MSDF in Predictive Maintenance - A Review

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***Abstract*— The concept of predictive maintenance, in which machines are monitored for the purpose of early fault detection and avoiding failure before it happens, has recently emerged as a trend in Industry 4.0. A single sensor concentrates only on one parameter, ignoring the more comprehensive aspects of the data; as a result, the data quality suffers, and it is more likely that errors will be introduced into the process of monitoring the critical equipment's condition. Therefore, a multi-sensory configuration technology has been developed for the purpose of collecting extensive information regarding a machine. This has been done with the intention of enhancing monitoring capabilities with regard to accuracy, data richness, and precision, resolution, efficiency, robustness, and dependability of the entire system. Nevertheless, the integration and analysis of the complex data collected by multiple sensors presents a challenge. As a result, strategies for the fusion of data from multiple sensors are in high demand for future applications. Data fusion can be broken down into several categories, including Data layer fusion, feature layer fusion, and decision layer fusion, depending on the level of processing information required to achieve the best possible integration. The purpose of this review paper is to offer a holistic perspective on machine monitoring by making use of a variety of sensors and the various techniques for fusing their data. In addition, the results of a case study that was conducted on four fault bearings and compared the results of single sensors to those of multi-sensors are presented.**

Keywords*— *Multi sensor, Data fusion, Predictive maintenance, Industry 4.0, Data acquisition, Processing

I. Introduction

Machine diagnosis through predictive maintenance has been widely used in all industrial sectors with the applicability in automated processes, maintenance, quality control etc. A number of data processing and early failure detection approaches have been implemented in this field [1]. Detecting the changes (e.g., faults, abnormalities) at early stages in dynamic motors is one of the main goal.

Maintenance cost runs deep in an organisation. It includes the cost of spares, sudden breakdowns etc. that may shoot up the production loss. Hence systematic maintenance practices need to be followed depending upon the criticality or priority of the equipment. Structured maintenance practice can assess in low cost, efficient working and continuous operation of the plant. The four different types of Maintenance practices are: Corrective Maintenance, Preventative Maintenance, Condition-based Maintenance and Proactive Maintenance. The corrective maintenance refers to simply run the plant until the machine fails, then rectify or replace the machine and continue the process. This can be applied to the machines which are of minimal criticality and whose repair cost may go higher than buying a new one. Preventive maintenance is a calendar-based maintenance where in life of a machine is estimated and then overhauling is scheduled before it fails. In this overhaul time needs to be predicted correctly or it will lead to production loss. A predictive maintenance is a "Condition based maintenance" where machine is monitored periodically and maintenance is scheduled if it gives a warning sign before failure. The process allows the repair to be made at time that suits the production and maintenance schedules. Proactive maintenance refers to Reliability based maintenance where a problem is anticipated and solved before it becomes a problem i.e., root cause failure analysis is done [2 – 6].

Rotating machineries face numerous defects due to many reasons. Rotational Mechanical defects of machineries are categorized into three main types [7]:

- Rotor body defects – Unbalanced blowers/fans, Misaligned shafts, bent shafts, fractures/cracks etc
- Rotor support – Problems in bearings such as inner race or outer race damage, roller damages, oil whirl, improper mounting, etc
- Transmission gear defects – Missing tooth, extensive backlash etc

The accurate detection of faults and going to the root of the cause is utmost priority for a machine to run smoothly and enhance its usability life. For this purpose, the most important step is correct data collection and selecting required parameters to effectively analyze the condition of machinery.

Analysis by vibration monitoring assist in about 60% of fault prediction. But as Machine complexity increases, single parameter is insufficient for analysis. To further enhance this accuracy, other parameters like temperature, Motor current analysis, sound level measurement needs to be accounted for better prediction of machinery condition. Technologies that employs multiple sensing configurations is used for this purpose in order to increase accuracy of measurement, data depth, precision, image quality, effectiveness, durability, and dependability across the entire system.

Employing multiple sensors introduce several other challenges for data analysis. A huge amount of data will be accumulated at the backend which requires proper evaluation. A systematic approach towards categorizing, processing and analysing the data is needed for reliable outcome. Combining the data collected from different sensors and processing appropriately to improve performance and accuracy is known as data fusion. Data fusion in turn has different methods that needs to be implied according to the type of data and outcome we require. This study reviews different aspects of data fusion techniques and aims to identify further gap in this field.

A. *Data Fusion*

The essential aspect of a multisensory based monitoring system is the merging of data from several sensors.

Techniques of data fusion helps to integrate data collected from several sensors and related databases which enhances its accuracy, maximise useful data content, and make more detailed conclusions than a single sensor could. General fusion system is depicted in Fig. 1. Input from n different sensors are fused in the fusion centre for processing and the fusion output is obtained. It is a simplified view of the procedure but the actual work is tedious and accurate decisions needs to made at every instant or stage from data collection to the decision level. If the sensors data is of similar type, it becomes easier for data analysis but due to influence of fault in the data, the data needs to be segregated well using the existing techniques that will be discussed further in this paper.

Data fusion has obvious applications in condition monitoring, as a huge amount of data must be analyzed to accurately estimate machine health. Vibration, sound level, temperature, pressure, oil analysis, and other data may arrive at the fusion module, encapsulating the system properties and aiding in its state assessment [8]. The sensor fusion technology eliminates irregularities in input and gives the most accurate measurement interpretation. As a result, the existing sensor data fusion method overcomes the disadvantage of single sensor monitored equipment failures.

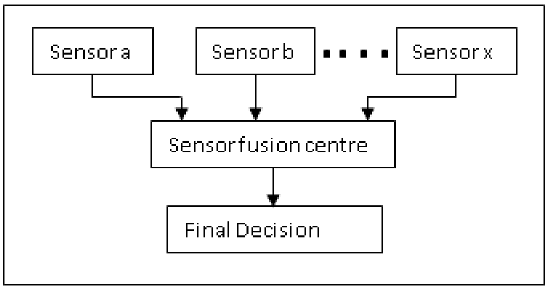

Fig. 1. Data Fusion

Below are the stages in the basic procedure for machinery fault diagnosis using multi sensor system to monitor multiple parameters:

1) Signal acquisition: This includes bottom end data collection. The selection and mounting of sensors play a critical role in data acquisition. In multi-sensor monitoring system, collected data could be three types of data: data that are redundant, data that do not overlap but are partial, and data that are complementary to one another.:

2) Pre-processing: Data pre-processing is reducing the amount of data collected while maintaining the useful information with improved quality and minimal data loss. This includes feature extraction and sensor validation.

3) Data alignment: The collected featured data from different sensors during pre-processing stage must be fused. For this purpose, different types of methodologies like Model-based techniques, association metrics, batch and sequential estimation procedures, grouping approaches etc. are used.

4) Data post- processing: post-processing is merging mathematical data with knowledge and then making a decision based on final processed outcome.

It is not always necessary to carry out all of the steps. It depends on the application, requirement, sensitivity of data, type of data etc. There is no one fusion approach that has been offered.

B. Selection of sensor and Data Acquisition Module

Before planning the architecture for Data fusion, the selection of sensor and building a data acquisition module is a priority. For fault diagnosis, certain parameters play an important role for detection and diagnosing the irregularity. Hence selection of appropriate parameters and related transducer, keeping the cost factor in mind, is the first step in building a data acquisition module. Employing the techniques of Industry 4.O for data collection, different sensing, detection and identification techniques can be enabled to build an effective IOT module. The sensor signals are transformed into domains with the greatest information to reflect the equipment's status, or a fusion of numerous domains, throughout the data collecting process [9-12]

C. Architecture

Engineering of a multi sensor system is a major task due to a huge amount of data that is generated. Managing the data poses a big challenge. The architectural selection, or when and how to merge or combine vibration data in the monitoring data stream, pose challenge. Architectures for data fusion from data collected through multiple sensors can be classified as below fusion levels:

1. Data Level Fusion

In this level, the raw information obtained by transducers is processed instantaneously at the data layer, the untreated data is completely processed, and the relatively low data is concentrated [13]. The sensors' synchronized data is instantly fused, followed by feature extraction and defect declaration through local decision making. [Fig. 2]. [14].
The capacity to obtain more characteristics from raw data which are not present in rest of the layers of fusion is one of the advantage of data layer fusion. Major drawbacks include high computing load, poor real-time performance, limited fault tolerant ability, less stable and data uncertainty [15].

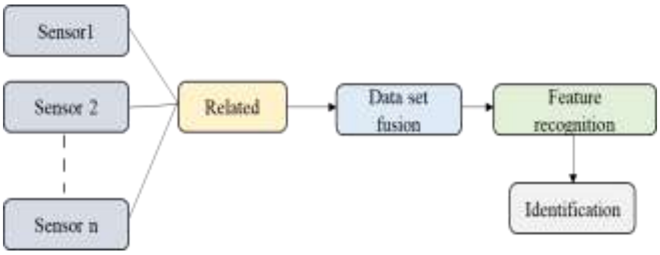

Fig. 2. Data level Fusion

2. Feature Level Fusion

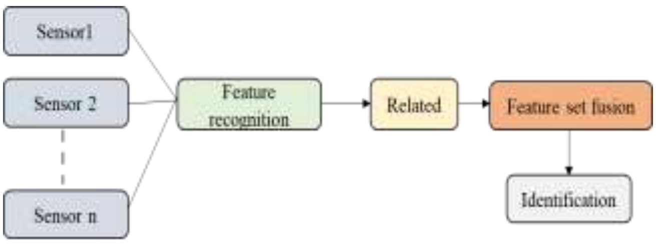

Fig. 3. Feature level fusion

Every transducer is utilized for the purpose of gathering type of signal in feature-level fusion. Feature vector is then obtained from the featured data using methods of feature extraction, and these vectors are then put into the classifier and fused to get the fault declaration. It makes sure that it retains enough information for future decision analysis. [Fig. 3]

Various techniques used in feature level fusion are: Kalman filtering, neural networks, fuzzy interference and so on. This technique contains fewer data and calculations than data layer fusion, resulting in better real-time performance following data processing [16-18]

3. *Decision Level Fusion*

This is the greatest degree of fusion level. Every sensor in this fusion technique, has a separate pre-processing unit before the data gets fused with other data. The fusion is done of the filtered data that is obtained after preprocessing every data collected at the sensor end to obtain the final result.

The Dempster–Shafer (DS) evidence inference method and the Bayesian probabilistic inference technique are the two often utilized decision-level fusion methodologies. [Refer Fig.4]. This technique has high fault tolerance, anti-interference, excellent flexibility, better real time process, low communication bandwidth requirements. Since a lot of data requires to be compressed during data collection, this method requires compressing sensor which not only adds to cost but also results in the loss of data [19-20.

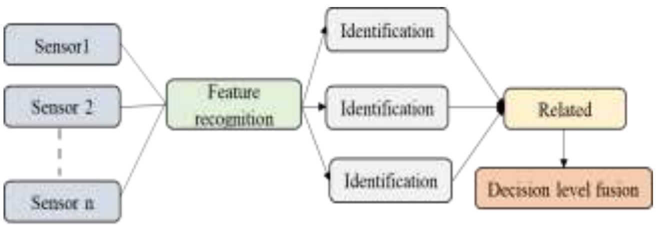

Fig. 4. Feature level fusion

D. Architecture Selection

According to the above study, every fusion technique has its own advantages and limitations. And whatever may be the strategy used, relevant data needs to be collected and analyzed properly. The essential guideline in selection of the architecture is that the data fusion should take place near to original data. Chances of the loss of data is higher in Feature level and decision level fusion as compared to the data level fusion. But data level fusion is only applicable in applications where the sensor data observations are identical. Even a slight difference in data from different sensors can cause problem in data level fusion. Hence architecture selection must be based on the type of signal collection [21-23].

E. Feature Extraction Techniques

Following Table I is stating some of the feature extraction techniques used at different levels of fusion.

TABLE I: FEATURE EXTRACTION TECHNIQUES

DATA LEVEL	**FEATURE LEVEL**	**DECISION LEVEL**
Nearest Neighbors	Maximum Likelihood	Bayesian methods
Probabilistic Data Association	Kalman Filter	Dampster – Shafer Inference
Joint PDA	Particle Filter	Abductive Reasoning
Multiple Hypothesis Test	Covariance Consistency Methods	Semantic Methods
	Fuzzy Logic	

II. LITERATURE REVIEW

Multi sensor data fusion has been the major research area in condition monitoring of the machines in various sectors since last decade. In this seminar, we review research and development of Data fusion technologies which is a challenging task when it comes to the implementation of multiple sensors. Various approaches for data fusion have been described taking into account the energy conservation aspects. Based on reported studies and development, the comparison between data fusion technologies and accuracy level using single and multiple sensors have been done. After comprehensive studies, it is deducted that diagnosis using multiple sensors gave much higher accuracy than single sensor diagnosis. However, the data fusion technology to be used depends upon the application and type of data collected. Data fusion using feature level extraction is widely accepted as it has advantages over the data level and decision level fusion technologies.

“A case study on multi-sensor data fusion for imbalance diagnosis of rotating machinery” was presented by Qing (Charlie) Liu et al. [1]. In this study, multi-sensors are utilized in this work to gather rotational imbalance vibration data from a test rig. A technique called auto-regressive (AR) model is utilized for extraction of the distinctive characteristics of each vibration signal. A Cascade Correlation (CC) neural network is then used to achieve data fusion. With statistical significance, the results show that multi-sensory fusion of data-based diagnostics beat single sensor diagnostics.

A Starr et al. [8] described data fusion applications in intelligent condition monitoring. With examples derived from manufacturing and plant applications, this article gives a fundamental understanding of architectures or frameworks. The main application shown gives key vibration monitoring data for paper mill equipment and aids in the maintenance optimization process.

For the process of fusion, (JDL) architecture of the US Department of Defense assumes a level distribution, describing the information gathered from the originating signal level to a refining level, in which data association, state estimation, or object categorization take place. Situation assessment fuses the object depictions offered by the refinement, at a higher level of inference. this design may be applied to condition monitoring issues. [Fig. 5.]

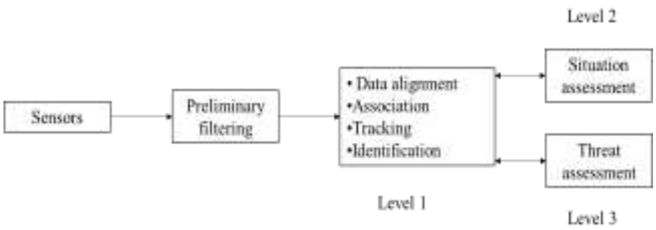

Fig. 5. JDL data fusion Architecture

The data fusion using multiple sensor architecture is presented in this paper by A. H. G. AI-Dhaher et al. [24]. The goal of design is to get fused measured data which accurately represents measured parameter. The design is built on usage of a Kalman filter and fuzzy logic techniques to create an adaptive Kalman filter. To process the collected data from each sensor, an adaptive Kalman filter is used. As a result, there are n adaptive Kalman filters running in parallel for n sensors. Each adaptive Kalman filter has a correlation coefficient, which is calculated by comparing the projected output to the observed data. The measurement noise covariance matrix was modified using fuzzy logic techniques depending upon magnitude of the correlation coefficient. The results obtained from adoptive Kalman filters then combined to create a single outcome. Results of the tests revealed that each Kalman filter outperformed the standard Kalman filter. Use of multi sensor data fusion techniques yielded better results than utilizing from individual sensors.

V. Sundararajan et al. [25] have categorized methods of condition monitoring into knowledge based, model based, and data based. Expert systems utilize procedures and inferential engines to detect breakdowns and their origins, and knowledge-based systems are subsets of such systems. Machine failure data is often derived during trials and used to educate a monitoring system in data-driven approaches. Using the findings of the training phase, pattern recognition algorithms try to categorize data from actual sensor. On the other hand, Model-based approaches, forecast machine performance using mathematical models. This paper has proposed the combination of the model and data-based approach for condition monitoring of electrical motors. [Fig. 6]

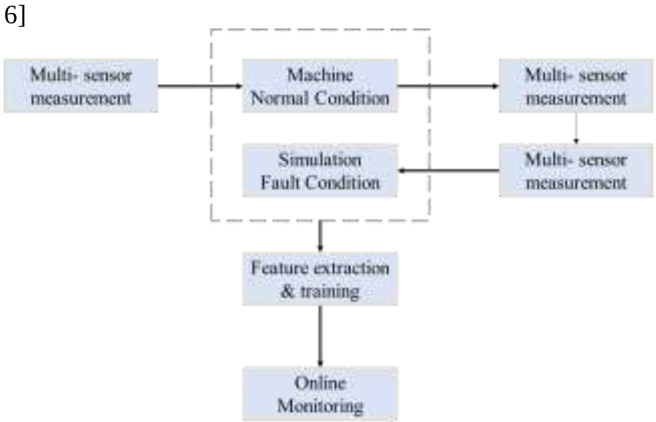

Fig. 6. Multiple Sensor Condition Monitoring Diagram

System initially determines the system parameters by monitoring the system's functioning in normal conditions. The model is then used to replicate the system under incorrect conditions, with the parameters highlighted. The extracted features and trained classifiers may then be utilized with the simulated data. Data from the sensors collected from machines is utilized to get characteristic data, which are then categorized using classifiers derived from simulated outcomes after system is implemented and operational.

Procedure

1. The first stage in achieving machine Faults condition monitoring is creating a mathematical model & recognizing the unit by detecting quantifiable signals in proper circumstances. Later, using collected data, calculate the system parameters.
2. The second stage is to recreate and simulate the machine systems that having faults under various load situations using these parameters. The classifier may then be trained using the simulated signals. If all of the characteristics from the first stage are known, then variety of the faults in motor can be simulated through the model.
3. The third stage is to create a classifier that can distinguish between healthy and defective machine inputs. The training data is derived from the healthy machine's measurement and also the signals that are simulated and created in the second phase.
4. The final stage is to program the classifier into the online sensor systems and then use it. When the machine's online measurements are input into the classifier, an alarm is generated when incorrect conditions are identified.

Ling-li Jiang et al. [26] proposed Fault Diagnosis of Rotating Machines related to fusion of Multiple sensor data with the use of SVM and Time-Domain Features. This study proposes a multi-sensor information fusion strategy for rotating equipment defect diagnosis, in which all characteristics are computed using the vibration data in the form of time domain characteristics to generate a fusional vector, and classification is done using the support vector machine (SVM). Three case studies are utilized to show the applicability of the methodology: faulty gear diagnosis, rolling bearing detection, and rotor fracture detection. Each case study investigates the sensitivity of the variables.

WEN Yan et al. [27] proposed a defect diagnostic system based on multi-dimensional and multi-level information system & information fusion respectively for a Numerically controlled machine [Refer Fig. 7]. To begin, increasing the numerical control machine's operating parameters resource creates a multi-dimensional information system that is able to comprehensively and totally represent fault information. Second, multi-level fusion extracts the useful defect information from the raw signals. Finally, the outputs of the classifiers are combined using fuzzy comprehensive assessment, that is a simulation of the human decision-making process. The output of each classifier is used as a criterion for making a diagnosis. This model combines a number of sophisticated defect diagnostic methods.

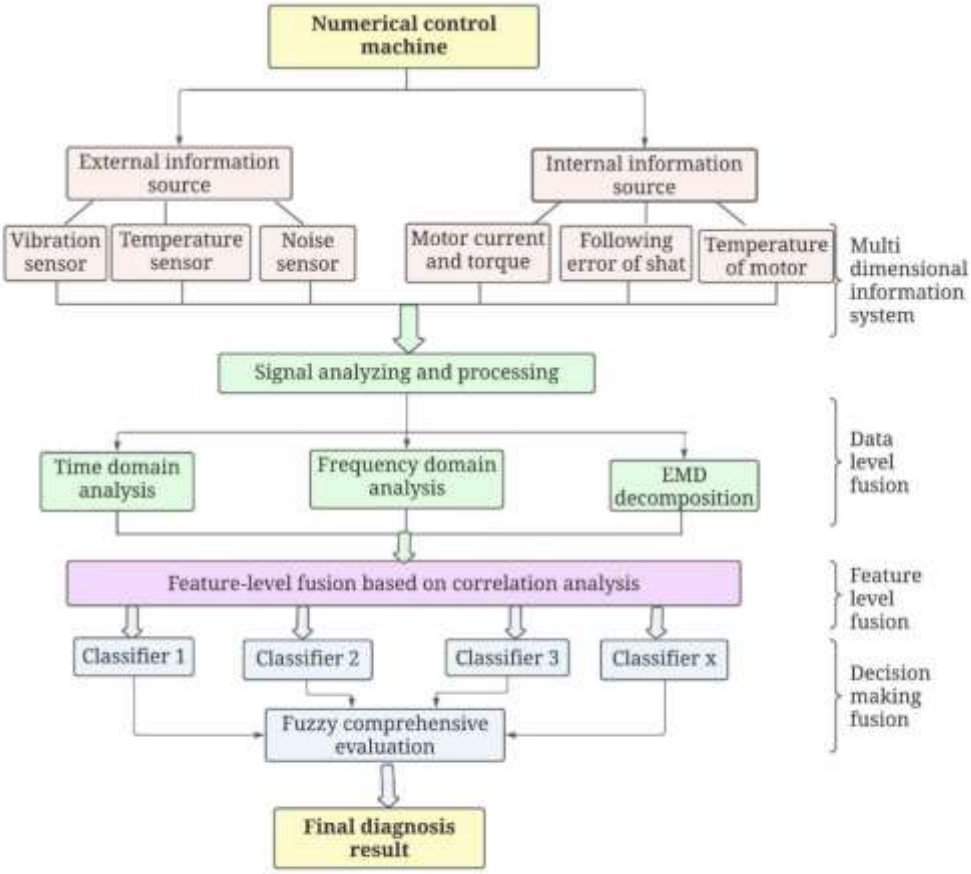

Fig. 7. Fault diagnosis model

Yuqing Tong et al. proposed multiple sensor data fusion architectures in 3 levels. They are Data level fusion, feature level fusion and decision level fusion. Sensor information fusion from multiple sources primarily gathers different sorts of data from numerous dispersed sensors that are all independent. The 3 levels of data set, feature level, and decision-making level will be merged at the level of fusion. In order to get the most optimum integration scheme for various practical issues, it’s essential to utilise a specific fusion level or a specific combination of two fusion levels, depending on the scenario. The future research will focus on combination of deep learning algorithms in fusion levels.

Reyana et al. [28] discusses the suggested system's energy saving module in terms of accuracy, processing efficiency, power usage, & total network operational life-time. In order to provide accurate and timely ecological awareness, the application "Condition-based Environment Monitoring System" uses an ADKF-DT-MF (Adaptive Decentralized Kalman Filter with Decision Tree Algorithm for Multi-sensor Fusion in WSN Environment) for multi-sensor data fusion to identify natural and human disturbances.

III. Scope of research work

The area of integration of deep learning and algorithms needs to be explored. The creation of relevant algorithms for real-world problems is also a study topic. Within the level 1 data fusion paradigm, analysis models have proven to be useful in decision-making process. There are a few instances, however, where intelligent systems could be more useful in the creation of this sort of system. Missing data in the original data, novelty detection inside parameter relationships, & root cause diagnosis are all examples of these problems. Future study will focus on improving methodologies in order to achieve higher levels of computing efficiency. Currently, multisensory data fusion approaches are restricted to mechanical operations. Future research might go beyond the current scope of study. Furthermore, every defect feature of condition monitoring of a certain machine has yet to be explored. This is a big gap that has to be filled by more research into diagnosing/detecting every machine failure and developing a high-level fault diagnosis module [29-32].

IV. Case study of Fault Diagnosis of Roller Bearing

For analysis, vibration data from rolling bearings with four fault models are used: normal bearing, bearings with inner race and outer race defect, and defected bearing balls. An eight-dimensional vector is formed from right different sensors (s1 to s8) by taking a fault sample and calculating its specific time-domain characteristics [26]. So, a total of 440 samples used that constituted the fault sample tests from 110 fault samples from each model. Fifty fault examples from each model, totalling 200 samples, are chosen at random as training samples, while rest of them are utilised as testing samples. One by one, the twelve time-domain statistics are examined.

LibSVM-mat-2.9 is used for State vector machine calculation. Gaussian kernel is selected as kernel function. The parameters C and g are searched using cross validation and the network search technique. For pattern identification, one-against-one multi classification is used [33-35].

A. Observation

TABLE II: DIAGNOSTICS RESULT OF ROLLER BEARING USING SELECTED CHARACTERISTICS FOR FUSION

	Diagnostic accuracy (On scale of 10)				
Feature	Normal	Defects in Inner race	Defects in Outer race	Ball defect	All testing samples
Mean	10	10	10	10	10
Peak	9.4	9.4	10	10	9.7
Amplitude square	10	10	10	10	10
Root mean square (RMS)	10	10	10	10	10
Root amplitude	10	10	10	10	10
Standard deviation	10	10	10	10	10
Skewness	6.5	8.4	6.2	8.0	7.3
Kurtosis	9.0	7.2	8.2	9.7	8.5
Waveform factor	8.1	7.0	8.0	9.8	8.2
Peak factor	6.4	6.4	7.8	9.5	7.5
Pulse factor	7.1	6.4	8.1	9.5	7.8
Margin factor	7.1	6.8	8.0	9.5	7.8

Table II shows the diagnostic findings of rolling bearings utilising various time-domain characteristics.
The mean, standard deviation, RMS, root amplitude, & amplitude square are 5 sensitive characteristics for recognising a roller bearing failure, as indicated in Table III [9]. Using these qualities, the diagnosis accuracy is 100 percent.

To identify roller bearing issues, consider 8 characteristics from a sensor and create 8-D vector as fault sample to compare with one sensor. Eight sensitive features for diagnosing failure selected based on the above study are mean, amplitude square, RMS, root amplitude, standard deviation, peak, kurtosis, and waveform factor.

Before inputting SVM, normalised eigenvector is treated to eliminate orders of magnitude differences between various characteristics. One by one, the sensors s1 through s8 are examined. Table 4.2 shows the diagnostic findings of rolling bearings utilising various single sensors.

TABLE III: DIAGNOSTIC RESULTS OF ROLLER BEARING USING MULTIPLE SINGLE SENSORS

	Diagnostic accuracy (On the scale of 10)				
		Defects in bearing race			
Sensor	Normal	Inner	Outer	Ball	testing samples
s1	8.5	8.8	10	9.8	9.3
s2	5.8	5.8	10	10	7.9
s3	9.6	7.8	10	9.8	9.3
s4	10	8.5	8.3	9.8	9.1
s5	10	9.6	10	10	9.9
s6	9.7	9.6	10	9.1	9.6
s7	9.8	9.0	10	8.8	9.4
s8	6.1	5.1	5.3	8.7	6.3

B. Conclusion of the case study

A feature-level information fusion method is studied, in which features are computed involving vibration information in time-domain characteristics to generate a fusional vector, which then classified using SVM. The raw signal acquired in this approach just requires a vibration testing device, making the procedure easier. The sensitivity of 12 time-domain characteristics is focussed in a case study on roller bearing defect diagnostics. For a rolling bearing defect, the mean, RMS, standard deviation, root amplitude, & amplitude square are sensitive. When comparing Tables 4.1 and 4.2, it can be shown that the multi-sensors information fusion technique has a greater diagnostic accuracy than the single sensor method as a whole. Although, characteristics utilised & described in the work are entirely in the time domain, defect detection of rotating machinery may also be done with features in the frequency domain.

V. SUMMARY

The term "multiple sensor system" refers to an integrated system that uses a number of sensors to acquire information about the system's environment. There are three types of sensor layer integration methods: dataset fusion, feature level integration, and decision-making level integration. Different fusion procedures are used to combine data. The degree of integration level ranges from low to high, depending on the data layer, feature layer, & decision-making layer. Amount of data required varies, and the real-time ranges from low to high. Different fusion methods might be chosen for various challenges. Multi-sensor diagnosis surpasses single-sensor diagnosis when phase information is unavailable. To understand probable machine faults, it's critical to choose sensor placement and mounting direction carefully. A multilayer diagnostic system can be employed to diagnose a complicated mechanical system or process. On the comparable data, data fusion using data-level technique is implemented at the first layer. At the second layer, many diagnostic cells (or units) are built based on sensor signal correlation, with feature-level data fusion implemented inside every cell. On every diagnosis cell identification, declaration-level data fusion is performed at the top layer, and final diagnosis is delivered. The further research approach will focus on use of deep learning and algorithms in tandem. The development of appropriate algorithms for real issues is also a subject of research.

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