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Research Paper

Optimizing the Transition: Replacing Conventional Lubricants with Biological Alternatives through Artificial Intelligence

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Abstract. In today's modern industry, artificial intelligence (AI) is revolutionizing the formulation, performance optimization, and monitoring of lubricants. By enabling the analysis of large datasets, AI facilitates the development of customized formulations and predictive maintenance strategies. Traditionally, synthetic lubricants have been widely used due to their superior performance characteristics; however, they pose significant environmental and health risks. In contrast, bio-based lubricants offer a sustainable and biodegradable alternative, aligning with growing environmental and health-conscious trends. This study aims to leverage AI to assess the feasibility of replacing conventional synthetic lubricants with bio-based lubricants in vibrating mechanical structures. By employing AI-driven analysis, the research investigates the performance characteristics of bio-greases compared to their synthetic counterparts, focusing on signal vibration responses. The findings demonstrate that AI can effectively optimize lubricant performance, reduce operational costs, and enhance sustainability in the lubricant industry. The present study underscores the critical importance of evaluating the differences between conventional commercial and bio-based lubricants in an innovative way through vibration signals, highlighting their potential applications across various industrial sectors. The integration of AI not only enhances performance and sustainability but also paves the way for innovative advancements in lubricant technology.

Keywords: Vibration; Lubricants; Artificial Intelligence; Artificial Immune Systems; Negative Selection Algorithm.

1. Introduction

Lubricants play a fundamental role in a wide variety of industries and applications, ranging from industrial machinery maintenance to automotive engine lubrication [1]. These viscous fluids, often underestimated, are essential for reducing friction and wear between moving surfaces, extending the lifespan of equipment and ensuring smooth and efficient operation [2]. By providing a protective barrier between moving parts, lubricants not only increase energy efficiency but also contribute to preventing mechanical damage and maintaining material integrity [3]. In this context, exploring the different types of lubricants, their compositions, properties, and applications becomes crucial to understanding their vital role in various aspects of modern life [4].

Conventional commercial lubricants are typically produced from mineral or synthetic bases, specifically designed to reduce friction and wear between moving surfaces. The literature provides a comprehensive understanding of the principles behind commercial lubricants and their industrial applications [5, 6]. These lubricants are widely used in industrial machinery, automobiles, and mechanical equipment due to their chemical stability and ability to withstand extreme conditions of temperature and pressure.

However, conventional commercial lubricants also present some significant disadvantages. For example, many of them contain chemical additives that can be harmful to the environment and human health. Additionally, their production and disposal can contribute to air, water, and soil pollution, making them a concern in terms of sustainability [7].

On the other hand, bio-based lubricants are formulated from natural materials such as vegetable oils, waxes, and other biodegradable compounds [8, 9]. The principles behind bio-based lubricants and their potential in various applications were explored. Bio-based lubricants offer a more sustainable and environmentally friendly alternative to conventional lubricants. They are renewable, biodegradable, and in many cases, exhibit lubrication properties comparable or even superior to those of traditional commercial lubricants. Additionally, their production typically requires fewer natural resources and energy, thus reducing the environmental impact associated with their manufacturing and usage [10-12].

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The use of lubricants is essential in various fields, from the automotive industry to personal healthcare. In this perspective, it is important to examine the differences between traditional commercial lubricants and biologically derived lubricants, which are produced from natural materials or are biodegradable. This analysis aims to highlight the distinct characteristics of each type of lubricant, considering their properties, environmental impact, and applicability in different contexts [5].

Artificial intelligence (AI) has been playing an increasingly important role in the development and optimization of lubricants across various industries. The application of AI in this context can be observed in several areas:

- **Lubricant Formulation:** AI can be used to analyze large datasets on lubricant properties, including viscosity, flash point, thermal stability, among others [5]. With machine learning algorithms, it is possible to identify complex patterns and develop more effective and customized formulations for specific applications [6].
- **Performance Optimization:** AI can be employed to optimize the performance of lubricants under varying operational conditions. Through computational simulations and predictive modeling, AI algorithms can predict the behavior of lubricants at different temperatures, pressures, and loads, helping to adjust formulations to maximize efficiency and reduce wear.
- **Condition Monitoring:** AI-based condition monitoring systems can be deployed to track the performance of lubricants in real-time [7]. Sensors integrated into equipment can collect data on temperature, pressure, vibration, and other relevant parameters, while AI algorithms analyze this data to detect signs of wear, contamination, or lubricant degradation, enabling proactive maintenance interventions.
- **Predictive Maintenance:** AI can also be used to develop predictive maintenance systems that forecast the optimal time for lubricant replacement or replenishment based on actual operating conditions and performance history. This helps to avoid unexpected failures and prolong equipment lifespan, reducing maintenance costs and increasing operational reliability.
- **Research and Development:** Finally, AI can accelerate the research and development process of new lubricants by analyzing vast datasets on materials, properties, and performance [4]. AI algorithms can identify promising candidates for lubricant formulations based on specific criteria, enabling a more targeted and efficient approach to product innovation.

Recently, several significant studies have advanced the development of liquid lubricants using nano-additives to enhance tribological properties. A notable work [25] focused on creating a synthetic lubricant incorporating a $Cu/TiO_2/MnO_2$-doped GO nanocomposite, demonstrating significant improvements in viscosity, viscosity index, flash point, pour point, and reduction in friction and wear. In [26], lubricating oils containing nano-MoS_2 and nano-ZnO at different concentrations were compared, revealing improvements in tribological and thermophysical properties, notably increasing the flash point with ZnO. Additional studies [27, 28] explored diesel oil-based nanofluids with ZnO and MoS_2, observing significant benefits in tribological properties and pumping efficiency. Mousavi et al. [29] investigated the impact of MoS_2 on viscosity and viscosity index, while Khouri et al. [30] evaluated the graphene nanofluids for optimizing heat transfer in thermal systems. Finally, in [31], MWCNTs and SDS were added to crude oil to improve thermophysical properties, highlighting reductions in interfacial tension and electrical conductivity. These studies underscore the potential of nanomaterials to advance industrial applications such as oil extraction and thermal system optimization.

Nowadays, the integration of artificial intelligence in the field of lubricants offers significant opportunities to improve performance, reduce operational costs, and promote sustainability across a wide range of industrial and commercial applications [13]. This work aims to develop artificial intelligence (AI) using the artificial immune system, specifically the negative selection algorithm, in a vibrant mechanical structure with commercial and biological lubricants, and through the collection of vibrational signals to verify the replacement of commercial lubricants with biological ones.

2. Immune System

2.1. Biological natural

The Biological Immune System (BIS) represents the primary defense of living organisms against infectious agents invading the human body. This system plays a vital role in acting instantaneously against pathogens and identifying them to protect the human body from diseases. It is composed of two distinct lines of defense: the innate immune system and the adaptive immune system.

The innate immune system is the first line of defense, reacting rapidly to any invasion. It is characterized by the presence of dendritic cells (APCs - Antigen Presenting Cells) and phagocytes (such as granulocytes, macrophages, among others), which are responsible for ingesting foreign particles. Additionally, the innate immune system includes physical barriers, such as the skin, and chemical barriers, which act as the first line of protection against pathogens [14].

On the other hand, the adaptive immune system is the second line of defense and is highly specialized in identifying and neutralizing specific microorganisms, such as viruses, bacteria, fungi, protozoa, and helminths. This system is capable of recognizing and responding to antigens more specifically and efficiently after the initial contact with the infectious agent. Moreover, it has the unique ability to create immunological memory cells, allowing for a faster and more effective response to future exposures to the same infectious agent.

These two lines of defense work together to ensure the protection of the organism against a wide range of pathogens, playing a crucial role in maintaining health and defending against infectious diseases [15].

2.2. Artificial

Artificial immune systems (AIS) are a class of computational systems inspired by the principles and mechanisms of the biological immune system to solve a wide range of problems in various domains [21, 22]. Since their conception, AIS have garnered interest in several areas, including computer science, engineering, computational biology, and medicine, due to their unique ability to provide adaptive and robust solutions to complex challenges [16].

The origin of AIS dates back to the 1980s and 1990s, when researchers began exploring analogies between biological systems and computing systems. Inspired by the effectiveness and efficiency of the natural immune system in defending against pathogens, these pioneers proposed computational approaches based on immunological concepts such as pattern recognition, learning, immunological memory, and adaptive response [17].

Since then, AIS has evolved significantly, encompassing a variety of techniques and algorithms such as clonal selection algorithms, Negative Selection Algorithm, anomaly detection algorithms, artificial immune neural networks, and immunity-based classification systems. These approaches have been applied to a variety of real-world problems including intrusion detection in networks, pattern recognition in large datasets, optimization of complex systems, and vaccine design [18-20].

2.3. Negative Selection Algorithm (NSA)

Negative selection algorithm (NSA) is a computational technique inspired by the principles of the human immune system, particularly the process of thymic selection, to detect anomalies or non-self-patterns in data [16]. This algorithm mimics the way the immune system distinguishes between self and non-self-antigens, thereby providing a powerful tool for anomaly detection in various applications.

At its core, the negative selection algorithm operates by generating a set of artificial detectors, or detectors, that represent self-patterns within a given dataset [17]. These detectors are typically represented as strings of binary or real-valued features, analogous to antigen receptors in the immune system. During the training phase, the algorithm selects a subset of the dataset to serve as self-patterns and generates a diverse set of detectors that cover the feature space adequately.

Once the detectors are generated, the negative selection algorithm employs a process akin to immune surveillance to identify non-self patterns or anomalies in new data. When presented with a test sample, the algorithm compares it to each detector in the set. If the sample fails to match any detector within a predefined threshold, it is classified as non-self or anomalous.

One of the key advantages of the negative selection algorithm is its ability to operate in an unsupervised manner, meaning it does not require labeled data for training [16]. This makes it particularly useful for anomaly detection tasks where labeled data may be scarce or expensive to obtain.

Applications of the negative selection algorithm span various domains, including computer security, intrusion detection, network traffic analysis, fault detection in industrial systems, and bioinformatics [16]. In computer security, for example, NSA can be used to detect novel malware or cyber threats by identifying patterns that deviate from normal system behavior.

In summary, the negative selection algorithm offers a bio-inspired approach to anomaly detection, leveraging principles from the immune system to effectively identify non-self patterns in data. Its versatility, robustness, and ability to operate in an unsupervised manner make it a valuable tool for addressing anomaly detection challenges in diverse domains.

The negative selection algorithm (NSA), proposed in [16], operates in two phases, as described below [16, 17]:

- **Censor Phase:** Define a set of proper chains (S) to be protected. Generate random chains and evaluate the affinity (Match) between each chain and the proper chains. Reject the chain if the affinity is greater than a predefined value; otherwise, file the chain into a detector set (R).
- **Monitor Phase:** Given a set of chains to be protected (protected chains), evaluate the affinity with each chain and the detector set. Identify a non-proper element if the affinity is superior to a predefined value.

The censor phase of NSA primarily involves generating a detector set from randomly chosen data and verifying which data can recognize a non-proper pattern. The detectors are akin to mature *T* cells, capable of recognizing pathogenic agents [18]. The monitoring phase involves monitoring a system to identify changes in behavior; thus, this phase classifies the change using the detector set created in the censor phase. The censor phase takes place offline, whereas the monitoring phase operates in real-time [17, 18]. Figure 1 illustrates the censor phase and monitoring of the NSA.

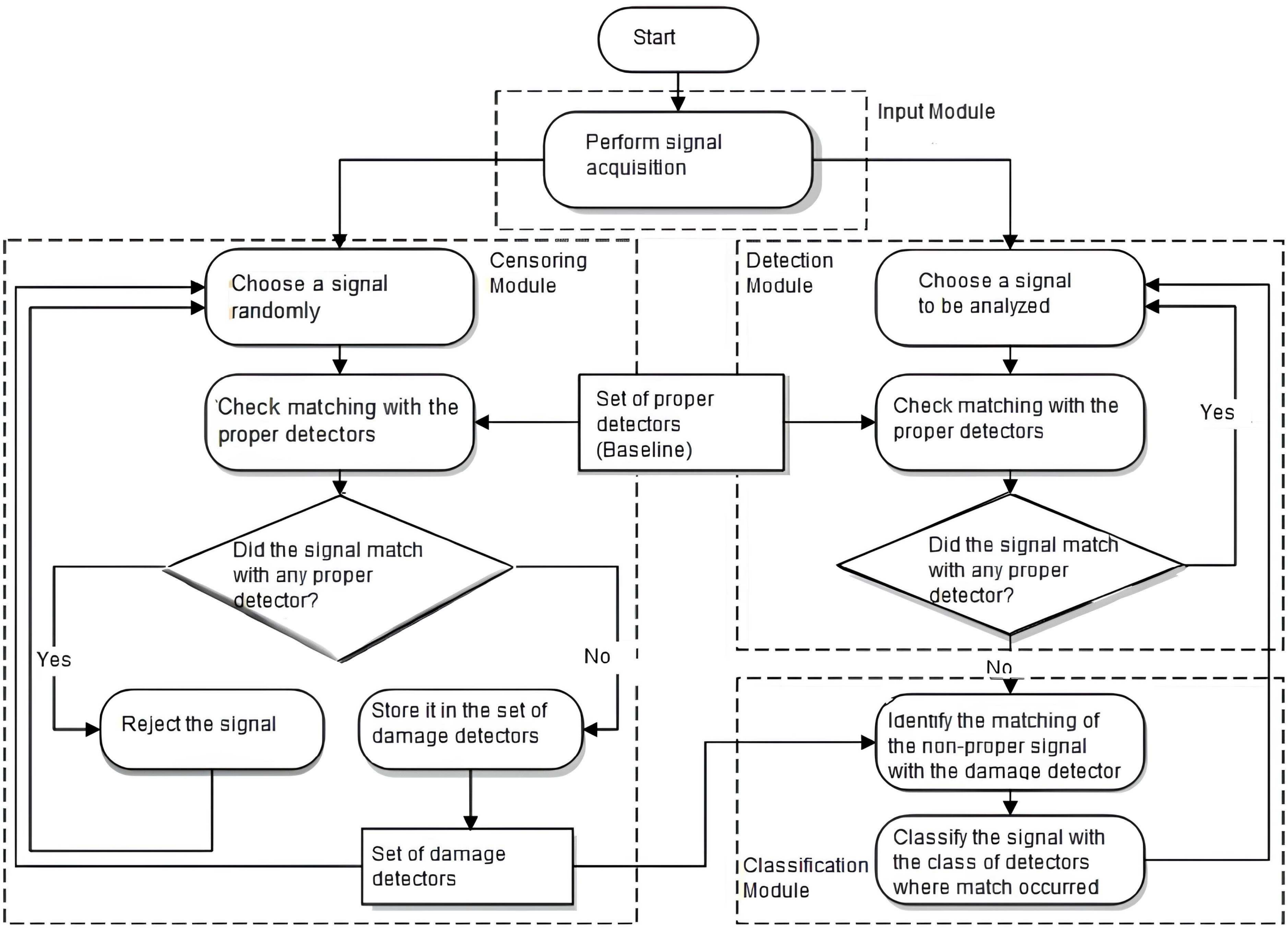


Fig. 1. Flowchart of the censor phase and monitoring of the NSA [17].

The antigen (Ag) is the signal analyzed in the negative selection algorithm and can be represented as:

$$Ag = Ag_1, Ag_2, Ag_3, Ag_4, \ldots, Ag_L \tag{1}$$

The detectors represent the antibodies (Ab) and are expressed as:

$$Ab = Ab_1, Ab_2, Ab_3, Ab_4, \ldots, Ab_L \tag{2}$$

where L is the dimension of the space of the antigen and the antibody.

2.4. Matching criterion

To evaluate the affinity with the chains and demonstrate their similarity, a matching criterion is used, which functions similarly to a combination. The matching can be perfect or partial. A perfect match occurs when the two analyzed chains have the same value in every position, while a partial match occurs when the patterns have only one identical position value, confirming the match. This quantity is known as the affinity rate, representing the degree of similarity for matching between two analyzed chains [16]. The affinity rate is defined as:

$$TAf = \left(\frac{An}{At}\right) \times 100 \tag{3}$$

where TAf is the quantity of normal rates, An in the problem (proper rates), and At is the total number of chains in the problem (proper and non-proper chains).

Equation (3) allows for the precise calculation of the affinity rate for the proposed problem and represents the statistical analysis with the samples of the problem.

To dynamically improve diagnosis, a deflection attached to the antibody (detector pattern - Ab) is proposed, i.e., a tolerance with which it is possible to accept the combination with the patterns. This tolerance is defined according to Eq. (4):

$$\underline{Ab}_i \leq Ag_i \leq \overline{Ab}_i \tag{4}$$

where Ag_i is the nominal value of position i of the antigen (pattern under analysis), $\underline{Ab}_i$ is the nominal value of position i except for the deflection adopted at the antibody (detector pattern), and $\overline{Ab}_i$ is the nominal value of position i plus the deflection adopted at the antibody (detector pattern).

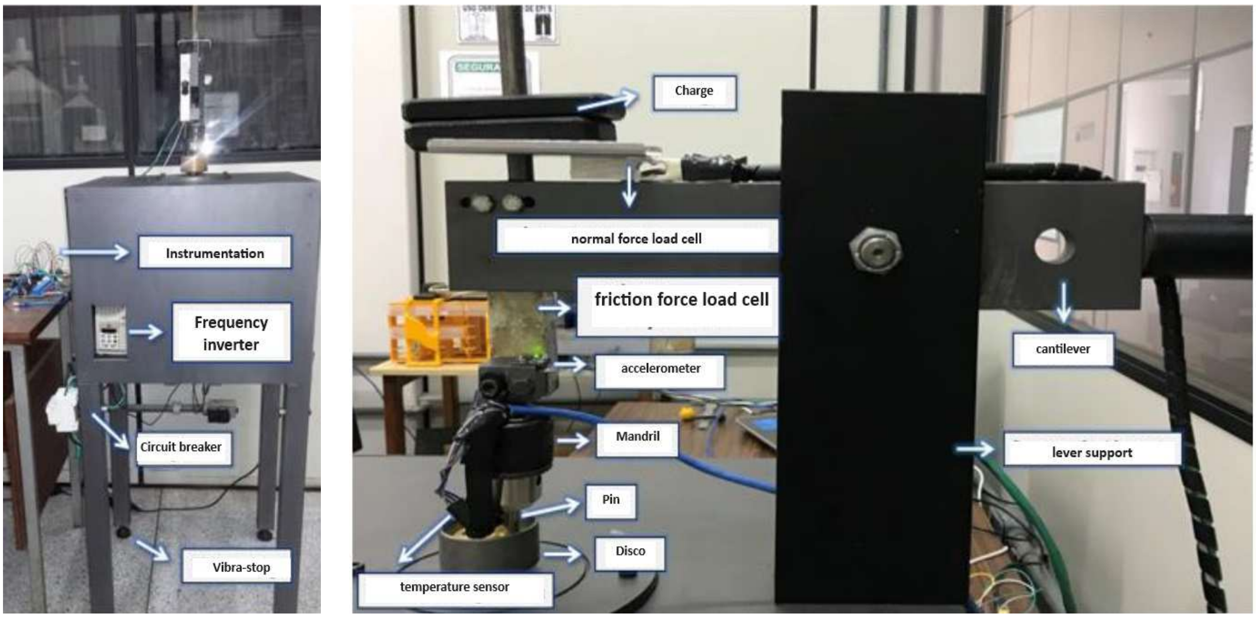
This approach quantifies affinity using patterns, analyzing position-by-position. Equation (5) represents the method for quantifying the total affinity with the analyzed patterns:

$$Aft = \sum_{i=1}^{L} Pc_i \tag{5}$$

where Aft is the percentage of the affinity with the patterns analyzed, L is the total quantity of positions, and Pc is the matched position. If Aft is greater than TAf, then the combination/matching with the patterns occur, and the patterns are considered to be similar. Otherwise, there is no matching with the patterns.

3. Materials and Methods

To start the development, it is crucial to begin by presenting a detailed description of the experimental setup. This description is essential for obtaining the dataset needed in the subsequent phases, which involve censoring and monitoring the negative selection algorithm. Next, we will proceed to study Artificial Immune Systems (AIS), with a specific focus on the negative selection algorithm. This study is essential for the development of the application for classifying lubricant behavior.



(a) (b)

Fig. 2. Pin-on-disc tribometer: (a) front view and (b) side view [23].

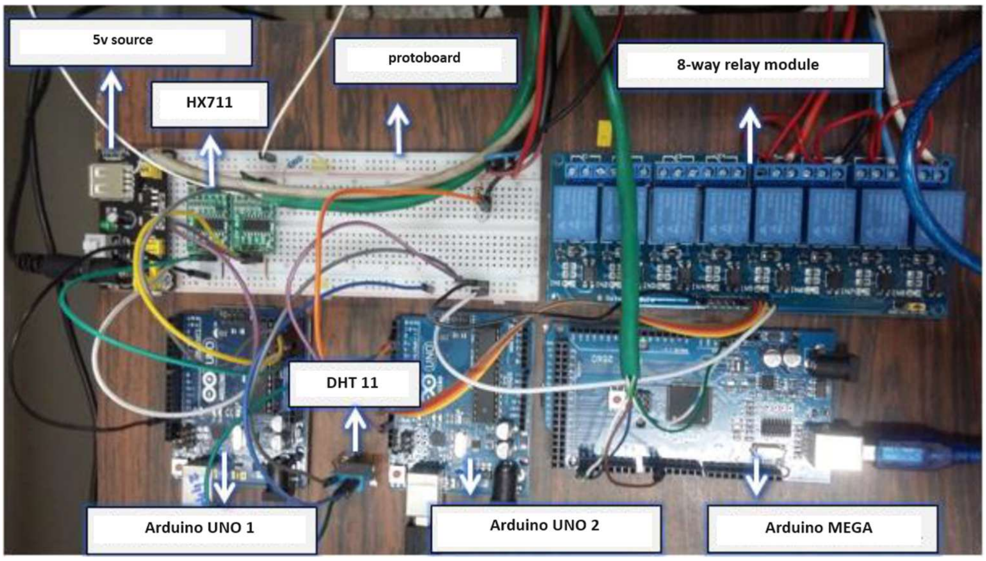


Fig. 3. Electro and electronic components coupled to the tribometer [23].

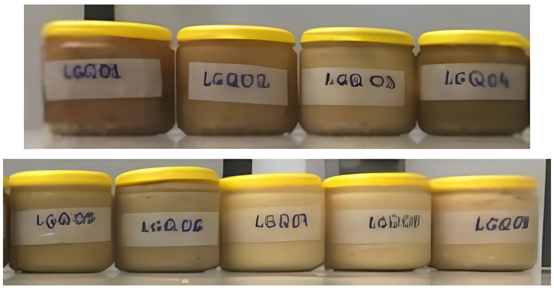


Fig. 4. Bio greases.

3.1. Experimental setup

The experiment and its equipment were designed to represent the behavior of a pin on disk system [23], aiming to demonstrate the simulation of the system's behavior and its corresponding vibration. The experimental concept dictates that the dynamic system must include sensors and equipment for data acquisition, algorithms for signal processing and treatment, data modeling, algorithms for behavior determination, and mechanisms for data storage.

To assess the efficiency of the synthesized Bio Grease (bio lubricant), lubricant vibration analysis was employed. The tests were conducted on a pin on disk experimental setup illustrated in Fig. 2. The frontal view of the equipment is highlights in Fig. 2(a), and its lateral view is shown Fig. 2(b).

Additionally, Fig. 3 highlights the electrical and electronic components used in the instrumentation of the equipment. This instrumentation is low-cost and controlled through an open-source platform.

A microcontroller of the Arduino UNO type, a frequency inverter, a reflective infrared sensor of the E18 - D80NK type, a circuit breaker, and an 8-channel relay module, of which only 4 channels were utilized, were employed, all powered by a 5V source. To capture vibrational signals, an MPU6050 accelerometer and an Arduino MEGA were employed.

For the experimental tests, the tribometer components are sanitized with ethanol and dried to remove impurities or contaminants, ensuring greater accuracy in the experimental results. Regarding the lubricants used, the bio greases, made from soybean oil, consist of 9 types (LGQ01 to LGQ09), with 3 synthesized based on sodium and 6 based on lithium. The proportions were made with 10, 20, and 30%. Two production processes were conducted. For those based on sodium (LGQ01 to LGQ03) and 3 based on lithium (LGQ07 to LGQ09), direct saponification of the bio-oil was used, while the other 3 based on lithium were made by mixing soap with oil (LGQ04 to LGQ06). The specific data properties for each bio greases are presented in Table 1. Additionally, a commercial lubricant with a mineral base, the blue FAG multipurpose grease, was used for comparative purposes. Figures 4 and 5 present the bio greases and commercial mineral greases, respectively.

Table 1. Composition and properties of bio greases and commercial greases.

Greases	Composition	Dropping Point (°C)	National Lubricating Grease Institute
LQG01	Sodium 10% (saponification)	103	0
LQG02	Sodium 20% (saponification)	118	1
LQG03	Sodium 30% (saponification)	149	2
LQG04	Lithium 10% (mixture)	144	2
LQG05	Lithium 20% (mixture)	161	3
LQG06	Lithium 30% (mixture)	173	3
LQG07	Lithium 10% (saponification)	133	0
LQG08	Lithium 20% (saponification)	156	0
LQG09	Lithium 30% (saponification)	165	1

Fig. 5. Commercial mineral greases.

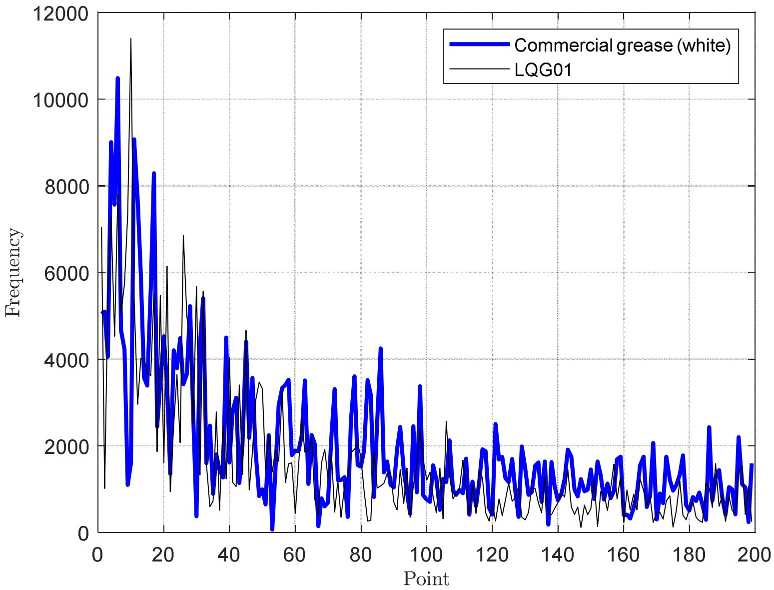


Fig. 6. A representative graph of a signal emitted by the structure with commercial grease and bio grease.

4. Proposed Methodology

The proposed methodology in this work is based on a structural integrity monitoring system, composed of three modules for data classification, data acquisition, censoring, and monitoring of the negative selection algorithm [16].

Data acquisition: Data will be obtained through the experimental setup and will be used in the censoring and monitoring phases of the artificial immune system.

Censoring module: In this stage, a census is conducted on the data, creating a set of detectors to identify anomalies in the monitoring process. This process is carried out offline.

Monitoring module: Fault signals are detected by evaluating and verifying their match with the set of self-detectors (baseline signals). Thus, fault signals are detected based on self/non-self-discrimination. If the identified signal is self, it is instantly classified as the normal condition of the structure. Otherwise, the signal represents an abnormal condition (non-self). Therefore, in this phase, the data are analyzed in real-time and compared with the set of detectors created in the censoring phase, aiming to provide a diagnosis (decision-making) through self/non-self-discrimination. Signal monitoring is performed online. This methodology is detailed in the Negative Selection Algorithm illustrated in Fig. 1. All tests were conducted using a PC equipped with a 13th Gen Intel(R) Core (TM) i7-1355U 1.70 GHz processor, 16 GB of RAM, and the Windows 11 64-bit operating system. The proposed method was developed using MATLAB® [24].

Table 2. Experimental parameters used.

Parameters	Values
Distance (m)	1000
Rotational speed (rpm)	60
Velocity (m/s)	0.0879
Radius of friction track (mm)	14
Load (kg)	1.02
Normal force (n)	10
Ambient temperature (°C)	22-24
Relative humidity (%)	32-35

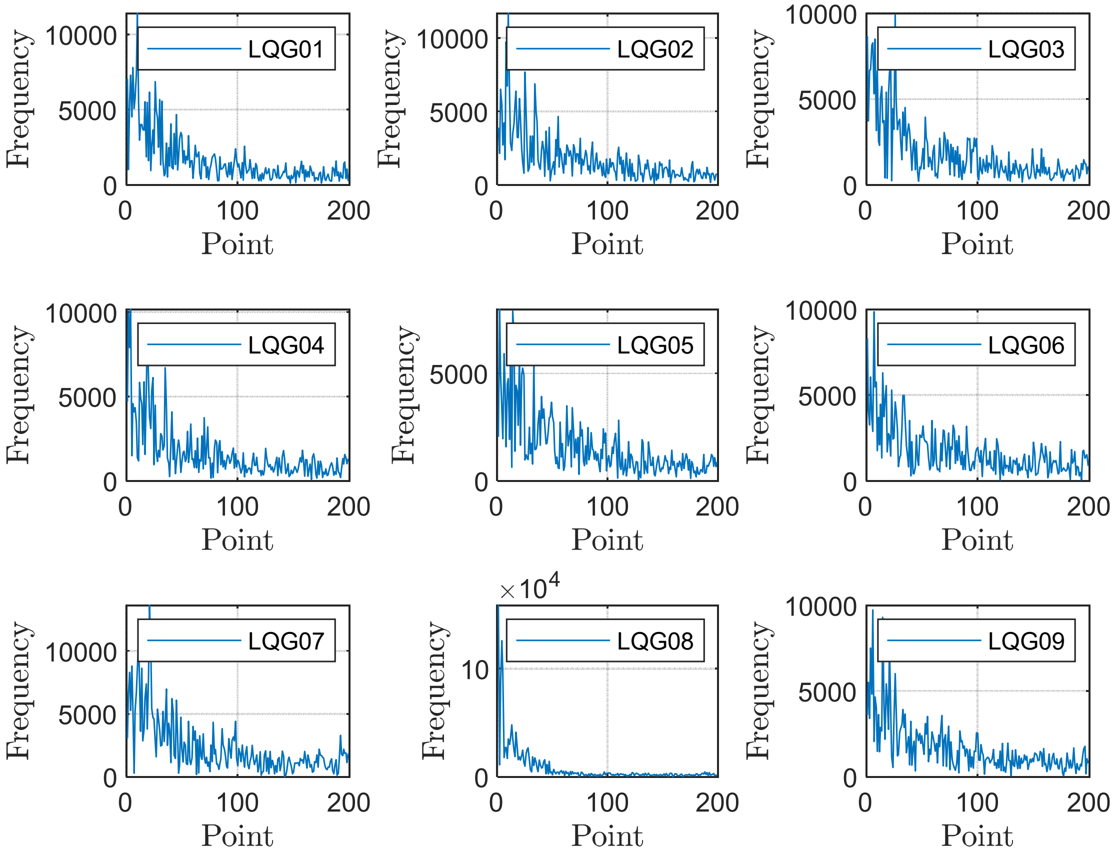


Fig. 7. Representative graphs of signals emitted by the structure with bio grease.

5. Results and Discussions

In this section, we present the tests and results obtained by applying the proposed methodology to the signals from the database obtained from the experiments.

The experimental collection was conducted using a system with commercial lubricant and bio lubricants in a pin on disk test, as described in the previous section. Following the established procedures, 2253 vibration signals were recorded for the commercial lubricant (white), and 2253 signals for each of the bio lubricants (LQG01 to LQG09).

The parameters chosen for a comparative analysis with the same data are presented in Table 2, with each lubricant tested in triplicate.

The system frequency was 1 Hz, so each cycle of it represents the capture of a vibration signal, in addition to controlling the properties according to the distance traveled by the pin on the disc.

Figure 6 shows an example of a randomly collected signal from the experimental setup using the commercial grease (white) compared with bio grease LQG01. Figure 6 presents the signal randomly collected for each bio grease prepared in this study.

In the tests conducted with the Negative Selection Algorithm, the objective was to assess efficiency, precision, affinity rate among detectors, and computational time across different configurations of the detector set for both bio grease and the commercial grease. The parameter used for the affinity rate was 70%, calculated through Eq. (3). It was decided to conduct the tests with 30% of the sample detector set.

To ensure the reliability of the results, the tests were repeated 20 times. It was observed that the Negative Selection Algorithm demonstrates satisfactory performance, with an accuracy rate above 90%. It is concluded that the quantity of detectors does not directly influence pattern recognition, and an improvement in results can be observed as the amount of information available in the database increases. Furthermore, it is recommended to use 30% of the database information to generate the detector set, aiming for system robustness.

Table 3. Results obtained by NSA for comparing signals with commercial grease (white).

Greases	Percentage of similar vibration patterns
LQG01	93.7778
LQG02	95.5556
LQG03	93.3333
LQG04	95.5556
LQG05	96.4444
LQG06	96.8889
LQG07	94.2222
LQG08	92.8889
LQG09	95.1111

6. Conclusion

Through this work, it is evident that the selection between commercial and biological lubricants is contingent upon the specific requirements of each application, factoring in performance, cost, environmental impact, and regulatory constraints. While commercial synthetic lubricants are well-established and effective across many industrial uses, bio-based lubricants offer a promising sustainable alternative for those prioritizing environmental stewardship. This study specifically examined the feasibility of substituting conventional commercial grease (white - Calcium 8 - 10%) with bio-based greases in vibrating mechanical structures. Utilizing a negative selection algorithm, we found that, to meet a vibration pattern similarity of 95% or higher, bio greases LQG01, LQG03, LQG07, and LQG08 are unsuitable. However, at a similarity threshold above 93%, only LQG08 remains unsuitable, and at 92% similarity, all bio greases tested are viable replacements. These results highlight that bio-based lubricants can match the performance of their commercial counterparts under certain conditions, presenting a viable option for many industrial applications. The integration of AI in evaluating these lubricants ensures precise performance optimization, making bio greases a feasible and sustainable alternative. Ultimately, the decision to use commercial or biological lubricants should be informed by a comprehensive assessment of application-specific needs, environmental impact, and regulatory requirements. The continuous advancement in research and development is crucial to expanding the use of environmentally responsible lubricants across various sectors. This study underscores the potential of bio-based lubricants to enhance sustainability in the lubricant industry, encouraging broader adoption of eco-friendly practices in industrial applications.

Author Contributions

All authors contributed equally to the development of the work.

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Conflict of Interest

The authors declared no potential conflicts of interest concerning the research, authorship, and publication of this article.

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Data Availability Statements

The corresponding author can provide the datasets generated or analyzed during this study, upon a reasonable request.

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