Predictive Maintenance of Industrial Shredders: Efficient Operation through Real-Time Monitoring Using Statistical Machine Learning

Federico Pittino, Dominik Holzmann, Krithika Sayar-Chand, Stefan Moser, Sebastian Pliessnig, Thomas Arnold

Abstract—The shredding of waste materials is a key step in the recycling process towards circular economy. Industrial shredders for waste processing operate in very harsh operating conditions, leading to the need of frequent maintenance of critical components. The maintenance optimization is particularly important also to increase the machine's efficiency, thereby reducing the operational costs. In this work, a monitoring system has been developed and deployed on an industrial shredder located at a waste recycling plant in Austria. The machine has been monitored for several months and methods for predictive maintenance have been developed for two key components: the cutting knives and the drive belt. The large amount of collected data is leveraged by statistical machine learning techniques, thereby not requiring a very detailed knowledge of the machine or its live operating conditions. The results show that, despite the wide range of operating conditions, a reliable estimate of the optimal time for maintenance can be derived. Moreover, the trade-off between the cost of maintenance and the increase in power consumption due to the wear state of the monitored components of the machine is investigated. This work proves the benefits of real-time monitoring system for efficient operation of industrial shredders.

Keywords—Predictive maintenance, circular economy, industrial shredder, cost optimization, statistical machine learning.

I. Introduction

PREDICTIVE maintenance is a set of techniques aimed at deriving reliable predictions for the failure of machines and components. These techniques are becoming increasingly promising for fulfilling the emerging necessity of a well scheduled and prompt maintenance, with the aim of operating industrial machines efficiently and reliably [1], [2]. In particular, in the field of recycling, the shredding of waste materials is accomplished using industrial shredders, which need to operate in very harsh conditions, thereby requiring frequent maintenance of critical components. This work then focuses on deriving models for predictive maintenance of two key components of a commercial industrial shredder produced by Lindner-Recyclingtech GmbH: the cutting knives and the transmission belt.

Several methods for fault detection and predictive maintenance have been presented in the literature, mostly making use of statistical machine learning algorithms [3], [2]. Each of the presented approaches is, however, usually tailored to a specific application, and it is therefore difficult to generalize them to a similar yet different scenario. For example, in [3] the transmission belt of a rotating machinery is monitored, a scenario similar to ours, however this approach requires a sophisticated control of all phases of the motor current, rendering it inapplicable in our case.

On the other hand, the emergence of IoT devices has enabled the collection of large amounts of data, commonly referred to as Big Data, which allow the derivation of models that do not require deep technical knowledge of the machine or advanced sensing techniques [4]. The availability of Big Data allows also for the usage of very powerful Deep Learning techniques, [5], [6], [7], [8], [9], which benefit from very complex measurements with multiple input sources to create accurate representations of the underlying phenomena without requiring any particular knowledge of the machine. The models resulting from these techniques are, however, so complex that they have to be treated usually as black-boxes, therefore negating the possibility of providing insights about the status of the machine. As mentioned, they also require a large amount of inputs to be meaningful. In our case we then decided to focus on more traditional techniques which ensure that our results are interpretable by the end-users. This is possible since our measurement scenario, while involving a very long measurement campaign, does not feature the large input dimensions required to benefit from Deep Learning techniques.

This paper is structured as follows. Sec. II presents our use-case, the system for data acquisition and the models that have been derived for performing predictive maintenance on the two considered components of an industrial shredder. Sec. III then presents the results of the application of these models to our scenario. Finally, Sec. IV draws the conclusions.

II. Methods

The industrial shredder studied in this work is sketched in Fig. 1, where the monitored components are highlighted: the cutting knives and the transmission belt. These two components are the most important ones in terms of wear during the normal operation of the shredder. More in detail:

- *Cutting knives*: this part needs replacement every few months, and its state is crucial for an efficient operation of the machine.
- *Transmission belt*: this part needs periodic re-tensioning and replacement every 1-2 years, and it also has a high impact on the machine's power consumption, and thus operating costs.

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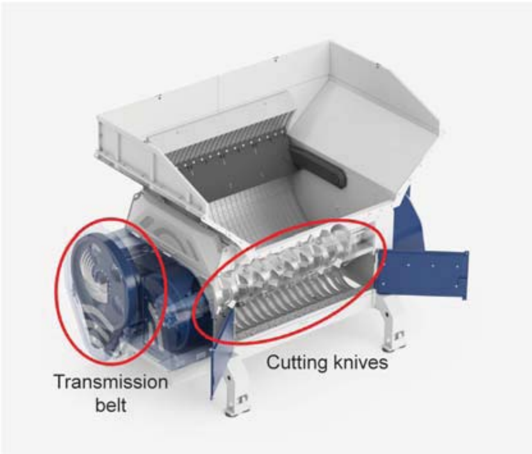

Fig. 1. Scheme of the industrial shredder considered in this work. Highlighted with red circles are the two components that have been monitored: the cutting knives and the transmission belt.

Fig. 2. Arduino datalogger for accelerations and motor parameters recording.

In this work we focused on monitoring over an extensive period of almost a year on an in-production machine, located at a recycling plant in Austria. The workload on the machine is not known, and the monitoring system has been operated continuously to cover the whole working time. The machine, on the other hand, does not operate continuously, but rather switches between periods of heavy workload to inactive periods, which can last up to a few days.

A. Data acquisition

In order to monitor both components from Fig. 1, various devices were installed at the recycling plant to record data:

- A custom datalogger, based on an Arduino platform, to measure accelerations and some parameters of the motor control, i.e., motor current and rotation speed;
- A Logic analyzer to record the signals of the incremental encoders.

A mobile hotspot is used to connect the devices, through a laptop, to a central database. Due to the harsh environment (dust, dirt, water, cold, heat, ...) at the shredder site, care was taken to adapt the equipment for such special needs, employing for the datalogger sealed housings and robust cables.

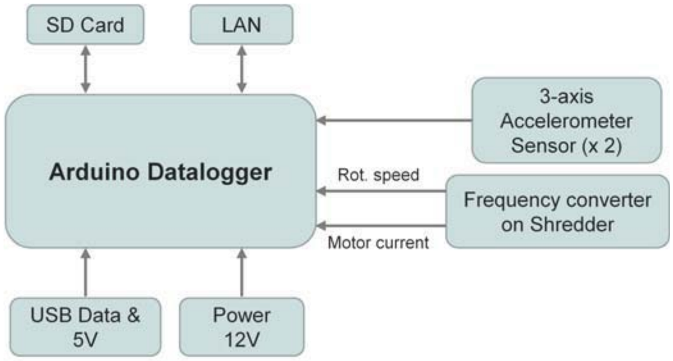

Fig. 3. Scheme of the Arduino datalogger.

Fig. 4. Incremental encoder sensors on the shredder, mounted on the motor and rotor.

An overview of the Arduino datalogger is shown in Fig. 2, while its logical scheme is in Fig. 3. To measure the machine's vibrations, two three-axis acceleration sensors were mounted on separated positions on the shredder and their analog outputs recorded by means of the datalogger. This datalogger also records two analog outputs from the motor control unit, representing the motor current in [A] and motor speed in [rpm]. A memory card is used to record the data within the datalogger, which is then remotely accessed and transferred through a LAN interface.

On the other hand, the signals of the incremental encoders (motor, rotor) representing the rotational speeds, were directly recorded through a Saleae Logic Analyzer (Fig. 4). This Logic Analyzer is able to record digital signals over a long period of time and store them in a compressed format. These files can then be remotely accessed and transferred.

B. Models for knives condition

As mentioned above, the shredder is not operated continuously, and therefore every acquisition day consists both of operational and idle times, with days with no operational time at all. An algorithm has then been devised to identify the time intervals pertaining to the operational time. The algorithm works by identifying the time instants in which the motor speed rises above a set threshold (1000 rpm in our case) and by retaining only the intervals in which such speed remains above the threshold for at least 1 minute.

The data is then processed on a daily basis, calculating the 50% and 95% percentiles of motor current and accelerations per each day. The average daily current consumption is then calculated as the average of the daily current up to the 95% percentile. This method has been used to discard the large outliers in the current, that are usually caused by tough material falling in the shredder and are not representative of the normal operation.

During our data acquisition, the knives were changed twice on the machine. For the derivation of the knives condition predictive models, therefore, following standard practices in statistical machine learning [10], the data has been divided into a training set, containing all days between the two knives changes, and a test set, containing all days after the second knives changes. The model has been derived to predict the increase in daily current average, calculated up to the 95% percentile as discussed above. To this purpose, the value of the average current I_0^{avg} on the day of knives change has been set as a reference, and the subsequent values are standardized by dividing by I_0^{avg}. The chosen model is a simple linear regression algorithm, that uses as input the cumulative operational time of the machine since the last knives change. The reason for choosing a simple model relies on the high interpretability and ease of implementation in an industrial environment. The model's training and test have been performed in Python using the library *Scikit-learn* [11].

The usage of a simple linear model allows also the derivation of a closed formula for minimizing the cost of operation by optimally selecting the time for the next maintenance. It can be derived assuming that the average current consumption for a day, indexed by n, exactly follows the linear model:

$$I_n^{avg} = \left(a_l \sum_{i=0}^{n} H_i + 1 \right) I_0^{avg} \tag{1}$$

where I_0^{avg} is again the average current consumption on day 0 (the one right after the knives change, assumed as reference by the model), a_l is the slope coefficient of the linear model and H_i the total operational time of day i.

In order to derive a closed formula, some more simplifying assumptions can be made, although these are not necessary in the general case. Assuming then that I_0^{avg} is always the same after each a knives change, that $H_i = H \, \forall \, i$ (i.e., every day has the same number of operational hours) and that the total energy consumption in a day can be approximated as $E_n = V_0 I_n^{avg} H_n$ (where V_0 is the effective voltage), the total energy consumption between days n and $n+m$ can be written as:

$$\frac{E_{n,n+m}}{V_0 I_0^{avg}} = \sum_{i=n}^{n+m} \left(a_l \sum_{j=0}^{i} H_j + 1 \right) H_i = \sum_{i=n}^{n+m} \left(a_l H i + 1 \right) H \tag{2}$$

It can then be estimated the difference in energy between the scenario in which the considered m days start n days after the knives change, and the one in which the m days start right after the knives change. This gives an indication of the excess energy spent on running the machine with an old set of knives, that have already been used for n days, instead of using a new set of knives. The equation, after some algebraic simplifications, reads:

$$\frac{E_{n,n+m} - E_{0,m}}{V_0 I_0^{avg}} = a_l H^2 n \left(m + 1 \right) \tag{3}$$

If it is finally assumed a cost per unit of energy of c_E and a total cost of the knives change of C_K, the maintenance should then be scheduled for a day n and for a defined m days in advance so that:

$$C_K \leq c_E V_0 I_0^{avg} a_l H^2 n \left(m + 1 \right) \tag{4}$$

C. Models for belt condition

To obtain a model for the belt condition, we employed the data acquired by the encoder sensors. The assumption is that the belt, as it wears out, is not capable of efficiently transmitting the torque from the motor to the rotor due to increased slipping, and that such slipping events can be identified from the encoders data. The encoder sensor mounted on the rotor features 12 teeth, while that on the motor 3 teeth. Run-length encoded data is then obtained from both sensors, providing a square signal with alternating high (1) and low (0) periods. The time spent by a tooth on the sensor is considered high period and the one on the gap between the teeth is considered low period. The sampling rate of the sensors is 1 MHz.

For each day of operation, an encoder data file is generated, while the days with no operation on the machine are automatically discarded. However, outliers in the data are still present, because the sensors sometimes fail to record the correct values, resulting in data points having unusually small values. To reject such outliers, a lower threshold has been defined for the encoder measurements. The value of such a threshold depends on the number of teeth on the sensor, being it at 4400 for a sensor with 3 teeth and at 100 for a sensor with 12 teeth. The calculation of the total speed per full rotation of the encoder wheel ρ (in rpm) is then carried out as:

$$\rho = \frac{60}{\sum_{i=1}^{N_t} T_i} \tag{5}$$

where T_i is the time spent on the sensors on tooth i and on the gap next to it, in seconds, and N_t is the number of teeth on the sensor. In addition, in order to compare the speeds calculated on the two encoder sensors, the values for the rotor speed are compensated with the gearing ratio between the two wheels.

To assess the status of the belt, the presence of slipping events has to be detected. Such a detection has been performed by comparing the synchronicity of the signals between the two encoder wheels and calculating the delay between the two of them. For this purpose, the negative peaks of the signal have been detected, using only the times in which the rotation speed is above 1000 rpm, and the data has been divided in 30-minutes-long bins. Inside each bin, it is then calculated the average delay between the peaks of the motor and rotor signals. Finally, the rates of variation of delay $r_V^{i,j}$ are calculated between consecutive bins i and j with $j > i$, defined as:

$$r_V^{i,j} = \left| \frac{d_j - d_i}{T_B (j - i)} \right| \tag{6}$$

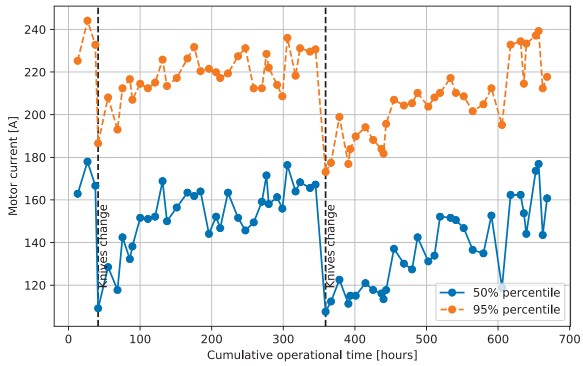

Fig. 5. Percentiles of the recorded motor current. The two knives changes are marked as dashed vertical lines.

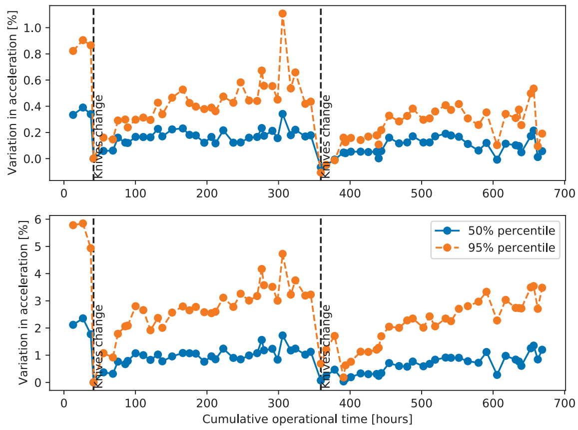

Fig. 6. Percentiles of the variation in accelerations, with accelerometer 1 on the top and 2 on the bottom. The two knives changes are marked as dashed vertical lines.

where d_i and d_j are the average delays in bin i and j, respectively, and T_B the total length of each bin in seconds, in our case 1800. Finally, the 10%, 50% and 90% percentiles of r_V are calculated on a daily basis, and a linear model is trained to predict the increase of these values over time. To this purpose, the percentiles are normalized by the value of the first day of measurement and the first 75% of the data is used for training the linear model, again using the library *Scikit-learn*.

III. Results

A. Knives condition

As a preliminary investigation on the impact of wear on the cutting knives, Fig. 5 shows the daily percentiles of the motor current for the whole data acquisition as a function of the operational time. It is clearly visible the sharp decrease in motor current right after the change of knives, and the gradual increase due to degradation. Moreover, both the 50% and the 95% percentiles convey similar information, assuring on the fact that outliers are not influencing the measurement. On the other hand, Fig. 6 shows the same 50% and the 95% percentiles for the two accelerometers measurements. In this case the values of acceleration are calculated as variations with respect to the value at the day of the first knives changes. Also in this case there is an evident decrease in acceleration after the knives change, due to the higher effectiveness of the new knives, causing less vibrations on the machine. In this case, though, on the 95% percentile the effect is much more evident than on the 50% percentile. Moreover, the reading from accelerometer 2 gives usually a clearer signal, indicating that the positioning of the accelerometer is important for an accurate measurement. However, since the degradation effect is clear already on the motor current, and this is also the parameter of interest to be optimized by the machine's operator, the remaining of the investigation will not consider the accelerometers.

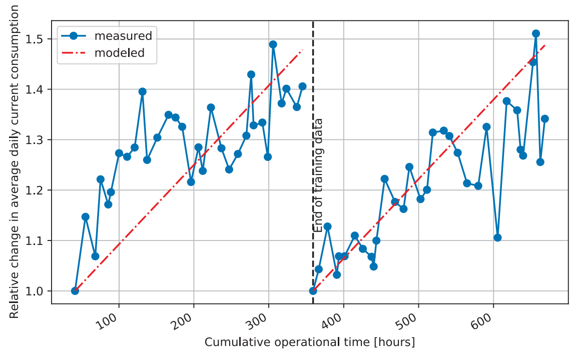

Fig. 7. Relative variation of motor current after the knives changes, and its prediction through a linear model. The model has been trained on the data on the left of the vertical dashed line, that marks the second knives change.

Concentrating then on the motor current, Fig. 7 shows the change in average daily current consumption up to the 95% percentile relative to the day when the knives were changed. The reference day for the relative current calculation is always the closest previous knives change, so that after each of these events the value in the figure is 1 by construction. The figure also shows, as dash-dotted lines, the predictions derived with the linear model from Sec. II-B. The model has been trained on the data before the second knives change, while it is only tested on the data after this event. With this in mind, the performance of the model is particularly good in predicting the degradation of the knives on the test data, i.e., the data after the second knives change, which was not part of the training.

B. Belt condition

In a typical day of operation, the machine can be active for several hours. Fig. 8 shows an example of one day of operation, where the rotation speed of the motor and the rotor are shown (corrected by the gearing ratio). As explained in Sec. II-C, to calculate the delays between the two signals, the negative peaks are first detected. Fig. 9 show two zoom-ins in different points at the beginning and the end of Fig. 8, where it is clearly visible the loss of synchronicity between the two signals. The negative peaks are also highlighted by the triangles. Using these negative peaks, the average delays between the signals in 30-minutes bins are calculated as in Sec. II-C, and are shown in Fig. 8 in green with the scale on

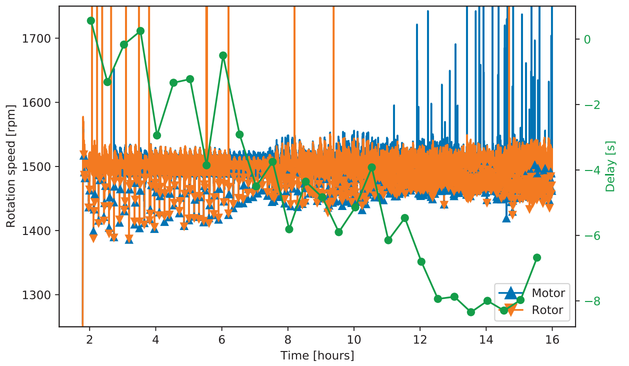

Fig. 8. Rotation speed on the encoder wheels and associated delays for one day of operation.

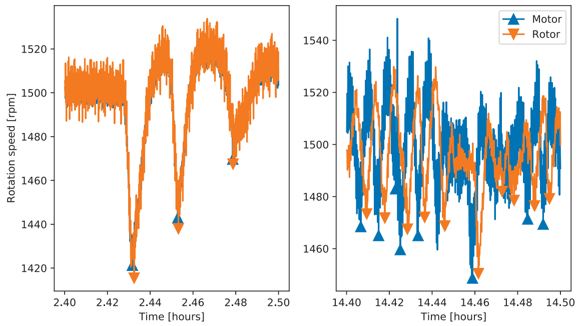

Fig. 9. Zooming in two sections of Fig. 8. The negative peaks on the signals are highlighted with the triangles.

the right y-axis. It is immediately evident that this calculated delay is able to capture the loss of synchronicity between the signals over time.

In order to derive a model for the progressive wear on the belt, Fig. 10 shows the rates of variation in delay r_V calculated with Eq. 6 and aggregated on a daily basis. There is a clear upwards trend, confirming our prediction that the progressive wear of the belt results in more frequent slipping events. Moreover, the figure shows a linear model of the daily median of r_V, which is only trained on the 75% of the data until the dashed vertical line. Despite its simplicity, the model is clearly capable of predicting the increase in slipping events due to the belt's degradation.

IV. Conclusion

In this work we have presented a system for data collection and processing on an industrial shredder during its in-production operation, with the purpose of developing models for predictive maintenance on two key components of the machine. Provided that the machine is monitored for a long enough time and with sufficient accuracy to observe all its states of wear, we have proven that even simple linear models can give very accurate predictions on the expected degradation. Such prediction models should be used in a predictive and preventive maintenance strategy, to optimize the cost of operation of the machine and to prevent any downtime.

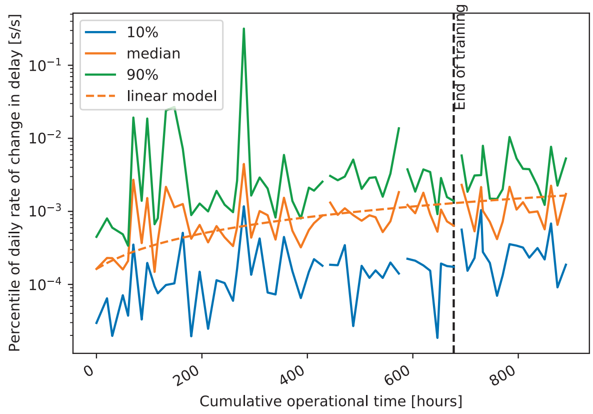

Fig. 10. Delay variation rates calculated with Eq. 6 and aggregated on a daily basis using three different percentiles. The dashed coloured line is instead the linear model predicting the median of r_V, which is trained only on the data on the left of the vertical dashed line.

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