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AI FOR DETECTING VARIATIONS IN THE OEE DATA RECEPTION RATE IN THE MANUFACTURING INDUSTRY

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Abstract. Industry 4.0 provides a favourable environment for processing and analysing massive amounts of data by implementing and integrating innovative Internet of Things (IoT), artificial intelligence (AI) and machine learning (ML) techniques. Their use permits to identify opportunities for improvement and increases the efficiency of the equipment and overall manufacturing process, which industrial companies strive for. One of the most common measures of efficiency is the Overall Equipment Effectiveness (OEE), which quantifies the efficiency of a manufacturing system or piece of equipment. It considers factors such as availability, performance, and quality of the equipment. This work presents a methodology to detect, in a robotic antenna manufacturing line, variations in the OEE data reception rate leveraging IoT and ML techniques. The line consists of a set of robotic cells and machines that sequentially execute each one of the production processes required for the manufacture of antennas. The study aims at identifying patterns in the reception of data from machines, propagating alerts when data that do not follow these patterns are found. Firstly, a dataset containing the OEE historical information for each machine is created. Secondly, the dataset is split into train and test sets. Lastly, different ML algorithms are trained to create a model capable of detecting unusual variations in the OEE data reception rate, and later on compared. Fluctuations in the rate at which data is received could indicate issues on the production line, and detecting these anomalies automatically enables proactive maintenance to be performed without human involvement. The analysis results show that more accurate results are obtained by using supervised ML classification techniques instead of unsupervised learning for anomaly detection.

Key words: machine learning, supervised learning, unsupervised learning, Overall Equipment Effectiveness, smart manufacturing, industry 4.0

1 INTRODUCTION

Industry 4.0 [1], also known as the Fourth Industrial Revolution, is a current trend of automation and data exchange in manufacturing technologies. It is experiencing a strong impact on all areas of manufacturing, leading to increased efficiency and productivity, as well as the

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creation of new business models and value chains. This revolution is marked by the emergence of new technologies such as robotics, analytics, artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT), among others. Manufacturers are incorporating these new technologies into production facilities and throughout their operations. These technologies enable the integration of physical and digital systems, resulting in the creation of smart factories [2] that are capable of autonomous decision-making and self-optimization.

There are several problems associated with traditional assembly lines that Industry 4.0 technologies are seeking to address. These include i) inefficiency: traditional assembly lines can be inefficient due to bottlenecks, errors, and waste, ii) inflexibility: it can be difficult and time-consuming to change the production process on an assembly line, iii) quality control: quality control on an assembly line can be challenging because it is difficult to inspect each product individually and iv) labour costs: assembly lines can be labour-intensive, leading to high production costs. In order to measure the efficiency of assembly lines, Overall Equipment Effectiveness (OEE) [3] measure is used. This metric indicates the percentage of manufacturing time that is truly productive, identifying inefficiencies in the assembly line while reducing costs, reducing downtime and supporting quality control.

ML is a subset of AI that involves the use of algorithms to analyse and learn from data. It can identify patterns and trends in data which enables data classification, anomaly detection or making predictions. In [4] ML is used for estimating the OEE of machines in a production line using historical data (dataset) obtained from real machines in a factory. The authors proposed an approach for predicting the OEE values by using supervised and unsupervised learning. In [5], the application of different AI and ML algorithms in real-case industrial scenarios, such as quality prediction, process characterization, and predictive maintenance, and their impact on OEE is described. In [6] it is proposed the use of hybrid analysis to improve the OEE of semi-automatic assembly lines in the automotive industry. It presents a case study in which hybrid analysis is used to identify the root causes of equipment failures and optimize production processes, resulting to a significant increase in OEE. The work described in this paper aims at detecting variations in the OEE data reception rate in a robotic antenna manufacturing line. The manufacturing process for the antennas involves arranging a series of robotic cells and machines in a sequence and performing the necessary production steps in turn. Variations in the data reception rate may indicate anomalies in the production line and their automatic detection allows proactive maintenance which does not require human intervention.

In this study, four supervised learning techniques (Decision Trees [7], Random Forest [8], k-Nearest Neighbors [9], and Naïve Bayes [10]) and one unsupervised learning algorithm (Isolation Forest [11]) are used to detect variations in the OEE data reception rate. Two experiments to evaluate the performance of the algorithms are conducted. In the first experiment, the IF algorithm is used in an unsupervised setting to detect anomalies in the OEE data reception rate. In the second experiment, the four supervised learning algorithms are employed to perform the same task.

The rest of the paper is structured as follows: Section 2 describes the methodology and experimental setup. Section 3 includes a discussion of the results obtained. Finally, the concluding remarks are presented in Section 4.

2 MATERIALS AND METHODS

2.1 OEE data

As introduced before, manufacturing industries are constantly striving for higher profits by optimizing their processes and increasing efficiency. To reach these objectives, the OEE global indicator is used. OEE is a metric that measures the operational efficiency of equipment. It reflects the real production capacity of industrial equipment and reveals process wastage (rejects, interruptions, breakdowns, slow speed, etc.) that prevent it from operating at full capacity. The correct implementation of an OEE system has a direct impact on the performance to be obtained from the manufacturing process. This is because machine downtime is reduced, the causes of yield losses (bottlenecks and reduced speeds) are identified, and the product quality index is increased, minimising rework and losses due to defective product production. This metric is calculated taking into account three parameters:

- Availability: Measures actual productive time versus available time.
- Performance: Measures the actual production obtained against the production capacity.
- Quality: Measures the good parts produced against the total number of those produced.

The OEE data analysed in this work pertains to a robotic antenna manufacturing line. The assembly line allows automatic assembly of antenna modules.

2.2 Data collection

The data used in this work was acquired by using a IoT agent to retrieve OEE data from the antenna manufacturing line.

The dataset consists of 431,923 OEE data records obtained between September 1, 2022 and January 15, 2023. The OEE data records include information such as the timestamp, the identifier of the machine to which the OEE values refer, the number of good, bad or missing parts, the efficiency or the amount of time that the machine has been in operation.

2.3 Data selection and pre-processing

After obtaining the historical data, records containing incomplete fields were deleted. The resulting dataset contains 373,436 records. After this, the dataset features used to train the algorithms were established. First, in order to detect variations in the OEE data reception rate, a new feature is added by using data fusion techniques. The new feature indicates, for each machine in the antenna manufacturing line, the seconds elapsed since the last measurement received of this machine. Moreover, one-hot encoding is used to produce a Boolean feature for every day of the week. This is intended to enable algorithms to be able to detect patterns in events occurring on certain days of the week. Additionally, hour is extracted from the timestamp field and used to create an additional feature.

The initial dataset does not contain labels. After an analysis of the dataset, patterns that follow anomalous data were detected. The majority of the records have a delta time of between 60 and 70 seconds. Most of the remaining records are considered anomalous, with two exceptions. Firstly, early on Mondays after the weekend shutdown, the first record received has a high delta time (between 190,000 and 240,000 seconds). Secondly, the rest of the days of the week a similar behaviour is appreciated. When the production line starts up, each machine starts operating and records with high delta times are received. These records should not be considered anomalies, as they follow the expected behaviour of the production line.

Table 1 shows the features used during the experiments.

Table 1: Features used for the experiments.

Feature	Type	Description
Monday	Boolean	Indicates whether the record was taken on a Monday
Tuesday	Boolean	Indicates whether the record was taken on a Tuesday
Wednesday	Boolean	Indicates whether the record was taken on a Wednesday
Thursday	Boolean	Indicates whether the record was taken on a Thursday
Friday	Boolean	Indicates whether the record was taken on a Friday
Hour	Numeric	Hour at which the record was taken
Delta time	Numeric	Seconds elapsed since the last record for a given machine
Anomaly	Boolean	Indicates whether the record is anomalous

2.4 Unsupervised anomaly detection

Nowadays, there is an extensive range of outlier detection algorithms based on unsupervised learning. Model-based approaches to anomaly detection typically involve building a profile of normal instances and identifying deviations from this profile as anomalies. This approach is exemplified by statistical methods, classification-based methods, and clustering-based methods. However, these methods have two main shortcomings. Firstly, the optimization of the anomaly detector prioritizes profiling normal instances over detecting anomalies, leading to potentially inaccurate results and a high rate of false alarms, or missed anomalies. Secondly, many existing methods have high computational demands, limiting their use to smaller, low-dimensional datasets.

Isolation Forest (IF) [11] is an unsupervised learning algorithm that specifically targets anomalies by isolating them, rather than by creating a profile of normal instances. It builds an ensemble of isolation trees for a given data set, and anomalies are identified as instances with short average path lengths in the isolation trees. This method only requires two inputs: the quantity of trees to construct and the proportion of outliers (contamination parameter) in the data set. Utilizing a limited data set, IF is able to provide high-performing anomaly detection.

The contamination parameter is calculated during pre-processing by dividing the number of anomalies by the total amount of available data. Its definition is given by:

$$contamination \quad parameter = \frac{number \quad of \quad outliers}{number \quad of \quad records} \tag{1}$$

2.5 Supervised classifiers

Classification algorithms are a specific type of supervised learning algorithms that are used to categorize data into discrete classes. These algorithms learn from labelled training data to predict the class label of new data points based on their similarity to the patterns in the training data. In addition to their traditional applications, classification algorithms can also be used for anomaly detection. Anomalies, or instances that deviate from the expected normal behaviour, can be treated as a separate class and detected through the use of classification algorithms.

This section describes the supervised ML algorithms used to create a model able to correctly classify the rate of the received OEE data as normal or anomalous:

- Decision Trees (DT) [7]: This non-parametric method is used for both classification and regression tasks. It has a hierarchical tree structure, consisting of a root node, branches, internal nodes and leaf nodes.

- Random Forest (RF) [8]: It is a meta estimator that fits several decision tree classifiers on several subsamples of the dataset and uses averaging to improve prediction accuracy and control overfitting.

- K-Nearest Neighbors (KNN) [9]: This non-parametric method calculates the probability of an element belonging to one group or another depending on the group to which the nearest elements belong.

- Naïve Bayes (NB) [10]: Naïve Bayes is a probabilistic classifier based on Bayes' theorem. The model is called naïve because it treats all proposed predictor variables as independent of each other.

2.6 Validation metrics

Through an experimental evaluation, the performance of the models obtained during the experiments has been verified. The metrics used for validation are the confusion matrix, accuracy, precision, and recall. The confusion matrix (Table 2) is a tool used in classification models to assess their performance. The matrix provides a summary of the number of correct and incorrect predictions made by the classifier, and it organizes the results by each class in the dataset. The confusion matrix is based on the terms:

- True Positives (TP) are instances where the algorithm correctly indicates the presence of a condition or characteristic.

- True Negatives (TN) are instances where the algorithm correctly indicates the absence of a condition or characteristic.

- False Positives (FP) are instances where the algorithm wrongly indicates the presence of a condition or characteristic.
- False Negatives (FN) are instances where the algorithm wrongly indicates that a particular condition or attribute is absent.

Accuracy is a performance measurement that defines the proportion of correct predictions made by a model compared to the total number of predictions. Its definition is given by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Precision is a performance metric that evaluates the quality of predictions made by a classifier. Its definition is given by:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Recall is a metric that evaluates the ability of a classifier to identify all relevant positive instances. Its definition is given by:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Table 2: Confusion matrix for two-class classification problem.

		Predicted values	
		Negative	Positive
Actual values	Negative	TN	FP
	Positive	FN	TP

3 RESULTS AND DISCUSSION

In this section, the performance of the proposed experiments is evaluated through statistical measures. As stated in the previous Section, the validation metrics used are the confusion matrix, accuracy, precision, and recall.

As a preliminary step to the experiments, the data are labelled as anomalous or non-anomalous according to the details given in Section 2.3.

3.1 Unsupervised learning experiment

During the first experiment, the IF algorithm was trained to detect anomalies in the OEE data reception rate. A first estimate of the contamination was calculated (0.0054) and subsequently tuned to achieve greater precision.

From the experimental results, it is observed that the obtained model provides a poor precision to identify the anomalies. Table 3 shows that this model is capable of successfully identify

631 anomalies. However, it mistakenly identifies 1,386 records as anomalous and misses 1,398 anomalies. It is important to highlight that, although at first glance the 99.2% accuracy may seem good (Table 6), models that always classify the data as normal would achieve a similar score. This is because the dataset is unbalanced (due to the inherent nature of anomalies). Therefore, two additional metrics have been used to analyse the behaviour of the model: precision and recall. Both metrics show a result of 0.65. The value of precision indicates that when the model predicts an anomaly it is correct the 65% of the times. On the other hand, the recall reports that the model correctly identifies the 65% of the anomalies.

Table 4 and Table 5 present the confusion matrices obtained from the models with a contamination factor of 0.005 and 0.0058, respectively. The model with the contamination factor of 0.0058 performs better as it is able to detect more anomalies, 661 in total. In the problem under consideration, false negatives carry a higher cost than false positives. Thus, it is desirable to increase recall at the expense of precision. As seen in Table 6, the model with a contamination factor of 0.0058 also exhibits better recall (0.66). While it may be possible to slightly improve the results through fine-tuning the contamination factor, the IF algorithm struggles to identify anomalies with good precision. IF is not capable of detecting anomalies with a recall of more than 0.7. It often misinterprets periodic events, such as the commissioning of facilities after the weekend or the start of the workday, as anomalies (FP), or classifies anomalies as normal records (FN).

Table 3: IF - Confusion matrix (contamination parameter = 0.0054).

		Predicted values	
		Negative	Positive
Actual values	Negative	370,021	1,386
	Positive	1,398	631

Table 4: IF - Confusion matrix (contamination parameter = 0.005).

		Predicted values	
		Negative	Positive
Actual values	Negative	370,109	1,298
	Positive	1,466	563

Table 5: IF - Confusion matrix (contamination parameter = 0.0058).

		Predicted values	
		Negative	Positive
Actual values	Negative	369,908	1,499
	Positive	1,368	661

Table 6: Anomaly detection - results of the evaluation metrics.

Contamination parameter	Accuracy	Precision	Recall
0.005	0.92	0.65	0.64
0.0054	0.92	0.65	0.65
0.0058	0.92	0.65	0.66

3.2 Unsupervised learning experiment

The second experiment was conducted by applying supervised learning techniques. More concretely, four classification algorithms have been selected and trained (NB, DT, RF and KNN). During this experiment, the dataset has been divided into training data (60%) and test data (40%). For this reason, confusion matrices of these experiments do not contain the same number of records that in the previous experiment.

As seen in Table 7, the performance of NB is worse compared to results obtained in the previous experiment, correctly identifying 141 anomalies. Moreover, although its precision is better (0.74), recall only reaches a value of 0.57 (Table 11). The model is therefore discarded.

Table 8 contains the results of the confusion matrix of the model resulting from training the DT algorithm. It can be observed that this model succeeds in correctly classifying 955 of the 965 anomalies of the data. In addition, it does not make any false-positive error (precision=1), only failing to misinterpret 10 anomalies as regular data (recall=0.99).

On the other hand, RF model performs slightly worse than DT. Table 9 indicates that this model has 955 true positives, 0 false positives and 30 false negatives. This implies that its precision is 1 and recall is 0.98. Lastly, the KNN model achieves nearly the same result as DT model. KNN model satisfactory identifies 954 out of 565 anomalies (Table 10), having a precision of 0.99 and a recall of 0.99.

Table 7: NB - Confusion matrix.

		Predicted values	
		Negative	Positive
Actual values	Negative	148,259	150
	Positive	824	141

Table 8: DT - Confusion matrix.

		Predicted values	
		Negative	Positive
Actual values	Negative	148,409	0
	Positive	10	955

Table 9: RF - Confusion matrix.

		Predicted values	
		Negative	Positive
Actual values	Negative	148,409	0
	Positive	30	935

Table 10: KNN - Confusion matrix.

		Predicted values	
		Negative	Positive
Actual values	Negative	148,386	23
	Positive	11	954

Table 11: Classification - results of the evaluation metrics.

Model	**Accuracy**	**Precision**	**Recall**
NB	0.9934	0.74	0.57
DT	0.9999	1	0.99
RF	0.9997	1	0.98
KNN	0.997	0.99	0.99

3.3 Comparison of machine learning models

After comparing the results of the different models, it is concluded that supervised learning methods are better able to model the problem under study. The fact that patterns resulting from the start-up of the production line after certain periods of inactivity are unusual and at the same time should not be considered as anomalies, makes it difficult for unsupervised anomaly detection algorithms to detect real anomalies.

For this problem, training the dataset using labelled data allows the supervised algorithms to correctly infer which records are anomalous. Of all the models obtained during training, the best is the one trained using the DT algorithm, being able to correctly identify 955 out of 965 records and only failing to incorrectly identify 10 anomalies.

4 CONCLUSIONS

This paper presents a methodology to detect variations in the OEE data reception rate in a robotic antenna manufacturing line using IoT and ML techniques. The ability to detect unusual variations in the OEE data reception rate leads to proactive maintenance for the manufacturing industry. Therefore, the use of IoT and ML technologies provides a valuable tool for industrial companies to monitor and optimize their equipment and production processes.

The results of the study show that supervised ML classification methods are more effective in detecting variations in the OEE data reception rate compared to unsupervised learning methods. Unsupervised methods struggle to distinguish between real anomalies and patterns resulting from the start-up of the production line after periods of inactivity. Thus, supervised algorithms that are trained with labeled data are more effective in accurately identifying the anomalous records. Among the models obtained during training, the best model was obtained using the DT algorithm, which was able to correctly identify 955 out of 965 records and only failed to identify 10 anomalies.

Future work will be directed towards integrating the selected model into an end-to-end system capable of retrieve OEE data in real time. The system will make use of the model to identify whether the data is non-abnormal and if so, notify the production line managers.

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