_1V_4P_2A_3$	0.13	$C_1V_4P_2A_4$	0.13
$C_2V_4P_2A_1$	0.13	$C_2V_4P_2A_2$	0.13	$C_2V_4P_2A_3$	0.13	$C_2V_4P_2A_4$	0.13
$C_3V_4P_2A_1$	0.13	$C_3V_4P_2A_2$	0.13	$C_3V_4P_2A_3$	0.13	$C_3V_4P_2A_4$	0.13
$C_1V_4P_3A_1$	1.45	$C_1V_4P_3A_2$	1.45	$C_1V_4P_3A_3$	1.45	$C_1V_4P_3A_4$	27.91
$C_2V_4P_3A_1$	27.91	$C_2V_4P_3A_2$	1.45	$C_2V_4P_3A_3$	1.45	$C_2V_4P_3A_4$	1.45
$C_3V_4P_3A_1$	27.91	$C_3V_4P_3A_2$	1.45	$C_3V_4P_3A_3$	1.45	$C_3V_4P_3A_4$	1.45

Note: If valve V_4 is substituted with either V_1, V_2, or V_3 in all FMs, then the resulting FP will be equal to zero.

Table 5. HS Steady State.

Steady-state	Cooler	Valve	Pump	Accumulator	HS
[AB]	F	H	H	H	SF_1
$[CD]$	$C_{i=2}$	H	H	F	SF_1
[EF]	H	H	H	F	SF_1

Note: **F**: failure; **H**: non-failure or healthy

Table 6. HS Transient State.

Transient State	Cooler	Valve	Pump	Accumulator	HS
$[BC]$	$C_{i=1..3}$	$V_{i=1..4}$ $P_{i=1}$	F	$A_{i=1..4}$	SF2
$[DE]$	$C_{i=1..3}$	$V_4 \rightarrow V_1$	$P_{i=2..3}$	$A_{i=1..4}$	SF1
$[FG]$	$C_{i=1..3}$	H	H	$A_i \rightarrow A_{i-1}$	SF1

Note: **F**: failure; **H**; non-failure or healthy

the critical component that leads to system failure, whereas Table 6 reveals that HS is failed with a sequence or a combination of events. A basic fault tree can model HS failure mode in the first case but not in the second one. Therefore, additional modeling techniques are needed to capture the system's behavior. Among them, dynamic fault trees and, stochastic Petri net which is an extension of basic fault trees, and also Markov models are potential probabilistic tools that can be used for this purpose.

4. Conclusion

This paper addresses the failure analysis of industrial systems by diagnosing failure modes with the aid of the proposed approach. In the first step, a Multi-Class Multi-Output (MCMO) classification was applied for forecasting the state of multiple components in a hydraulic system (HS) and the corresponding overall state. This approach differs from conventional classification, which typically involves using one model for each component. The results demonstrate that MCMO outperforms traditional approaches in terms of accuracy and precision. One of the key advantages of using MCMO is that it allows for the simultaneous diagnosis of the state of all components in parallel using a single machine learning (ML) model. This not only saves time and computational resources but also ensures consistency across all predictions. Additionally, the MCMO is also able to diagnose the final state of the HS, which is useful for applications where the overall state of the HS is more important than the individual component states. In the second step, combinations of events leading to system failure mode were identified. This diagnosis step is the basis of the industrial failure analysis. This latter shows that the HS failure mode could not be explained completely only considering independent components as in the construction of a common fault tree. For this reason, future works will emphasize other ways to conduct the failure analysis. One perspective would be to conduct this analysis with a probabilistic modeling approach accounting for dependencies such as dynamic fault trees or stochastic Petri nets. A second perspective would be to learn the combinations of events involving dependencies at the ML stage of the approach.

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