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Guidelines for Machine Tool Sensing and Smart Manufacturing Integration

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Abstract

Nowadays the Industry is becoming increasingly competitive with the emergence of even more advanced technologies. This environment leads the companies to look for a bigger availability of the assets, a higher quality of the products and consequently less costs. Thus, is because of this purpose that Maintenance is becoming even more fundamental. The focus of this paper was to develop a strategy of Predictive Maintenance on a Machine Tool with the aim of reducing the unplanned stops, increasing the productivity and creating the bases for an Industry 4.0 environment in the short term. Thus, a model has been created in order to fulfil this goal. The first step was the selection of the critical component of the machine tool that would be studied. In the next phase the variables that will be monitored were selected and their trigger limits. Finally, the necessary components to monitor this system were chosen. In order to reach the objective, a system of condition-based maintenance where the acoustic emissions and vibration of the bearing of a machine tool were monitor was proposed.

Keywords: Machining; Machine Tools; Maintenance; Industry; Industry 4.0; Smart Manufacturing; Vibration; Acoustic Emission, Bearing.

1. Introduction

Maintenance represents a significant part of the costs in an organization, because impacts in the productivity, availability and quality of the equipment and final products [1]. In this way, Condition-Based Maintenance (CBM), or Predictive Maintenance, is an important tool to reach these objectives in a more automatized and effective way. CBM consists of monitoring the condition of an asset in real time, using sensors that can measure different parameters according to the component under monitoring. By being aware of the current state of the equipment, it is possible to know the existence of failures, predict when they will arise and, thus, planning the maintenance actions correctly in a timely manner, avoiding unplanned downtime. This reduces maintenance costs, increases machine availability and thus increases productivity [2,3].

This paper is divided into five chapters. In the Introduction, an approach to the problem is performed, in the Literature Review, the theoretical foundations that underlie the development of the model are described, in the Methods the main characteristics of the problem and model to solve them are presented, in the Results are presented the outcomes, in the Case Study the developed model is validated and in the Conclusions the achievements are highlighted.

2. Literature Review

The changes that have been happening over the years in the industry have been brought important technological developments. This evolution has enabled organizations to acquire tools to improve their maintenance strategy, to achieve the excellence and competitive advantage required for their success [3].

Condition-based maintenance (CBM), or predictive maintenance, is a technique that defines maintenance actions based on the actual condition of an asset [4]. The main advantage is these actions are only triggered when there is

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evidence of poor equipment condition, reducing the number of unnecessary maintenance tasks, prolonging the equipment's service life and thus reducing maintenance costs [5,6]. This maintenance technique can only be applied because, before a failure occur, some components undergo a degradation mode or display indication that it will happen. Another relevant advantage of this technique is that the measurement can be done without interrupting the machine operation [7]. Thus, in an industrial unit, the application of a predictive maintenance technique is an advantage [8]. It applies devices such as sensors to detect failures, which were otherwise unnoticeable. With the emergence of the fourth Industrial Revolution, Industry 4.0, there is the possibility of adding more sophisticated, intelligent and higher value devices, and to offset the disadvantage of CBM's implementation of collecting and analyzing a large amount of data [9]. Industry 4.0 involves the incorporation of tools and methodologies into the productive system. Emerging technologies will lead to today's isolated productions becoming fully integrated, automated and optimized throughout the value chain [9,10].

In the field of computer numerical control (CNC) machines, particularly in Swiss lathes, predictive maintenance plays an important role. These machine tools are responsible for producing high precision and quality parts, and so their degradation must be known. CNC lathes have the advantage of being programmable, which translates into great dimensional accuracy and good reproducibility of the manufactured parts. These lathes have tool-holder systems that include the various cutting tools the programmer can use [11]. The spindle system is one of the critical subsystems of this type of machine tool [12]. The spindles on these machines have two tasks: rotate the work-piece precisely, and transmit the required energy in the cutting zone for metal removal [13]. Therefore, they have a direct influence on the quality of the work-piece [12]. The main components that fail in the spindles are the stator, the rotor and the bearings, being that bearings account for about 50% of failures in electrical machines [14]. Failure of bearings causes catastrophic damage to the spindle, which in turn causes machine failure [15–17]. These components are not expensive when timely replaced, but when damage spreads to the spindle and consequently to the lathe, the costs can be severe. Some of the reasons for failure of this component are low lubrication, overload, improper installation and spindle imbalance and misalignment [18]. Bearings are widely used as they are economical and reliable [19]. However, implementing a predetermined maintenance strategy on this component becomes difficult as machines work at different rotational speeds, in different environments and with different cutting tools and materials [12]. In this sense, condition monitoring establishes a more advantageous strategy for maintaining these machines, with bearings being the components selected for monitoring. These spindles usually have angular contact ball bearings, because they provide low friction and increased bearing capacity axially and radially. They consist of the outer and inner ring, the balls and the cage [13]. As for the types of defects that arise, these can be:

- Localized: These include cracks or splinters due to fatigue, starting to spread below the surface. The higher the bearing load and rotational speed, the faster this spread [2];
- Distributed: arising from the first one over time [20]. They may also arise due to errors in their manufacture, assembly or coupling on the shaft. They are characterized by surface roughness, track misalignment, or the rolling elements may not have the same diameter [21].

Therefore, the predictive maintenance of this component has the main objective of detecting localized defects as soon as possible, before they spread and become distributed, resulting in catastrophic equipment damage. To implement the CBM strategy, there is a need to use equipment such as sensors so that they can collect, analyze and interpret data from a company's critical equipment [21]. To implement this strategy, the following steps are required [5,6]: acquisition of data, data processing and decision making. The signal acquisition step aims to make the measurement of one or more physical quantities of a certain component or system, in order to collect data [23]. Data processing of wave form type can be divided into three techniques [6]:

- Time domain analysis is the simplest approach and it comprises calculating the statistical values such as mean, standard deviation, kurtosis, among others. This analysis only makes it possible to detect the existence of a defect;
- Frequency domain analysis has the advantage over the previous of identifying and isolate specific frequencies of interest to localize the defect. Usually, it is used the Fast Fourier Transform (FFT) to convert the time domain signals into the frequency domain;
- Time-frequency domain analysis is the most suitable approach to the non-stationary signals.

The decision-making stage consists of two phases, diagnosis and prognosis. While the first one identifies the location and type of failure, the second estimates the remaining useful life [21]. The prognosis is more efficiency in avoiding stoppages, but, when it fails, the diagnosis is important.

Regarding the measurement of parameters in a CBM program, it is subdivided in the literature on direct and indirect. Starting with direct measurement, its main advantage is accuracy, but it is often not possible to apply it in an industrial environment, either due to accessibility problems, or due to the use of fluids such as lubricating oil in CNC machining. Indirect techniques are, for example, visual inspection using a camera and laser beams. Indirect measurements are the most used, due to its ease of use and placement in the manufacturing environment because many of them have small dimensions and / or resist to high temperatures and fluids. However, unlike direct measurements, they are less accurate [23].

ISO 230:2012 [24] establishes vibration as the most suitable parameter for machine tool monitoring [12]. In the literature, it is often found vibration as the most used and effective parameter for bearing analysis. [17] argue that this choice is supported by the ease of its measurement. It is known that a machine in current operation has a certain vibration pattern, which changes with failure growth [12,16,25]. However, according to [3], vibration is a suitable method for bearing monitoring, but is ineffective in detecting defects in the early phase, only detecting them when they reach the surface. Thus, it proposes the analysis of acoustic emissions (AE) as a complementary technique, as it presents great sensitivity to incipient defects.

The reason for this difference in the monitoring method is that, as a rule, vibration measuring instruments only pick up signals below a frequency of 20 kHz, some below 50 kHz, i.e. low frequency problems. such as serious damage to the bearings. The EA, in turn, detects signals from 100 kHz to 1 MHz frequency, and there is no interference of the low frequency problems, and damage in the early stage of the bearings can therefore be easily detected [2,3].

Some of the AE disadvantages are the complexity of signal processing, interpretation and classification, and the high noise on the shop floor that can compromise measurement. Despite, some techniques have been successfully developed to eliminate these unwanted noises [2,25].

3. Methods

The implementation of predictive maintenance on Swiss lathe bearings is intended to monitor the condition of this component over time so the replacement can be timely planned, sometimes even included in maintenance of other components, or even in setups, to reduce machine downtime. Thus, the aim of the companies is to reduce the high number of unplanned stops, which cause significant costs for the company, associated with unproductivity, non-compliant parts, overtime, and even catastrophic failures as these are not detected in the initial state. The final goal would be to increase machine productivity and increase machine efficiency.

As said before, the first step to the development of the CBM system for the bearings is the selection of the parameters to be monitored. ISO 17359: 2011 [26] sets out the following parameters as suitable for monitoring electric motors: temperature, current, vibration, acoustic emissions, among others. ISO 230: 2012 [24], in turn, recommends vibration for machine tool monitoring [12]. Starting with vibration, although it is effective due to the characteristic signature of each machine failure and is a non-destructive method, it has the disadvantages of high costs, the fact that the measuring equipment must be coupled inside the machine, the need of a skilled person in the early stages, and the inherent failure of the devices themselves, as bearings typically have a high Mean Time to Failure (MTTF), so measuring equipment must have a higher value. Acoustic emissions often compete with vibration analysis, the former having better noise signal ratios but higher implementation costs [14].

In the literature, vibration is often found to be the most used and effective parameter for bearing analysis, for example, according to [15–17,27,28]. [17] argue that this choice is supported by the ease of its measurement. A machine in normal operation is known to have a certain vibration pattern, which changes with failure growth [12,16,25]. However, according to [3], vibration is a suitable method for bearing monitoring, but it is ineffective in detecting early stage defects, only detecting them when they reach the surface. Thus, [3] proposes the analysis of acoustic emissions (AE) as a complementary technique, as it has great sensitivity to incipient defects. As previously mentioned, AE also have disadvantages regarding vibration, such as the complexity of signal processing, interpretation and classification, and the high noise on the shop floor that can compromise measurement [2,26]. Therefore, the variables selected were the Vibration and the Acoustic Emissions, which are both non-destructive techniques, with no influence in the normal operation of the machine, and which application was before experimental proved. The choice of two measurement variables, not just one, is due to the higher efficiency when monitoring with multiple sensors, and as it was saw earlier, vibration detects damage that AE does not detect, and vice versa, complementing it [6]. Regarding the output variables, starting with the time domain analysis, the most used statistical parameters are: the crest factor, the kurtosis, the asymmetry, the counts and the global level or root mean square value (RMS) [29–31].

Starting with kurtosis, for both vibrations and AE, for a defect free flap this is approximately 3. A value higher than this is considered as an indication of failure. When the kurtosis coefficient decreases after an increase in previous measurements has been recorded, then we are in the presence of generalized failures, i.e. the component is in an unacceptable state and a work order needs to be generated. In the case of the crest factor (CF), for both vibrations and AE, when it exceeds the value of five, is an indication of the appearance of defects. If the CF value decreases with increasing RMS, then the bearing has widespread failures and a work order must be generated. In the case of asymmetry, it should be zero for both vibrations and AE when there are no defects, otherwise it is indicative of their presence. This parameter should be used in conjunction with others for more accurate analysis [30]. In the case of RMS, it is only applied to Vibrations, and its value can be calculated for bearings velocity or acceleration. The limits for these values as a function of spindle speed are set by SS 728000-1:2014 [32]. In the case of acceleration, this represents problems associated with the bearing condition, while the vibration speed is indicative of spindle imbalance or misalignment which lead to bearing defects [33].

For frequency domain analysis the FFT is used. A defective bearing generates a certain frequency depending on the location of the defect, whether it is in the outer ring, the inner ring, the balls or the cage [3,21,30]. Thus it is necessary to calculate these frequencies through the equations [21]:

$$\mathrm{BPFI}\ [\mathrm{Hz}] = \mathrm{w} * \frac{\mathrm{Nf}}{2} * \left(1 + \left(\frac{\mathrm{d}}{\mathrm{D}}\right) * \cos \mathrm{a}\right) \tag{1}$$

$$\mathrm{BPFO}\ [\mathrm{Hz}] = \mathrm{w} * \frac{\mathrm{Nf}}{2} * \left(1 - \left(\frac{\mathrm{d}}{\mathrm{D}}\right) * \cos \mathrm{a}\right) \tag{2}$$

$$\mathrm{FTF}\ [\mathrm{Hz}] = \frac{\mathrm{w}}{2} * \left(1 - \left(\frac{\mathrm{d}}{\mathrm{D}}\right) * \cos \mathrm{a}\right) \tag{3}$$

$$\mathrm{BSF}\ [\mathrm{Hz}] = \frac{\mathrm{w}}{2} * \frac{\mathrm{D}}{\mathrm{d}} * \left(1 - \left(\frac{\mathrm{d}}{\mathrm{D}}\right) * \cos \mathrm{a}\right) \tag{4}$$

Where,

- BPFI = Ball Pass Frequency of the Inner Race
- BPFO = Ball Pass Frequency of the Outer race
- FTF = Fundamental Train Frequency
- BSF = Ball Spin Frequency
- N = Number of rolling elements
- fi = Rotation frequency of inner race
- d = diameter of rolling element.
- Dp = Pitch diameter

- θ = Contact angle

Thus, whenever one of these frequencies is detected, it is possible to be aware of the location of the defect. In Fig. 1 is the flowchart explaining the steps to analyze the collected data from vibration and AE, in time and frequency domain.

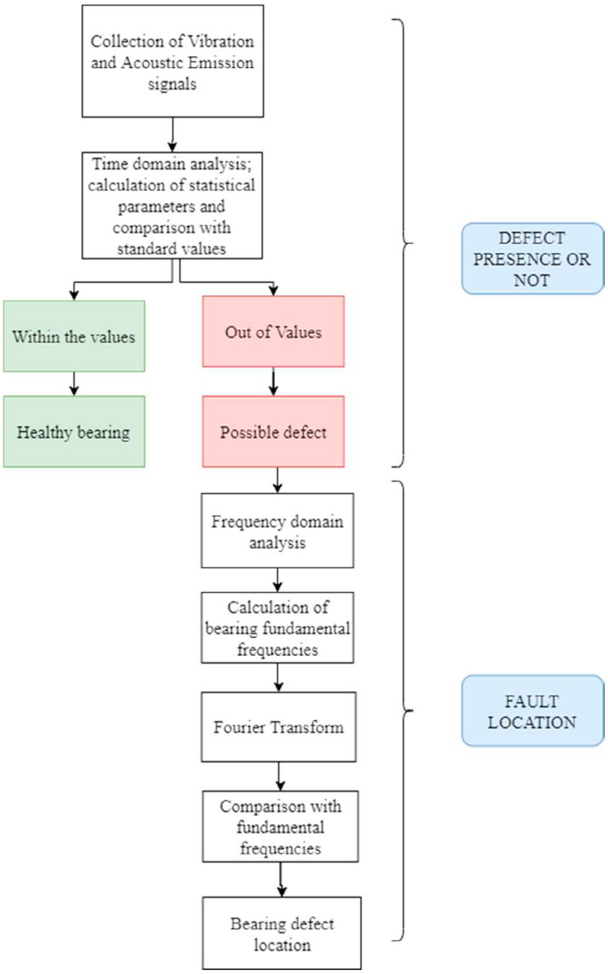

Fig. 1. Failure data analysis flowchart.

As represented in Fig. 2, a CBM system consists of transducers that sent the collected signals to the electronics diagnostic. The acquisition and analysis of data is realized in this device in the time and frequency domain. After this analysis, the data is sent to a computer. Here, and using the appropriate software, the operator assigns the reference values for each type of threshold: type 1 alert, normal behavior, type 2 alert, keep under control, and type 3 alert, generate work order.

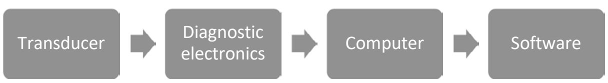

Fig. 2. Means to implement a CBM system

To monitor vibration, an acceleration transducer or accelerometer was selected as they are the most used for this specific application. These have a wide frequency response band, are light in weight, compact and robust and are ideal for monitoring machines with components such as bearings and gears [11,28,32].

According to [35,36], the most common types of accelerometer are piezoelectric and capacitive MEMS (micro-electromechanical systems). A capacitive MEMS accelerometer was chosen due to its low cost, easy processing, low variation with temperature changes and excellent sensitivity.

As for location, there is not a single optimal place to measure all types of vibration, so it is relevant to know the conditions of different locations in order to define which ones are most effective. [29] argues for the importance of selecting the positioning position of the sensor regarding bearing defect detection, since the associated frequencies are relatively high, recommending various measurement locations and directions. Thus, according to this author, the sensors should be placed as close as possible to the bearings. [37], in turn, tested the different possible locations for a sensor to detect a defective bearing on a machine tool spindle by vibration analysis. The locations selected are shown in Fig. 3.

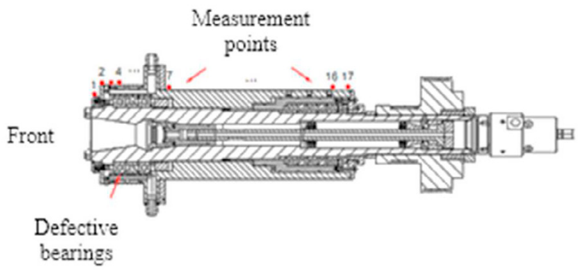

Fig. 3. Vibration measurement points.

According to their experimental results, [37] obtained the largest amplitude of the vibration response at point 1, thus, according to the authors, this is the best position to measure the vibration responses of the first bearing, so it is not the closest place to this. However, point 4 seems to be the best solution, as argued by [29].

Regarding the possible types of measuring direction, axially, horizontally or vertically, according to [33], the ideal would be a triaxial measurement when possible. If this is not possible, according to the same mark, the horizontal direction detects the most vibrations, followed by the vertical and, finally, the axial direction.

There are several possible methods for mounting sensors on machines or their components [29,34,38]

- Adhesive mounting: when the accelerometer is glued, it typically reduces its operating frequency response range and the accuracy of measurement. Also, replacing or removing it is more labor intensive than with any other fixing method.
- Magnetic mounting: this is typically used for temporary measurements and is not recommended for permanent monitoring.

- Threaded/Pin or Screw Mounting: according to [29], this is the best method available for permanent mounting applications. This method is expensive as well.

Regarding the rotation speed during the measurement, according to [16], it may vary or be constant, never in any case exceeding its maximum speed. For this author, if it is decided to vary the speed, there must be a ten-second threshold in which the speed is maintained, and if the maximum speed is between 600 and 30 000 rpm, which is the case, the speed ranges should be excluded.

According to [16], monitoring should not be done during production, for the case of spindle bearings in a Swiss lathe, and therefore periodically, also arguing that low speed machines should be monitored monthly and high speed machines should be controlled. daily, or continuous. Also [26] state that, as a rule, the vibration analysis is done monthly, and compared with the previous measurements.

For measuring acoustic emissions, a piezoelectric transducer, which has a high natural frequency and resonant response, a preamplifier, which may include a filter to control the bandwidth of the signal, and a signal processor are needed [15].

4. Results and discussion

In order to implement predictive maintenance on a Swiss lathe, two magnetically coupled sensors will be required, a vibration sensor, which will be capacitive MEMS type, and an acoustic emission sensor, which will be piezoelectric. The first will be installed at measuring point 1 shown in Fig. 4, as [37] concluded in his study as the best measurement location, while the Acoustic Emissions sensor will be coupled to point 2 (Fig. 4). The monitoring will be carried out monthly and at no load, i.e., out of production, at the maximum spindle speed.

To make the most of this system, it needs to be integrated into the company's local network, allowing the different departments involved in maintenance to know its status. Thus, when maintenance alerts are triggered, maintenance, production and purchasing departments will be automatically notified so that maintenance actions can be planned carefully without interrupting production, maximizing component life and eliminating the unplanned stops. This monitoring system with integration with the local network is advantageous for small businesses, where there is only one manufacturing plant. An Internet connection can be justified, so that equipment condition data can be accessed at any time anywhere. Thus, the proposed operating model is represented in Fig. 4.

Thus, first, after installation of all equipment and software, and assignment of Maintenance alert levels as explained, an initial stabilization test is performed to ensure that it has been properly performed. The sensors then collect the signals and send them to the data acquisition systems. They, in turn, will send them to the computer, where their software is installed. By means of a time analysis and comparison with the standard values, the program will inform you of whether a bearing defect is present. If the possibility of a defect is detected, a frequency domain analysis is performed. In this analysis, the software will compare the measured values with the fundamental frequencies of the bearing under study according to their characteristics. If any of the fundamental frequencies is present in the collected signal, then there is indeed a defect and its location will be known according to the fundamental frequency that has been detected.

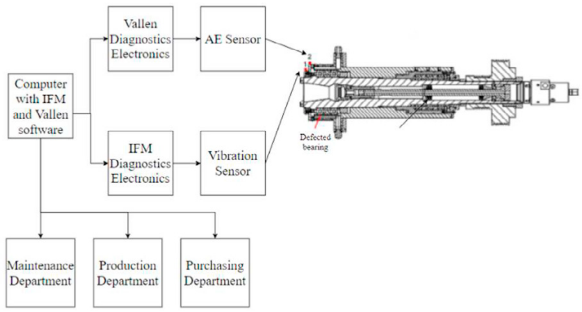

Fig. 4. Operating model

There is also a possibility to use only Vibration or AE. However, this does not allow such a reliable diagnosis to be obtained because, as explained above, the first one only detects defects when they have already appeared on the surface, and the AEs are detected in the initial phase, so it is essential to use both [3].

After the Maintenance alert is triggered, an action is required, as summarized in Table 1.

Table 1 - Types of alert and actions required

Alert Triggered	Action
Type 1	No action needed
Type 2	Monitoring frequency adjusted to biweekly
Type 3	A Work Order is generated

When it comes to the Type 3 alert, besides the maintenance department having to intervene in the replacement, the Production Department is advised that a machine will need to be replaced for the bearing replacement, and the Purchasing Department will need to check for replacement bearing stock, ordering it needed.

Differing from the work of [12,17,25], this work proposes a system that combines acoustic emissions with vibrations, which allows more accurate results in defect detection, especially in the initial phase, essentially to prevent machine failure. In addition, the approaches proposed by these authors are quite complex, requiring the study of the CBM bases to implement the system proposed by them. Another advantage of this system is that only the definition of the limit values for the bearings, which are identified here, is required, since the software analyzes the data and draws the conclusions, simplifying the processing of the collected signals.

The work proposed by [3], on the other hand, only includes acoustic emissions, and although it mentions the parameters that can be used for monitoring in the field of time such as peak value, crest factor, among others, does not refer their limits in the case of a healthy bearing, making the analysis and implementation more complex.

In conclusion, the papers present in the literature are complex, and since there is still little information about this type of maintenance and how easily it can be applied to the industry, organizations are still reluctant to implement it. In this way, this work shows easily how to implement condition monitoring to a machine tool, using two techniques to a more accurate result, what are the necessary equipment, what parameters and limits must be known, and the software manages the different situations, i.e. it automatically processes the data and trigger the adequate alarm.

5. Conclusions

Conclusions remarks

When analyzing the literature, we often found vibration or acoustic emissions analysis for bearing monitoring, each one having its corresponding advantages. However, there is still missing some works that combine both techniques in order to bring together their benefits. Thus, a major contribution of this work lies in complementing this lack of information about how these two techniques can be correctly combined for a more accurate analysis.

Although the lack of literature about these techniques is a significant weakness, the main disadvantage of this technique is the high cost of implementation, which includes the purchase of the equipment, i.e. transducers and accessories, diagnostic electronics/data acquisition equipment and software, needing sometimes as well training, so that maintenance technicians have the necessary knowledge to understand software data and in what situations they should act. The costs also need to cover expenses with the time spent to analyze the best alternative for the company, although companies that market these systems may have this knowledge. However, with the industrial evolution that has been experienced, predictive maintenance is adopting solutions more economical and with more reliable equipment, that can make it a viable solution for smaller scale organizations.

This system is not limited to this specific machine, it can be easily adapted to other industrial realities, since Vibration can be applied to other rotating machines as they emit a characteristic vibration signal that changes in the presence of failures, and in the case of Acoustic Emissions, they arise through the interaction of two relative moving surfaces, so they can also be applied to other rotating machines. However, it is important to realize that the parameters selected for analysis in time and frequency domain are specific to this installation, i.e. for bearing analysis.

Outlook

There was positive feedback from the company's management, for now just the concept, which will be implemented very soon.

With the development of this work it was clear which variables must be considered to proceed to an 'in situ' analysis of the condition of the main components of a complex machine such as a multi-axis CNC lathe. This analysis will certainly be useful to extend the study other sensitive parts of the same type of machinery or other similar machinery.

In this way, the next step will be to extend this same analysis to other sensitive parts of the same type of machines, namely the transmission system, and to verify which variables are the most important in this case, trying to establish a methodology that allows to address different cases within the same family of equipment.

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