AI based Predictive Maintenance as a Key Enabler for Circular Economy: The KYKLOS 4.0 Approach

Yacine Rebahi
Fraunhofer Fokus
Berlin, Germany
yacine.rebahi@fokus.fraunhofer.de

Benjamin Hilliger
Fraunhofer Fokus
Berlin, Germany
benjamin.hilliger@fokus.fraunhofer.de

Patrick Lowin
Fraunhofer Fokus
Berlin, Germany
patrick.lowin@fokus.fraunhofer.de

Alberto Cardoso
University of Coimbra, Dep of Informatics Engineering, CISUC
Coimbra, Portugal
alberto@dei.uc.pt

Abstract— **Circular economy (CE) is a recent model of production and consumption. According to the European Parliament, this model simply extends the life cycles of products through sharing, leasing, reusing, repairing, refurbishing, and recycling existing materials as much as possible. Digitalization plays a crucial role in the transformation towards a sustainable circular economy. By providing accurate information about appliances and machines conditions, minimizing waste and promoting a longer life for them can be achieved. Predictive maintenance (PdM) is a service using data analytics and aiming at detecting machine failures, degraded performance, or a downtrend in product quality before one of these occur. Due to the advantages that artificial intelligence (AI) techniques currently offer, more and more predictive maintenance solutions start incorporating them in order to better analyse the gathered data. This paper gives an overview of the Deep Learning toolkit that has been developed within the European project KYKLOS 4.0, and which provides a bunch of functionalities including data collection and pre-processing, models definition, and models validation. This toolkit is also endowed with a graphical user interface facilitating its use. It has also been tested with publicly available datasets as well as datasets collected in manufacturing environments. In the current paper, the toolkit will be described in the context of a pilot where the data were collected from a shipyard located in the Astander city, in Spain.**

Keywords— Circular Economy, Predictive Maintenance, Artificial Intelligence, KYKLOS 4.0, Deep learning, Industry 4.0

I. INTRODUCTION

Industrial maintenance is the service that technicians perform regularly or on demand to keep machines and equipment operational and meet business objectives. Traditionally, maintenance is done in one of two ways, corrective, or preventive. Corrective maintenance aims to repair a given part once it is broken. Preventive maintenance aims to replace a part before it is broken, for example by defining a fixed lifetime for each part. The problem with corrective maintenance is that one might have long downtimes. Preventive maintenance, on the other hand, might be cost inefficient because most of the time, the replaced parts are still in good condition and could run for a little longer [1].

Another term being used for industry 4.0 is smart manufacturing. This terminology seems to be more appropriate as it tells us that the manufacturing processes have to be smart. Embedding intelligence into processes needs prior knowledge of machines behaviors. This cannot be achieved without building blocks such as better connectivity, IoT platforms, cloud computing, and data analytics. All these factors contribute to what is called “predictive maintenance”.

The goal of predictive maintenance is to detect machine failures, degraded performance, or a downtrend in product quality before one of these occur [2]. Predictive maintenance can be implemented in different forms. One form is the data driven way. This means a model can learn the machine behavior by looking at past data from the machine. Another way is to use expert knowledge to build a predictive maintenance model. This has the disadvantage that one needs a lot of expert knowledge to build a model that could not be easily adapted if the machine changes behavior [3].

Artificial intelligence (AI) can be seen as a natural enabler for industry 4.0, and particularly for data driven predictive maintenance. Thanks to the use of sensors and the digitalization of the manufacturing systems, more and more data is generated. If this data is correctly analyzed and evaluated by engineers and data scientists, it could lead to productivity improvement, material waste reduction, and improved machines diagnosis support. As the amount of data generated by machines and processes is in general huge, the use of artificial intelligence and machine learning techniques appears to be conclusive and mandatory.

According to the European Parliament News[1], circular economy (CE) is a model of production and consumption. This model simply extends the life cycles of products through sharing, leasing, reusing, repairing, refurbishing, and recycling existing materials as much as possible. Digitalization plays a crucial role in the transformation towards a sustainable circular economy. Indeed, by providing accurate information about products conditions and enabling processes in companies helping minimizing waste and

[1] https://www.europarl.europa.eu/news/en/headlines/economy/20151201STO05603/circular-economy-definition-importance-and-benefits

promoting longer life for them, the material loops can be closed[2].

With all the benefits that AI techniques offer in terms of data analysis, predictions, and more informed decisions, we can state that AI based predictive maintenance will be an efficient solution in extending the lifecycles of machines and equipment, and therefore boosting circular economy.

Concretely, if we take the electric cars industry, when a car is sold, the battery in this car is only leased for some monthly fees that are based in particular on how much the car will be used[3]. The sensors embedded in the battery and the engine will inform the manufacturer about the battery conditions. If a serious anomaly is detected, the battery will get replaced. The replaced batteries could be given a second life through refurbishment or simply recycled in case there is no way to extend its life cycle.

In the near future, it is expected that the above-mentioned strategy will also affect other sectors than "heavy" manufacturing. So far, appliances such as fridges, and washing machines are produced with a few years lifetime as the consumer wants to buy cheap products and replace them in case they are defect. The mentioned "leasing" strategy offers a business model that is more compliant with circular economy. The manufacturers will produce more robust appliances with longer lifetime and rent them against some monthly fees. These appliances will be embedded with sensors that monitor their conditions and inform the manufacturer in case an anomaly is detected. The latter will schedule a maintenance task to repair the appliance or to replace it. It is also worth to mention that the strategy discussed earlier reflects what it is called "product as a service"[4] in the literature. This new business model promises, in addition to the product itself, added value services such as long-life support against monthly or yearly fees.

In this paper, a short overview of the cognitive toolkit developed in the KYKLOS 4.0 project will be presented. This toolkit - called KYKLOS 4.0 DL toolkit throughout this paper - is based on some deep learning techniques and includes a variety of modules and functionalities addressing the needs of data driven predictive maintenance. To ease the toolkit presentation, the related modules will be discussed in the context of the Astander use case, which is reflected by a crane related to KYKLOS 4.0 pilot that runs in the city of Santander, Spain.

II. Related Work

The detection of anomalies is at the core of PdM, with the main focus early detection of anomalies in equipment and its components, as well as the generation of alerts that allow the proper scheduling of maintenance activities. Being a relevant topic for industry 4.0 and circular manufacturing, there have been several activities related to the detection of anomalies with predictive maintenance, using different data-driven approaches and applications. For example, Kamat and Sugandhi present in [4] a survey where the challenges of traditional anomaly detection strategies are described and where a deep learning technique is proposed to early predict anomalies. Tercan and Meisen in [5] conduct a systematic review on predictive quality in manufacturing, Carvalho et al in [6] present a systematic literature review of machine learning methods applied to predictive maintenance, and Sharma et al in [7] present a review on condition-based maintenance using machine learning. In particular, deep learning algorithms used for predictive maintenance are discussed by Soahaib et al in [8].

In terms of application examples, the work by Davari et al in [9] propose a data-driven PdM framework for a system in the railway industry using a deep learning based approach to detect abnormal data and reduce the false alarm rate. A PdM approach using deep learning is developed by Neto et al, in [10], for predicting the current health status of rolling bearing components. In this article, two algorithms for detection of anomalies based on deep learning in predictive maintenance of metal press machines are implemented and compared.

It is worth to mention that some of the algorithms performing the data analysis and failures prediction in the DL toolkit were discussed in more details in [12]. On the other side, a very short description of the DL toolkit was presented in [13].

III. The KYKLOS 4.0 Approach

A. *The KYKLOS 4.0 Project*

The KYKLOS 4.0 project[5] is a H2020 project aiming at developing an innovative Circular Manufacturing ecosystem based on novel CPS (Circular Production System) and AI (Artificial Intelligence) technologies, enhanced with novel production mechanisms and algorithms, targeting personalized products with extended life cycle and promoting energy efficient and low material consumption.

In this project, a deep learning-based toolkit has been implemented. Its objective is to monitor the conditions of machines or parts of them in a shop floor and predict potential breakdowns or their Remaining Useful Life (RUL). In the following sections, we will discuss some of the functionalities of this toolkit.

B. *Main Frame*

Fig. 1 shows the first window when opening the toolkit. On the left side, one can see the steps to create a new model.

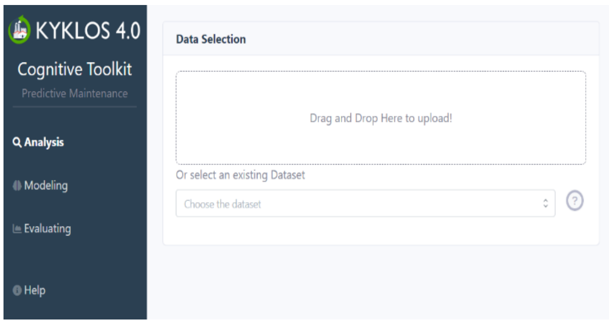

Fig. 1. The main page of the DL toolkit.

It starts by selecting a dataset, analyzing this dataset, and applying preprocessing to this dataset, all of these steps are summarized in the tag "Analysis". The DL toolkit allows to

[2] M. Antikainen, and Al, „Digitalisation as an Enabler of Circular Economy", 10th CIRP Conference on Industrial Product-Service Systems, IPS2 2018, 29-31 May 2018, Linköping, Sweden.

[3] https://iot.eetimes.com/intelligent-assets-a-key-building-block-for-circular-economy/

[4] https://www.billwerk.plus/wiki/business-model/product-as-a-service-paas/

[5] https://kyklos40project.eu/

use a fixed dataset or to deal with a data stream. After the dataset was preprocessed, a model can be created and trained. After training, the model needs to be evaluated and if the results are sufficient, it can also be deployed. The steps will be looked at in more detail. First, in the main frame, the data selection is already shown. There, one can upload a dataset in form of a csv file or select one of the existing datasets.

C. *Data Collection*

The data for the ASTANDER Use Case is made available through the KYKLOS 4.0-backend. From there, it can be retrieved via a REST API or downloaded as a csv file. The toolkit downloads new data automatically once every hour.

Before an anomaly detection model can be created, the data needs to be analyzed. For this, the toolkit provides a bunch of different options. There are options to view different plots and tables of the data, like the raw data, the distribution, the correlation matrix, and some more. With these tools, a good first step is to figure out how big the dataset is and what kind of data is represented. This can be done best, by looking at the descriptive data for each column, like the count, minimum and maximum. The raw dataset consists of 110 non-constant features, sampled once a minute over one year. Of the 110 features, 80 are binary values, while the other 30 are numeric. Once the general shape of the data is clarified, it is important to also consider any other information that was provided with the data. This helps to get a better understanding of what the data is coming from, and what it might represent.

This dataset originates from a shipyard crane (Fig. 2) with different components and each of the components has different features that are reflected in the dataset. An example component is the Translation system which moves the crane sidewards. There are different features for this component. For example, the input of the joystick controlling it, the number of hours the system has been running, and a few more.

Similar to this, there are other components, like the main and auxiliary hook, the rotation movement and the extension of the arm. Because the data comes from a complex machine and degradation in one component will most likely not lead to anomalies in another component, anomaly detection will be applied to each of the components separately.

Fig. 2. The Astander Shipyard.

Besides studying the information provided within the dataset, it is also important to understand how the data behaves and how complex it is. To do this, one can look at how the data could be reduced using Principal Component Analysis (PCA)[6]. From Fig. 3, one can derive that only around 30 principal components are necessary to describe over 80% of the variance in the data. This points to that many features are correlated, and thus multiple features can be described by one principal component.

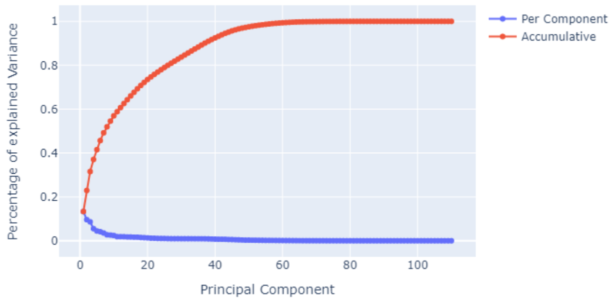

Fig. 3. Variance represented by Principal Components.

The assumption that many features are correlated is underlined when a look at a certain component is taken. In Fig. 4, the correlation matrix for different features of the translation system is shown. One can see that many features have a high correlation with others. This also makes sense, for example, that when the number of starts of the crane increases the number of running hours will most likely increase as well. Or when certain buttons are pressed, certain things will be visualized and other buttons will be pressed as well.

After a closer look at the data is taken, an anomaly detection model is to be created. For this, certain preprocessing needs to be applied first. Then an anomaly detection model is created and evaluated. Because the workflow for each component of the crane is similar, this paper will focus on creating an anomaly detection model for the translation system of the crane.

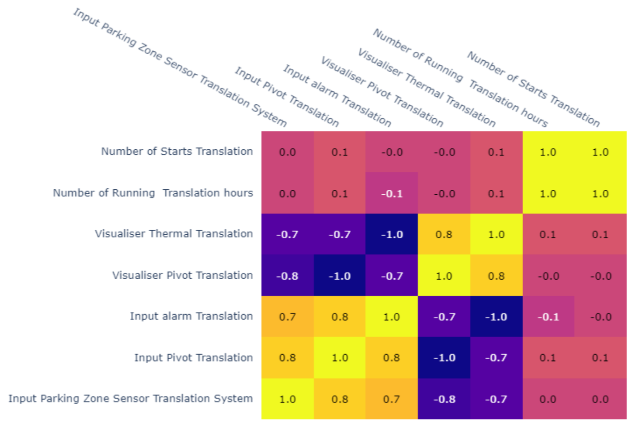

Fig. 4. Correlation matrix of selected features from the translation system.

D. *Data Preprocessing*

There are many different preprocessing options available in the toolkit. Not all of them are used for the preprocessing of this dataset, but to get a feeling of the capability, the preprocessing for this dataset is looked at in more detail. An overview of the preprocessing for the translation system is shown in Fig. 5.

[6] https://www.turing.com/kb/guide-to-principal-component-analysis

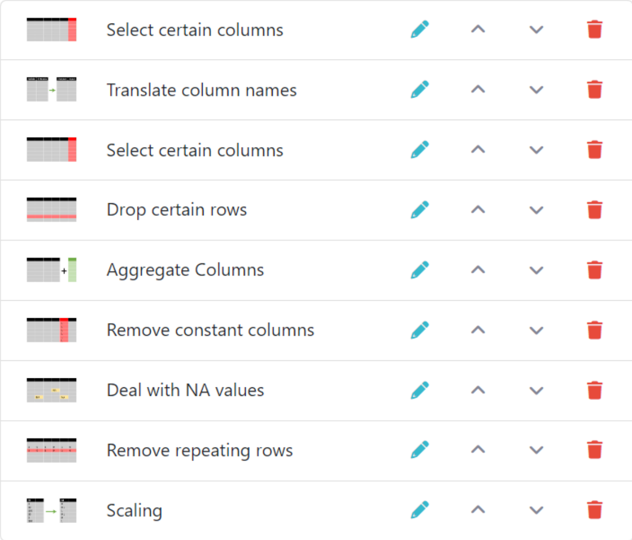

Fig. 5. Preprocessing functions for the translation system.

The first of the preprocessing steps shown in Fig. 5 are to clean the data. For this, some features are dropped, the feature names are translated from Spanish to English, and outliers have to be removed by dropping the rows with the outliers.

One of the biggest problems with this dataset is, the low sampling rate of one minute. The problem with this is that most of the movements of the crane take less than one minute so a lot of stuff that is happening in the crane are not reflected in the data. This makes it very hard for a neural network to learn what the normal behavior of the crane looks like, as the behavior might seem random, with such a low sampling rate. To work around this problem, the data is aggregated over at least an hour. Of these aggregated values, the mean, minimum, maximum and standard-deviation is then taken. This will make it easier for the neural network to learn how these values behave in normal operation, instead of trying to learn the accurate behavior of the machine.

After the values are aggregated, the data is cleaned once again by removing constant columns, filling non-available data and removing repeating rows. Last, the data is scaled to have a zero mean and unit variance, to make it easier for a neural network to learn.

E. Models Definition and Evaluation

The goal is for a neural network to learn how the machine normally behaves. Thus, if the machine behaves in a different way than what the neural network has learned the error will be high. To achieve this, an autoencoder based on Long Short Term Memory (LSTM) cells is trained.

The evaluation algorithm we have been using works as follows:

1. Measure Error of predicted values. Here, the squared error was chosen because it penalizes a large difference between predicted and true values. The squared error is defined by the following formula:

$$error_i = (y_{true_i} - y_{predicted_i})^2 \tag{1}$$

2. Define a threshold from training error. With N being the number of training samples, the parameter σM can control the likelihood of sample to be classified as anomalous and $\sigma(trainerror)$ being the standard deviation of the train error computed with Equation (1).

$$threshold = mean(trainerror) + \sigma M * \sigma(trainerror) \tag{2}$$

$$threshold = \mu + \sigma M * \sqrt{\frac{1}{N}\sum_{j=1}^{N}(trainerror_j - \mu)^2}, \quad with\ \mu\ \frac{1}{N}\sum_{j=1}^{N} trainerror_j \tag{3}$$

3. Test the error for each sample against the defined threshold:

$$low\_level\_anomalies = \begin{cases} 1 & \text{if } error_i > threshold \\ 0 & else \end{cases} \tag{4}$$

4. As the LSTM Autoencoder outputs a sequence of predicted values for each vector in the original dataset, there will be $seqlen$ vectors to test against the threshold. To reduce this down to one majority voting is applied. This means that if more than half of the errors corresponding to a certain vector is higher than the threshold, the corresponding vector will be classified as an anomaly. This idea was already discussed in [11].

5. Count how many samples surpassed the threshold in last WS timesteps ($WS = window\ size$):

$$anomalyscore_i = \frac{1}{WS}\sum_{j=i-WS}^{i} low\_level\_anomalies_i \tag{5}$$

The resulting $anomalyscore_i$ can be seen as the likelihood of the of the i-th sample to be anomalous.

This evaluation algorithm is for a univariate dataset. If it is applied on a multivariate time series, the steps 1-5 are the same, but they need to be applied for each variable in the dataset. Before this algorithm is deployed, it is useful to do two more steps.

6. For each column in a subcomponent in the machine, we take the mean of each anomaly score, thus deriving with an $anomalyscore$ for the whole subcomponent.

7. Define an anomaly-score-threshold (AST) for each subcomponent above which the subcomponent will be defined as “anomalous” or “broken”.

$$high\_level\_anomalies_i = \begin{cases} 1 & \text{if } anomalyscore_i > AST \\ 0 & else \end{cases} \tag{6}$$

If $high\_level\_anomalies_i$ is equal to one, maintenance personnel should check out the machine or a certain component of the machine.

A subcomponent in this case can be for example a motor with different sensors, like torque, energy consumption and drawn current. Of course, it is also useful to have a subcomponent which includes all columns of the machine which could be described as the overall state.

F. Some Experimental Results

The inputs of the autoencoder are the preprocessed values, and the output are the preprocessed values as well. The autoencoder learns to compress and decompress the data, in an efficient manner. The Autoencoder was trained over 300 epochs and the training process is shown in Fig. 6.

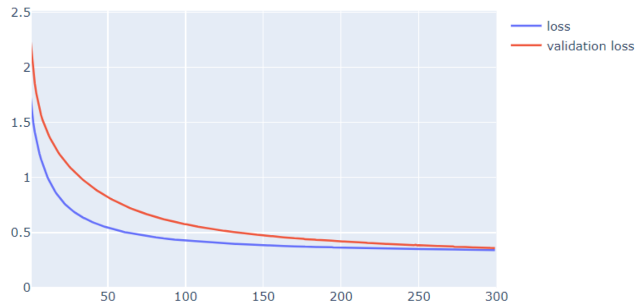

Fig. 6. Training process of model.

When data with different inner structures than the training data is fed into the autoencoder, it will have trouble to reconstruct the data and thus the error between reconstructed and actual data will be much higher than what it has been in the training set.

The defined threshold of when the error becomes too large is based on the error of the training set, combined with some parameters that need to be set, after the model is trained.

This is then combined with a windowing technique to better detect slow degradation. From this, an anomaly score in percent can be derived.

The resulting anomaly score for the translation system can be seen in Fig. 7. Even though the anomaly score is still quite low (around 0.3 maximum), it is visible that the anomaly score goes up between January and March of 2023, indicated by the red rectangle. This indicates that the machine is behaving slightly different from what the model has learned, and if the score keeps rising, this could indicate an anomaly, with preceding degradation.

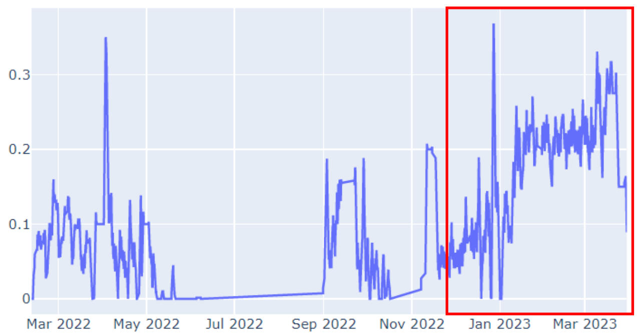

Fig. 7. The resulting anomaly score.

G. *Validation*

Contrary to the experiments performed for instance in [12], where a dataset from the company Continental was analysed and some anomalies were detected, no known anomalies in the Astander use case dataset were noticed. One way to validate the model is to see, if it makes sense, what this model predicts, by comparing the anomaly score with the input data. For example, to try to figure out, what caused the spike in the anomaly score in Fig. 7 in April of 2022. In this case, the anomaly is partly caused by a sensor that was turned on much longer than it usually was, so the model predicted the sensor to turn off again.

IV. CONCLUSION

In this paper, we have provided an overview of a toolkit enabling the extension of the life cycle of machines and appliances, thus boosting circular economy. This toolkit is data driven and uses artificial intelligence to predict potential failures in the considered equipment. Concretely, this work gives an overview of the main modules of the KYKLOS 4.0 DL toolkit. The latter offers a variety of functionalities including preprocessing, data plotting, and creating new anomaly detection models. This toolkit was tested on a variety of industrial datasets collected within the pilots defined by the KYKLOS 4.0 consortium. Examples of these datasets have been described in [12] and in the current paper. The related investigations have shown that the toolkit is able to perform anomaly detection even on low quality datasets.

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