PREDICTIVE MAINTENANCE BASED ON FOUR PARAMETERS ON AN INDUSTRIAL TEST BENCH

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ABSTRACT

This project aims at validating the assumption of predictive maintenance based on four parameters. The economy of Northern Quebec region is highly dependent on iron and aluminium production and transformation. Related industrial activities ensure employment for a large proportion of the population. Traditional maintenance is no longer enough to ensure competitiveness of these companies. Optimised asset management and maintenance is essential to reduce production cost and machine downtime. This project has as objective the development of a high precision maintenance method embodying instrumentation, statistical and numerical modeling techniques.

The targeted technology will have as objectives to increase condition monitoring precision, reduce required maintenance interventions, improve reliability, reduce maintenance cost and allow better recognition of factors (internal and external) influencing machine element deterioration. The developed model is tested and refined on an industrially inspired test bench at Cégep de Sept-îles. The final aim is to compare the different trends (statistical, specifications and numerical simulation) to establish a mean algorithm that will encourage the achievement of the enumerated objectives. In this paper, we establish the motivation of the work, definition of the test bench, experimental model, simulation model and manufacturer's specification model. Preliminary results are also presented as well as future work required for the final definition of this technique. Final results and technique efficiency validation will be obtained and performed once all experimental results on "in operation" test bench are obtained.

Keywords: *predictive maintenance, instrumentation, test bench, numerical simulation, wear, degradation, multiphysics.*

Abbreviations:

PM Preventive maintenance
i ordinal load cycles
$h_i(t)$ system hazard rate function prior to the ith preventive maintenance, PM, activity
T_i time interval for PM prior to the ith PM
r radius
R system reliability threshold for scheduled PM
C_{up} expected cost rate for unscheduled PM
C_{sp} expected cost rate for scheduled PM
τ_p duration of PM, same for scheduled PM and unscheduled PM
$Cost_r$ additional replacement cost
CE_r expected cost per unit time for the system in the residual life

INTRODUCTION

For most systems, failure is a dangerous or costly event. In a region like Sept-Iles, on the North Shore of Québec province, production needs to be continuous in order to ensure availability of spare parts for major mining companies of the region which operating on an incessant basis. The available information on the failure time is often not very accurate because of the great variability of elements belonging to the same population. Classical preventive maintenance policy leads to elements being replaced before complete exploitation of the useful life. Hence, failure risk is reduced but maintenance costs and maintenance frequency is increased. The need for accurate condition based maintenance, that is, predictive maintenance based on precise recognition of element health in real time is important for risk free and low cost maintenance policy application. This paper focuses on the preliminary work and results obtained within a project at developing a new predictive maintenance technique. The project aims at the validation of the assumption of predictive maintenance based on four parameters: manufacturer's specifications, statistical data, instrumentation and numerical simulation. The "Institut Technologique de Maintenance Industrielle (ITMI)" has as mission to accompany companies in achieving maximum efficiency and optimized asset management. Based in the region of Northern Quebec (Sept-Îles) and part of the Cégep de Sept-Îles (CSI), the Institute is in the heart of Northern Quebec mining industry development. Optimised asset management and maintenance is essential as it highly reduces production cost and avoids machine downtime - essential in the present economic situation. Worldwide competition is fierce and the price of iron and aluminium low. Numerous small and medium enterprises (SME) are subcontractors of the major mining and metal transformation companies and ensure employment for a large proportion of the population as well as the development of communities where they are located. Traditional maintenance is no long enough to ensure competitiveness of these companies. This paper illustrates a project aiming the development of a high precision maintenance method that will significantly reduce cost and frequency of checks as well as better asset management.

In this paper, we establish the motivation of the work, definition of the test bench, experimental model, simulation model and manufacturer's specification model. Preliminary results are also presented as well as future work required for the final definition of this technique. Final results and technique efficiency validation will be obtained and performed once all experimental results on "in operation" test bench are obtained.

BACKGROUND

CSI has ensured training and technical help regarding traditional maintenance of the numerous industries harboured in Northern Quebec region for more than 20 years. The need for more cut edge maintenance has encouraged the college to set up ITMI which sets the path for more sophisticated and result oriented maintenance that blends itself in the present economic condition. Predictive maintenance allows scheduling maintenance with the least effect on activities and unexpected equipment breakdowns and scheduled maintenance downtime is virtually eliminated. Literature undoubtedly encourages predictive maintenance over traditional routine maintenance. Our on field evaluation supports this need. [1-5] all justify the advantages of using predictive maintenance to even quantify the relative per horsepower cost of maintenance. However, as [6] puts it – preventive or predictive maintenance is rarely performed in industries due to time pressure. Therefore, there is need to develop a tailor made approach that perfectly inscribes the maintenance measures in the activities of the industry. Furthermore, literature shows that predictive maintenance is most of the time based on the follow up of one parameter as in [7]. The need to be more precise in predicting failure in machines and in an attempt to encourage training allowing optimised and diligent implementation of predictive maintenance routines in companies has been the motivation to the project illustrated in this paper. The methodology was developed and tested with Métal 7 Company. Located in the main industrial region for iron ore in Canada, Metal 7 has a very firm grasp of the needs of major mining companies and SME for whom, through its R&D department, manufactures durable, high-performance equipment. Metal7 dynamism and involvement in the community as well as worldwide business will propose a number of advantages on training, the local community and for knowledge improvement in the field.

PROJECT DESCRIPTION

Industrial activities rely on the proper functioning of mechanical equipment. It is necessary to control the reliability of the equipment to optimize maintenance planning and minimize costs. Various methods can be used to assess the remaining lifespan of a machine element prior to next failure. Condition based maintenance information can be inferred from:

1.the manufacturer's specifications, duration of operation and operating conditions; 2.instrumentation data from installed sensors;
3.statistical data on failure ; 4.numerical simulation results.

When maintenance is planned according to manufacturer's specifications, duration of operation and operating conditions, the equipment is replaced in accordance with manufacturer's specifications regardless of the actual wear. Manufacturer's specifications are usually built according to machine element degradation trend in controlled environment which may differ from actual situation. When maintenance plan is based on instrumentation and statistical data, the machine element is replaced according to measured values from sensors or when the probability of failure is greater than or equal to a selected threshold. Systematic and random errors from sensors as well as installation limitations can limit sensors' accuracy. During operation, conditions vary, the probability of failure is calculated with conservative parameters and calculated life is less than the actual life. When maintenance is scheduled based on the results of numerical simulation, it is possible to take into account the variation of the operating conditions in the calculation of the probability of failure. This allows for a more precise calculation of remaining lifespan and machine element is kept in operation longer. Furthermore, simulation allows us to study the effect of modifying the design of a product over its useful life. It also allows infer the effect of chosen operating parameters on the lifespan of a product. The simulation is useful to optimize the design and operation of industrial equipment. However, numerical simulations have numerous limitations including: model precision, mesh precision, resolution scheme precision… The idea behind this project is to evaluate the correlation between degradation trends monitoring according to the four different techniques and compare the techniques within a mathematical model for error cancellation between the trends.

COST MOTIVATION

In this section, we wish to demonstrate the cost effectiveness of this four parameter damage accumulation monitoring policy versus a traditional preventive maintenance policy. Using 4 different parameters of wear and degradation monitoring, the aim is to increase the number of cycles by a more precise wear and degradation monitoring scheme – the aim is to increase the number of cycles of a given machine element whilst ensuring reliability of system.

According to [8-11], reliability can be expressed as follows:

$$e^{-\int_0^{T_1} h_1(t)dt} = e^{-\int_0^{T_2} h_2(t)dt} = \cdots . e^{-\int_0^{T_N} h_N(t)dt} = R \ldots\ldots\ldots\ldots (1)$$

From figure 1, excerpt from [12], showing hazard rare evolution against hybrid evolution model for system hazard, we note that the relationship between hazard rate functions before and after *i*th PM can be expressed as:

$h_{i+1}(t) = b_i h_i(t + a_i T_i)$ for $t \in (0, T_{i+1})$……………………………(2)

$0 < a_i < 1,\ b_i > 1$ are age reduction factors and hazard rate increase factor respectively.

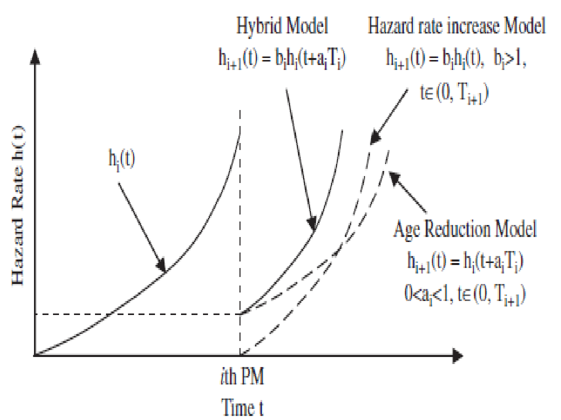


Figure 1: Hybrid evolution model for system hazard rate

Replacing equation (2) in (1), we have:

$$\int_0^{T_1} h_1(t)dt = \int_0^{2} h_2(t)dt = \cdots\ldots = \int_0^{T_N} h_{(N)}(t)dt = -Ln\ R \ldots\ldots\ldots\ldots (3)$$

$\int_0^{T_1} h_1(t)$ represents the cumulative failure risk in maintenance cycle *i*. This implies that cumulative cycle is equal to –R.

We will now compare maintenance cost efficiency for our aimed model versus traditional preventive maintenance models.

For preventive models:

$$R = e^{-\int_0^{T_N} h_N(t)dt}$$

In our case:

$$R^1 = \frac{e^{-\int_0^{T_N} h_{N'}(t)dt} + e^{-\int_0^{T_N} h_{N''}(t)dt} + e^{-\int_0^{T_N} h_{N'''}(t)dt} + e^{-\int_0^{T_N} h_{N''''}(t)dt}}{4}$$

…………(4)

For the same reliability, the number of cycles can be increased and hence relative maintenance cost is reduced for same reliability as expressed by equation (5). As numerators (function of R) are logarithmic functions, and cycles as denominators, for same R, *i* is increased and maintenance cost is reduced:

$$C_{Eri} = \frac{C_{up}\tau_p(-\ln(R)) + C_{sp}\tau_p(1 + \ln(R))}{T_i + T_p}$$

………………(5)

TEST BENCH

Four parameters based predictive maintenance calibration and study was performed on an industry inspired and supported test bench at "Cegep de Sept-Îles". The test simulated a braking system on an inertial rotating mass. The inertial start – braking system was automated using an Allen bradley programmable logic controller. Figures 2 and table 1 illustrates the test bench set up and tested for the purpose of this project.

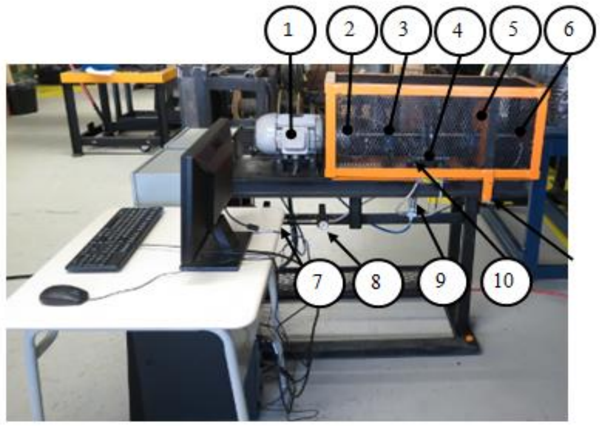


Figure 2: Test bench used for technique validation

Table 1: Test bench description:

#	Description
1	Electrical engine 208V 2hp
2	Pneumatic clutch
3	Bearing
4	Pneumatic brake
5	Inertial disc
6	Pressure power transmitter
7	Pressure regulator #1
8	Pressure regulator #2
9	Pressure sensor
10	Temperature sensor on brakes
11	Security button

A *Horton/ Nexen*@ brand 835000 model DB caliper less brake disc was used. The brake was pneumatically activated. A Red Lion angular speed sensor was used to measure this quantity on the brake at all times. The idea is to be able to ensure reproducibility of the experiment and availability of enough information for the construction of numerical and manufacturer`s specifications correlation. The *Red Lion*@ IFMA model accepts a frequency input, and outputs an analog voltage or current in proportion to the input frequency, with 0.1% accuracy. The programmable minimum and maximum response times provide optimal response at any input frequency.

The objectives of the project, as mentioned in the abstract are not only to better predict wear level but, also, to understand wear triggering parameters. A pressure sensor was used to evaluate the pressure applied by the brake pads on the inertial disc. This data was also used to build the numerical model. The *Dwyer*@ 626 pressure transmitter converts a single positive pressure into a standard 4-20 mA output signal. Accuracy of instrument is specified at 0.25 to 1%.

For similar motivations as the pressure sensor, a *Phoenix*@ brand, configurable temperature transducer for thermocouple types J and K was used (model: MINI MCR-SL-TC-UI). The sensor accuracy is specified to be 0.2 %.

Finally, in order to measure the wear on the braking pad, a *Hoskin*@ (KL series) conductive plastic potentiometric position transducer was used. The accuracy of the sensor is specified at 0.1 %.

INSTRUMENTATION ERROR ANALYSIS

The brake pad wear measurement is dependent of 1) the accuracy of the *Hoskin*@ sensor, 2) the quality and accuracy of the sensor fixture and 3) the alignment accuracy of the inertial disc as can be inferred from figure 3 below, which illustrates the sensor fixture relative to the inertial disc and brake pad.

Figure 3: Hoskin displacement *sensor fixture*

Such analysis is essential as the wear is very small for 20 000 cycles – around 0.12 mm. Hence, even minor errors in the alignment or fixture can bring large percentage errors in the wear value. This was actually the case for our measurements. Figure 4 shows results we obtained from our bench test when we compared wear (in mm) against energy developed and dissipated by the inertial-braking system after 150 hours operation. For increasing developed and dissipated energy, simple logic will lead us to anticipate increasing wear on the pad. However, we noticed that, the wear trend is basically unchanged and we can even detect wear reduction at certain intervals of increasing dissipated energy. It is clear that this is impossible. The reason behind such irrational measurement is that alignment error increased at a comparable rate to wear rate with energy application.

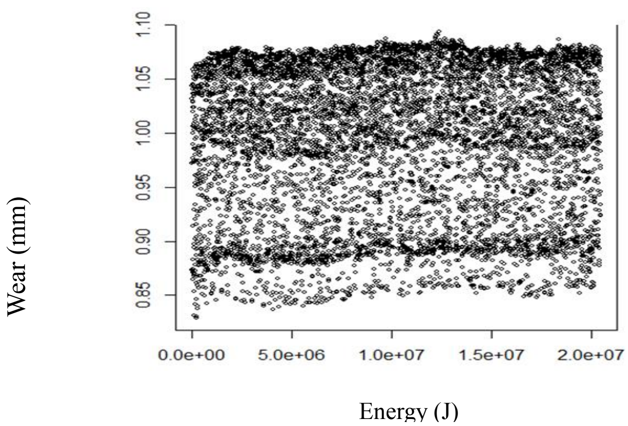


Figure 3: Results obtained after 150 hours operation

In order to cancel the errors, preliminary measurement tests were performed with pre-measured and known wear at the same energy operating regimes to evaluate the errors. The corrections were brought to minimize the errors. The interest here is that our model can, hence, be applied to high precision requirements where minor wear needs to be detected. Furthermore, it is interesting to note that statistical means exist to identify and correct such errors: figure 4 represents the probability density of the residuals of the linear regression model whereas figure 5 represents the probability density of misalignment.

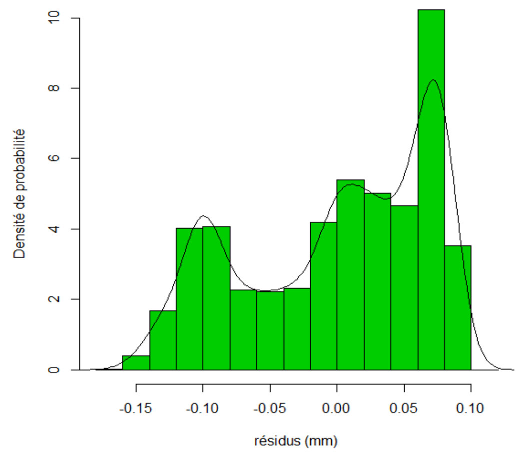


Figure 4 : Probability density of the residuals of the linear regression model

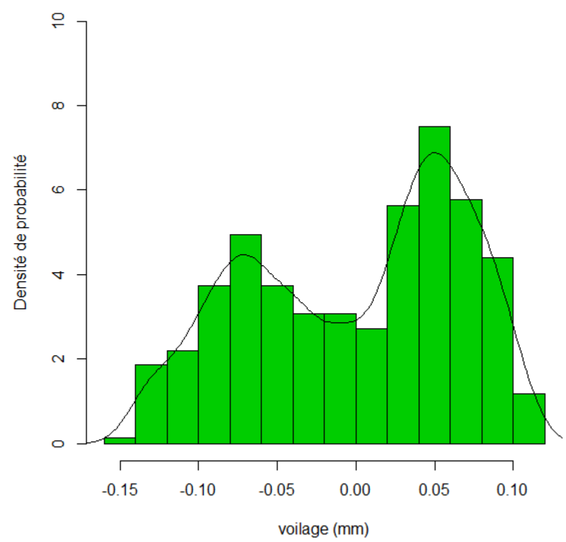


Figure 5: Probability density of misalignment

Figures 4 and 5 show that the shape of the probability density of the residuals of the linear regression model is very similar to the probability density of misalignment of the inertial disc. The difference between the minimum and maximum alignment values as well as the minimum and maximum residuals of the regression model are presented in table 2 which follows.

Tableau 2 : Comparison of the deviation of alignment value and residuals of linear regression model

Parameter	
Alignment deviation	0.254 mm
Deviation of residuals of linear regression model	0.265 mm

The two values are very close to each other. Figures 4 and 5 show that the dispersion of wear measurements can be explained mainly by the misalignment of the inertial disc.

The mode of operation of the inertial-brake system has been established by the Grafcets presented in figure 6.

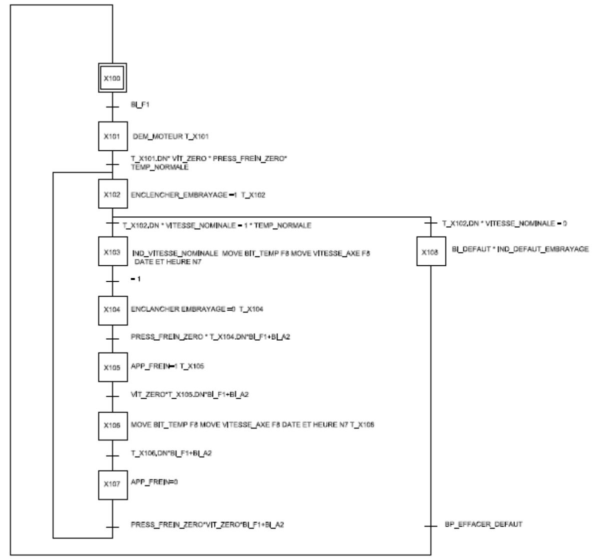
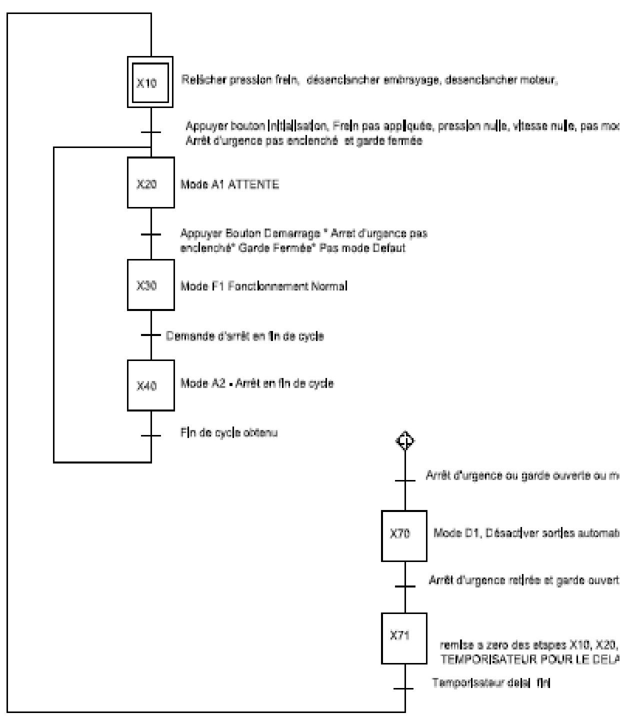


Figure 6 : Grafcets set up for operating regimedefinition of test bench in programmable logic controller



SIMULATION MODEL

Numerical simulation model as an intrinsic part of predictive maintenance can be of upmost interest. A numerical model may have numerous limitations including disturbance modelling limitations, mesh precision, resolution scheme… However, numerical models can simulate results according to any operating regime and external conditions (intrinsic of model) and becomes an excellent comparison trend to identify bad quality instrumented data, systematic and random errors. Furthermore, numerically generated degradation trend according to actual operating parameters and external conditions can be valuable data to correct manufacturers' specifications data usually generated according to different operating and external conditions.

In our case, a numerical model simulating the inertial-brake system was built using ANSYS and the model was calibrated using a Matlab based finite element model:

$$\frac{\partial \sigma_r}{\partial r \partial t} = \frac{\partial \left[E\alpha\Delta T + E\frac{\partial \omega_1}{\partial r} + F(brake) \right]}{\partial r \partial t} \dots\dots (6)$$

The system is discretized over finite elements and integrating over a rotating disk

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of radius r. The applied force F is discretized over same finite elements but integrated over a smaller disk of radius r''. The area of the disk corresponds to the area of the braking pad with an error of 4%.

Therefore:

$$\int_0^{2\pi} \frac{\partial \sigma_r}{\partial r \partial t} - \frac{\partial \left[E\alpha\Delta T + E\frac{\partial \omega_1}{\partial r}\right]}{\partial r \partial t}(rdrd\theta) - \int_0^{2\pi} \frac{\partial [F(brake)]}{\partial r \partial t}(r''dr''d\theta) = 0 \dots\dots\dots\dots\dots\dots. (7)$$

Local displacements are then expressed as nodal displacements:

$$\omega'(r') = \omega'_1 + (\omega'_2 - \omega'_1)\frac{r'}{r}$$

$$\omega'(r') = \left[(1-\frac{r'}{r})(\frac{r'}{r})\right]\begin{Bmatrix}\omega'_1\\ \omega'_2\end{Bmatrix}$$

$$\omega'(r') = [N_1\ N_2]\begin{Bmatrix}\omega'_1\\ \omega'_2\end{Bmatrix}$$

Hence:

$$[N] = \left[(1-\frac{r'}{r})(\frac{r'}{r})\right]$$

$$\left[\frac{\partial N}{\partial r'}\right] = [N'] = \left[(-\frac{1}{r})(\frac{1}{r})\right]$$

Shape function development leads to the first contributing term to the matric rigidity:

$$\int_0^r \frac{d\partial\omega'}{dr'} EA \frac{\partial \omega'}{\partial r'} \partial r' = \int_0^r [\partial\omega']\{N'\} EA [N'] \{\omega'\} \partial r' = [\partial\omega'][S']\{\omega'\} \dots\dots\dots (8)$$

Comparing and developing equations:

$$[S'] = EA\begin{bmatrix}\frac{1}{r} & -\frac{1}{r}\\ -\frac{1}{r} & \frac{1}{r}\end{bmatrix}$$

Similarly, other matrix rigidity terms are developed. The model allowed us to define functioning temperature and stresses for one operating ω value and applied brakes pressure. This model was used to build and calibrate an ANSYS based model used for establishment of the 4 parameters based predictive maintenance policy.

The ANSYS based model was built and run for the following compared test bench operating parameters. Manufacturer's specifications data were also correlated to the same parameters. Figure 7 illustrates the Thermal distribution on the brake inertial disk just after zero angular velocity is attained after brake application. Table 3 describes operating parameters and conditions used for experimental measurements, numerical model design and manufacturer's data correlation.

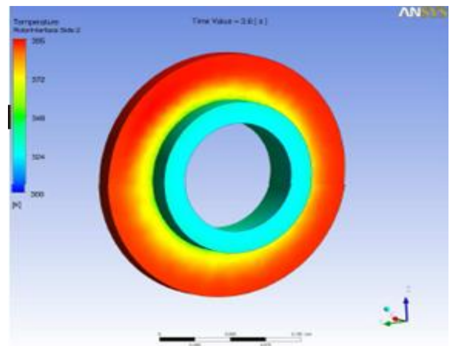

Figure 7 : Thermal distribution on inertial brake disc at establishment of zero angular velocity.

Table 3 : Operating parameters and conditions of numerical, experimental and manufacturer's models.

Working, simulated and specification corrected parameters	Value	Unit
Total inertia	507,44	lb/in^2
static torque factor	144	lbf
Dynamic torque factor	122,4	
Baking torque	520,2	lbf.in
Rotating speed, ω	180,118	rad/s
Brake disc inertia	50	lb.in^2
Specific heat capacity of brake disc	0,5	kJ/(kg°K)
Mass of braking disc	1,8	kg
Time to accelerate the drive wheel	5	s

Brake pad thickness	7,87	mm
Time to brake	0,455076549	s
Number of cycles in an hour	360	

MANUFACTURERS' SIMULATED MODEL

The life cycle of the manufacturer is defined to be 1244 hphr which is a measure of energy. The maximum power applied on the system was averaged over the disk acceleration and braking cycles and the estimated manufacturer specified life cycle is 1386388.

RESULTS

At this point, experimental data have been acquired for 18 816 cycles. The wear values obtained experimentally from the test bench were corrected to mitigate errors and compared to results generated by the numerical model and the manufacturer's specification to test bench operation correlated values. Statistical models were used to correct and improve quality of the experimental data. Table 4 presents the results obtained according to the different models.

Table 4: Wear values obtained according to instrumentation, numerical model and manufacturer's specification data correlation

cycles	wear in mm (instrumentation)	wear in mm (numerical model)	wear in mm (manufacturer's spec)
0	0	0	0
855	0,01651	0,01543	0,004787
3495	0,01651	0,01685	0,019567
4660	0,03556	0,03356	0,026089
5203	0,03683	0,03645	0,029129
6224	0,04699	0,04452	0,034846
7013	0,04826	0,046522	0,039263
7839	0,04826	0,047899	0,043887
9096	0,05715	0,05252	0,050925
10297	0,05715	0,05822	0,057649
18816	0,0889	0,089125	0,105343

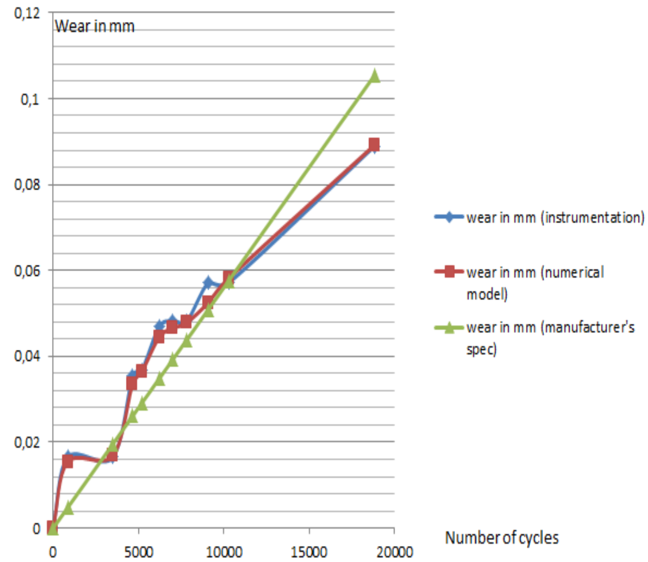

Figure 8 : Wear trend obtained according to instrumentation, numerical model and manufacturer's specification data correlation

It is interesting to note that 1) the three models provide very close values and 2) that the manufacturer's specifications data are more conservative than the data generated by the other models. This was actually anticipated and was actually the aim of the study. The idea is to develop precise degradation monitoring models that provide close values to manufacturer's specified data that are usually used for preventive maintenance. The precise but less conservative trends will allow for less frequent maintenance, lower maintenance cost but high reliability level. In order to establish an algorithm that will use the different models to establish more precise failure occurrence, the experimental tests needs to be run a few reproducible time till failure.

However, in anticipation of the experimental data availability, a preliminary function tending to identify anticipated failure has been built using Matlab$^{@}$. The algorithm based function is expected to be an average of the different models as illustrated in figure 9 below:

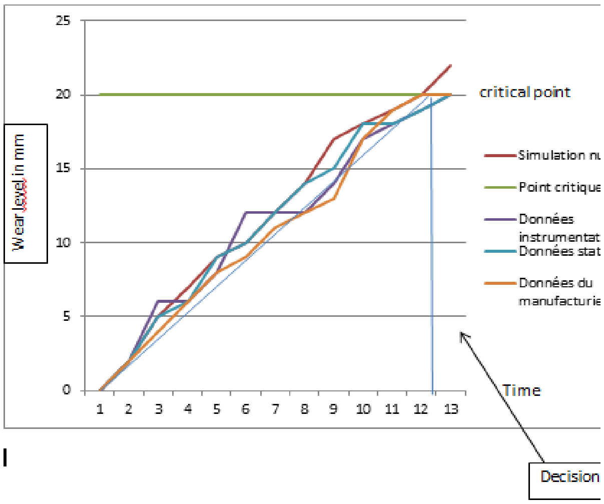

Figure 9: Expected averaged function attempting to predict failure such that reliability is maintained while maintenance frequency and cost reduced.

Using Excel and Matlab[@], polynomial functions of each model were built with criterion- close fit of model data:

1) Numerical function model :

$$f(x) = 3.10^{-18}x^4 - 9.10^{-14}x^3 + 7.10^{-10}x^2 + 4.10^{-6}x + 0.004$$

2) Experimental function model :

$$f(x) = 5.10^{-18}x^4 - 2.10^{-13}x^3 + 1.10^{-9}x^2 + 3.10^{-6}x + 0.0047$$

3) Manufacturer's specification correlated function:

$$f(x) = -3.10^{-30}x^4 + 2.10^{-25}x^3 + 3.10^{-21}x^2 + 6.10^{-6}x + 8.10^{-14}$$

Matlab[@] was used to generate an average function illustrated in thicker blue which is anticipated to provide a better predictive maintenance policy according to objectives specified in this project. The generated trend is illustrated in figure 10.

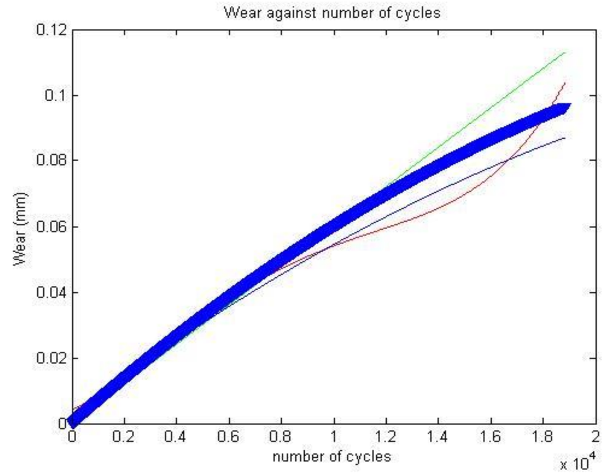

Figure 10: Matlab generated averaged wear function

Green trend: Manufacturer's specifications

Red trend: Experimental data

Purple trend: Numerical data

Thick blue trend: Averaged function

CONCLUSION AND FUTURE WORK

This paper illustrated work performed to set up a new predictive maintenance technique aiming at improving reliability whist reducing maintenance frequency and cost. The test bench used to develop the experimental model has been illustrated and explained in this paper. Particular emphasis was laid on the need for data quality control in order to ensure accuracy of instrumented data. A numerical model was also made and illustrated. The numerical model was itself counter compared with another model to ensure accuracy. The two models were compared with manufacturer's specifications to calculate an averaged function which could be used to identify failure and help for decision taking for maintenance activities. Future work will comprise of the conclusion of experimentation on the test bench until failure. The aim will then be to improve the different models and the averaged function such that it can fit to identify the failure at the same cycle number or before but with less conservativeness than the manufacturer's specified data. Afterwards, the model will need to be validated and performance analysed for different machine element operating regimes and different machine elements.

SUPPORT

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