A Comparative Analysis of Condition Monitoring Techniques for Predictive Maintenance in bearings' failure prevention

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Abstract— **The manufacturing industry became a competitive market that requires each manufacturer to pursue operations excellency to maintain profitability and customers satisfaction. With machines and equipment acting as the bloodline for many industries including manufacturing, transportation and services, their efficiency and reliability are essential to ensure the continuity of the industry. With time being of a critical element for the delivery and reliability of any industry, assets breakdowns are incorporated with delays and substantial financial costs. Considering these concerns, predictive maintenance (PdM) emerged as a strategic approach that offers a proactive approach to mitigate the risks of machines' sudden breakdowns. The current research focuses on the applications of PdM with a focus on a comparative analysis of the existing condition monitoring (CM) tools that support machines' failure identification. CM is a key component for PdM that involves the continuous assessment of machines' components health to identify any deviation from normal operating conditions, facilitating the early identification of failures. The efficiency of CM is an impacting key on organisations ability to maintain machines' reliability, reduce downtime and support maintenance schedule optimization. This paper supports the selection process of CM techniques based on their principles, applications, and limitations, offering a comprehensive overview to support decision making process in the selection of the most suitable techniques for different machines bearings' failure modes. The research utilises vibration, thermography, and current analysis for various bearing failure modes simulated on an experiment test rig at various speeds. The research offers a comprehensive literature review on maintenance strategies, machines failure modes, CM techniques, their applications and limitations. The research offers a practical insight into bearings failure modes and suggests the optimum CM technique that supports PdM applications for failure prevention.**

Keywords—Maintenance, condition monitoring, Vibration analysis, Thermography, Current signature, Bearings.

I. LITERATURE REVIEW

It is well-established that poorly maintained equipment tends to consume more energy than well-maintained equipment [16]. While energy consumption can provide valuable insights into equipment condition, it is mostly limited to machines with relatively stable duty cycles. In the United Kingdom, energy monitoring at the machine level, particularly among Small to Medium Enterprises (SMEs), is not widespread, and the adoption of Industry 4.0 technologies is poor. A recent survey by a sector body suggests that this is primarily due to a misunderstanding of the benefits of Industry 4.0 [34]. Additionally, Machining Centres have several factors that can explain the increase in energy consumption, which may not be linked to their primary function, such as removing metal. Much of the vibration analysis research has focused on the tooltip, and therefore, ancillary equipment such as coolant pumps and table motors could provide the necessary data to establish a link between higher or erratic energy consumption and machine condition [2].

The research indicates that maintenance costs in industrial plants can account for a significant portion, ranging from 15% to 60% of overall operating expenses [21]. However, companies often overlook the proper measurement of these costs. This oversight has led to the emergence of advanced maintenance strategies, such as PdM and Condition-Based Maintenance (CBM), to address the challenges of effective maintenance management [7]. Corrective Maintenance is a basic maintenance approach where repair actions take place only after a breakdown occurs. It can be cost-intensive, especially for large-scale applications, due to potential catastrophic failures and production capacity impact due to extended unplanned downtime [26]. Preventive Maintenance (PM) is considered a proactive approach based on scheduled maintenance tasks to prevent failures. PM takes place based on a periodic schedule carrying out pre-planned tasks. Tasks are mainly basic checks, lubrications, and the change of degrading parts. Even though the strategy prevents sudden unexpected failures, catastrophic failures might still occur. PM drawbacks can be expressed in the fact that it does not have a direct link to assets. As a result, components and their actual conditions are not determined [9].

Total Productive Maintenance (TPM) is a maintenance strategy that originated in Japan in the 1970s, TPM is a holistic strategy to optimize equipment effectiveness and eliminate breakdowns. It involves all organizational levels to improve manufacturing equipment efficiency [38]. TPM focuses on multiple areas that would impact the assets directly and indirectly including the surrounding environment, training, and staff engagement from all levels [39]. A different approach for maintenance is Condition-Based Maintenance (CBM), which originated in the 1940s, CBM has expanded across various industries, from railways to manufacturing, due to advancements in information technology [40]. CBM assesses real-time machine data to detect functional parameter fluctuations and potential abnormalities. It combines diagnostics, which handles fault detection, with prognostics, which manages fault prediction [20].

CM involves measuring machine characteristics, such as vibration and temperature, to identify potential defects. Comprehensive CM strategies consider various criteria, including machinery type and operating conditions [29]. Vibration measurement is a cornerstone of CM, with advanced systems relying on vibration sensors. The ISO establishes standards for equipment vibration, and thorough analysis of vibration data aids in assessing machine health [14].

TABLE I. MAINTENANCE GENERATIONS

	1st generation 1940s-1950s	**2nd generation 1960s-1970s**	**3rd generation 1980's- current**
Description	Run-To-Fail	Simple maintenance schedules Systems for planning and controlling work Slow computers	Condition monitoring Failure modes and effect analysis Reliability and maintainability design Effect analysis Hazard studies Expert systems High skills and teamwork
Technical definition	Corrective maintenance	Preventive Maintenance (PM)	Reliability centred maintenance (RCM) Total productive maintenance (TPM) Condition monitoring (CM)

Condition-Based Maintenance (CBM) is a technological advancement that uses health indexes provided by sensory devices to improve the insight into the internal components' conditions and performance of machines [8]. CBM mainly focuses on scheduling maintenance activities based on real-time data collected from the field using condition monitoring tools [39]. CBM eliminates unnecessary maintenance tasks that may be scheduled to take place when the current state of the machine's measurements in real-time indicates that it is unnecessary to carry out the planned maintenance tasks. This results in high-cost savings associated with spare-parts replacement labor costs and costs incurred due to machine stoppage [7]. Another significant benefit of CBM is that it helps reduce machine breakdown rates and downtime [39]. CBM can provide a safety measure to warn operators and stop the machine when it reaches certain predefined levels of vibration or noise parameters, helping the maintenance team take necessary precautions to avoid machine breakdowns.

CBM has three primary aspects that define the necessary maintenance tasks and schedules [2]. Failure Diagnosis involves detecting the failure and associating irregular behavior with identifying the cause and related parts in the equipment. Failure Prognosis is the prediction of the future state of the equipment and provides an estimate of the predicted failure times. Optimising Maintenance as a Crucial Component of Condition-Based Maintenance: Exploring the Nexus between Anticipated Failure Occurrences and Maintenance Scheduling [20].

The criticality of maintenance optimisation within the context of condition-based maintenance (CBM) cannot be overstated. A core aspect of this process involves establishing a relationship between anticipated failure occurrences and maintenance scheduling, while also ascertaining the requisite types of maintenance to be performed in tandem with each expected failure [17]. The burgeoning potential of large-scale deployment of embedded, interconnected sensor technologies to generate voluminous data has become increasingly accessible for numerous manufacturing organisations [31].

Recent innovations, such as those originating from the Advanced Manufacturing Research Centre (AMRC) in Sheffield, UK, have substantiated the feasibility of obtaining copious amounts of valuable data through a network of cost-effective sensors integrated within the Industrial Internet of Things (IIoT). Although it would be reductive to equate Industry 4.0 solely with the utilisation of linked sensors for timely and intelligent data provision to aid managerial decision-making, this approach serves as a suitable and, in many respects, fitting point of departure for manufacturing managers perpetually concerned with cost-efficiency. The existing literature offers a comprehensive overview of the pertinent technologies [20, 16].

A. *Vibration Diagnostics and Analysis*

Vibration is a fundamental phenomenon that occurs in both natural and man-made systems. It is the repeated movement of an object or system about an equilibrium point [12]. Vibration signatures, signals from machines under normal operations, are crucial in revealing the state of a mechanical system [18]. When a machine faces issues, these signatures change, showing variations in frequency, amplitude, or phase connections, crucial for detecting faults [32].

Vibration analysis emerged in the mid-20th century as a pivotal tool for machine condition monitoring. With advancements in sensor technology and signal analysis, it became essential for assessing rotating machinery health, and detecting potential defects [7, 9]. Vibrations, oscillatory motions and their accompanying forces can strain machine components, affecting performance [12][30].

In condition monitoring (CM), vibration analysis is paramount. It aids in maintenance decisions by tracking real-time signals from machinery [23]. Vibration-based bearing CM has become integral to systematic maintenance over the years [25]. The varied vibration patterns under different fault conditions allow professionals to analyse a machine's internal workings without disassembly, making vibration analysis a top choice for machine CM [24].

B. *The Pivotal Role of Vibration Analysis in Industrial Machinery Health and Safety*

Vibration analysis is a premier technique for machinery assessment [3]. It offers benefits such as early fault detection and predictive maintenance [19]. This method not only reduces costs and downtime but also enhances equipment longevity and safety [30, 27]. Its accuracy in fault identification is over 82% [28], but its effectiveness requires expert analysis, quality equipment, and a holistic maintenance strategy [60][6]. A Swedish case study on Vibration-Based Maintenance (VBM) highlighted its efficiency, revealing an annual maintenance profit of 3.58 million SEK (USD 0.358 million) and potential savings of SEK 30 million (USD 3 million), emphasizing its pivotal role in boosting operational efficiency [4].

Vibration analysis is pivotal in various industrial contexts. In pulp mills, it's essential for detecting bearing faults, with machinery signatures offering insights into system health [7]. Vibration analysis ensures the safety and performance of mechanical systems, such as the elevator chassis design [15].

C. *Vibration analysis limitations*

A key problem with VA is the amount of data that requires analysis in real time and the algorithms necessary for accurate prognosis of potential issues [2]. Er at al [1] proposed a protocol for vibration sensor placement and analysis in machine tools. The results presented in their paper are extremely encouraging for those with an interest in machine condition, but the work also raises some significant questions. Firstly, it may prove difficult to place sensors in the optimum positions for the analysis required. Secondly, the vibration signals will vary significantly between machine tools and between operations making it difficult to differentiate between legitimate vibrations and that caused by deterioration in the machine tool of cutting tips and/or bearings. Thirdly, any changes in the operating parameters, such as cutting speed, feed rate and depth of cut, i.e., the metal removal rate (MMR) will result in a change in the signal to be processed. This has the potential to flag up false alarms, although the authors concede that it will also flag up potentially unauthorised changes to an agreed cutting strategy. Finally, not all maintenance issues will produce a vibration signature [17].

D. *Thermography*

Thermographic analysis has the advantages of being non-invasive and having the ability to monitor more of the kinematic chain associated with an induction motor and its ancillaries. It achieves this through identifying “hot spots” within the system or chain such as damaged bearings. A thermographic camera takes images of the system and some points within the chain will glow brightly, indicating a problem or fault [6]. Some of the most frequently studies faults in motors are bearing faults, broken rotor bars, shaft misalignment, and mechanical or electrical imbalance, In the case of a bearing damage, the fault would cause abnormal levels of friction within the bearing housing that would result in an increase in temperature [6]. Likewise broken rotor bars may propagate increased temperatures in adjacent bars due to the increase in current through these coils. Misalignment and mechanical imbalance would exhibit themselves in increased friction within the rotating components of the motor leading to higher-than-normal temperatures [16]. This may be caused by the loads exerted upon the motor by the kinematic chain. the associated rubbing and friction will reduce the operational life of bearings. Additionally, voltage imbalance, when one or two of the phases of the line supply are out of phase, can produce significant thermal increases.

E. *Current signature*

Fault detection and diagnosis for electric motors can be provided using relatively inexpensive current monitoring techniques such as current transformer (CT) coils. Bravo-Imaz et al [10] have shown that analysis of the current signature of the supply current to an induction motor may be used to diagnose gearbox faults. Such techniques are also used to provide a non-intrusive method for diagnosing issues with the motor itself. One common technique for detecting and diagnosing problems in induction motors is Motor Current Signature Analysis (MCSA) [26]. MCSA is used to diagnose motor problems such as broken rotor bars, unbalanced voltages, stator winding issues, eccentricity by carrying out spectral analysis of the supply current (stator current). MCSA relies on changes in torque producing fluctuations in current and voltage due to various faults in the motor or associated equipment such as gearboxes [10]. As such it provides a comparatively inexpensive method for condition monitoring and diagnosing of faults within electrical motors and the associated mechanical systems. The various electrical or mechanical fault conditions appear in the supply current spectrum as sideband harmonics that may be used to diagnose fault types. The presence of noise from other nearby motors in operation can complicate the analysis and necessitate the use of filtering to clean the signal. The strength of the signal allows the system to interpret the severity of the fault and thus practitioners may be able to predict the time to failure and thus take advantage of any opportunistic maintenance windows to replace or repair the faulty component [26]. However, this method has significant drawbacks when dealing with industrial motors that have variable torque and load signatures as MCSA has been developed to be used in steady state. That is motors that do not experience frequent changes in load and torque. Fast Fourier transforms are commonly used to analyse the current signals. This isolates the potential fault frequencies allowing the system to accurately diagnose problems. However, this does not usefully incorporate time issues. In stationary signals, that is motors with a steady operating state, this is not important [22]. However, with motors that experience fluctuating load demands it is important to understand not only what but when certain fault conditions are experienced. To overcome this Transient MCSA has been proposed. This method usually applies a Wavelet Transform to the transient stator current to characterise non-stationary signals [16].

II. METHODOLOGY

In the conducted study, a positivist research philosophy was adopted, emphasizing controlled settings and statistical analyses to explore the relationship between vibration, thermography, and current withdraw signatures in relevance to various bearings’ failure modes. The research approach and strategy were logical and experimental, utilizing established theories to guide data collection and hypothesis testing. Quantitative methods are primarily used, focusing on analysing various CM techniques to identify patterns among bearings’ fault situations. The foundational literature review provided a comprehensive understanding of Maintenance Strategies, condition monitoring, and the intricacies of different CM standards. This review also highlighted the potential use of CM techniques in predictive maintenance and early bearings’ fault detection.

The CM techniques were applied and data (vibration, temperature and power withdraw) where collected for different bearing failure modes at rotational speeds ranging from 1000 rpm to 3500rpm. The failure modes considered were damaged ball, inner race, and outer race as well as cocked bearing housing.

The experimental setup in Fig. 1 shows the Multi-Belt Drive, belt tensioner, ¾" bearings, ¾" shaft, router, ¾" coupler, various sensors for CM data collection, and reciprocating mechanism included in the kit.

Benchmarking: It was of utmost importance to establish a benchmark which served as a standardised reference point for evaluating the performance of various malfunctioning systems. The experiment procedure described was initially performed using fault-free components referred to as ***good bearing***. The meticulously documented data points depict the system's ideal, error-free behaviour. The benchmarked data is then kept for later use as a baseline for comparison when performing tests on damaged components.

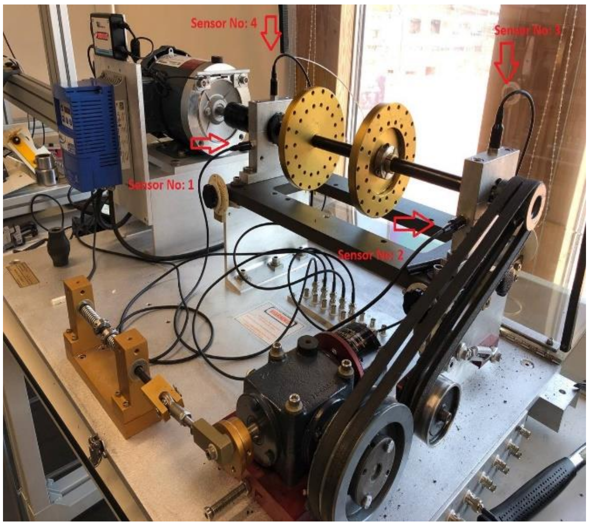

Fig. 1. Experiment setup for obtaining CM data of Benchmark.

III. RESULTS AND DISCUSSION

The results from the experimental tests on the benchmark and then the failure modes introduced in section 3 will be discussed here. Comparative analyses of the data obtained from the CM techniques (power withdraw, vibration and temperature) are done to ascertain which method outperforms the others.

A. *Power Consumption*

From a standstill power consumption of 4.7W, the electric motor withdraw was measured for benchmark and then the failure modes.

In table II, it is observed that the benchmark consumed the least power of 182 W at the fastest speed while the most power withdraw of 185W occurred for the cocked bearing housing. There is a direct relationship between the amount of power consumed and the increasing rotational speed of the motor for all the condition settings. This relationship is clearly displayed by the upwards trajectory of the curves in Fig. 2.

TABLE II. POWER WITHDRAW (W) WITH INCREASING ROTATIONAL SPEEDS FOR DIFFERENT SYSTEM CONDITIONS

Rotational speed (rpm)	**Good Bearing**	**Damaged Ball Bearing**	**Damaged Inner Race**	**Cocked Bearing Housing**	**Damaged Outer Race**
1000	85.2	84.8	85.1	85.5	84.5
1500	107	104.5	105.4	106.7	104.5
2000	126.5	123.5	124.1	125.6	123.6
2500	143.8	141.5	143	145	142
3000	161.2	157.2	161.7	165.5	160.1
3500	182	182	183	185	183.6

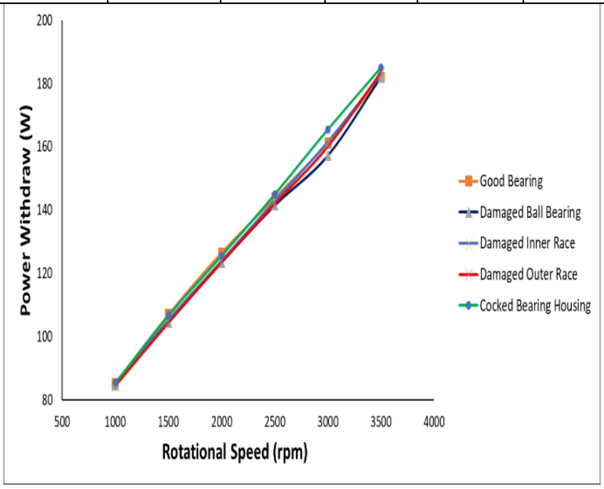

Fig. 2. Power Withdraw (W) with Increasing Rotational Speeds for Different System Conditions

The scatter of the power withdraw data seen in Fig.2 is closely packed hence there is not much disparity between the system conditions. However, when each condition is taken in isolation, there is considerable difference in power consumption as the speed increases from the lowest setting. Table III presents the percentage power withdraw at increasing rotational speeds with reference to the lowest speed of 1000rpm for the system conditions. The good bearing recorded the lowest percentage power withdraw of 113.62% at the top speed 3500rpm while the highest rise in power was for the damaged outer race at 117.28% when compared to their respective values at the lowest rotation 1000rpm.

TABLE III. PERCENTAGE POWER WITHDRAW WITH INCREASING ROTATIONAL SPEED (%)

Rotational speed (rpm)	Good Bearing	Damaged Ball Bearing	Damaged Inner Race	Cocked Bearing Housing	Damaged Outer Race
1500	25.59	23.23	23.85	24.80	23.67
2000	48.47	45.64	45.83	46.90	46.27
2500	68.78	66.86	68.04	69.59	68.05
3000	89.20	85.38	90.01	93.57	89.47
3500	113.62	114.62	115.04	116.37	117.28

B. *Vibration*

All the vibration data were taken over a 4 second period for the benchmark and failure modes. Sensors 2 and 4 were positioned horizontally and vertically respectively along the shaft to capture the vibration data.

The readings from the horizontal sensor, presented in Table IV and Fig. 3, show that the benchmark demonstrated the least vibration of all the system conditions at different rotational speeds. The only exception occurs at 3000rpm where the cocked bearing house recorded the lowest vibration of 6.23E-02. It can be observed from Fig. 3 that the trajectory of the curves is generally upwards which largely suggests, a direct proportionality between rise in vibration and increasing rotational speeds for all system conditions. There are a few exceptions with the benchmark and damaged ball bearing where both curves peak at 3000rpm and then drop.

The damaged inner race consistently recorded the highest vibration at all the speeds. In some cases, the gap between its readings and the other system conditions is significant. At the maximum speed of 3500rpm 5.01E-01 was recorded for damaged inner race compared to 6.15E-02 for the good bearing.

The vibration data captured by the vertical sensor, as seen in Fig. 4 does not demonstrate any clear trends. The readings could have been affected by the positioning of the sensor or interference from other devices.

TABLE IV. HORIZONTAL SENSOR VIBRATION WITH INCREASING ROTATIONAL SPEEDS FOR DIFFERENT SYSTEM CONDITIONS

Rotational speed (rpm)	Good Bearing	Damaged Ball Bearing	Damaged Inner Race	Cocked Bearing Housing	Damaged Outer Race
1000	1.49E-02	4.85E-02	5.25E-02	1.76E-02	3.86E-02
1500	2.04E-02	8.82E-02	1.43E-01	2.66E-02	5.08E-02
2000	3.10E-02	1.10E-01	1.65E-01	3.98E-02	1.08E-01
2500	4.29E-02	2.00E-01	2.39E-01	5.67E-02	1.26E-01
3000	8.82E-02	2.66E-01	3.35E-01	6.23E-02	1.23E-01
3500	6.15E-02	2.14E-01	5.01E-01	6.85E-02	1.66E-01

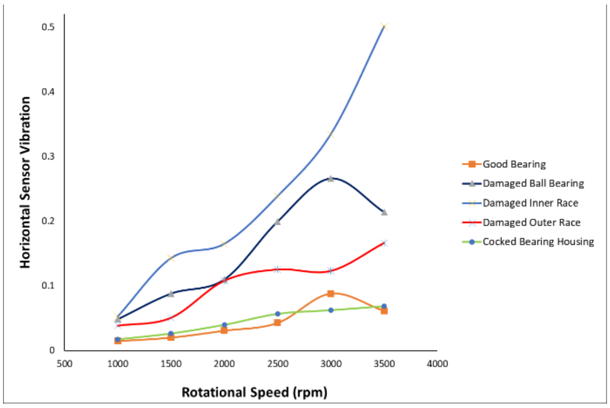

Fig. 3. Horizontal Sensor Vibration with Increasing Rotational Speeds for Different System Conditions

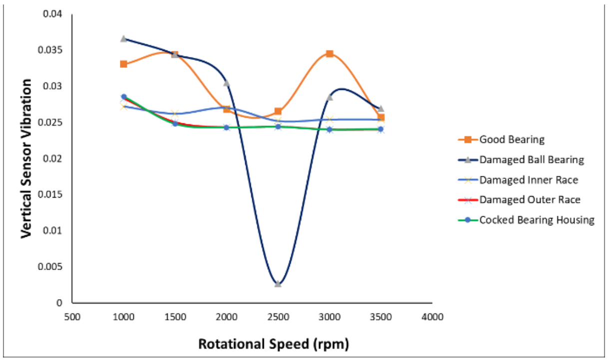

Fig. 4. Vertical Sensor Vibration with Increasing Rotational Speeds for Different System Conditions

C. *Temperature*

The temperature readings were taken using a thermal camera placed at sensor position 1 facing the bearing along the axis of the shaft (see Fig. 1). Similar to the experimental procedure carried out, temperature is recorded for the benchmark and then the failure modes.

In Fig. 5, the curves tend to move upwards which means that generally, temperature increases with rotational speed. However, there is no system condition that consistently recorded the highest temperature at all the speeds.

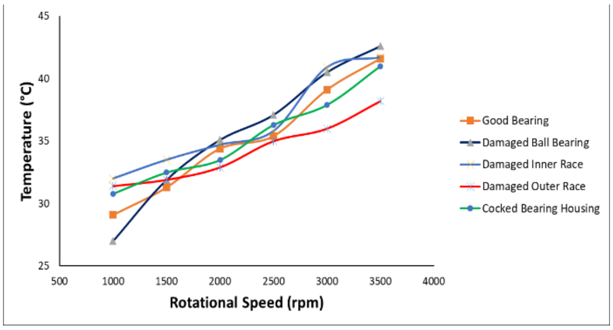

Fig. 5. Temperature (°C) with Increasing Rotational Speeds for Different System Conditions

As shown in Table VI, at the lowest speed of 1000rpm, the damaged ball bearing recorded the least temperature of 27 °C and the highest temperature of 42.6 °C at the top rotation. The damaged outer race displayed the least temperature of 38.2 °C at the fastest speed of 3500rpm.

TABLE V. TEMPERATURE (°C) WITH INCREASING ROTATIONAL SPEED FOR DIFFERENT SYSTEM CONDITIONS

Rotational speed (rpm)	**Good Bearing**	**Damaged Ball Bearing**	**Damaged Inner Race**	**Cocked Bearing Housing**	**Damaged Outer Race**
1000	29.1	27	32	30.8	31.4
1500	31.3	31.9	33.5	32.5	31.9
2000	34.4	35.1	34.7	33.5	32.9
2500	35.4	37.1	35.8	36.3	35
3000	39.1	40.5	40.9	37.9	36
3500	41.6	42.6	41.7	41	38.2

TABLE VI. PERCENTAGE TEMPERATURE WITH INCREASING ROTATIONAL SPEED (%)

Rotational speed (rpm)	**Good Bearing**	**Damaged Ball Bearing**	**Damaged Inner Race**	**Cocked Bearing Housing**	**Damaged Outer Race**
1500	7.56	18.15	4.69	5.52	1.59
2000	18.21	30.00	8.44	8.77	4.78
2500	21.65	37.41	11.88	17.86	11.46
3000	34.36	50.00	27.81	23.05	14.65
3500	42.96	57.78	30.31	33.12	21.66

Table VI presents the percentage temperature at increasing rotational speeds with reference to the lowest speed of 1000rpm for the system conditions. Observing the individual columns, temperature rises as rotation increases for all conditions. Although the damaged outer race had a considerably high temperature of 31.4°C at 1000rpm, it displayed a slow percentage temperature rise as rotational speed increased and attained a 21.66% rise at 3500rpm. On the other hand, the damaged ball bearing started off with the lowest temperature of 27 °C but rose by 57.78% at the fastest rotation.

The benchmark recorded a high percentage temperature rise at 42.96% second only to the worst performing system condition. Readings could have been influenced by the ambient temperature in the laboratory and time given for the set up to cool down before another set of data collected.

IV. DISCUSSION

Analysing the different data sets presents that with the increment in speed, all health indexes values increase. Looking into the individual health indexes, the current signature provides a clear indication of the bearing's failure, but it does not provide any different in the current withdraw with the different failure modes, which indicates that current measurement can support identification of bearing's failure but would need further investigation to identify the failure mode. The temperature signature shows a slight increment in temperature with the different failure modes which again could support a general identification of a bearing failure, but it cannot provide an insight into the type of failure the bearing would have. Regarding the vibration signature, there is a clear difference between the setup of the accelerometer data, as with the horizontal and the vertical setup, the vibration signature shows different readings and provide different insights. The horizontal accelerometer setup can provide a clear support to the identification of the bearing inner race, outer race, hearing housing and the bearing's balls with clear increment in the readings. The vertical setup on the other hand shows fluctuation in the readings only regarding the bearing's ball but it does not show any clear deviation when it comes to the inner race, outer race, or the bearings housing. Such observations indicate the efficiency of the horizontal accelerometer setup in detecting the various bearings failures. The main output of the experiment shows that the utilisation of various condition monitoring tools can support the identification of failures and they complement each other when it comes to in-depth analysis for the root cause of failure. Carrying out current or temperature measurement is considerably easier and requires less experience when carrying out routine checks in comparison to the vibration monitoring and analysis, which can save considerable amount of time when carrying out routine checks on large amount of equipment. In the case of existing failures, further analysis can be carried out using vibration analysis on the affected components only. As a result, highly experienced members of staff can have the time needed to carry out investigations on specific equipment which increases the quality of the maintenance applications.

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