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INCREASING OF OEE IN WIRE DRAWING PROCESS USING MACHINE LEARNING TECHNIQUE

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Abstract. *Wire drawing process is a cold plastic deformation of a metal that depends on the raw material quality to reach good performance. When a failure happens, due to the arising chemical inhomogeneity, the equipment stops after a broken wire detection, interrupting a long sequence of circular cross-section reduction. It drastically compromises the entire process since the restart can be time-consuming. Different monitoring methods for the wire drawing process have been studied for decades, but still, there are no commercialized systems delivering consistent results. The lubrication failure detection has shown promising results since components such as thermal imaging became more available recently. Considering the interior of a drawing machine submerged in coolant lubrication, the data acquisition still awaits investigation. The key question examined in this work is the use of machine learning techniques to predict and prevent failures in continuous processes. Focused on the applicability of multi-motor drawing machines, instant measurements compared with references can indicate the necessity of fine adjust in parameters. After determining a critical scenario in real-time, actions are taken to avoid failures. In this regard, we have developed an algorithm that controls a multi-motor system through in situ physical measurements. Our results reveal that by monitoring the synchronism, we can modulate a better operation in a drawing process according to the metal quality. The expected outcome is to enhance the Overall Equipment Effectiveness (OEE), contributing to better reliability when working with recycled raw materials.*

Keywords: *Wire drawing, machine learning in multi-motors system, drawing process monitoring, residual stress, OEE.*

1. INTRODUCTION

The drawing process has been defined as a vast field of studies with research of aspects related to the process itself, such as the approach to the drawing forces, lubrication, and friction until the analysis of behavior or subsequent properties of the processed material (Dieter, 1988).

Currently, the main focus of the drawing machinery industries is to develop and implement new technologies that increase the speed of this mechanical forming process (Suliga, 2015). However, increasing line speed implies improvements in the process due to challenges such as increasing of temperature at the interface between tool and raw material. Since friction is not a directly measurable parameter and requires extreme attention, the quality of the raw material becomes an important variable.

To allow a small chemical inhomogeneity of raw materials, the wire drawing machine needs to be adapted with systems that permit a tolerance in a narrow range. With the development of multi-motor techniques, the traditional drawing machine composed of big transmissions linking the axis has been slowly replaced by multi-motor systems (Perez-Pinal et al, 2003). In this case, each shaft is controlled by a separate motor, which is not physically linked to other shafts. Instant measurements from the drives compared to recorded references can provide information to improve the process, punctually or even in the entire synchronization among the axis.

In this direction, we define the main object of this study as the development of an algorithm that controls a multi-motor system through in situ physical measurements. After determining a critical scenario in real-time (Wang et al., 2018), actions can be taken in the control of the system. This systematic simulates a wire drawing machine to overcome one of the biggest challenges in this process, which is to keep the straining force of the wire almost constant in reference to the maximum allowed. Fine torque adjustments can be applied with the system running, to stabilize better the drawing forces. As a last option, the reduction of line speed can be activated, or even a warning message will improve the system's reliability, indicating defective lubrication for instance. By monitoring the entire synchronism, we can modulate a better operation in a drawing process.

Nowadays it is still not common to use a system to predict or even give a warning if the current operating conditions may lead to a failure in the process. When quality inspection of the wire is required, analysis of samples is performed in the finished wire product. Generally, it is done with the eddy-current (EC) testing method (Enghag, 2009).

Different monitoring methods for the wire drawing process have been studied and tested for decades, but still, there are no commercialized systems that deliver consistent results. Among them, the detection of a failure in the lubrication has shown promising results since components such as thermal imaging became more available recently.

Considering the interior of a drawing machine submerged in coolant lubrication, data acquisition becomes a challenge. This characteristic motivated us to find a technique in software, able to be applied in the drives and continuously updated, which is the case of Machine Learning (Moreira et al., 2021).

Machine learning is a study of computer algorithms that uses data and produces a program to perform a task, usually when handwritten rules or equations are too complex to be implemented (Lu, 2017). It is very applicable in situations with a big amount of data that needs a rapid analysis to take a decision. Mitchell (1997) says that Machine Leaning improves automatically through experience and by the use of data. These algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so (Arthur Samuel, 1959). Algorithms as it is try to identify patterns testing data and cluster or predict future values (Kubat, 2017). These are various applications, such as computer vision, email filtering, recognizing patterns and also, preventive maintenance.

2. MATHEMATICAL MODEL OF THE DRAWING PROCESS

The basic principle of the process has been the same for decades, being carried out through passes, consecutive or not, in strategically positioned dies that cause small reductions in the cross section of the material. In a practical view, the non-ferrous materials maximum area reduction by drawing pass can reach 35% (Kim T.H., 1997). Figure 1 exemplifies one pass wire drawing machine. Through the proper control of these section reductions and with the use of efficient lubricants, the process makes it possible to obtain products with high dimensional, surface, and geometric quality (Button, 2008).

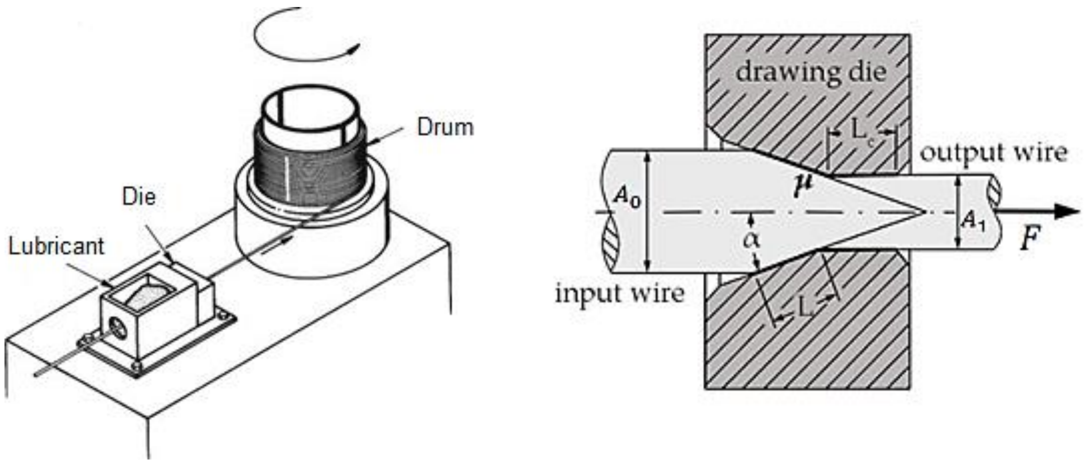


Figure 1. Schematic diagram of a drawing machine (a) and the wire-die interface (b).

The drawing force is commonly calculated using the formula derived by Siebel and Kobitzsch (Siebel, 1942):

$$F = A_1 R_{em}\left(ln\frac{A_0}{A_1} + \frac{2\alpha}{3} + \frac{\mu}{\alpha} ln\frac{A_0}{A_1}\right) \tag{1}$$

Where F is the total drawing force, A0 and A1 are the initial and final area respectively of the cross section of the wires, R_{em} is the mean flow tension for the material before and after the reduction, 2α is the semi-die angle, and μ the coefficient of friction between the wire and the die, shown in the Figure 1b. For the lubricated part of the experiments, the friction coefficient should be between 0.03 and 0.06 (Filho et al. 1997).

As a reference, the theoretical drawing forces for the lubricated condition calculated by Eq. (1) considering the copper as raw material will meet forces between 5558 N and 6350 N, for an initial reduction from 8 mm to 6.9 mm for a commercial drawing machine. It was considered 373MPa and 471 MPa respectively as the range of copper tensile strength for the forces mentioned, based on (ABNT EB-11, 1978). The scope of this work also considers a functional lubrication process.

3. METHODS AND PROCESS PARAMETERS

New techniques have been evaluated for monitoring the drawing process, most of them focused on a feasible way of acquiring data. Recently, thermal imaging cameras have been less costly which makes their applicability more available. Many new applications use this solution as fault diagnostic in rotary machinery, monitoring of heat distribution systems, control of laser welding, and fault detection in induction motors (Singh, 2016) and (Espinoza-Sepulveda et al., 2021).

An increase of the friction between the wire and the die leads to an increased amount of energy that goes to the wire, which causes a higher wire surface temperature. (Larsson et al., 2019) have presented substantial results monitoring of the wire drawing process using a thermal imaging camera. The temperature of the wire increases as the wire is drawn through the die. The increase in temperature is mostly not only due to the plastic deformation but also because of the friction between the wire and the die.

Another key process parameter we used was the torque analysis of the motors. Acquiring measurements from the frequency drives, we could detect the variation when different loads are applied to the system. These distinct torque profiles are like the variation of chemical inhomogeneity present in the raw materials, since the motor shaft is totally linked with the drawing block, in our case of study with independent motors electronically synchronized.

In order to simulate the drawing process and considering the resources available at L.E.I.A lab at FEM in Unicamp, a multi-motor system was assembled composed by two drives synchronized by a PLC. A rotational brake coupled in the shaft of drive #1 simulates the cross section reduction of the material in the die, with parameters analogous when the friction really occurs. The variation of torque detected by the frequency drive controlling this axis was our main process parameter. With the analog activation of this brake, it was possible to make the system work with different drawing forces, simulating different kinds or qualities of raw material. Drive #2 works synchronized with drive #1 in a higher speed reference, following the principle of a drawing machine in closed loop speed control. In combination, the wire temperature in the die body was simulated with calculations based on the torque measurements, being possible to predict the overview of a real drawing machine system in operation. In Figure 2 we can see the topology of the components:

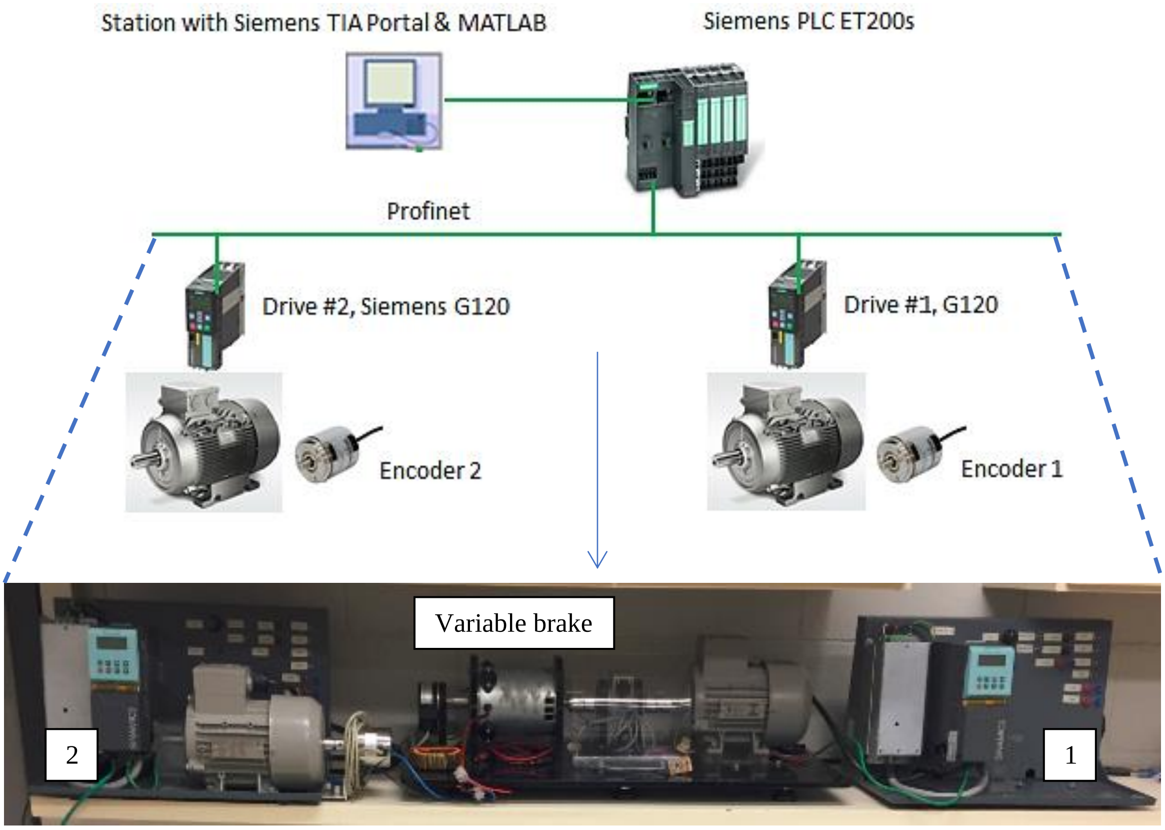


Figure 2. Topology of the multi-motor simulator, experiment at L.E.I.A. lab at FEM, Unicamp

Using a PID controller implemented in the Matlab as the main control for the drives and motors, the speed was settled as constant following the experiments set points and the torque was modulated according to the activation of the electronic brake (disturbance). This simulates the processing of different kinds of raw materials in a wire drawing machine. All the parameters were read in the frequency drives using the Siemens Drive-ES Starter software. Some key parameters as speed and torque of the drives were processed in the Matlab, which communicates directly with the PLC.

In Figure 3 we detailed the electronic circuit of the brake control and also the resistance load, which is activated according to the profile of torque defined among the simulation of the raw material.

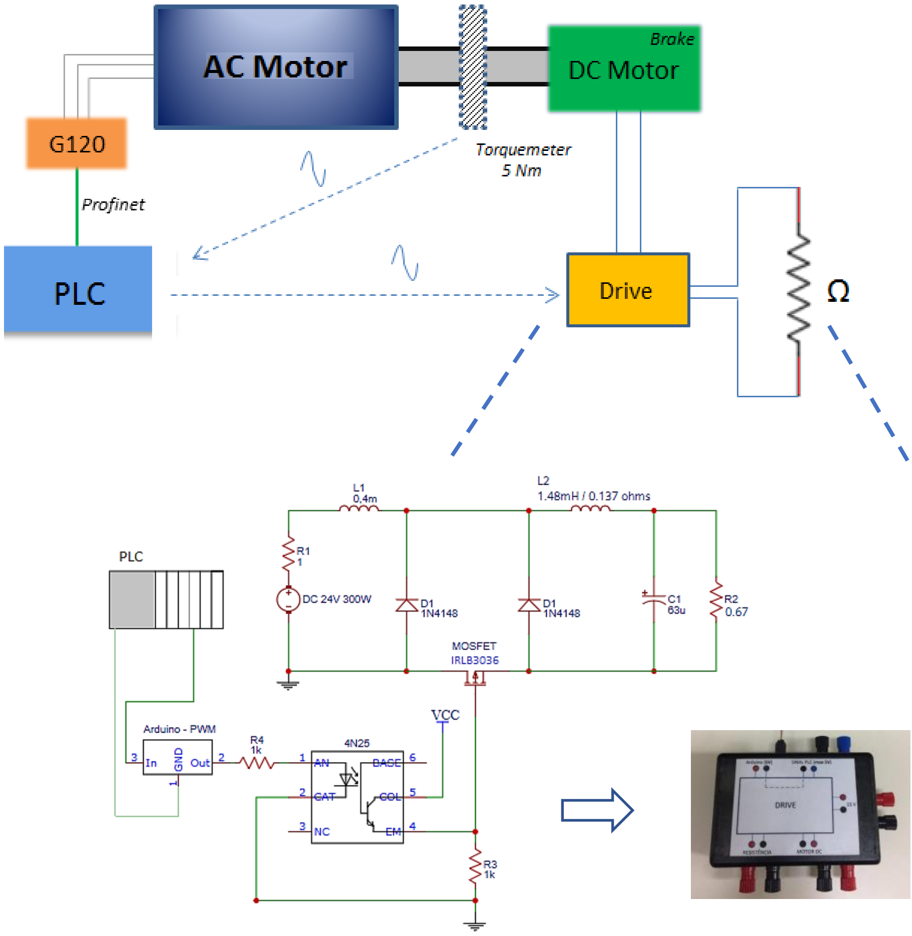


Figure 3: Resistive load for the variable brake (DC motor) with the PWM control

Based in the acquisition of torque data from the drives, we defined five profiles of torque which indicate distinct types of raw material. They are labeled as shown below in the Table 1:

Table 1. Range of torque for each profile in the tests

Profile	Torque range (Nm)
Very low (without load)	0.2 up to 0.40
Low	0.2 up to 0.80
Normal	0.2 up to 2.10
High	0.2 up to 2.68
Extreme	0.2 up to 2.99

After the detection of real measurements in our experiments, we generate more data using Matlab to be able to feed the machine learning technique and obtain a proper performance. The dataset consists of random values generated from 0.20 up to 2.99 Nm. The data contain fixed-width sliding windows of 2.56s (128 readings / window).

The process data follows the diagram of Figure 4, and later on, the machine learning algorithm provides the results, which can trigger actions. As a strong requirement, a significant volume of data is needed for a reasonable accuracy of the system. After having the proper model trained, it can be integrated into a production system.

The comprehension of using machine learning techniques instead of conventional statistics was decided by the purpose of making the most accurate prediction possible. In using traditional statistical models, the inference about the relationship of our process variables could be critical. Another key approach is the amount of data generated by a multi-motor drawing machine, which generally has around 14 synchronized drives providing a range of parameters, updated in real-time. Usually, the machine learning technique uses redundancy in features, and the algorithms are often designed to handle many variables. On the other hand, in traditional statistics, a typical requirement is to have independent features, preferably with fewer inputs (Bzdok et al., 2018). To sum up, one of our motivations was to implement a system capable of learning from data of all sorts, eventually considering non-rigid pre-assumptions. Conversely, statistics would prefer tight assumptions about the data distribution (Nielsen, 2019).

The data sets used for the training phase to have known labels for each profile of process parameter. The algorithm learns the features between the input values and labels, later on tries to predict the output values of the testing data.

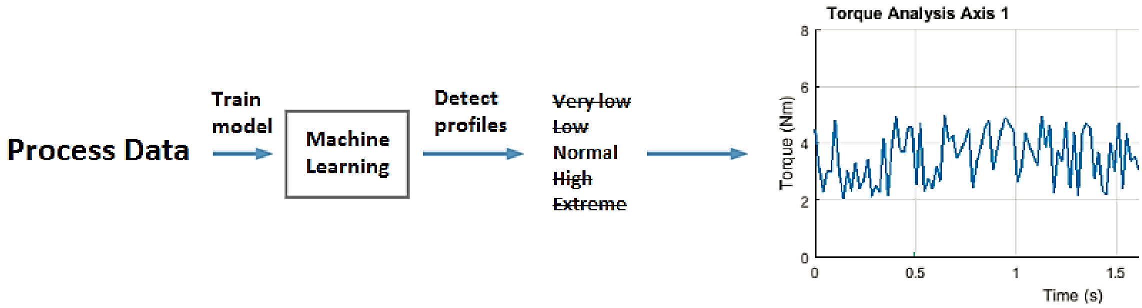


Figure 4. Machine Learning flowchart

4. RESULTS AND DISCUSSION

With all the data generated based on real characteristics of our drawing process simulation, using Matlab we performed the training of the machine learning algorithm. Since machine learning focuses on prediction, based on known properties learned from the training data (Thorsten Wuest et al., 2016), we considered this data as different kinds of raw materials as shown in Figure 5:

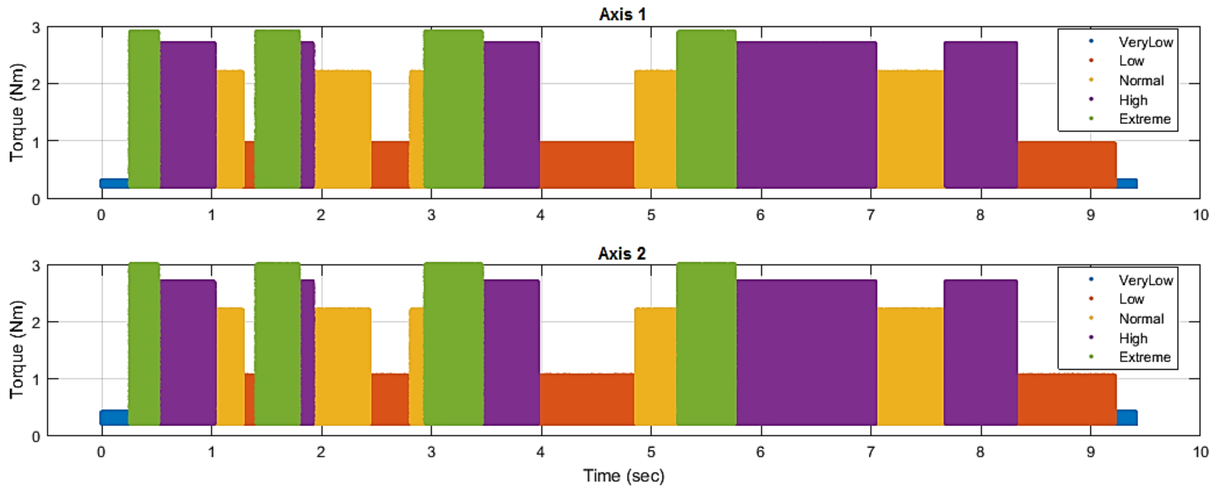


Figure 5. Data used for training of the Machine Learning algorithm, axis 1 and 2.

After having a considerable volume of data, we classified the data using a clustering method. Appling pre-processing techniques to extract basic features of the data, we segmented the data collection in groups with distinct attributes as the average value, standard deviation, and principal component analysis of each row in the torque data. It created the following groups displayed in Figure 6.

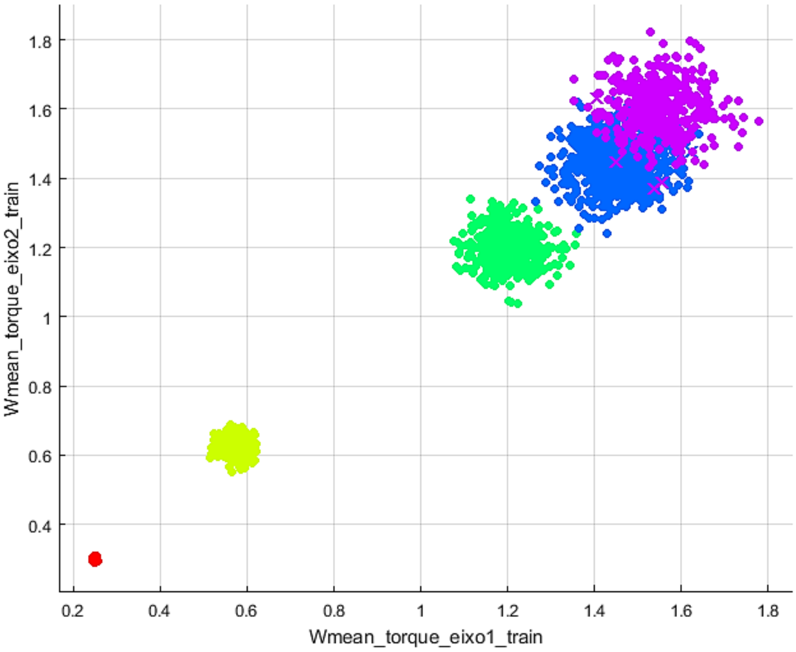


Figure 6. Clustering of the training data in the Classification Learner toolbox (Matlab)

With the clusters defined, we performed the training of different models to find the best model based on the holdout validation accuracy. The best result was the model Support Vector Machine (SVM), a supervised learning model that divides the data into regions separated by a linear boundary. Other models presented less accuracy, as described below in Figure 7:

History	
SVM Linear SVM	99.4%
Tree Complex Tree	99.0%
Tree Medium Tree	98.2%
Tree Simple Tree	96.5%
KNN Fine KNN	99.1%
Ensemble Boosted Trees	57.2%

Figure 7. Accuracy of the methods tested to create the final model

After selected the best model considering 70% of data for the training, we performed the tests with 30% of the remaining data. The different profiles of torque can be visualized in Figure 8. The critical area is with high and extreme conditions of torque, which we explored as the focus of attention.

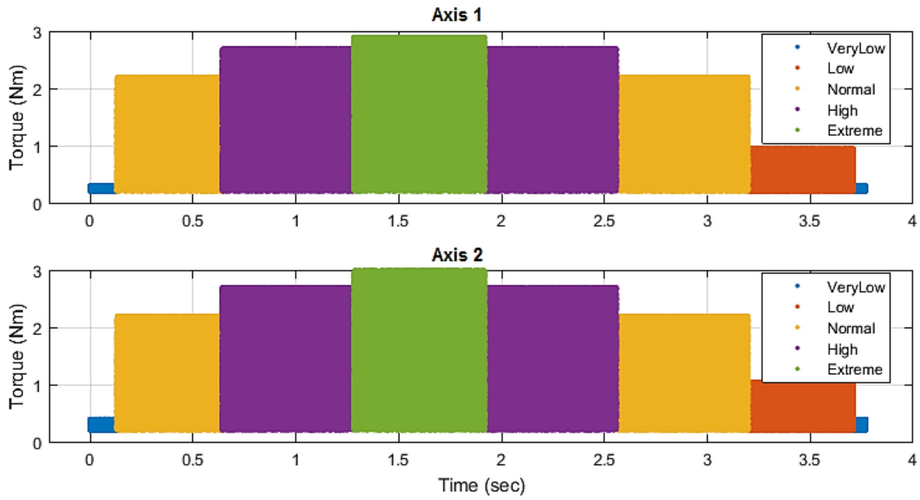


Figure 8. Data used for tests of the model, axis 1 and 2.

The results were very satisfactory considering the 99.4% of accuracy of the best-selected model. The most critical area was when occurs an overlapping of data in the profiles of high and extreme torque. At this point, the model gets confused with the prediction but with a very small error as illustrated in the confusion matrix shown in the Figure 9.

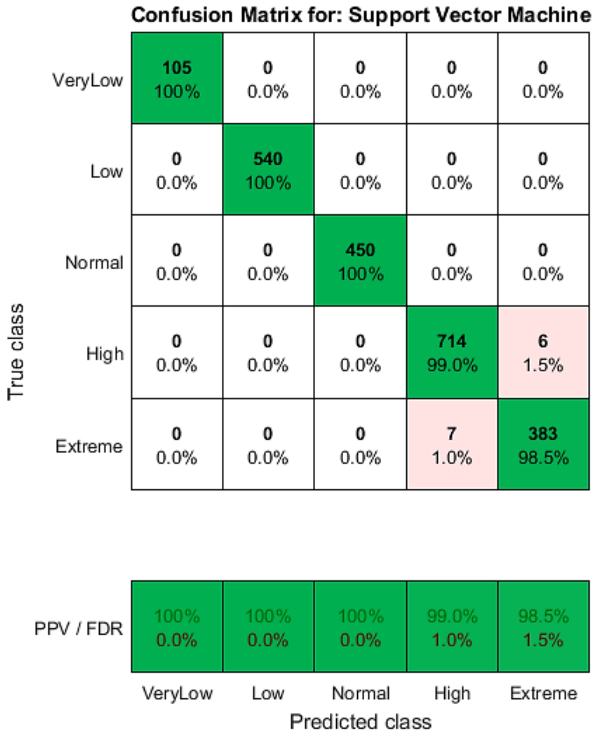
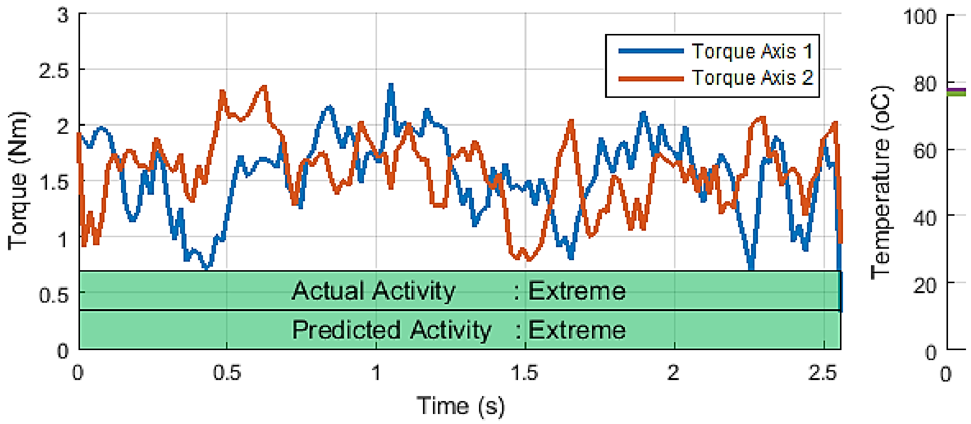
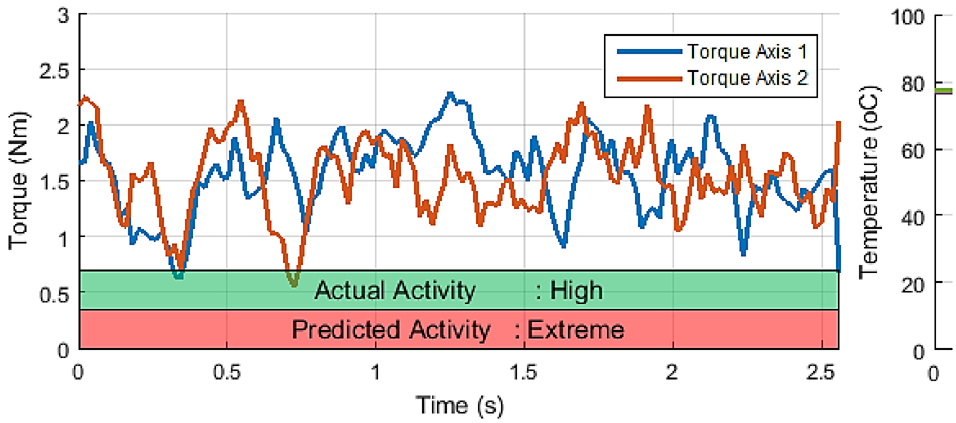


Figure 9. Confusion matrix of the final model selected (SVM), Support Vector Machine

The model performed very well predicting the trend of next behavior of the material. In the figure 10a we can see the predicted activity with the actual activity in conditions of extreme torque, when the material is considered with high Tensile strength (MPa). In a case of failure of prediction as shown in the figure 10b, with a confirmation of a failure considering a repeat error, immediately a reduction of drawing speed could be applied. Eventually, the new analysis in the sequence will indicate the correct prediction. Beside the torque analysis on the Figure 10a and 10b, there are the simulated temperatures in the drawing body, as other important process parameter we considered.



(a)



(b)

Figure 10. Prediction detection: (a) 99.4% Success (b) Failure with 0.4% (only).

Based on our results, in the PLC program we could use the prediction from Matlab to take actions, meeting the goal of our work. Initially the PID will respond adjusting the variation of torque to try a better performance. If this step does not perform well, a reduction of speed is recommended since the torque is bigger in higher speed level.

The last task we implemented to treat the problems was an alarm, indicating an imminent failure. These preventions can avoid a stopping in the process, something costly in terms of time-consuming and also loss of efficiency.

5. CONCLUSIONS

The present work shows a way to increase the flexibility of a wire drawing machine modulating a better operating condition based on predictions detected by a machine learning algorithm. With this improvement we can significantly enhance the Overall Equipment Effectiveness (OEE) of machinery, applying fine tunes in real-time or even indicating actions to prevent a failure in the continuous process. Our results reveal that by monitoring the entire synchronism in a multi-motor system, the control can be better adjusted for the instant condition leading to a better reliability or an energy saving, when high torque levels are not required.

The following contribution of our work is to present a way to improve the reliability of a multi-motor system, exemplified in our study as a wire drawing machine. Based on practical feedback we collected in cable factories to which we had access, considering the copper drawing as a highlight for the capability of recycling and economic facts, this process can collapse up to three times a day. After this breakdown, a new setup can be costly in time, reaching two hours to reestablish the process in a critical case. This fact indicates that our ambition with this work can reduce one breakdown a day. In other words, at least 20-30% of the runtime can be increased in this process. The availability of multi-motor drawing machines in the market dedicated to copper material is still rare. Based on recent claims for energy saving, the coming years should bring more intelligent machinery.

The trend of using raw materials resulted from recycled processes brings challenges for systems with limited flexibility. Considering a wire drawing machine as the case of study, better performance can be reached when the systems sense key process parameters and auto-adjust to them, even momentarily. It can also minimize downtime since the restarting process can be time-consuming.

The multi-motor technology recently applied in wire drawing machines contributed for a better monitoring, and several new parameters are available to complement further analysis and techniques. The slip control technology is one suitable task now, with independent shafts electronically synchronized.

The machine learning technique is very dedicated to finding generalizable predictive patterns. In this direction, the process variables we considered for this work were the torque and die temperature, calculated by the torque spam. This case of study became the input features very related to each other. This decision put in future tasks the performance of the conventional statistics approach which we intend to collect real values for the die temperature. This task will demand the availability of a multi-motor wire drawing machine and the apparatus necessary to collect the individual temperature in each body die.

Industry 4.0 already in motion will change several traditional manufacturing systems. The smart factory concept will confront multifaceted challenges creating a rapid technological development, i.e., short product life cycles, volatile demand, and highly customized products. Substantial research has been dedicated to initiate smart factories, extracting new features, and implementing new optimizations in processes. The purpose of this work also goes to the direction of the implementation of Industry 4.0 with the goal of create smart machines that will be able to improve with runtime.

The results obtained in the experiments can be used to guide new analysis of process parameters, which can increase energy saving with a significant improvement of the entire process.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Button, Sérgio Tonini. Trefilação. Belo Horizonte: REDEMAT-UFOP, 2008.

Bzdok, Danilo & Krzywinski, Martin & Altman, Naomi. (2018). Machine learning: Supervised methods. Nature Methods. 15. 10.1038/nmeth.4551.

Dieter, G. E. Mechanical Metallurgy. 2. ed. London: SI Metric, 1988. 751 p.

Enghag P (2009) Steel wire technology. Örebro: Materialteknik HB.

Espinoza-Sepulveda, N.; Sinha, J. Mathematical Validation of Experimentally Optimised Parameters Used in a Vibration-Based Machine-Learning Model for Fault Diagnosis in Rotating Machines. Machines 2021, 9, 155.

Filho et al. 1997 Filho, E. B.; Zavaglia, C.; Button, S.; Gomes, E.; Nery, F. Conformação plástica dos metais. [S.l.]: Ed da Unicamp, 1997.

Kim T.H., K.B.C.J. Prediction of die wear in the wire-drawing process. Journal of Materials Processing and Technology. [S.l.: s.n.], 1997. v. 65

Kubat, M. An Introduction to Machine Learning; Springer: Cham, Switzerland, 2017.

Larsson, J., Jansson, A. & Karlsson, P. Monitoring and evaluation of the wire drawing process using thermal imaging. Int J Adv Manuf Technol 101, 2121–2134 (2019).

Lu, Y. Industry 4.0: A survey on technologies, applications and open research issues. J. Ind. Inf. Integr. 2017, 6, 1–10.

Mitchell, Tom (1997). Machine Learning. New York: McGraw Hill. ISBN 0-07-042807-7.

Moreira, L.; Figueiredo, J.; Vilas-Boas, J.P.; Santos, C.P. Kinematics, Speed, and Anthropometry-Based Ankle Joint Torque Estimation: A Deep Learning Regression Approach. Machines 2021, 9, 154.

Nielsen, Aileen. Practical Time Series Analysis: Prediction with Statistics and Machine Learning. United States: O'Reilly Media, 2019.

Perez-Pinal F., G. Calderon and I. Araujo-Vargas, "Relative coupling strategy," in Electric Machines and Drives Conference, 2003. IEMDC'03. IEEE International, 2003.

Thorsten Wuest, Daniel Weimer, Christopher Irgens & Klaus-Dieter Thoben (2016) Machine learning in manufacturing: advantages, challenges, and applications, Production & Manufacturing Research, 4:1, 23-45.

Samuel, Arthur L. (1959). "Some Studies in Machine Learning Using the Game of Checkers". IBM Journal of Research and Development. 44: 206–226.

Siebel E, Kobitzsch R (1942) Die Erwärmung des Ziehgutes biem Drahtzienhen. Stahl und Eisen 63(6):110–114

Singh G, Anil Kumar TC, Naikan VNA (2016) Induction motor inter turn fault detection using infrared thermographic analysis. Infrared Phys Technol 77:277–282.

Suliga, M. The influence of drawing speed on surface topography of high carbon steel wires. Metalurgija 2017, 56, 182–184.

Wang, J.B.; Wang, J.; Wu, Y.; Wang, J.Y.; Zhu, H.; Lin, M.; Wang, J. A Machine Learning Framework for Resource Allocation Assisted by Cloud Computing. IEEE Netw. 2018, 32, 144–151.

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