Paraconsistent annotated logic applied to industry assets condition monitoring and failure prevention based on vibration signatures

Lógica anotada paraconsistente aplicada ao monitoramento de condição de ativos da indústria e prevenção de falhas com base em assinaturas de vibração

Lógica anotada paraconsistente aplicada a activos de la industria y Monitoreo de condición y prevención de fallas basada en sinais de vibración

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Abstract
In this study, we introduced an expert system (ESvbrPAL2v), responsible for monitoring assets based on vibration signature analysis through a set of algorithms based on the Paraconsistent Annotated Logic – PAL. Being a non-classical logic, the main feature of the PAL is to support contradictory inputs in its foundation. It is therefore suitable for building algorithmic models capable of performing out appropriate treatment for complex signals, such as those coming from vibration. The ESvbrPAL2v was built on an ATMega2560 microcontroller, where vibration signals were captured from the mechanical structures of the machines by sensors and, after receiving special treatment through the Discrete Fourier Transform (DFT), then properly modeled to paraconsistent logic signals and vibration patterns. Using the PAL fundamentals, vibration signature patterns were built for possible and known vibration issues stored in ESvbrPAL2v and continuously compared through configurations composed by a network of paraconsistent algorithms that detects anomalies and generate signals that will report on the current risk status of the machine in real time. The tests to confirm the efficiency of ESvbrPAL2v were performed in analyses initially carried out on small prototypes and, after the initial adjustments, tests were carried out on bearings of a group of medium-power motor generators built specifically for this study. The results are shown at the end of this study and have a high index of signature identification and risk of failure detection. These results justifies the method used and future applications considering that ESvbrPAL2v is still in its first version.
Keywords: Paraconsistent annotated logic; Maintenance; Preventive; Corrective; Assets; Artificial intelligence; Industry 4.0.

Resumo
Neste estudo apresentamos um sistema especialista (SEvibrPAL2v) responsável pelo monitoramento de ativos baseado na análise de assinatura de vibração por meio de um conjunto de algoritmos baseados na Lógica Anotada Paraconsistente

- LPA. Por ser uma lógica não clássica, a principal característica do LPA é suportar entradas contraditórias em sua fundação e, portanto, é adequado para a construção de modelos algorítmicos capazes de realizar o tratamento adequado para sinais complexos, como os provenientes de vibração. O SEvibrPAL2v foi construído em um microcontrolador ATMega2560, onde os sinais de vibração foram capturados das estruturas mecânicas das máquinas por sensores e, após receberem tratamento especial através da Transformada de Fourier Discreta (TFD), foram então modelados adequadamente para sinais lógicos paraconsistentes e padrões de vibração. Usando os fundamentos da lógica paraconsistente, padrões de assinatura de vibração foram construídos para diferentes problemas de vibração possíveis e conhecidos, armazenados no SEvibrPAL2v e continuamente comparados através de configurações compostas por redes de algoritmos paraconsistentes, que detectam anomalias e geram sinais que informam o status de risco atual em tempo real da máquina. Os testes de comprovação da eficiência do SEvibrPAL2v foram realizados em análises inicialmente realizadas em pequenos protótipos e, após os ajustes iniciais, foram realizados testes em um conjunto mecânico de média potência construído especificamente para este estudo. Os resultados são apresentados ao final deste estudo e possuem um alto índice de identificação de assinatura e detecção de risco de falha, o que justifica o método utilizado e futuras aplicações considerando que o SEvibrPAL2v ainda está em sua primeira versão.
Palavras-chave: Lógica paraconsistente anotada; Manutenção; Preventiva; Corretiva; Ativos; Inteligência artificial; Indústria 4.0.

Resumen
En este estudio presentamos un sistema experto (SEvibrPAL2v) responsable de monitorear activos basado en el análisis de firmas de vibraciones a través de un conjunto de algoritmos basados en la Lógica Anotada Paraconsistente - PAL. Al ser una lógica no clásica, la principal característica del LPA es soportar entradas contradictorias en su base y, por tanto, es adecuado para construir modelos algorítmicos capaces de realizar un tratamiento adecuado para señales complejas, como las que provienen de vibraciones. El SEvibrPAL2v se construyó en un microcontrolador ATMega2560, donde las señales de vibración fueron capturadas de las estructuras mecánicas de las máquinas por sensores y, después de recibir un tratamiento especial a través de la transformada de Fourier Discreta (TFD), luego modeladas apropiadamente a señales lógicas paraconsistentes y patrones de vibración. Usando los fundamentos PAL, se construyeron patrones de firma de vibración para diferentes problemas de vibración posibles y conocidos almacenados en SEvibrPAL2v y se compararon continuamente a través de configuraciones compuestas por redes de algoritmos paraconsistentes, que detectan anomalías y generan señales que informan el estado de riesgo actual en tiempo real de la máquina. Las pruebas para confirmar la eficiencia de SEvibrPAL2v se realizaron en análisis inicialmente realizados sobre pequeños prototipos y, tras los ajustes iniciales, se realizaron pruebas en rodamientos de un grupo de motogeneradores de media potencia de los construidos específicamente para este estudio. Los resultados se muestran al final de este estudio y tienen un alto índice de identificación de firmas y riesgo de detección de fallas, lo que justifica el método utilizado y futuras aplicaciones considerando que SEvibrPAL2v aún se encuentra en su primera versión.
Palabras clave: Lógica paraconsistente anotada; Mantenimiento; Preventivo; Correctivo; Activos; Inteligencia artificial; Industria 4.0.

1. Introduction

In any industry, asset condition monitoring is vital and has been enhanced with new technologies and methodologies aiming failure predictions and optimization of time and costs related to corrective and preventive maintenance. Several factors can be taken into consideration when determining the condition of an asset, from electrical parameters such as power and current consumption to mechanical parameters such as vibration and thermals such as ambient and asset temperature. With plenty of data, a computational model is needed that can determine what and when a given asset will or may fail. Regardless of the industry, reliability is the ability of a device to perform within the performance requirements in a specific period and conditions of use (Giantomassi et al., 2015) (Song et al., 2018). Eliminating downtime altogether is impossible to achieve, but reducing it is essential for the plant to achieve an increasingly profitable operation. There are currently studies and applications for failure detection using a range of aspects such as Visual, Acoustic, Electrical and Thermal Analysis (Hemmati et al., 2015) (Weijtjens et al., 2017). In modern high speed bearing failure diagnosis, methods based on vibration signals are widely used and continuous online monitoring of rotating machines is necessary to assess real-time health conditions reducing the possibility of downtime (Kwon et al., 2016) (Chen et al., 2016) (Ince et al., 2016) (Lei & Wu, 2020) (Janssens et al., 2016).

A bearing vibration monitoring system must be accurate when detecting the equipment operation state. The system must be able to collect and analyze the data correctly and offer an efficient diagnosis. It also needs to be able to avoid losses and excessive downtime in production equipment. An incorrect diagnosis will cause incorrect replacement and/or equipment downtime or even an incorrect estimation for a maintenance causing unnecessary costs to the plants and companies (Weijtjens et al., 2017) (Zhang et al., 2017). To contribute to the mitigation of this problem, a robust Monitoring System, named ESvbrPAL2v, was built, based on the Paraconsistent Logic concepts. This can analyze bearings vibration in real time and using patterns learned by the algorithm itself to compare and provide diagnostics in real time. Therefore, the objective of this work is to show an algorithmic structure based on Paraconsistent Logic (PL) working as an expert system (ESvbrPAL2v) capable of continuously monitoring the vibration of bearings to warn about risks of breaking an industrial machine (Da Costa & Abe, 2000) (Côrtes, et al.,2022) (Da Silva Filho et al., 2021).

1.1 Paraconsistent Annotated Logic – PAL

Paraconsistent logic (PL) is a non-classical logic that is capable to deal with contradictions in a discriminating way. The foundations of PL allow contradictory signals to be equated without weakening the logical conclusions (Da Costa & Abe, 2000). The Paraconsistent Annotated logic (PAL) belongs to a family of Paraconsistent logics and can be represented through a lattice associated of four vertices. These four vertices represent extreme logical states referring to the proposition P that will be being analyzed (Da Silva Filho et al., 2010) (De Carvalho Jr et al., 2021) (Garcia et al., 2019) (Abe et al., 2018).

1.2 Paraconsistent Annotated Logic with Annotation of two values – PAL2v

According to [15] through the PAL, a representation of how the annotations or evidences express the knowledge about a certain proposition P. This is done through a lattice on the real plane with pairs (μ, λ), which are the annotations as seen in Figure 1. In this representation an operator is fixed: $\sim: |\tau| \to |\tau|$ where $\tau = \{(\mu, \lambda)|\mu, \lambda \in [0, 1] \subset \Re\}$, and defined as follows: if P is a basic formula then $\sim [(\mu, \lambda)] = (\lambda, \mu)$ where $\mu, \lambda \in [0, 1] \subset \Re$. The operator $\sim$ stands for the "meaning" of the logical symbol of negation of the system to be considered (Abe et al., 2018) (Da Silva Filho et al., 2010).

The introduction of the extreme logical Paraconsistent states that there are the four vertices of the associated PAL2v lattice with favorable Degree of evidence (μ) and unfavorable Degree of evidence (λ). They were read in the following way:

PT = $P(1, 1) \to$ The annotation $(\mu, \lambda) = (1, 1)$ assigns intuitive reading that P is inconsistent.

Pt = $P(1, 0) \to$ The annotation $(\mu, \lambda) = (1, 0)$ assigns intuitive reading that P is true.

PF = $P(0, 1) \to$ The annotation $(\mu, \lambda) = (0, 1)$ assigns intuitive reading that P is false.

P$\perp$ = $P(0, 0) \to$ The annotation $(\mu, \lambda) = (0, 0)$ assigns intuitive reading that P is Indeterminate.

In the internal point of the lattice which is equidistant from all four vertices, we have the following interpretation:

PI = P(0.5, 0.5) $\to$ The annotation $(\mu, \lambda) = (0.5, 0.5)$ assigns intuitive reading that P is undefined.

The logical negation of P is defined as: $\neg P(\mu, \lambda) = P(\lambda, \mu)$

Figure 1 shows the Lattice associated with PAL2v with the extreme logical states and the corresponding annotations.

Figure 1: Lattice of four vertexes and representation of the Paraconsistent Annotated Logic.
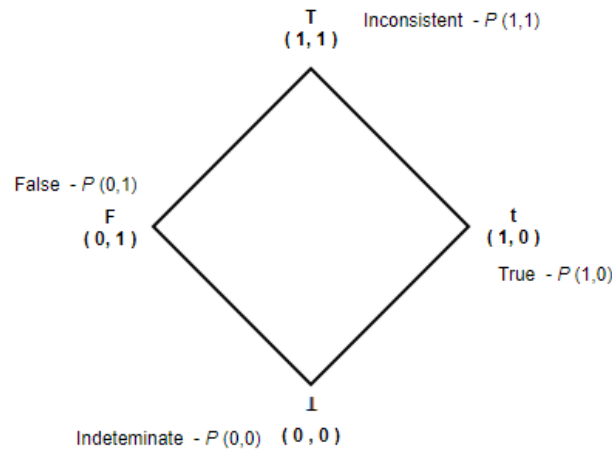
Source: Da Silva Filho et al. (2010).

As seen in Da Silva Filho et al. (2010) and Abe et al. (2018), we can obtain, through mathematical transformations, an equation of the Lattice associated with PAL2v that results in values considered as degrees of certainty (Dc), represented on the x axis and values considered as degrees of Contradiction (Dct) on the y axis. The equations corresponding to these degrees are shown below.

$$Dc = \mu - \lambda \qquad\qquad (1)$$

$$Dct = \mu + \lambda - 1 \qquad\qquad (2)$$

where:

$\mu 1$ is the favorable Evidence Degree of information source 1.

$\mu 2$ is the favorable Evidence Degree of information source 2.

And λ is the unfavorable Evidence Degree obtained by

$$\lambda = 1 - \mu 2 \qquad\qquad (3)$$

By definition, a Paraconsistent logical state $\varepsilon\tau$ is represented by:

$$\varepsilon\tau = (Dc, Dct) \qquad\qquad (4)$$

The following straight line (distance d) between the logical state and one of the extreme logical states (True t or False F), when projected on the x-axis, results in the real Degree of Certainty (Dcr) (Da Silva Filho et al., 2010).

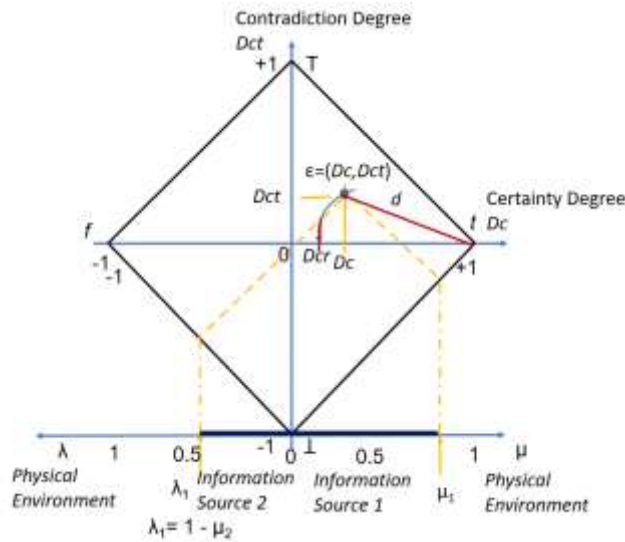$$d = \sqrt{(1 - |Dc|)^2 + Dct^2} \qquad\qquad (5)$$

Thus, with the value of the distance d, the Dcr is calculated using the conditional equations below.

$$Dcr = 1 - \sqrt{(1 - |Dc|)^2 + Dct^2} \qquad \text{If } Dc > 0 \quad (6)$$

$$Dcr = \sqrt{(1 - |Dc|)^2 + Dct^2} - 1 \qquad \text{If } Dc < 0 \quad (7)$$

Figure 2 shows how Dcr is calculated in the Lattice associated with PAL2v.

Figure 2: PAL2v Lattice of four vertexes with representation of the calculation of the real Degree of Certainty Dcr for Dc > 0.

Source: De Carvalho Jr et al. (2021).

1.3 Paraconsistent Analysis Node – PAN

The element capable of treating a signal that is composed of one degree of favorable evidence and another of unfavorable evidence (μ_{1a}, μ_{2a}), and provide in its output a Resulting Evidence Degree (μER), is called basic Paraconsistent Analysis Node (PAN). A lattice description uses the values obtained by the equation results in the Paraconsistent Analyzer Node Algorithm that can be written in a reduced form, as follows (Coelho et al., 2019) (Mario et al., 2018) (Mario et al., 2021) (Da Silva Filho et al., 2016) (Da Silva Filho & Da Cruz, 2016).

PAN Paraconsistent Analysis Node Algorithm

1) Enter with the input values.

μ */ favorable evidence Degree $0 \leq \mu \leq 1$

λ */ unfavorable evidence Degree $0 \leq \lambda \leq 1$

2) Calculate the Contradiction Degree: $\boldsymbol{Dct = \mu + \lambda - 1}$

3) Calculate the Certainty Degree: $\boldsymbol{Dc = \mu - \lambda}$

4) Calculate the distance d of the extreme Paraconsistent logical state True or False, until Paraconsistent logical state $\varepsilon\tau$ into

Lattice. $\boldsymbol{d = \sqrt{(1 - |Dc|)^2 + Dct^2}}$

5) Compute the output signal.

      If $\boldsymbol{d \geq 1}$, then do S1= 0.5   Go to the steep 9

     Or else,   Go to the next step

6) Calculate the real Certainty Degree.

    If $Dc > 0$ then $Dcr = (1 - d)$

    If $Dc < 0$ then $Dcr = (d - 1)$

7) Calculate the real Evidence Degree.

    $\boldsymbol{\mu ER = \dfrac{Dcr+1}{2}}$

8) Present the output

Do   S1 = μER

9) End.

The systems with the Paraconsistent Analysis Nodes (PAN) deal with the received signals through algorithms and present the signal with the real Evidence Degree value in the output (Mario et al., 2018) (Ricciotti et al., 2019) (Garcia et al., 2019).

1.4 Paraconsistent Artificial Neural Cell – (PANCell)

Paraconsistent Artificial Neural Cell (PANCell) is the PAL2v structure capable of, after presented with a pair of favorable and unfavorable evidence (μ , λ) at its input, providing a result at its output, composed of a resultant degree of evidence value (μE) of the analysis and a value of Normalized contradiction Degree (μCtr) (Mario et al., 2021).

The equation of a Paraconsistent Artificial Neural Cell – (PANCell (Da Silva Filho et al., 2010) is given by:

$$\mu E = \frac{(\mu - \lambda) + 1}{2} \; , \tag{8}$$

where

μE = Output evidence Degree.

$$\mu Ctr = \frac{(\mu + \lambda)}{2} \; , \tag{9}$$

where μCtr = Normalized contradiction Degree.

Figure 3(a) shows the symbol of a Paraconsistent Artificial Neural Cell – (PANCell.

1.5 Paraconsistent Artificial Neural Cell of Learning – (LPANCell)

Paraconsistent Artificial Neural Cell of Learning (LPANCell) is basically an ordinary PANCell having its initials input values ($\mu 1A$ and $\mu 1B$) defined as 0.5 and its output (μER) connected to its unfavorable evidence inputs, further referenced as $\mu 1Bc$ (Da Silva Filho et al., 2010).

$$\mu E = \frac{(\mu 1A - \mu 1BC) + 1}{2} \tag{10}$$

$$\mu Ctr = \frac{(\mu 1A + \mu 1BC)}{2} \tag{11}$$

Where $\mu 1BC = 1 - \mu 1B$.

Through training by iteration, which consists in successively applying a pattern ($\mu 1A$) at the input of the favorable evidence degree signal (μ) until the contradictions diminish, and a resultant evidence degree equal to one is obtained as the output. In the learning process, an equation for the values of the successive resultant evidence degree, $\mu E(k)$, is considered until it acquires a value of one. Therefore, for an initial value of $\mu E(k)$, the values $\mu E(k+1)$ are obtained up to $\mu E(k+1) = 1$.

Considering the learning process of the truth pattern, the learning equation is obtained through the calculus of the resultant evidence degree equation (Da Silva Filho et al., 2010):

$$\mu E(k + 1) = \frac{\{(\mu 1A) - (\mu E(k) C * FL\} + 1}{2}, \tag{12}$$

where FL is a real value, in the closed interval [0, 1] that adjusts the learning speed of *L*PANCell.

Figure 3(b) shows the symbol of a Paraconsistent Artificial Neural Cell of Learning (*L*PANCell)

Figure 3: Paraconsistent Artificial Neural Cell Symbols. a)Paraconsistent Artificial Neural Cell – (PANCell). b) Paraconsistent Artificial Neural Cell of Learning – (*L*PANCell).

(a)   (b)
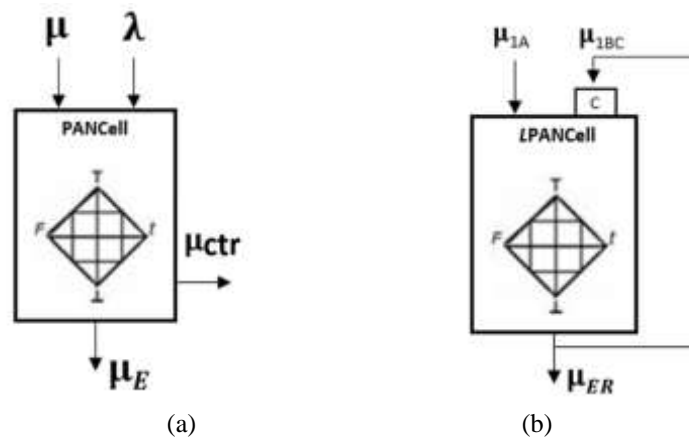
Source: Da Silva Filho et al. (2010).

In this work, a signal filter composed of an architecture composed of 10 *l*PANCells interconnected in cascade will be used, as will be presented in the Materials and Methods section.

1.6 Paraconsistent Artificial Neural Cell of Learning – (*l*PANCell)

The Paraconsistent Algorithm Extractor of Contradiction effects (ParaExtrctr) is composed by connections among PANs. This configuration forms a Paraconsistent Analysis Network capable of gradually extracting the effects of the contradiction of information that comes from Uncertain Knowledge Database. The hypothesis of extraction of the effects of the contradiction has as principle that; if the first treated signals are the most contradictory, then the result of the paraconsistent analysis will converge for a consensual value. In this typical operation, the ParaExtrctr receives a group of signals of information represented by degrees of Evidence (μE) the regarding certain proposition *P* and, independently of other external information, it makes paraconsistent analysis in their values where, gradually, it is going extracting the effects from the contradiction to remain as output a single resulting Real Evidence Degree (μER) (Da Silva Filho et al., 2010).

The μER is the representative value of the group of input signals after the process of extraction of the effects of the contradiction.

The description of the ParaExtrctr Algorithm is shown to proceed (Garcia et al., 2019) (Da Silva Filho et al., 2021).

ParaExtrctr Algorithm

1) Present n values of Evidence Degrees that it composes in the subset.

Gμ = (μA, μB, μC, ⋯, μn)   */Evidence Degrees $0 \leq \mu \leq 1$*/

2) Select the largest value among the Evidence Degrees of the subset.

$\mu maxA = max\ (\mu A,\ \mu B,\ \mu C,\ \cdots,\ \mu n)$

3) Consider the largest value among the Evidence Degrees of the of the group in study as favorable Evidence Degree.

$\mu maxA = \mu sel$

4) Consider the smallest value among the Evidence Degrees of the of the group in study as favorable Evidence Degree.

$\mu minA = min\ (\mu A,\ \mu B,\ \mu C,\ \cdots,\ \mu n)$

5) Transform the smallest value among the Evidence Degrees of the of the group in study in unfavorable Evidence Degree.

$1 - \mu minA = \lambda sel$

6) Make the Paraconsistent analysis among the selected values:

$\mu R1 = \mu sel\ l\ \Diamond\ \lambda sel$　　　　　　　　　*/where l ◊ is a paraconsistent action with the PAN */

7) Add the obtained value $\mu R1$ from the group in study, exclusive of the two values μmax and μmin, selected previously.

$G\mu = (\mu A,\ \mu B,\ \mu C,\ \cdots,\ \mu n,\ \mu R1) - (\mu maxA,\ \mu minA)$

8) Return to the item 2 until that the of the group in study has only 1 element resulting from the analyses.

Go to item 2 until $G\mu = (\mu ER)$

2. Methodology

In general, ESvbrPAL2v was developed with a set of paraconsistent algorithms building analysis units interconnecting two flow segments. The first segment consists of a unit for Data Acquisition, a unit for PAL Data Modeling, a unit that applies PAL analysis to create signatures with paraconsistent standards and a unit that stores these standards classified into types of risks for the assets.

The second ESvbrPAL2v segment is made up of a unit that monitors information in real time, a unit that compares the values captured with the stored signatures and the output unit that presents the results according to the asset risk of failure based on the vibration.

Figure 4: Block diagram of ESvbrPAL2v with two segments and units analysis built with paraconsistent algorithms.
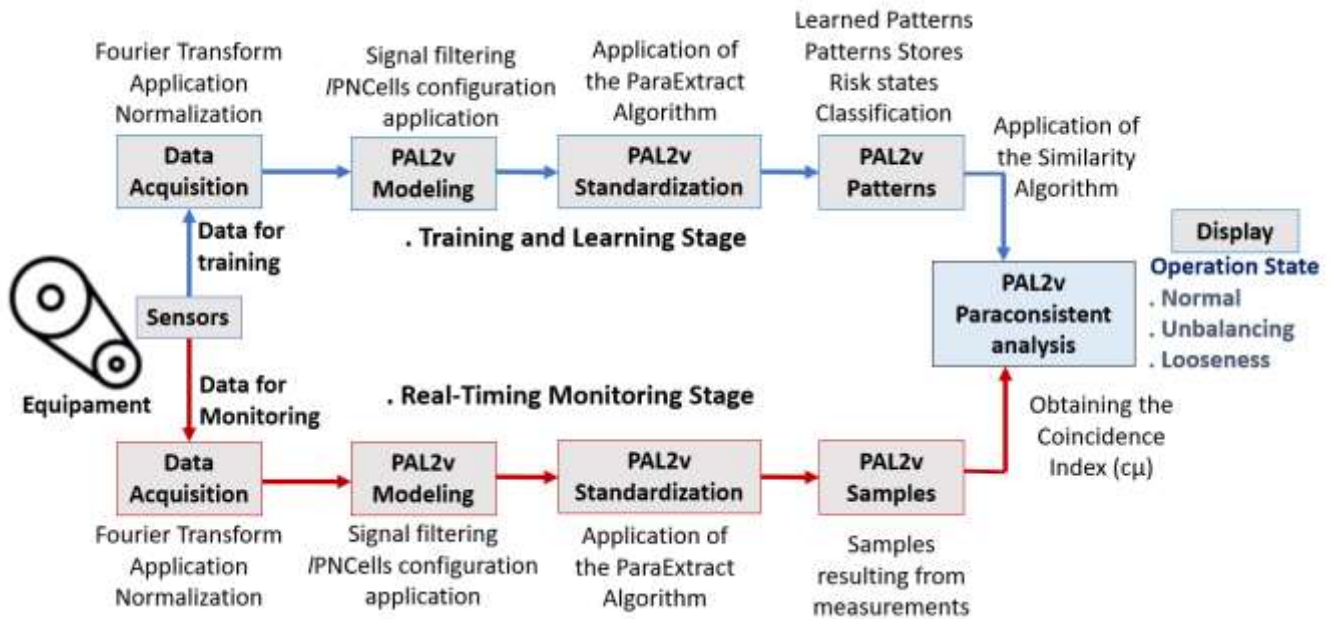
Source: Authors

2.1. Data Acquisition

For this experiment, an equipment was built and equipped with a 1/3 hp motor model Schultz JetMaster2, 1750 rpm, 0.25 kW at 220V; a 110mm diameter driver pulley; a 110mm diameter driven pulley, tied by a 300mm diameter type V belt; the driven pulley was assembled on a SKF ball bearing model explorer 6305-2Z/C3.

This bearing was assembled on a 130mm long cantilever shaft; a Sparkfun Triple Axis Accelerometer model MMA8452Q assembled to the cantilever shaft.

Figure 5(a) shows the details of the equipment used in data acquisition and generation of risk studies caused by vibrations.

The Sparkfun accelerometer was connected to an Arduino Mega 2560 microcontroller equipped with ATMega2560 microprocessor, through the SDA and SCL interfaces. This monitored and sent the vibration readings to a computer where a signal processing script written in MatLab read and processed the readings as well as identified possible vibrational disturbances, subsequently persisting the data on appropriate media. Therefore, all data vibration readings were sent to MatLab using serial communication protocol (RS-232) at 115200 bauds.

Figure 5(b) shown the data flow in the acquisition data step.

Figure 5: Mechanical acquisition and testing system. a) Details of the equipment used. b) Data flow in the acquisition data step.

(a)

(b)
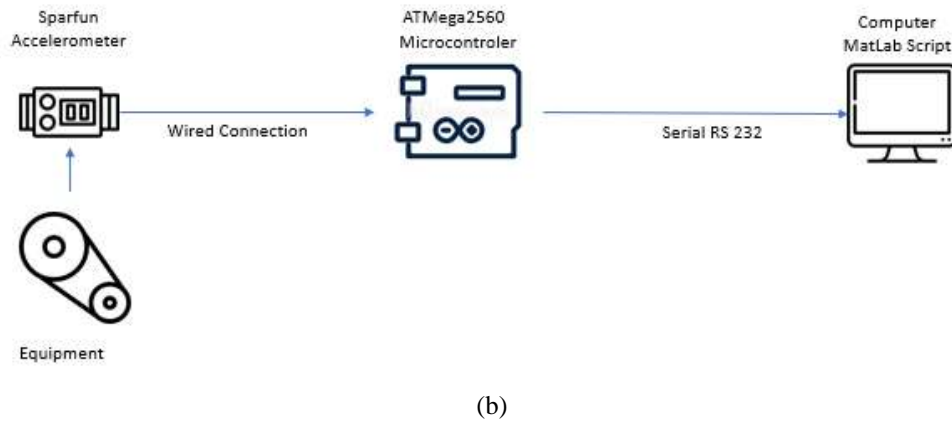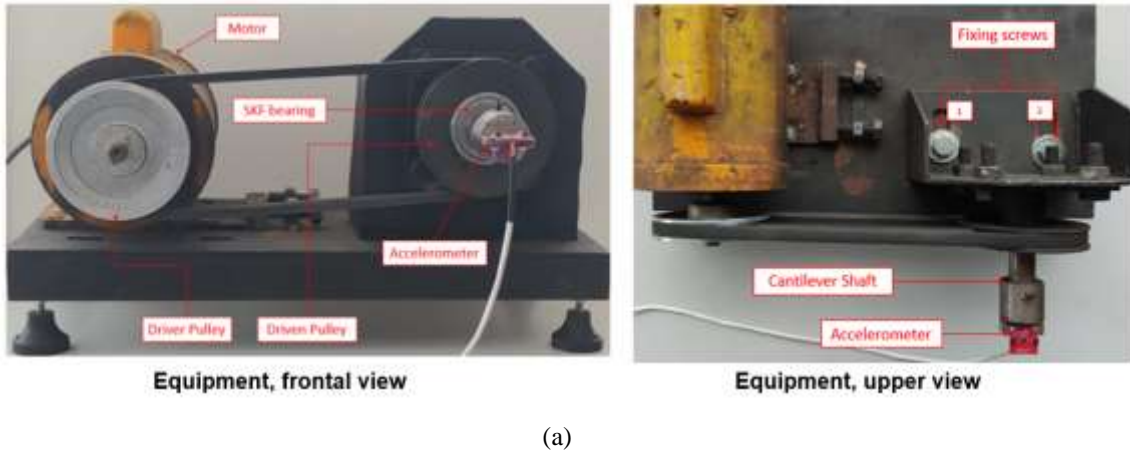
Source: Authors (2021).

2.2 DFT – Discrete Fourier Transformation

All vibrations readings were initially processed in the time-domain but to monitor for frequency failures, the system had to transform all readings to the frequency-domain.

The Discrete Fourier Transform of Vector is a built-in Matlab function, and its result is acceleration/vibration amplitude as a function of frequency. This allowed analysis in the frequency-domain to gain a deeper understanding of the vibration readings.
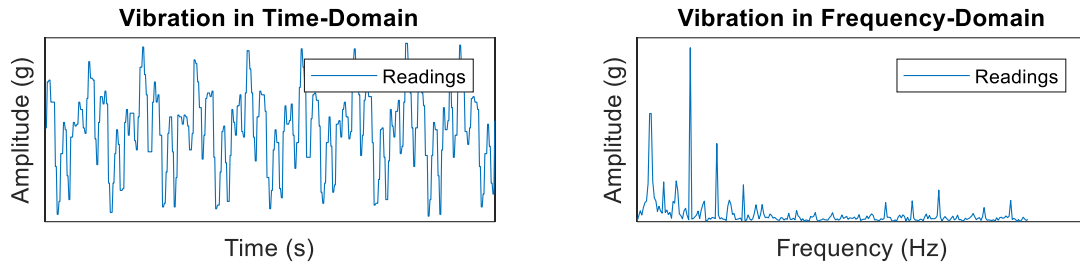
The MatLab FFT(X) function is given by the equation:

$$X(j) = \frac{1}{n}\sum_{k=1}^{n} Y(k) W_n^{-(j-1)(k-1)} , \quad \textbf{(13)}$$

where: $W_n = e^{(-2\pi i)/n}$ is one of n roots of unity.

Figure 6 shown the Graphical results of the signals obtained after applying the Fast Fourier Transformation.

Figure 6: Graphical results of the signals obtained after applying the Fast Fourier Transformation.

Source: Authors.

2.3 Normalization

The PAL2V requires input values as Evidence Degrees and these values must be normalized into infinite values between Zero and One (0 and 1). Within a set of reading values, already transformed from time to frequency domain, the system identifies the minimum (*Vmin*) and maximum (*Vmax*) values, and these are considered further as 0 and 1 respectively. Therefore, once received, all data were normalized as Evidence degrees (Values between 0 and 1) through the equation of the PAL2V Normalization equation:
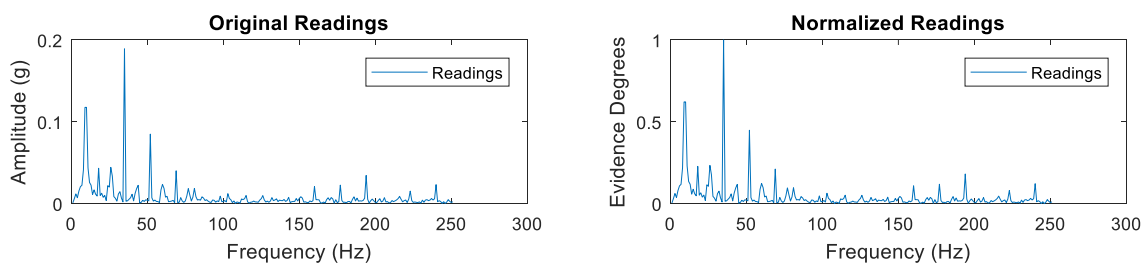
$$N = \frac{(V - Vmin)}{(Vmax - Vmin)} \;, \tag{14}$$

where **V** is the value read from the sensors;

Vmin and **Vmax** correspond to the minimum and maximum values obtained within the same set of readings, respectively.

Figure 7 shown the values normalized between this range following the PAL2V equation.

**Figure 7:** PAL2V Normalization results.

Source: Authors

2.4 PAL2V Paraconsistent Signal Filter

To benefit PAL analysis, a PAL2V signal filter was built using PANCells to obtain more linear spectrum, this was especially beneficial when creating and comparing patterns. For this purpose, a block of 10 Paraconsistent Artificial Neural Cell of Learning (*L*PANCell) has been implemented to perform a Paraconsistent signal filter, across all readings.

Figure 8 shown the LPANCell configuration used as a signal filter in this work.

Figure 8: Paraconsistent signal filter built with paraconsistent learning artificial neural cells (LPANCells).
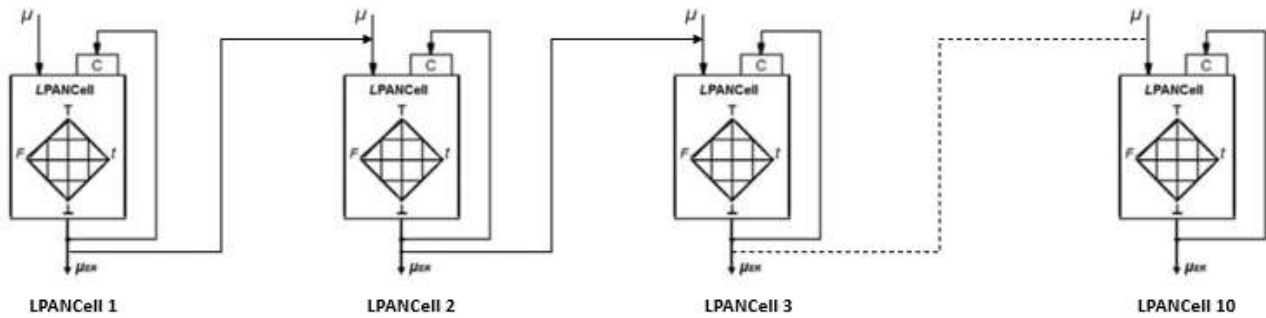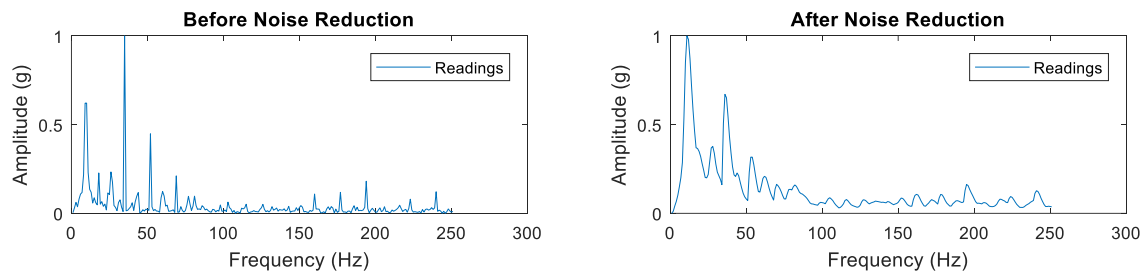

Source: Authors

PAL2V **Paraconsistent signal filter** equation used is:

$$M = \frac{\mu a - (1 - \mu) + 1}{2},$$ **(15)**

where **μa** is the prior evidence degree, and **μ** is the current evidence degree, both contained in the same set of values.

As shown in Figure 9, the result is a more linear signal that maintains the critical frequency peaks.

Figure 9: Paraconsistent signal filter results.

Source: Authors

2.5 Training and Learning Stage

2.5.1 PAL2v Standardization

Standardization is the process used for creating a unique pattern based on multiple similar, but not identical set of readings. In this implementation, after the readings are processed, transformed and normalized they are submitted to the ParaExtrctr algorithm, and the output is a pattern that represents the vibration condition in a given moment in the equipment life cycle.

The 3 past steps (DFT, Normalization and LPA2V Paraconsistent signal filter) are repeated 30 times and the result is a matrix of 30 rows by 750 columns (Table 1).

This matrix serves as the input for ParaExtrctr where each column represents a group of study. The output pattern is obtained after the iteration of all 30 columns.

Table 1: ParaExtrctr subset.

	Reading 1	**Reading 2**	**Reading 3**	**...**	**...**	**Reading 750**
Row 1	0.17	0.17	0.05	0.05	0.4	0.4
Row 2	0.01	0.01	0.01	0.04	0.04	0.25
Row 3	0.23	0.23	0.08	0.08	0.17	0.17
...	0.12	0.12	0.12	0.18	0.18	0.11
...	0.41	0.26	0.26	0.02	0.02	0
Row 30	0.01	0.01	0.01	0.04	0.04	0.25

Pattern	x	X	x	...	...	x

Obs: Second column = Resulting degree   Min degree = 0.01 and Max degree =0.41. Source: Authors

The ParaExtrctr algorithm processes each subset described in the table 1, and a single evidence degree will remain for each row position. The result is a matrix of 3 rows by 750 columns (table 1). The row 1 stores the resulting evidence degree for that subset. Rows 2 and 3 store the Min and Max evidence degrees from each subset. The *Min* and *Max* degrees are also saved and used in the monitoring phase. When this process is finished, the pattern is considered learnt and persisted in the system – patters will be used in the monitoring segment.

2.5.2 Patterns

To distinguish among possible vibration failures, ESvbrPAL2v had to learn these failures prior to the monitoring phase so that it could compare to the real-time vibration readings. For each failure type, a unique pattern has been created and persisted. For this experiment, through laboratory tests with stimulation of defect in the bearings, a total of 3 failure types were classified. The Learned Patterns used in this work are:

A. Normal Operation Pattern
B. Looseness Failure Pattern
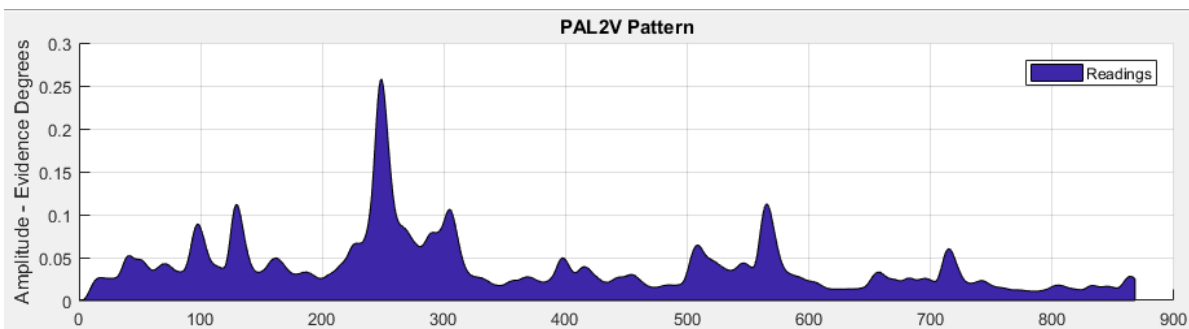C. Unbalancing Failure Pattern

A. Normal Operation Pattern

Condition where the equipment is free of problems and considered as optimum for normal operation. A maintenance technician certifies the equipment conditions.

Figure 10(a) shows the Normal Operation spectrum and Figure 10(b) shows the graph Normal Operation PAL2v Pattern.

Figure 10: Graph Results of the Normal Operation state. a) Normal Operation spectrum. b) Normal Operation PAL2v Pattern.
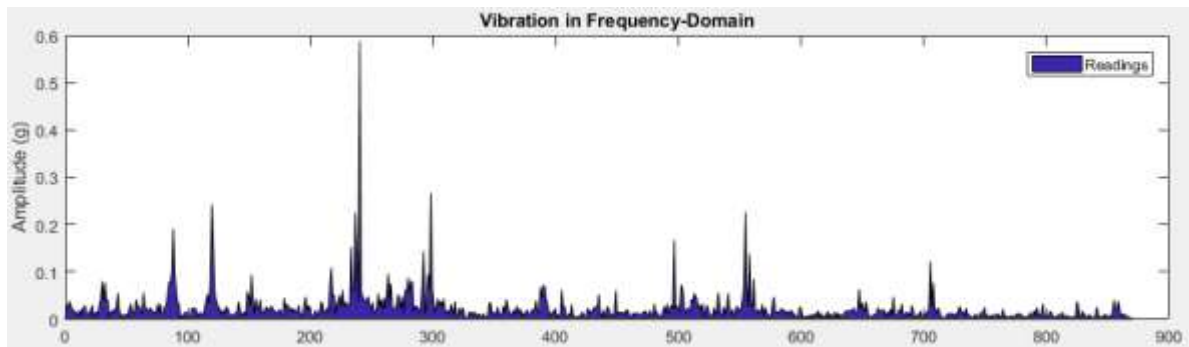
(a)

(b)

Source: Authors.

B. Unbalancing Failure Pattern

Condition where the rotor center of mass does not match the rotation center.

Unbalancing failures can happen due to manufacturing defects, e.g. pump rotors not balanced during manufacturing, as well during operation. e.g. exhaust rotor with too much particulate matter; rotor material loss due to erosion or corrosion; and propeller damage.
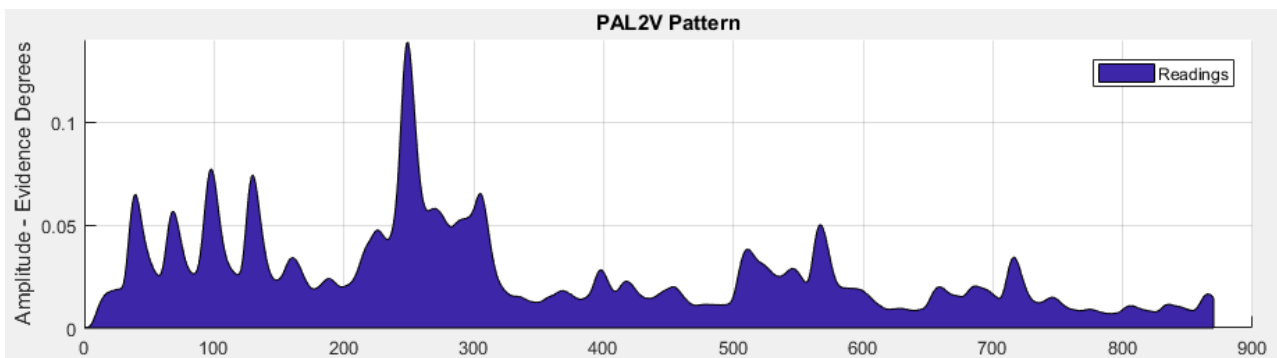
Method:

A metal body was fixed to the edge of the driven pulley and then the vibration was measured. This failure was observed in the vibration spectrum as a sharp signal, with greater vibration amplitude, commonly in the machine rotation frequency, expressed as 1X, denoting 1 time the rotation speed/rpm.

Figure 11(a) shows the Unbalanced failure spectrum and Figure 11(b) shows the graph Unbalanced failure PAL2v Pattern.

Figure 11: Graph results of the Unbalanced failure state. a) Unbalanced failure spectrum. b) Unbalanced failure PAL2v Pattern.
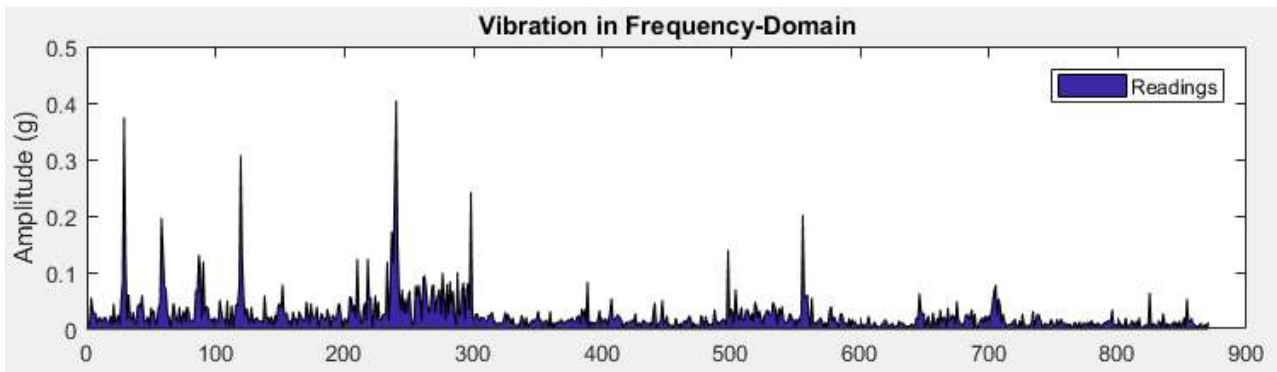
(a)

(b)

Source: Authors

C. Looseness Failures Pattern

Mechanical looseness failures are caused by lack of tightness or lack of proper torque of screws, loose nuts, shaft wear and incorrect dimensioning.

Method:

The fixing nut 2, as indicated in figure 6, was completely loosened; the motor was safely started and then the vibration signals were read. Vibration amplitudes of 0.02g were observed at frequencies lower than 30Hz, characterizing looseness.

Figure 12(a) shows the Looseness failure spectrum and Figure 12(b) shows the graph Looseness failure PAL2v Pattern.

Figure 12: Graph results of the Looseness failure state. a) Looseness failure spectrum. b) Looseness failure PAL2v Pattern.

(a)

(b)
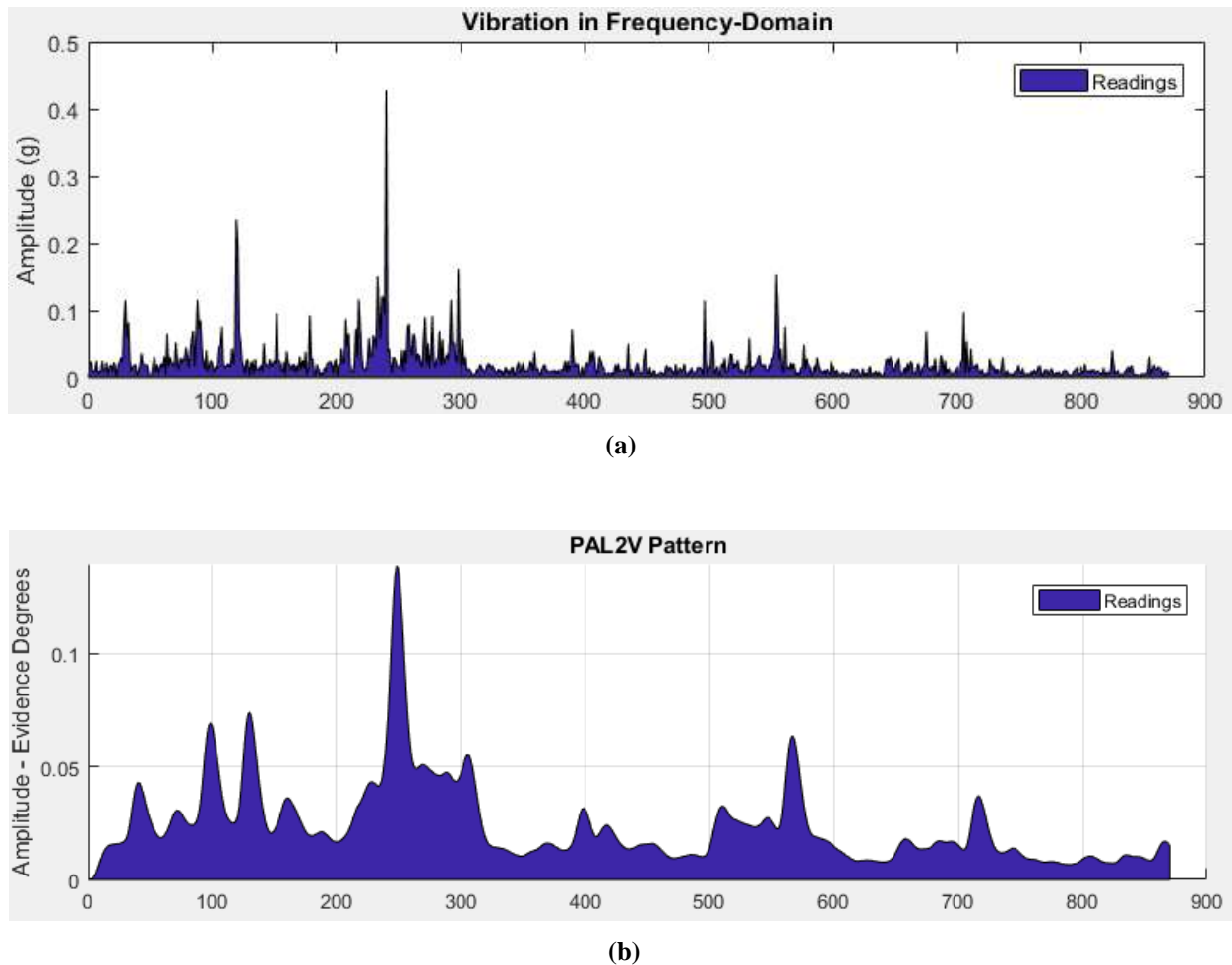
Source: Authors

After the patterns were learnt, the system was ready to monitor the equipment vibration conditions and able to anticipate changes in the vibration signatures that could represent possible failures.

2.6 Real-Timing Monitoring Stage

2.6.1 Monitoring Pattern

The Standardization process described during the PAL Modeling unit consists in 30 subsequent readings from the device so that the pattern sample can represent more accurately the equipment conditions.

For the monitoring, it was decided to collect a shorter dataset with 10 subsequent readings so that the signal processing sample obtained can be as near as possible to real-time.

The steps described for Fast Fourier Transformation, Normalization, PAL2v Paraconsistent Signal Filter and Standardization are repeated for each monitoring dataset. The result is again a sample pattern that can shift along the time called Monitoring Pattern.

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2.6.2 PAL Analysis

This unit is critical in the system and the Monitoring Pattern is compared to the learnt patterns using PAL2V techniques. This comparison is done by applying the PAL2v -Similarity Algorithm that results in the Coincidence Index ($cIndex$) as shown below.

PAL2v - Similarity Algorithm

1) Iterate the Monitoring Pattern (750 positions) and collect the Evidence Degree for each position.

2) Normalize the Evidence degree based on the saved *Min* and *Max* values obtained from the same position, from the Learnt Patterns:

Do μ_{mon} = Evidence degree from Monitoring Pattern position

Do μ_{learn} = Evidence degree from Learnt Pattern position

Do μ_{Min} = Min degree from Learnt Pattern position

Do μ_{Max} = Max degree from Learnt Pattern position

$$\mu N = \frac{(\mu_{mon} - \mu_{min})}{(\mu_{max} - \mu_{learn})}$$

where μN is the normalized Evidence Degree

3) Discard values if lesser than 0 (zero) or greater than 1 (one)

If $\mu N < 0$ or $\mu N > 1$ then $\mu N = 0$

4) Calculate the distance between the Learnt Pattern and Monitoring degrees

$$d = |\mu_{learn} - \mu N|$$

5) Consolidate results

If $d > 0.1$ then add index_true + 1

or else add index_false + 1

After all, 250 positions are iterated, calculate the resulting coincidence index.

$$cIndex = \frac{index\_true}{index-true + Index-false} * 100$$

6) Repeat steps 1 to 5 for each failure pattern learnt.

7) Present Output

2.6.3 Output

The ESvbrPAL2v output was based on the PAL Analysis between the monitoring pattern and the known failures patterns. The result is a coincidence index, expressed in percentage.

With this approach, the system was able to properly identify how more likely the monitoring pattern could look like a known failure pattern.

3. Results and Discussion

The results of this study can be spitted by the known failure types ESvbrPAL2v was able to properly identify and report on. This approach allowed focus on each pattern coincidence index, hereby considered as success index as well.

3.1 Normal Operation Results

As part of this study, the Normal Operation state is as important as all the known failures pattern learnt by ESvbrPAL2v.

Figure 13(a) shows an analysis result that coincidence index was 97.2% indicated a Normal Operating State Machine. The coincidence index has 97.2% similarity with "Normal Operating State", 34.0% similarity with "Looseness Failure State", and 62.81% similarity with "Unbalancing Failures State".

Figure 13(b) shows an analysis result that coincidence index was 84.42% indicated a Unbalancing Failure Machine. The coincidence index has 84.42% similarity with " Unbalancing Failure State", 73.53% similarity with "Normal Operating State ", and 45.04% similarity with "Looseness Failure State".

Figure 13(c) shows an analysis result that coincidence index was 97.2% indicated a Looseness Failure State Machine. The coincidence index has 96.14% similarity with " Looseness Failure State", 42.24% similarity with " Normal Operating State", and 43.69% similarity with "Unbalancing Failures State".

Figure 13: Results compiled by ESvbrPAL2v showing analyzes classified in three different operating states of the Machine. a) Output with Normal Operation satate. b) Output with Unbalanced Operation state. c) Output with Looseness Operation state.

(a)

(b)

(c)

Source: Authors.

As expected ESvbrPAL2v was able to properly identify when the equipment was operating on normal conditions, reporting a higher coincidence index of 97.2%. The proper identification of normal conditions is as important as the known failure conditions. Although the looseness index is also above 62%, the Normal Operation index is still higher. (See Figure 13a).

Based on the patterns learnt, where specific situations where focused, the ESvbrPAL2v could identify unbalancing failures with a very high coincidence index. The system achieved a high coincidence index of 84.42%. (See Figure 13b). Using the same approach for the Looseness condition, ESvbrPAL2v achieved a higher coincidence index as well, ESvbrPAL2v was able to properly identify and report an index of 96.14% (See Figure 13c).

4. Conclusion

This study purpose was to apply the Paraconsistent Annotated Logic with Annotation of Two Values (PAL2V) methodology along with Internet of Things and Artificial Intelligence concepts in Vibration Analysis, building condition patterns from vibration signatures and comparing to known failure patterns. The Paraconsistent Annotated Logic with Annotation of two values (PAL2V) methodology proved capable of processing vibration signatures, building patterns and performing pattern comparison with high success rate. The results showed that ESvbrPAL2v was able to autonomously learn, analyze and identify the mechanical failures proposed in this study and delivered satisfactory results with mechanical support. As in any AI systems, some concerns were considered during this study such bias, transparency, trust and explainability. We considered ESvbrPAL2v compliant with these concepts given the simple and clear code and methodology used during its development.

Future studies and research may focus on other vibration failures including bearing inner and outer race issues. Other vibration indicators such Crest factor and Kurtosis to be included along with the PAL2V analysis may enrich the results.

Acknowledgments

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