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IFAC PapersOnLine 55-2 (2022) 561–566

Towards a Circular Rotating Blade Wear Assessment Digital Twin for Manufacturing Lines

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Abstract:
Circular blades are well known in sawmills and other fabrication sites such as tyre industries. The cutting process produces wear on the blades which gradually decreases the quality of the goods being cut, and, eventually, it might cause the stoppage of the production line. At the same time, assessing the wear of the blades to avoid these quality losses and breakdowns is not easy, as there are many factors affecting the cutting process and the direct inspection of wear is not practical.

This work proposes the development of a Digital Twin that is linked to the manufacturing line. The twin includes a wear model that is based on the data generated in the line, and, hence, it can be used to identify the wear status of the blade as well as to prognose the development of that wear based on future cutting schedules.

Keywords: Digital Twin, Manufacturing, Wear, Blade, Optimization, Diagnosis, Prognosis.

1. INTRODUCTION

Circular blades are tools widely used for cutting purposes with a considerable presence in the wood machining industry. For that reason, most of the works related to circular blades wear assessment are related to wood material science or wood machining. Nevertheless, cutting is not only present on sawmills, other industries such as the tyre industry also employ circular blades for tread cutting, and the faults and stoppages derived from worn blades have great impact on the tyre production line. For that reason, developing blade wear assessment systems is of great interest.

Assessing wear on a circular blade is complex. The type of material (which impacts on tool wear mechanism), the combination of the different cutting parameters and the mechanical properties of the workpiece make it a complex process to predict (Nasir and Cool, 2020). Common methods to evaluate wear in laboratories are scanning electron microscopy and energy-dispersive spectrometry (Porankiewicz et al., 2015). However, they can not be used for online wear monitoring. For that reason, some works have tried to detect blade condition based on sensor measurements. For example, in Mohammadpanah et al. (2019), different saw deviations or faults are identified by means of microphone, accelerometer, temperature, acoustic emission (AE) and a displacement sensor; other works measure wear by means of acoustic emissions alone, as Siebald et al. (2017); Lemaster et al. (1985) and Nasir et al. (2019). Although promising, the extrapolation of laboratory level sensor data models to real conditions has been questioned (Lau et al., 2000; Nasir and Cool, 2020), particularly in harsh environments as sawmills (Nasir and Cool, 2020).

* This project, known as AI-PROFICIENT, has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 957391

The techniques used in the past for blade wear assessment show some limitations in practice. Regarding pure physical modeling techniques, this type of models are known to require of high detail of the system (An et al., 2013) and tend to generalise badly in applied domains, and other data-based techniques such as the ones based on reliability do not consider the effect of differences on cycle types during a single life observation (Lin, 1998) to the best of our knowledge. On the top of that, the works measuring wear in different periods of time during blade lifes have reported wear rates that follow quite simple patterns. For instance, Porankiewicz et al. (2015) reports edge radius of a circular blade being increasing proportionally with the number of logs cut; Kminiak et al. (2015) identifies three linear relations (one per number of teethes per blade) between the edge recession with sawn distance; and, more complex but yet similar wear rate functions are obtained in Lau et al. (2000), where thin-edge blades with different coatings are compared.

In this scenario, emerging technologies such as Digital Twins (DTs), gain interest. Digital-twins are virtual counterparts of physical devices, representations based on semantic models that allow simulations in different disciplines that can be continuously updated by a real time synchronization with sensed data (Negri et al., 2017). Recently, DTs have gained increasing popularity in fields

10.1016/j.ifacol.2022.04.253

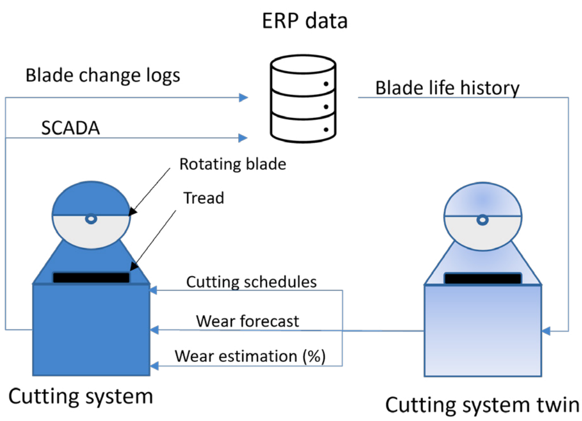

Fig. 1. Schema of the Digital Twin proposed for blade wear assessment.

such as Prognostics and Healh Monitoring (Tao et al., 2019), due to their capability to produce smarter, more efficient and more convenient manufacturing among others (He and Bai, 2020).

Mainly, DTs are built on three basic elements: The physical asset, a digitalized version of the asset, and the data flows that connect them both. Those different levels of integration between the physical and digital counterpart can be distinguished (Kritzinger et al., 2018). Additionally, according to Tuegel et al. (2011), DT should be capable of: Monitoring the product in real time; simulate different operation conditions and environments of the asset; and, based on real-time and historic data, be able to predict the remaining life.

This paper proposes the development of a DT of a cutting blade system. The proposed method is evaluated based on simulated data which is similar to the one produced on a manufacturing line. The data is used to model the wear generated on the blade of a cutting system and the error in the estimation is lastly studied. The solutions tries to overcome the difficulty to adapt modelling methods obtained on laboratory to manufacturing real conditions. For that purpose, the development of the model is based on data produced in the manufacturing line.

2. METHODS

This model relies on the use of historic data of the manufacturing ERP that can be combined with SCADA data to obtain a blade life usage (BLU) history database. The BLU data consists of the ordered cuts per type of tread a blade makes until the end of it's valid life. The DT here proposed might serve for the following purposes:

- Asses current health status (wear) of the cutting system
- Predict the evolution of the wear status based on production schedules
- Propose alternative production schedules to minimize downtime due to repairing

As the model is connected to the manufacturing line, every time new blade lifetimes are stored they can be used to improve/readjust the wear model parameters in a constant manner. Fig. 1 displays the data flows of the proposed solution.

Essentially, this work follows this steps:

(1) Data from a manufacturing line is simulated
(2) Optimization algorithms are used to adjust wear model parameters
(3) Errors are measured

2.1 Simulation

To validate the concept of DT for wear assessment, this work considers that wear is the cause of blades being changed at the end of the life (EOL). At the same time, other factors affecting the life of the blade (such as other failures not related to wear) cause to change the blades before their EOL. These other factors are considered noise.

Wear model

Cutting blade wear modelling has been broadly studied in sawmills. The review provided by Nasir and Cool (2020) compiles the most important sources of variation in wood machining into three groups:

- Blade factors
- Work-piece factors
- Feed factors

In a manufacturing scenario, blade and feed factors can be considered ideally constant, considering the same type of blade is being used and no alterations of the cutting parameters are done during the production.

Regarding the work-piece factor, this work assumes, based on the works showing empirical wear rate measurements, that:

(1) Wear rate follows a simple model
(2) Each material/workpiece/recipe has its own wear rate function

Even thought this model is simple, it addresses two key concepts of wear modelling: The wear variation over time and the different characteristics of each material. In an attempt to mimic wear rate behaviour, various potential wear models are considered, with different number of degrees of freedom. These models are depicted in Fig. 2.

In addition, it is assumed that all blades are changed when they are worn out, and that the other factors that cause blade being change too early or late are noise. Hence, instead of all blades reaching always the %100 of their allowed wear, some are changed slightly before and others slightly later (which is undesired due to decrease in the cut quality).

Observation creation

Estimated wear models are obtained by adjusting the parameters of the proposed wear model with the blade life observations. Ideally, these observations would come from a real manufacturing scenario. In this work, however, they have been created by following the next steps:

(1) Create end of life degradation value: The final wear value reached at the end of the blade life is assigned. The theoretical end of life degradation value (100%)

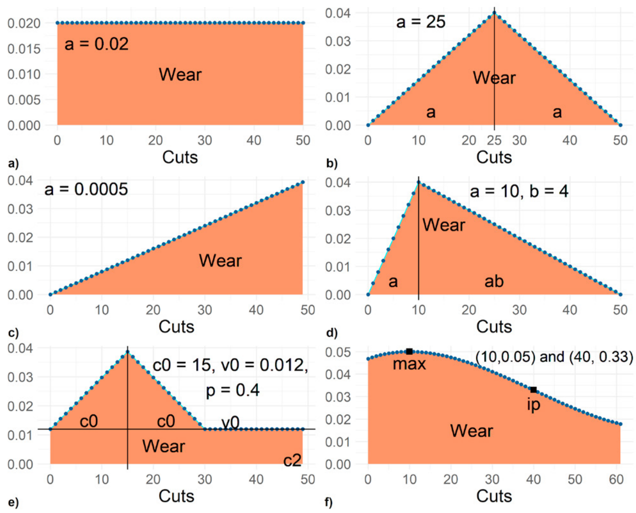

Fig. 2. Wear models considered for the simulation. a) Constant model, $df = 1$. b) Isosceles triangle model, $df = 1$. c) Linear model, $df = 1$. d) Sharp triangle model, $df = 2$. e) Triangle-rectangle model, $df = 3$. f) 3^{rd} grade polynomial model, $df = 4$.

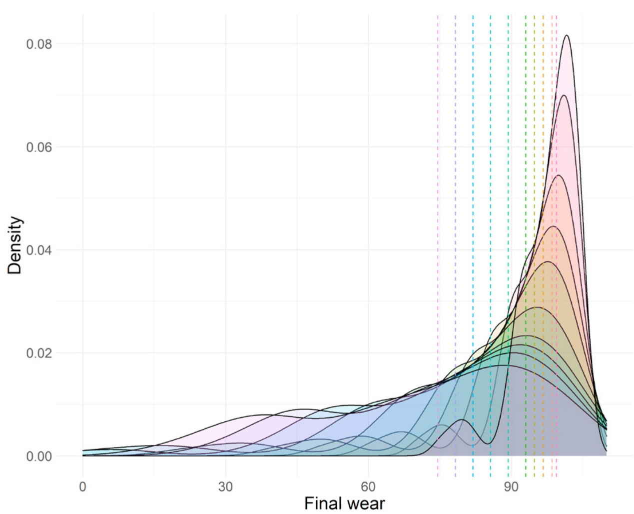

Fig. 3. Different degradation distributions used during the simulations. Vertical line represents meadian value.

is given some noise (that mimics the uncertainty caused by errors/other faults or a late changes of the blade). The distributions of the final degradations (theoretical plus the noise) are displayed in Fig. 3. Each distribution represents 150 blade samples that have different levels of noise.

(2) Assign wear fraction and order of recipes: Each of the previous final degradation values is taken, and, randomly ordering the recipes, fractions of wear caused by each recipe are assigned. The fraction of wear is a random number going from 0 to the final wear left when this recipe is chosen.

(3) Compute equivalent number of cuts: Finally, depending on the wear model that is considered for observation creation, a set of "true" parameters is assigned and used to compute the equivalence by number of cuts that were carried out by each recipe.

The following Table 1 shows an example of a blade life created following this process.

Table 1. Example of a single blade life observation created with a constant wear model, 4 recipes with 0.002,0.004, 0.003 and 0.01 parameter values. Table values in proportions.

Chronology	Recipe	Caused wear	Wear begin	Wear End	Cuts
1	4	0.415	0.000	0.415	41
2	2	0.051	0.415	0.466	12
3	4	0.052	0.466	0.518	5
4	2	0.069	0.518	0.587	18
5	1	0.337	0.587	0.924	169
6	3	0.062	0.924	0.986	21
7	4	0.014	0.986	1.000	1

Note that the final wear proportion (right down corner on Table 1) might not necessarily be 1, as the final degradation value is taken from a distribution.

2.2 *Optimization*

Once the artificial historic datasets are created, it is attempted to find which parameter values might be the real ones by having nothing but the chronology, recipe and amount of cut data of the datasets created in the previous step (Chronology, Recipe and Cuts columns of Table 1). This parameter search is carried out by means of meta-heuristic optimization. Grey Wolf Optmizer (Mirjalili et al., 2014), which mimics the behaviour of grey wolves to solve heuristic problems, is employed. This type of meta-heuristic algorithm is based on the social hierarchy that wolves have and assigns potential solutions a different degree according to their role on the wolf pack (alpha, beta, omega and delta), then, it reproduces the hunting process of the wolves by encircling, hunting, attacking and prey searching.

The objective function is based on the reduction of error for the whole dataset assuming all the blades were discarded at exactly the end of their life ($W_f = 100$) and there was no noise in the data. That is, for each solution (vector of parameters) the error generated by estimating with the potential model and the solution set of parameters the life of all the blades in the whole dataset (z or the total number of blade life observations) is computed, and averaged by meas of root mean square error (RMSE). This value is the fitness of that solution (see equation 1).

$$Fitness = \sqrt{\frac{\sum_{j=1}^{z}(\hat{W}_{fj} - W_f)^2}{z}} \tag{1}$$

2.3 *Error computation*

Throughout the different comparisons made along this work, error has been measured in different ways, according to the limitations of the compared models.

- Curve error
  This work considers that wear rate follows certain functions. When the true wear model is known, it is possible to compare that model with the one obtained from the data by comparing the surfaces of both models. This error is considered the curve error, which represents how well the original wear model has being

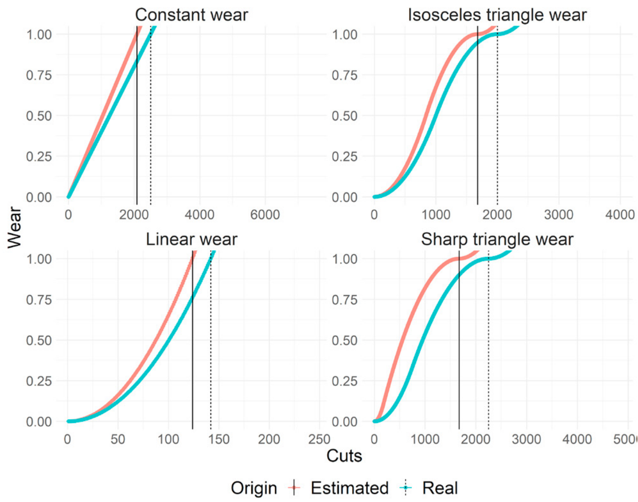

Fig. 4. Wear curves in different wear model experiments. Horizontal line represents 100% value reached.

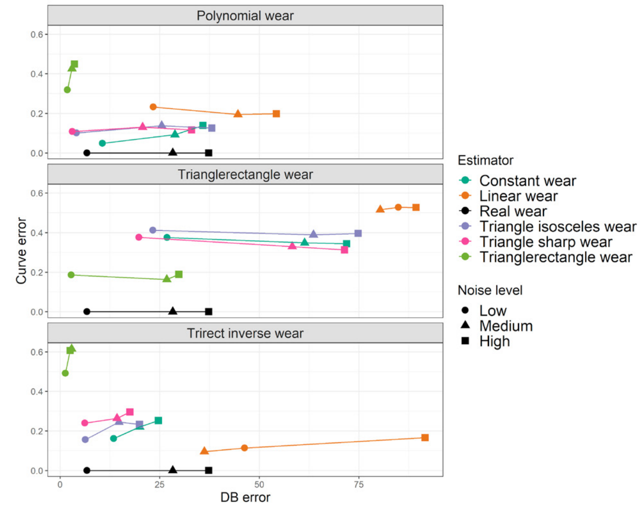

Fig. 5. Various complex wear models estimated with simpler models under different levels of noise.

captured by the estimated one. The error is computed as RMSE of the difference between the estimated wear function and the wear function of the original model.

- Blade database error
  In the case where the true wear model is unknown the curve error can not be computed. As in a real scenario this true wear model is unknown, this alternative metric is proposed to compute how well the model explains the database. This is computed as the RMSE between the final degradation estimated by the model and the theoretical degradation at the end (100%). Note that this metric is the same as the Fitness during the optimization process.

3. RESULTS

Within the simulation wear rate models are employed to create the blade life observations. Later, those observations are used to optimize the parameters of potential models that have similar shapes or potential models that are not so similar in nature.

Regarding the possibility to identify the parameters of the potential model when the real model that created the observations is known by only using the cuts per recipe, the following Fig. 4 shows the example of 4 types of models in which it was possible to identify the original parameters through the optimization. In general, tracing back the original parameters by using the same model is feasible, although there is some error that tends to be greater in more complex models, this error is, however, unavoidable, as the noise induced in the origin is unknown during the optimization and, as it tends to cause blade to be changed before really reaching 100% degradation, estimations, that fit the data, consider final degradation is reached earlier, as they also model the noise added to the theoretical degradation.

The following Fig. 5 displays the differences in errors when the models used for the wear modelling are more complex and unknown and they are approximated by means of simpler models. In general, the trend is to have lower errors in both database modelling and curve modelling with lower noise values, however, the impact is greater in the reduction of database error. This is related to the objective function, as the fitness tries to adopt parameters that already focus on reducing this error, the noisier the original distribution is, the more difficult it is to identify parameters that have lower errors within the database. Additionally, it is interesting to mention that even thought the curve error is always null for real wear models, its database error can be much higher than with the estimator models. This happens because the original wear model is not optimized to the database and uses noise as an input, at the same time, during the estimation the fitness causes the estimated model to decrease that error. Hence, estimated models do not model the original wear, they model the database, which causes interesting effects as the case of the triangle-rectangle wear model, that, having more degrees of freedom, is able to adjust the database (wear plus noise) with much higher accuracy but at the same time has highest curve errors, meaning it is not approaching to the real wear model. It is also remarkable to mention that this model works worse when it is used to estimate a database that has been created by a model of equal shape, which might be caused by the existence of local minimums.

Taking a closer look to the wear curve estimations for the polynomial case in Fig. 6, it is visible that while most of the models try to approach the original wear model, triangle rectangle model has a completely different shape, focusing on the minimization of the error in the database. In addition, note that most of the estimated models tend to converge the point in which the 100% wear is reached, which does not coincide with the real model that does not include the noise.

In addition to the effects of noise presented in Fig. 5, the following Fig. 7 provides a deeper insight on how the quality of the data could impact the estimation of the parameters. This is mimicked by using all the different distributions of Fig. 3 ordered from noisiest distribution to less noisy, and then, launching the optimization with a fixed window size of 60 observations which is passed

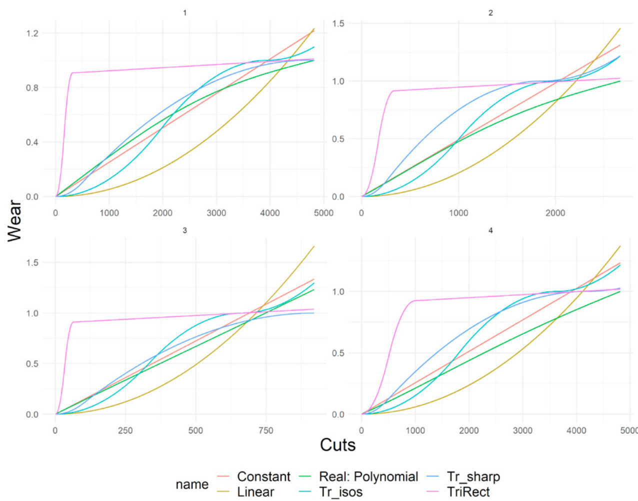

Fig. 6. Estimate wear profiles when polynomial model used for creation of real profile.

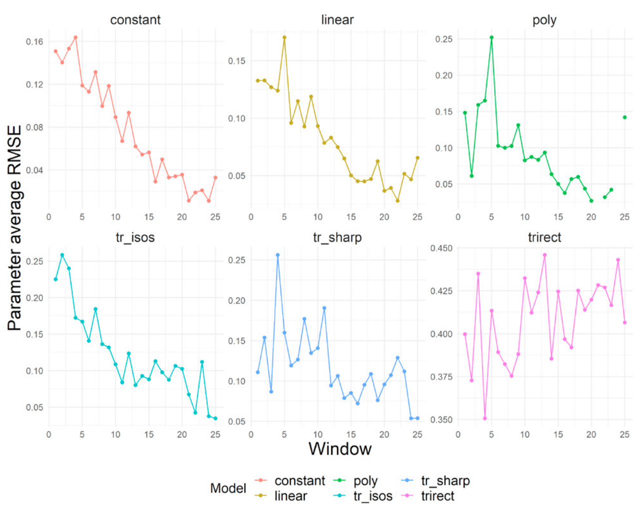

Fig. 7. Evolution of curve error with decreasing noise in degradation distribution.

over the whole dataset. With the results shown in Fig. 7 it is clear that the closer (more centered around) to 100% the degradation distribution is, the easier it is to approximate the real parameter values. Which does not occur for triangle rectangle model, which again with its more flexible modeling rules is able to focus more on the noise than in the underlaying wear model, hence, it does not converge if compared to the real model.

4. CONCLUSIONS

This work envisions and tests a simple DT twin of a cutting blade system that can be used for diagnosis and prognosis purposes on blade wear assessment. Furthermore, the simplicity of this DT allows to modify and optimize the scheduled cuts so that the repairments can be addressed minimizing production stoppage.

The interest on this work resides on the fact that holistic blade cutting physical models are complex, and, generally, they tend to be hardly extrapolable from laboratory validation to manufacturing sites. Instead, the method here proposed is based on the bottom up approach, where a simple wear model is deployed and linked to the manufacturing site and it is tuned through optimization with on-site data, which should provide a much better generalisation of the wear assessment. In addition, the consideration of different usage patterns through a blades life allows a better prognostic of life estimation and scheduling of productions, which provides greater insight than other widely used data-based models such as the ones based on reliability.

Although this work is a proof of concept and should be validated in real manufacturing scenarios, some interesting hints have been discovered.

Most importantly, the role of noise must be remarked. In this work noise is considered any factor which might impact the life of a blade which is not related to material mechanical properties and usage (number of cuts). This might include environmental parameters such as temperature or humidity; or other related to the cutting system that might affect the degradation of the blade. In any case, it is clear that the fewer noise there is in the blade observations the easier it is to model the real wear process with higher accuracy. Furthermore, having a Digital Twin model connected to a manufacturing line and being able to trim blade observations that are clearly not influenced by wear but by other phenomenons would improve the estimation of the blade degradation.

Another interesting finding is related to the importance of the objective function and the correct wear modelling. In a real scenario knowing which is the real wear model is not possible, hence, the curve error can not be measured and it is not possible to know which estimation model is better at capturing the true behaviour of the wear. However, and paradoxically, it is possible to find a quite simple model that captures the effect of the original wear model and the noise that causes early death of the blades. Even if this model is not physically accurate, it provides better estimations of the blade life, which is what the final user really wants.

In this scenario, two aspects must be remarked for a more accurate modelling of the wear process. Firstly, that simpler models with less degrees of freedom and based on physical constraints should be used; and, secondly, that more importance should be given to the observations (blades) with the longest lifetimes, as they should be the ones with less external effects.

In sight of these findings, the interest on testing this approach on real scenarios is clear, due to its simplicity and potential. However, as it is quite dependent on other factors that might alter wear, this basic model would probably need to be improved further by stacking additional technologies such as current/force sensors that would enable the real-time recognition of other non-wear related faults. Furthermore, studying methods to weight observations or to filter them might be of interest in order to better understand the behaviour of wear in this kind of manufacturing scenarios.

ACKNOWLEDGEMENTS

This project, known as AI-PROFICIENT, has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 957391

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