Significance of Multi-level Fusion in Multi-component Fault Diagnosis under Speed Varying Condition in Rotational Machinery

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Most well-known challenging effects of identifying multiple defects in a rotational machine when speed is varied, are illustriously inspected by many researchers. However, different fusion logics are evolved in the series of research attempt, but not paid much attention in interrogating it for unsteady speed signals.Addressing this literature void, this paper focusses on multi-level fusion strategy with the help of sensor-centric feature integration and Dempster Shafer's (D-S) theory of evidence for uncovering multi-faults in bearings, shafts and gears of rotational machines under speed variational condition. Primarily, instantaneous frequency and envelope from the acquired vibration and sound signals of complex system parts are evaluated and fed to Machine learning (ML) such as Support vector machine (SVM) and K-nearest neighbors (KNN) which verifies the classification performance. The propriety of D-S combination rule is credited by comparing it with the results of other renowned decision-based fusion such as Structural causal model (SCM) and weighted voting method (WVM). This enlightens the effect of imposing DS theory for combining the ML results of integrated vibration and sound signals which is symbolized as multi-level aggregation with 85.76 % accuracy. To illuminate more of this proposed method, a profound investigation over misclassified shaft classes for vibration signals using SVM-RBF are discovered and verified for single-level and multilevel fusion. This yields promising results for multistage fusion approach in rotational machinery fault diagnosis at varying speed rate.

Keywords: *Rotational machine, Fault diagnosis, Sensor signal fusion Decision-level fusion, Dempster Shafer theory, Multi-level fusion.*

1. INTRODUCTION

As a well-known fact, maintenance in rotational machinery acknowledges the lifetime of machine's reliability [1]. Factors such as vibration, temperature should be consistently monitored for earlier warnings to prevent unexpected breakdown [2]. In that case, condition monitoring (CM) identifies equipment health status by acquiring vibration and other signals with an aid of sensors and data acquisition (DAC) [1,2]. So far, fault diagnosis-based machine learning (ML) technique accomplish desirable results for larger dataset [3]. This is because of strong signal correlation with the presence of faults in mechanical elements such as gears, bearings, shafts, etc. under constant speed condition [4]. But, when the signal behaviour is non-stationary due to irregular speed, the fault analysis becomes challenging [5]. Predominantly, gearbox which are susceptible to defect causing factors [6], whereas functionality of rolling bearings in broader applications [7]and shaft are responsible in energy transfer [8]. Due to the prominence of these machine parts, major economic loss and catastrophic damage can occur if any failures are initiated. Thus, various advanced techniques are performed with careful considerations to provide accurate fault prediction in speed varying scenario.

The more relevant fault feature procured from complex signals under irregular speed are Instantaneous frequency (IF) [9]. In addition, signal envelope analysis proves its significance in extracting component fault characteristics for the same event. On applying Hilbert transform as well as Band pass filter (BPF), this information is intelligibly assessed [10]. Most common methods to extract such a prime attribute, short-time Fourier transform (STFT) [11], Wavelet transform (WT) [12], continuous WT [13], etc. struggles in providing clear signal representation. These popularly used time-frequency analysis (TFA) are best-fitting tool when signals are non-uniform [14]. But precise IF estimation is still tedious, but methodologies such as Advanced TFA [15], Adaptive Signal decomposition [16], Generalized-demodulation transform (GDT) [17], etc. have proven its ability in dealing with those com–putation, carrying their own demerits. Most importantly computing IF is to predict and detect different component failures in non-constant operating mode. So, emphasizing the current leading decision-making theory in these circumstances as a primary objective, STFT are

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adequately applied to the signal for representing the time-frequency domain to extract this eminent feature.

In the CM field, the Machine learning (ML) model in Artificial Intelligence (AI) are prevalently used for improving decisions from the learning experience [18]. This AI model lends a valuable support in dealing with fault prediction, especially in complicated operational state [19]. As an instance to put forth this subject, Support vector machine (SVM), Decision Tree (DT), Artificial Neural Network (ANN), Discriminant analysis with linear and quadratic functions (LDA, QDA) are adopted for multi-component fault classification under different speeds [20]. And, Multilayer perceptron (MLP), SVM and K-nearest neighbour (KNN) classifies bearing faults and its results are mixed to conclude the final end-result using deep learning-information fusion planning [21]. Furthermore, a study on examining the number of component health detection claims that the single health state is found to be analysed more than simultaneously occurring multiple component faults [22]. Thus, it is essential to bring out the need of multi-component fault identification using efficient ML algorithm for safe maintenance and expand number of researches in this area of exploration.

By leveraging sensor data, AI model can automa–tically monitor mechanical system health check and issues earlier with timely maintenance [23]. Assessment of the classifier model are achievable by confusion matrix which compares actual and predicted value [24]. Classification error occurs due to the fault class re–semblance and limited training dataset. This can be minimized by the reliable classification model [25]. Reduction of mis-categorization helps in gaining in-depth examination to estimate the machine irregu–larities. So appropriate ML classifiers are incorporated to enrich the distinctiveness of advanced fault detection techniques.

Understanding the limitations of single sensor insta–llation for extracting component's accurate information, the establishment of multi-sensor system incorporates the knowledge of obtaining detailed insight of machine's health [26]. Following this concept, by adopting feature extraction techniques, distinct signal attributes are obtained from multi-signals to give as a key input to the different fusion algorithms for efficient decision making. As an outline of this perception, infeasibility of data-level fusion in practical applications requiring inordinate larger data processing, promotes feature-based integration for its simple implementation [27]. Along with this, ML performance is enriched by feature-dependent fusion [28]. But then, decision-centric and multi-level fusion approach yields superior performance over aforesaid unified techniques in recognizing the faults [27]. Decision-oriented coales–cence preserves data integrity and reduces the missing data impact for enhancing fault-diagnostic performance and accuracy [29]. This conceptualization offers the better outcome based on the combination of different classifiers' output [30]. Well-recognized methods in this aspect are weighted voting method (WVM) [31], Bayesian network (BN) [32], Dempster Shafer (D.S) evidence theory [33], Structural causal model (SCM) [32], etc. These schemes are efficiently involved in fusing multi-classifier's accuracy results. From the research prospect, Decision-level fusion strategies are found to be lacking in rotary machines running in speed variational effect. Among the aforementioned concepts, D.S evidence theory are exceptionally popular in discovering multiple faults in the transmission element systems for the constant speed rate. To illustrate this, Hamda et al.,[34] have deployed this framework for predicting imbalance, shaft crack, misalignment and bearing loose by utilizing five different sensors. Mi et al.,[35] have recognized five rolling bearing faults by revealing higher accuracy results in D.S evidence theory than SVM classification result. Thus, this investigation influence has inspired to pay more attention towards failure classification using D.S evidence-based decision aggregation ideology under dynamic speed change operating manner. Subsequently, Kibrete et al., [27]have confessed that the single-level fusion encounters data redundancy and diminishing precision. This can be resolved by multi-level fusion with careful optimization. Thereby, this course of action again added value to the inquisition in formulating the proposed work.

Multi-sensors supported decision-level technique, assists in upgrading the fault grouping result by fusing multi-source information [29]. As an essence of this explanatory note, information from each sensor as each evidence are combined for final diagnostic result. In this valuation, Euclidean distance and evidence entropy helps in assigning the weighted factor for reflecting sensor data's importance. Then, probabilities are determined to hypothesis based on evidence and Dempster's combination rule are employed to merge the modified evidence's value for a comprehensive fault segmentation [36].

The previously referenced articles clarify the research direction from the feature-level to decision-scaled combination in rotational machine's abnormal state findings. Additionally, this is strengthened with the accordance of multiple fusion levels. As the earlier inspection of intense commitment in elevating IF by means of robust adaptive methods and lesser consideration of multi-component compound faults, the evolving integrated decision-reliant perception with the signal-level merging in condition-based maintenance have aspired to showcase its effectiveness in variable speed condition. Therefore, this paper proposes the most compatible D.S rule of evidence combination among other diagnostic fusion with the dissimilar signal composition for referencing multi-level integration to categorize the multi-component fault in rotational machine elements for the accelerating speed. SVM and KNN are utilized to classify signal-based aggregation and then these labelling accuracies for each state are integrated by prioritized decision-oriented algorithm for enriching the fault-accurateness. Implementing these two integrating action plans in a sequence, generate advantageous results.

Besides this study, the similarity between two defect states is engrossed and verified using the afore–mentioned fusion algorithms as research innovation to spotlight the sovereignty of the proposed study. The practical applications which are involving earlier fault detection by improving maintenance and reliability to prevent downtime error, are highly recommendable for electing the planned research study. Other among rotational machines which often face challenges in longer production time requiring high maintenance are wind turbines.

Through research exploration, examination studies in fault discovery under fluctuating speed state are developing progressively in furnishing the machine reliability. But still, they confront hurdles in offering high accurate fault findings. So, thoughtfully the intended research is structured firmly to confer the originality to meet up the requirement. Thus, the novelty of this planned work lies in the systematic fusion strategy with sequential classification and decision-based integration which is characterized as multi-level fusion in the rotational machinery under speed varying condition. As many researches in decision-oriented and multi-stage combination are found in fault diagnosis under constant speed rate, non-linear signal-based failure analysis approach of industrial machine elements are infrequently inves–tigated. This inspires to develop model under such complex unsteady operational mode.

The methodology proposed is explained in Section 2. Experimental studies that discuss on experimental setup and procedure are described in Section 3. Appropriate features of unsteady speed signal's extraction are expounded in Section 4. The classification algorithms are discussed in Section 5. Mathematical derivatives of decision-fusion algorithm in Section 6, followed by virtue of different fusion approach are elaborated in Section 6. From the previous section's purview, multi-level aggregation's notewor–thiness is clearly outlined and the results are pointed out in Section 7. In the end, the conclusions are annotated in Section 8.

2. METHODOLOGY OF PROPOSED WORK

The realization in the field of envisioning machine mal–functioning of complex non-static signals as an inves–tigative problem, accentuates the idea of employing D-S evidence concept with as core objective. The procedure of the proposed methodology is portrayed in Fig 1.

The acquired vibration signals through piezoelectric accelerometers and sound signals by microphone for 16 health states of mechanical components in alternating speed rate are processed. Fault-related features from these signals, IF, lower and upper envelope are evaluated and fused for classifying each health condition status using SVM, KNN. In this evaluation, 10-fold cross validation are adopted for testing and training the dataset. To proceed with, the output of ML classifiers are fed as an input to D-S evidence mathematical analysis for the result optimization.

Thus, to establish the hybridization of signal-focussed coalition and decision synthesis in a single paradigm, interconnected vibration and sound signal attributes are compiled to group the system health under time-varying speed. Besides this, to demonstrate the potentiality of D.S evidence rule, it is compared with WVM and SCM.

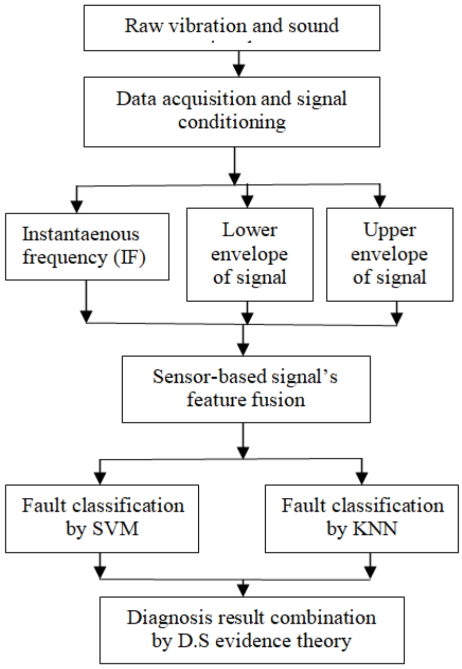

Figure 1. Flowchart of proposed multi-level fusion methodology

3. EXPERIMENTAL STUDY

This section discusses the overall experimental set up as well as follow-up process that are equipped with vari–able speed circuit connection for procuring data using vibration and sound sensor. In this test configuration, speed is dynamically changed from 200 to 2200 rpm for 16 machine condition states.

3.1 Experimental arrangement

As shown in Fig 2, machine fault simulator comprised of connecting 20 mm diameter short shaft at the motor's rotor shaft via flexible coupling for power transmission and shaft misalignment effect reduction. Maximum speed of 2200 rpm are achievable by 0.5 horse power (HP) Direct current (DC) motor. For supporting shaft ends, two ball bearings (SKF 6206/2Z open deep groove ball bearing) with specifications of 16 mm width, 30 mm inner diameter and 62 mm outer diameter are placed. Shaft can be made unbalanced for performing experi–ments by firmly attaching disc in the mid of the shaft. Near the engine, error-free bearings which is considered as good bearing are positioned and the bearing that will be tested are kept at the other end. With the ensuing actions, the free end of shaft is linked to single spur bevel gear box by V-belt pulley. The sensor is mounted on top of the bearing housing for data acquisition.

Vibration signals are precisely recorded by affixing tri-axial accelerometers (Kistler) on flattened smooth surface from top of the bearing housing I. Concurrently, a microphone which is kept adjacent to the bearing captures the sound signals. With regard to defect analysis for operating under speed acceleration, these gathered signals are then sent to signal conditioning unit after analogy to digital conversion and amplification. Universal Serial Bus (USB) connection helps in recei–ving these digitized signals to the computer system.

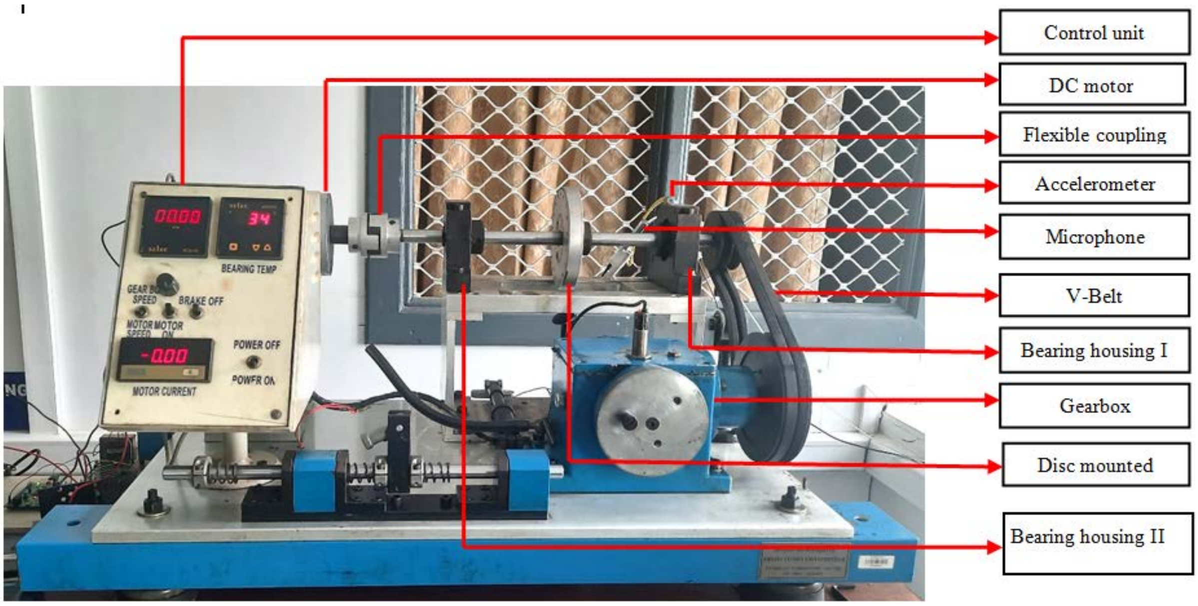

Figure 2. Rotational Machine Fault simulator with sensor installation

3.2 Test procedure

The experimentation procedure begins with the stability maintenance during complete machine run. Initially motor remains idle, then speed varies in DC motor between 200 and 2200 rpm for 10 seconds, then decelerates from 2200 to 200 rpm for another 10 secs and returns back to idle period. In this experimental analysis, acceleration time period is only considered for validating fault-relevant attributes and verify the results. Indeed, with the sampling rate of 15000Hz, data accumulation is preserved.

Faults in gear, shaft and bearings are artificially created to impose desired deformity for segregating unusual machine faults. Table 1 describes the possible defect combination for conducting experiments. This denotes s1 to s15 as fault classes and NOC as normal condition with whole of sixteen classes.

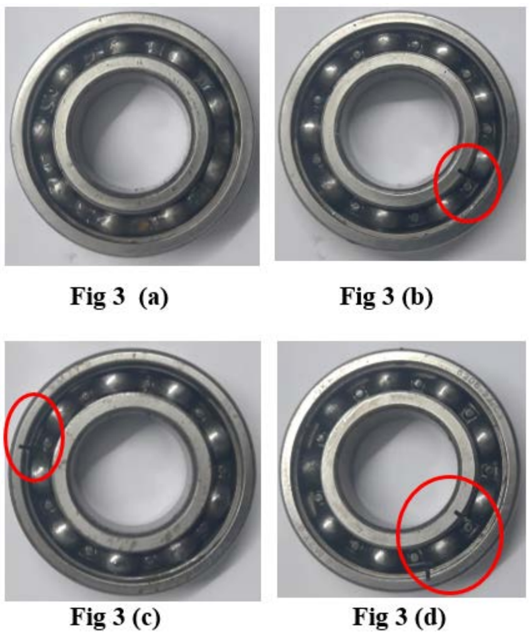

Figure 3. Different bearing health status (a) Good bearing (GB), (b) inner race fault (IRF), (c) outer race fault (ORF) and, (d) combined inner race and outer race fault (BOTHF)

Artificial desired imperfections of 0.8 mm width and 1 mm depth are created in bearings with the support of wire cut electric discharge machining (wire cut-EDM) as conveyed in Fig 3 accompanied with defect-free bearings.

Fig 4 (b) shows tooth breakage in gear which is addressed as most renowned gear defect among other gearbox failures, besides normal state gear as in Fig 4(a). Shaft imbalance which is a common cause of fatigue in shaft, are disclosed in Fig 4 (c).

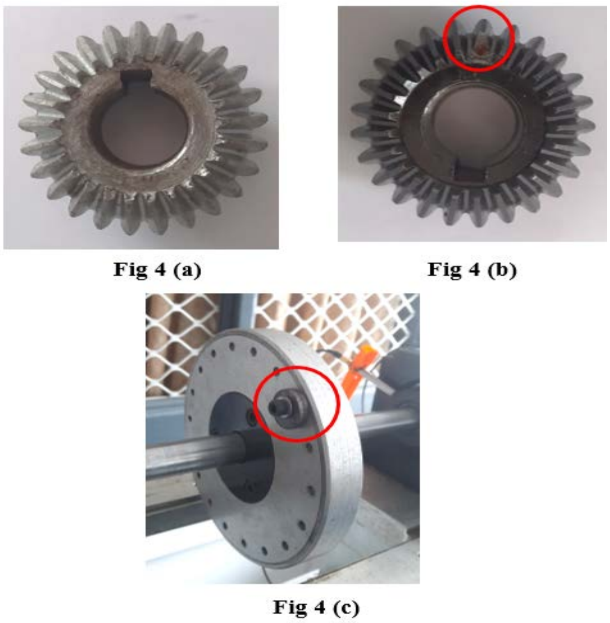

Figure 4. Health states of a)Good gear (GG), b) Faulty gear (FG)and c) unbalanced disc in the shaft

4. FEATURE EXTRACTION

Extracting well competent features from signals are most significant step for intensifying machine part faultiness prognosis [37]. While retaining the original information, the raw signal data are transformed to numerical aspects are termed as feature extraction [20]. For non-periodic pattern signals, IF and envelope are the most meaningful properties for figuring out machine shortcomings. Thus, considering signal behaviours in speed shifts, combinational influence of bothderivations are engaged in the current work to systematize component breakdown.

4.1 Instantaneous frequency

The term “instantaneous” is an adjective of modifying the standard concept of frequency, indicating how often it varies over specific point in time [15]. Interpretationof signal uncertainty are characterized by instantaneous frequencies which are correlated to fault indicators [38].

Table 1. Mixed composition of Equipment health condition in rotational machinery

S.No	Class	Health state indication	Abbreviation
1	s1	Fault gear with balan–ced shaft, both inner and outer race bearing fault	FGBSBOTHFB
2	s2	Fault gear with balan–ced shaft and good bearing	FGBSGB
3	s3	Fault gear with balan–ced shaft and inner race bearing fault	FGBSIRFB
4	s4	Fault gear with balan–ced shaft and outer race bearing fault	FGBSORFB
5	s5	Fault gear with unba–lanced shaft, both inner and outer race bearing fault	FGUNBSBOTHFB
6	s6	Fault gear with unba–lanced shaft and good bearing	FGUNBSGB
7	s7	Fault gear with unba–lanced shaft and inner race bearing fault	FGUNBSIRFB
8	s8	Fault gear with unba–lanced shaft and outer race bearing fault	FGUNBSORFB
9	s9	Good gear with ba–lanced shaft, both inner and outer race bearing fault	GGBSBOTHFB
10	NOC	Good gear with bala–nced shaft and good bearing	GGBSGB
11	s10	Good gear with ba–lanced shaft and inner race bearing fault	GGBSIRFB
12	s11	Good gear with ba–lanced shaft and outer race bearing fault	GGBSORFB
13	s12	Good gear with unba–lanced shaft, both in–ner and outer race bearing fault	GGUNBSBOTHFB
14	s13	Good gear with unba–lanced shaft and good bearing	GGUNBSGB
15	s14	Good gear with unba–lanced shaft and inner race bearing fault	GGUNBSIRFB
16	s15	Good gear with unba–lanced shaft and outer race bearing fault	GGUNBSORFB

Intentionally, vibration signals can be demodulated using Hilbert transform (HT) [39] and therewith instantaneous phase are estimated [40] to separate IF from intricate non-uniform signals. Another possibility of extricating this metric are by time-frequency rep–resentation (TFR), which also discloses other frequency components that changes over time [41]. STFT calcu–lates this perspective [40] for further endorsing its salience in fault-discernment. STFT extends the Fourier transform by introducing time localization using window function h(t), allowing time and frequency domain simultaneously for signal representation [42].

For the convenience of the planned work, to under–stand and analyse the complex behaviour of multicom–ponent signals, it is expressed as the sum of N mono-component signals as below

$$z(t)=\sum_{i=1}^{N} a_i(t)\, e^{j\Phi_i(t)} \tag{1}$$

As referred to (1), $a_i(t)$ denotes amplitude and $\Phi_i(t)$as phase of each single component signals [15]. Thus, for drawing IF from complex temporal signals in this multi-machine parts, TFR are depicted by STFT with an assistance of low pass filter as exhibited in Fig 5 a) and b) for FGBSIRFB and FGUNBSIRFB for z axis as an instance.

From Fig 5, separated IF are illustrated in Fig 6 a) and b) for the same health states. This clearly reveals that the variations in IF are an indicative of transient event in vibration signals of z-axis for both the machine health condition. This helps in being aware of rapid changes or machinery mishaps.

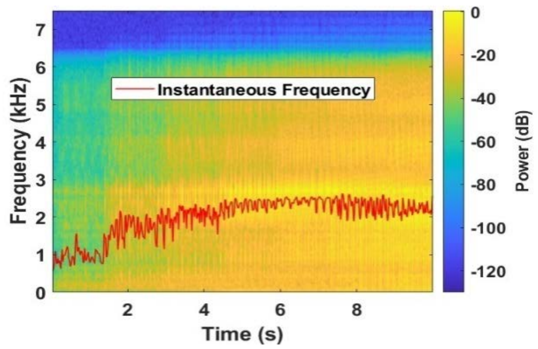

Figure 5 a)

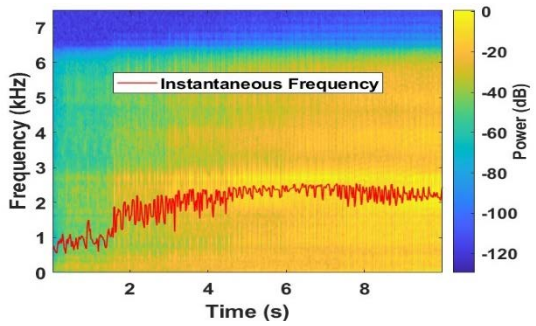

Figure 5 b)

Figure 5. Time-frequency representation with IF estimation of a) FGBSIRFB and b) FGUNBSIRFB

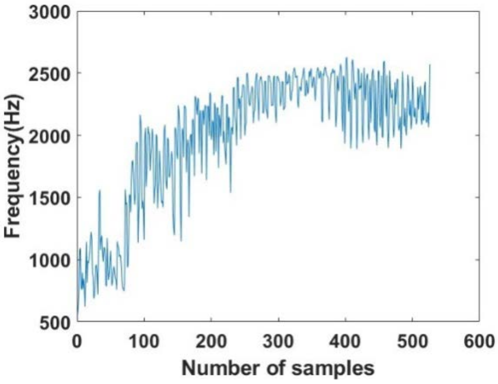

Figure 6 a)

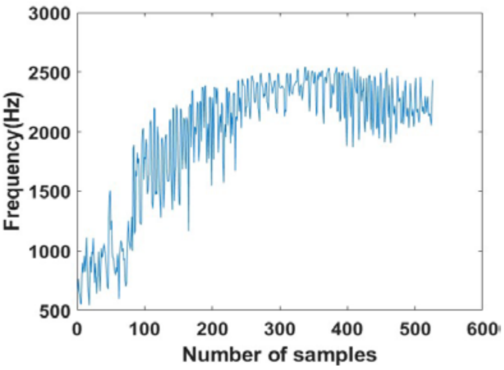

Figure 6 b)

Figure 6. Instantaneous frequency of a) FGBSIRFB and b) FGUNBSIRFB

4.2 Signal envelope extraction

Upper and lower envelope, which is retrieved from original signal are deployed in this proposed method. This provides amplitude variation over time for evaluating signal's overall characteristics. This can be detailed within a technique, Empirical mode decomposition (EMD).

Formerly when a series of intrinsic mode functions (IMF) which is obtained by decomposing non-linear signals by EMD, HT are employed to calculate IF. As an essential step, local maxima and minima are determined which are then calculated by cubic-spline interpolation for constructing lower and upper envelope. Then by taking mean of these envelope and subtracting it from main signal component, new signals are produced. This can be considered as IMF if this meets conditional criteria [42]. So as main theme of presented work, we keenly focus on eliciting envelopes from the time-domain signal using HT after filtering. As an instance, extracted signal envelopes are proclaimed in Fig 7 a) and b) for FGBSIRFB and FGUNBSIRFB.

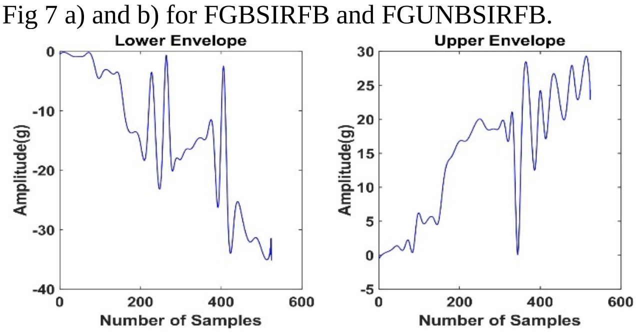

Figure 7 a)

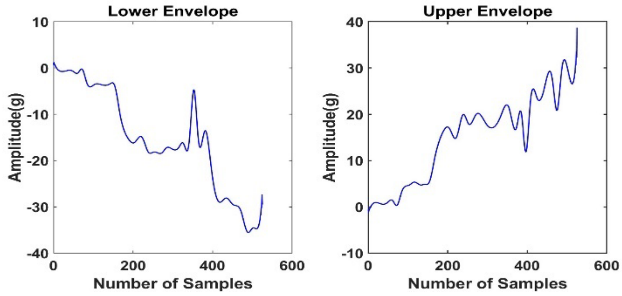

Figure 7 b)

Figure 7. Upper and lower envelope of a) FGBSIRFB and b) FGUNBSIRFB

5. PREDICTION OF MULTI-COMPONENT FAULTS USING VIBRATION SIGNALS

Classification is a method to organize and categorize data into distinct groups based on their own attributes. This way of approach helps in recognizing, differentiating and understand various entities by grouping them [43]. After extracting specific features from raw signals, this is given as an input to SVM with radial basis function (RBF) and KNN for typifying different faults existing in the industrial equipment.

5.1 Support vector machine (SVM)

Most popular ML algorithm for classification and regression is Support vector machine. [44]. It is well understood that the binary Support vector classification finds hyperplane for separating two classes with maximum margin [45]. Interpreting a detailed expression of SVM, facilitates in finding the optimal hyperplane for differentiating classes with better generalization ability. For binary classification, equation of finding optimal hyperplane are expressed as

$$w.x_i + b = 0 \tag{2}$$

where w is a weight vector and b is bias

Further initializing optimization problem, this is formulated as

$$\min \frac{1}{2}\|w\|_2 \text{ or } \max \frac{1}{2}\|w\|_2 \tag{3}$$

The condition $y_i(w \cdot x_i+b) \geq 1$ ensures that the data points are correctly classified.

For separating non-linearly separable data, the datapoints are mapped to the higher dimensional space [46] using kernel function [44].

The reason behind choosing support vector classifier for solving multi-anomalies classification problems, are because of its pairwise-classification method [46]. Among most popu–lar kernel functions, linear, polynomial, Gaussian RBF and sigmoid, a wise choice is required for diffe–rentiating multi-classes. So, SVM-RBF are recognized to be quite powerful in flexibly handling complex patterns by mapping input data into infinite-dimensional space. Mathematical properties of exponential function in this kernel makes infinite polynomial term series for capturing intricate pattern in data. Thus, Gaussian based RBF are chosen with SVM for the result endorsement.

Based on Gaussian-RBF kernel function, SVM classification are designed as

$$K\left(x_i, x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|}{2\sigma^2}\right) \quad (4)$$

where ||.|| is an Euclidean norm, x_i, x_j are input feature vectors and σ is free-parameter determining dispersion of support vectors[46].

Quantifying the percentage of correctly classified multi component defects validates the model's performance, while a contingency table can be used to analyze the relationship between predicted and actual defect categories**.** Three features such as IF, lower and upper envelope of each axis of vibration signals (x-, y- and z-axes) with total of 9 features are inputted into SVM-RBF classifier for attesting the model potency. To elucidate the ML model, the classification table communicates the intimate perception for which of the failures in mechanical equipment are precisely sorted and highly misclassified in Table 3 using SVM-RBF. The diagonal results in this matrix denotes the correctly classified instances as positive predictive value (PPV) and remaining implies misclassified instances as false discovery rate (FDR).

This yields 65.89% of accurately distinguishing the multi-fault labels as indicated in Table 2.

Table 2. SVM-RBF based fault estimation using vibration signals

Model	Classification accuracy (%)
SVM-RBF	65.89

Table 3 shows that the major FDR occurs between balanced and unbalanced shaft classes. Among the various health states, the highest misclassification arises between s3 and s7 classes. The positive classification of fault gear with balanced shaft and inner race bearing fault (s3) are 55.3%, whereas incorrectness between s3 and fault gear with unbalanced shaft and inner race bearing fault (s7) are 19.4%. Despite this, when s7 achieves better prediction of 51.2%, the misclassification of s3 from s7 reaches 30.7%. This strongly illustrates the classification error between balanced and unbalanced shaft when non-linear vibration signal characteristics are taken into consideration. For thorough insight, correct and incorrect classification of s3 and s7 classes are detailed in Table 4.

This infers detailed perception of how competently imbalanced shaft as well as good shaft are correctly identified. Noticeably, unbalanced and balanced shaft condition in s7 fault state is highly misclassified. This mislabelling is diminished by information fusion techniques that will be further valuated in upcoming sections.

Table 3. Confusion matrix (%) of SVM-RBF for vibration signals

	s1	s2	s3	s4	s5	s6	s7	s8	s9	NOC	s10	s11	s12	s13	s14	s15
s1	64.3	3.9	3.9	1.1	21.3	1	5.9	0	0.9	0	0	0	0	0.7	0	0
s2	0	61.2	0	0	0	11.5	1	0	0	1	0	0.9	0	6.7	0	3.1
s3	7.1	0.8	55.3	0	2.8	0	30.7	0	0	0	0	1.8	0	2.2	0	1
s4	2	3.1	1	70.5	0	5.2	1	16	3.5	0	0	0	1.9	1.5	0	1
s5	15.3	1.6	7.8	1.1	63.9	1	3	0	1.8	0	0	0	0	2.2	0	1
s6	0	19.4	1	1.1	0	69.8	0	2	0	1	0	0	0	5.9	0	0
s7	5.1	4.7	19.4	2.1	1.9	2.1	51.2	0	1.8	0	0	3.5	1	5.2	0	3.1
s8	1	2.3	1	15.8	0	1	0	79	0	0	1.1	0	0	2.2	0	2.1
s9	1	0.8	0	0	3.7	0	1	0	67.3	0	1.1	3.5	11.7	0.7	1.1	3.1
NOC	0	0	1	0	0	0	1	0	3.5	98	0	0	0	0	0	0
s10	0	0	1.9	3.2	0	0	0	1	4.4	0	78.9	0	0	2.2	15.8	1
s11	0	0	4.9	0	3.7	0	2	0	1.8	0	1.1	61.9	7.8	0	0	13.4
s12	1	0	0	1.1	0	0	0	0	7.1	0	2.1	12.4	71.8	0	0	5.2
s13	0	2.3	0	3.2	0	8.3	0	1	0	0	0	0	0	66.7	0	0
s14	0	0	0	0	0.9	0	0	0	3.5	0	14.7	0	1.9	2.2	82.1	3.1
s15	3.1	0	2.9	1.1	1.9	0	3	1	4.4	0	1.1	15.9	3.9	1.5	1.1	62.9
PPV	64.3	61.2	55.3	70.5	63.9	69.8	51.2	79.0	67.3	98.0	78.9	61.9	71.8	66.7	82.1	62.9
FDR	35.7	38.8	44.7	29.5	36.1	30.2	48.5	21.0	32.7	2.0	21.1	38.1	28.2	33.3	17.9	37.1

Table 4. Indication of PPV and FDR for vibration signals when grouping s3 and s7 classes

Class	Condition	Positive predictive rate (PPV) (%)	False discovery rate (FDR) (%)
s3	FGBSIRFB	55.3	19.4
s7	FGUNBSIRFB	51.2	30.7

5.2 K-Nearest Neighbour (KNN)

A fundamental and simple classifier which categorizes data based on proximity to other datapoint in feature space, is KNN. Without requiring prior-knowledge about underlying data distribution, this algorithm handles the problematic task by simple distance calculation and local approximation [47].Due to this low computation necessity and its simplicity, this algorithm is employed in this work. The steps for this supervised learning technique operation are

i) By selecting optimal k value
ii) Measuring similarity between training and target data points for finding its distance as in (5)

$$d(x,y)=\sqrt{\sum_{i=1}^{n}\left(x_i-x_j\right)^2} \quad (5)$$

iii) Finding nearest neighbours
iv) Choosing class with majority votes as predicted one.

Before the above mathematical calculations, the precautionary assumptions to follow as set forth in the given following point.

Assuming k =1, makes the prediction, less stable

i) Excessive increase of k value gives more accurate result but with large number of errors.
ii) Considering odd numbers for k helps to ensure clear majority.

Non-stationary signal attributes of vibration signals for three axes are given as an input to KNN model for detection of machinery health states. This results in prediction accuracy of 60.41% as shown in Table 5.

Further combining the classification result of both SVM and KNN models, enhance the prediction performance using decision level fusion. It combines the strength of both the classifiers which is discussed in section 7. Beforehand, inclusion of sound signals to the vibration signal that strategize as sensor-based signal integration are discussed in Section 6.

Table 5. KNN based fault estimation using vibration signals

Model	Classification accuracy (%)
KNN	60.41

6. CLASSIFICATION OF HEALTH STATES USING SENSOR-LEVEL FUSION

Adding features of two dissimilar signals are reasoned out as sensor-based signal combination. This integrates the information from both the signals and enhances the accuracy of identifying faults and reduce the incorrect labelling. In this current work, the signal attributes of sound data are added to the vibrational signal features to rationalize the combinational effect. This is rendered admirably using SVM-RBF and KNN in Section 6.1 and 6.2.

6.1 SVM-RBF based fault evaluation using sensor fusion techniques

This section discusses about the effectiveness of sensor fusion techniques in machinery fault detection under variable speeds. With the inclusion of IF, upper and lower envelope of sound signals to the features of three axes vibration signals, total of 12 signal aspects are fed to SVM classifier. The validity of fusing sound signals to the vibration signal are clearly evidenced with the classification accuracy of 73.98%, shown in Table 6. The result upgradation is endorsed in this fusion effect when compared with the results of ML model involves only vibration signals. This enhanced outcome, conceptualizes the effectuality of associating sound signals.

Table 6. Fault classification accuracy of combined effect of sound and vibration signals

Model name	Classification accuracy (%)
SVM-RBF	73.98

Table 7. Confusion matrix (%) for vibration + sound signals using SVM-RBF

	s1	s2	s3	s4	s5	s6	s7	s8	s9	NOC	s10	s11	s12	s13	s14	s15
s1	73.3	0.4	2.9	0.8	8.3	1	6.4	0.5	3.2	0	0	0.5	0.4	0.5	0	1.1
s2	0	74.3	0.7	1.5	0	10.8	1.2	0.8	0	0.2	0	0	0	4.7	0	0.3
s3	3.8	0.9	57	0	4.1	0.2	21.7	0	4.4	0	0	0.8	0.4	0.7	0	1.4
s4	0.7	1.3	1.5	74.2	1.1	2.2	1.7	16.4	0.2	0	0.8	0	4	0.5	0.5	0.3
s5	7.4	1.3	5.1	0.8	65.1	1.2	3.4	0.5	2.5	0	0	3	0.2	2	0	1.1
s6	0.5	11.7	0.2	1	0.2	79.3	0.5	1.3	0.4	0	0	0	0	4.5	0	0
s7	3.1	1.3	20.7	0.8	5.9	0.07	60.3	0.8	3.2	0.2	0	0.8	0	1.1	0	0.8
s8	0	1.5	1.3	18.7	0.4	1.9	0.5	77.7	0.3	0	0	0	1.1	2.3	0.7	0.6
s9	0.7	0	0.4	0.3	3.3	0	0	0	68.5	0	0.5	4.8	8.7	0.9	0.2	2.5
NOC	0	0	0	0.3	0.2	0	0	0	0.6	98.8	0	0	0.9	0.9	0	0.3
s10	0	0	1.1	0	0.4	0	0.2	0	1.3	0	80.4	0	1.6	0.2	17.2	3.1
s11	2.1	0	3.7	0.3	4.4	0	1.5	0	3.4	0	0.3	67.9	6.9	0	0.7	13.4
s12	3.3	0	0.7	0.3	1.5	0	0	0.5	7.8	0	2	4.3	69.6	0.2	1	4.2
s13	0	7.1	0.4	1.3	0.4	2.6	1.3	1	0.6	0.7	0.3	0	0.2	79.5	0	0.3
s14	0	0	0.2	0	0.7	0	0	0.3	1.1	0	15.8	0.5	1.1	0.9	79	1.7
s15	5	0	4	0	3.9	0	1.5	0.3	2.3	0	0	17.4	4.7	1.1	0.7	69.1
PPV	73.3	74.3	57	74.2	65.1	79.3	60.3	77.7	68.5	98.8	80.4	67.9	69.6	79.5	79	69.1
FDR	26.7	25.7	43	25.8	34.9	20.7	39.7	22.3	31.5	1.2	19.6	32.1	30.4	20.5	21	30.9

For further elaboration, the classification matrix reveals the transparency for all the component defect combinations in Table 7.As already pointed out in Section 5.1, the misclassification of s3 and s7 states are again overseen to inspect the misdiagnosis and the result advancement. In comparison to Table 4, PPV is increased when intermixing sound signal in vibration signal as displayed in Table 7 and 8.

When cross-verified with the involvement of vibration signals, there is a result progress in PPV for both the classes. Though, there is a slight rise of positive prediction in FGBSIRFB, a drastic result progress is witnessed in FGUNBSIRFB when compared with the true positive results of vibration signals. This eventually acknowledges the influence of the emphasized effect of signal fusion.

Table 8. Indication of PPV and FDR for signal fusion when grouping s3 and s7 classes

Class	Condition	Positive predictive rate (PPV) (%)
s3	FGBSIRFB	57
s7	FGUNBSIRFB	60.3

6.2 KNN based fault evaluation using sensor fusion techniques

Well-suited signal aspects of speed varying signals for the integrated signals which is examined in the previous section are again reconfirmed using KNN. This emerges with 69.34% accuracy due to the credibility of signal fusion routine as exhibited in Table 9.

Table 9. Fault classification accuracy of combinational signal influence using KNN

Model	Classification accuracy (%)
KNN	69.34

This reaffirmation of fidelity of adding sound signal properties with the characteristics of vibration signal, gives an augmented benefit in enhancing the fault identification rate via SVM as well as KNN model. Thisis taken forward by embracing the PPV values of both these ML classifiers and merging it for offering ideal result using decision-level fusion method. This can also be extended to multi-stage fusion strategy as narrated in Section 8. To promote the uniqueness of the research objective, two different fusion algorithms such as sensor signal fusion and diagnosis model result fusion are integrated to identify all the component health condition effectively under speed variation. To elect which of the decision fusion theory are more pertinent in implementing this proposed strategy, the comparative inquiry of three notable decision-focussed combination ideology are ratified in Section 7.

7. DECISION-LEVEL FUSION ALGORITHM

This section describes three decision-level aggregation concepts for vibration signals only to verify which of the theoretical basis are optimal to proceed for multi-level integration method.

Decision making-fusion processes highest level information by amalgamating multi-varied sources and traits [35]. This means it receives an output from diagnostic subsystems as an input to make final decision [48]. To highlight the impact of D-S theory concept, weighted voting and causal interference-focussed statistical model are also embraced for substantiation. The steps to combine model output for all the health states of rotational machine are elucidated in Section 7.1, 7.2 and 7.3. In account to this, the affirmation of which of these practises are highly competent to protract for multilevel synthesis approach are explored.

7.1 Dempster Shafer's theory of evidence

This theoretical concept discusses the probability prin–ciples to combine the multi-classifier's output [48]. But, dissimilar to the traditional probability mass allocation, this evidence-focussed hypothesis also allocates basic probability allocation (BPA) to a set of events flexibly with no precognition [34]. The major factors be noted for the mathematical formulation are uncertainty rep–resentation, conflicts of evidence and deciding capacity.
Furthermore, basic definitions in this analytical framework are

i) Frame of discernment, Ω represents all the possible outcomes and where 2^{Ω} are the power set representing all hypothesis combination.
ii) BPA is an indication of how much evidence supports to each subset by assigning probabilistic mass to it.
iii) In representation of uncertainness, belief function (*bel*) gives minimum degree of evidence whereas plausibility function (*pl*) estimates maximum degree of evidence. Distance or gap measure between these two functions signifies the amount of uncertainty exist.
iv) In Evidence combination rule, combinational evi–dence from two or more sources are turned to single BPA. This satisfies the condition of associativity and commutativity properties. As a note-taking, assume u as conflict coefficient which measures degree of conflict between two evidence's sources. If u=0, this implies consistent sources and u =1 as total conflict [34].

In this planned work, for each state of machine's status, the evidential-based fusion are devised as per the below steps

i) After attaining classification performance metrics of SVM and KNN classifier for 16 health condition, each of these probabilities are converted to belief structures.

Let's assume $m_i(\theta)$ as classifier's BPA and 'i' specifies number of model classifier. Hereθ_1 and $\theta_2$are null and alternate hypotheses. For each of the classifier's fault states, hypothesis-focussed mass allocation is assessed.

ii) Conflicts of these values are carried out by summing the belief mass's product which conflicts with each other in such a way that $m_1(\theta_1).m_2(\theta_2)$ + $m_1(\theta_2).m_2(\theta_1)$and these results are normalized.
iii) Finally, all the BPAs are consolidated for both hypothesis of the mentioned classification algorithm. Thus, let's say,

$$m_{combined}\left(\theta_1\right)=\frac{m1\left(\theta_1\right)\cdot m2\left(\theta_2\right)}{normalization\ factor} \quad (6)$$

$$m_{combined}\left(\theta_2\right)=\frac{m1\left(\theta_2\right)\cdot m2\left(\theta_1\right)}{normalization\ factor} \quad (7)$$

This assures which of the hypothesis are signi–ficantly true and predicted correctly.

7.2 Weighted voting method

A standard WV method offers weightage to each base model based on its performance. This can be expressed as $W_i=\frac{classifier\ result_i}{\sum_{i=1}^{k} classifier\ result_i}$, where $\sum_{i=1}^{k} W_i=1$, $W_i \geq 0$.And then normalization will be implied for data equalization to the derived values [49]. So relying more on model results, cause less flexible though this accords simple inference.

In this regard, optimization of weighted voting strategy proffers flexibility in availing custom metric errors and optimization constraints for effective combination. This context proceeds with normalizing the two classifier's confusion matrix and the objective function are defined here to compute error depending on combinational influence of each model. This is obtainable by accounting optimal weights implicitly in the loss function itself. Also, this compares the mixed confusion matrices by identity matrix and delivers classification error. Error reduction as an eventual purpose in this opinionated postulation, leads to refined end-results.

7.3 Statistical causal model

For non-linear or non-stationary conditions, improving causal inference's accuracy are accomplishable by leveraging distributional variation, causal discovery algorithm, domain-knowledge, etc. This uniquely follows causal graph representing nodes as variables, arrows as causal influence of one over other variable [50]. Be it non-linear model, SCM or other advanced causal-models, they validly deduce causal relationship in complex scenarios.

Besides the graph, structural equation and causal sequence are assimilated in SCM for distinguishing sequences of cause and effect. Primarily, advantagestate sets (ASS) are analyzed for each machine's status which highlights which classifier performs better in specific intervals. Then, directed acyclic graph (DAG) are built for all primary decision and global decision variables, followed by the construction of equations based on fusion-oriented objectives to assure the improvement of global decision [32]. This method as benchmarking study, initializes three sets for categorising states of two prediction results $R(d_1)$ and $R(d_2)$. Pursuing this, confusion matrices are converted to state vectors and certainly, DAG is created using construct_causal_graph function to define nodes and edges in python code. The fusion_objectives function defines how to combine 2 classifier outputs based on their performance across different states, as determined by ASS. Correspon–dingly, scm_fusion function then merges the state vec–tors from the two classifiers by applying these fusion-centered objective. Finally, the process concludes with averaging all the fused state vectors to generate the final decision-level result.

7.4 Comparative analysis of decision-making fusion strategies

Following up the steps involved in merging two diagnosis results of ML models for vibration signals using the above specified decision-fusion techniques, the classification results are computed. Table 10 expresses that the verification outcomes of DS evidence theory are greater than SCM and WVM method. This validates which of the theoretical concepts are proceeded to multi-level fusion by including sound signals to vibration signal.

Table 10. Comparison of results for vibration signals using Decision-level integration method

S.No	Decision-level fusion strategy	Classification accuracy (%)
1	DS theory	75.64
2	SCM	65.40
3	WVM	69.14

The combinational diagnosis result using DS theory are enhanced with 75.64%, when compared to the results of SVM and KNN of vibration signals in Section 5. But SCM and WVM seems to be not improved unlike the prominent DS evidence concept

By merging the model outputs of SVM-RBF and KNN of vibration signals, combinational theory of evidence renders fused outcome for each system health as illustrated in Table 11. This picturizes an optimized improved results for all the fault combinations when compared with the specified machine learning model. Further, to intelligibly concentrate more on health condition of shafts as persistently discussed in previous chapters, s3, s7 fault states are also pinpointed. Minor elevation of true prediction results in these two classes are clearly witnessed in contrast to the results of individual ML classifiers.

Table 11. All health state prediction accuracy for individual classifiers and diagnostic output fused model for vibration signal

Method	Prediction rate (%)															
	s1	s2	s3	s4	s5	s6	s7	s8	s9	NOC	s10	s11	s12	s13	s14	s15
SVM-RBF	64.3	61.2	55.3	70.5	63.9	69.8	51.2	79	67.3	98	78.9	61.9	71.8	66.7	82.1	62.9
KNN	69.9	56.2	51	52.8	67	55.6	51.4	50.5	74.3	84.2	60	58.1	77.8	47.1	65.9	53.3
DS theory	80.7	66.9	56.3	72.7	78.2	74.3	52.6	79.3	85.6	99.6	84.9	69.3	89.9	64.1	89.9	65.9

Conclusively, the corollary of this theoretical and experimental evaluation approves ds evidence concept to advance this to multistage composition framework.

8. MULTI-LEVEL FUSION ALGORITHM

The evaluated outcomes of coalesced signal-based feature fusion and decision-induced fusion are discussed in this section. From the previous section, DS combinational theory of evidence is acknowledged from the end-product results. To further corroborate this, sound signals are encompassed to the vibration signals and two model outputs of this intermingled signals are fused which is accredited as multilevel fusion strategy. The fault segmentation using three of these systematic approaches are depicted in Table 12 which attests the refinement when compared with decision-based merging using individual vibration signals in Table 10.

Amidst the amelioration for SCM model and WVM upon fusion of vibration and sound signals in contrast to examining only vibration signals, the classification ac–curacy is found to be lower than sensor fusion using SVM-RBF. But DS theory reveals its supremacy in this experimental study.Thus, it is decided to establish theory of combined evidence for the anomaly's classification of machine, operating under transitional speed condition.

Table 12. Comparison of results for vibration + sound signals using multi-level fusion method

S.No	Decision-level fusion strategy	Classification accuracy (%)
1	DS theory	85.76
2	SCM	70.41
3	WVM	71.53

In this continuation, the model outputs of intertwined sensor signals are integrated by this theory of belief function are exhibited in Table 13.

Table 13. All health state prediction accuracy for individual classifiers and diagnostic output fused model for combination of vibration and sound signals

Method	Prediction rate (%)															
	s1	s2	s3	s4	s5	s6	s7	s8	s9	NOC	s10	s11	s12	s13	s14	s15
SVM-RBF	73.3	74.3	57	74.2	65.1	79.3	60.3	77.7	68.5	98.8	80.4	67.9	69.6	79.5	79	69.1
KNN	79.6	64.3	67.4	56.7	77.1	67.6	65.7	60.8	79.6	71.1	71.4	63.9	80.2	74	72.4	62.5
DS theory	91.4	83.8	73.3	79	86.3	88.9	74.4	84.4	89.5	99.5	91.1	78.9	90.3	91.7	90.8	78.8

Superlative achievement for all equipment health status is distinctly revealed. Fault prediction value for consis–tently addressed shaft conditions are found to be superior to individual model classifier results as accentuated.

The confirmatory yield of implementing Dempster's aggregation rule for dissimilar signal blend are expo–unded in all aspects. To make more conspicuous about the interpretation of this multi-tiered fusion model, this is further reaffirmed in the next section for an extensive comprehension by exploring three levels of merging schemes.To stimulate the imperativeness of this course of action, recurringly stated shaft classes due to high inaccurateness in identifying shaft defects are deemed more important in this critique.

9. RESULTS AND DISCUSSION

The persistent approval of exploiting theory of belief function (DS theory) have induced the cognitive approach to look forward for the efficacy of each health state prediction of machine operating under speed varying condition in the earlier sections. A brief comparison elaborates the essentiality of multi-level fusion. With this concern, competency of three different level unification systematics with the comprehensive analysis of upgradation of positive prediction rate of shaft conditions using multi-level fusion technique are also exceptionally featured to deepen the knowledge of prioritizing this pre-planned proposed work.

9.1 Effectiveness of fusion strategy

The endorsement of different fusion techniques by entailing IF and two envelopes as signal ingredients from individual and dual signals are tested and trained using SVM-RBF and KNN initially. Accompanied by this, how influential is multi-layered integration over sensor-focussed signal fusion concept are also validated.

Reminiscing the validation check from Section 5 and 6, this is compared for understanding the impactful effect of sensor fusion for machine learning multi-fault classification. Table 14 clarifies that SVM-RBF are performing better in vibration as well as integration of vibration and sound signals than KNN model. But exceptionally observing sensor-dependent intermingled signals results, both the classifiers' fault identification accuracies are strengthened more than the model outcome of individual vibration signals.

From meticulous viewpoint, this outlines the progress of this model when sound signals are embodied to the vibration signals. This convinces the enactment of assimilating this intermixture of dissimilar signals for further fusion framework. In this concern, the most acknowledged decision fusion is also accounted for the comparative review in case of vibration signals, which is designated as single-level decision coordination. This is determined to be minimally increased as opposed to single-level sensor fusion. So, rigorous analysis is needed which may further prove the indispensability of preordained multilayered fusion strategy as investigated in Table 15 and 16.

Moreover, revisiting the integrated features of vibration and sound signals for the individual ML model which is referenced as sensor-based signal combination, this is extended for comparative analysis. Offering the theoretical orientation of signal-based feature-conca–tenation with decision-intended fusion, both the fusion methodologies are conjoined to inscribe it as multi-layered integration. The vitality of inducing two level fusion as technical concept are undoubtedly re–garded as highly proficient using theory of belief function as proclaimed in Table 15. This achieves supreme result of 85.76% by combining the output of sensor-based signal composition by SVM and KNN models and using D.S theory of evidence. This fosters the effectualness of D-S combination rule when combining sound signals with vibration signals.

Table 14. Compared outcomes of individual vibration signals and single-level fusion strategy

S.No	Model name	Classification accuracy (%)		
		Vibration signal	Single-level fusion	
			Sensor-signal fusion	Decision level using vibration signal (DS theory)
1	SVM-RBF	65.89	73.98	75.64
2	KNN	60.41	69.34	

Table 15. Results of fusion algorithm for the combined vibration and sound signals

Fusion technique	Model Classifier / Decision-level fusion	Classification accuracy (%)
		Vibration+sound signal
Sensor-signal fusion	SVM-RBF	73.98
	KNN	69.34
Multi-level fusion	DS theory	85.76

Critically inventive insight of highincorrect predictions in shaft health when using vibration signals are brought into sharper focus. From the standpoint of three fusion levels, this is verified for evaluating the vitalness of multilevel fusion in furnishing exemplary results. Articulating this into next extent, the outperformed SVM model and evidence-based decision coalition are firmly considered for vibration signals as well as two single-level and predetermined multilayered hybridization methodology as represented in Table 16.

Table 16. Result comparison of balanced (s3) and unbalanced shaft (s7) conditions for three level fusion as well as vibration signals

S.No	Fusion strategy	Model Classifier /Decision-centric integration technique	PPV (%)	
			s3	s7
1	Vibration signals	SVM-RBF	55.3	51.2
2 (a)	Single level fusion-Sensor level	SVM-RBF	57	60.3
2 (b)	Signal level fusion-Decision level	DS theory	56.3	52.6
3	Multi-level fusion	DS theory	73.3	74.4

Nuanced knowledge in scrutinizing PPV value of recognized s3 and s7 fault classes have placed more attention towards single and multi-level fusion methods in relation to vibration signals. This precisely indicate that single-level sensor fusion is modestly amplified compared to unfused vibration signal result.Extending this to decision based single-level fusion, true prediction results are underemphasized in contrast to signal fusion, even if the overall fusion results are presenting a marginal improvement. But when sound signals are embodied to vibration signals in this following, a remarkable progress is strikingly apparent. This adequate deliberation has proven the requisite of involving advanced fusion process.

An additional discussion of Table 16 is markedly portrayed through benchmarking chart in Fig 8. An accurate depiction of result variation in embracing sound signals in addition to vibration signals are scrupulously distinguished in single-level decision fusion and multi-level fusion. Among single-level fusion strategy, although PPV result of decision fusion have subtly changed when compared to vibration signals, it seems inferior to signal fusion. Taking this diligent affirmation into consideration, multilayered fusion has proved it outranking performance.

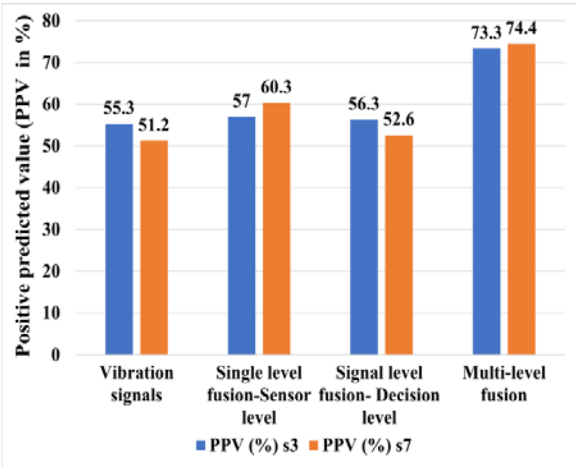

Fig 8. Comparison chart of positive predicted value between good and unbalanced shaft condition s3 and s7 for different fusion level method as well as individual vibration signals

Pertaining to this subject matter, individual and dual signals are also emphasized to narrate the signal de–pendence. This broad assessment culminates the signi–ficance of multi-tiered conjunction approach and also the essence of embodying sound signals towards vibra–tion signals. Breakthrough of shaft health misclas–sification instances have expanded the ingenuity in this field of inquiry.

10. CONCLUSION

The feasibility of multi-level fusion technique using sensor-signal fusion and D-S rule of combining evidence for multi-component fault analysis under time-varying speed are successfully proved. The novelty in this research finding is deliberatively explained by exclusively focussing on the considerable misclas–sification in shaft health conditions and how optimally results are enriched using this main concerned approach.

As foremost step, the most well-suited properties of accrued non-static vibration as well as sound signals associated to machine fault-existence are quantified and conjoined for discerning dissimilar machine deficit using SVM-RBF and KNN models. The validation proof of better optimization by SVM-RBF for vibration signals are directed towards false categorization of two shaft health conditions. The positive prediction for these fault states are intensified when sound signals are encompassed to vibration signals. Further, overall result upgradation are beneficially verified by integrating two classifier outputs using decision-fusion technique. This is substantiated by benchmarking it against the evalu–ations of other prevalent diagnostic model aggregation approach promptly.

The most predominant decision-induced aggre–gation technique are opted by validating the results of D-S evidence postulation, SCM model and WVM for non-stationary characteristics of individual vibration signal associated features. The satisfactory end results of DS evidence concept are put forward for spotlighting the credibility of multi-level fusion technique. This again certifies the endorsement of DS theory for the sensor-focussed signal fusion with promising outcome. In other words, dual signal amalgamation as well as dempster shafer's evidence theory for the decision-level combination which is referred as multi-level fusion environment have reached premier achievement with 85.76%. Nuances of each fault which is encountered in rotary machine are keenly keyed for sensor-level combination and multi-staged fusion strategy using D-S evidence conceptual theory in the signal-focussed trial study. The integrity of the proposed ideology is highly proven for the intermixing sound along with vibration signals in this transparent view of each specific component deficiencies as well. Predominantly spotted s3 and s7 class's fault enhancement are observed relying on this single-level decision aggregation and multi-level integration method.

The contrasted result findings of pluralistic pers–pective have unveiled the substantiation of hierarchical fusion scheme. The result advancement of positive pre–diction of two shaft classes using multi-level fusion are larger than the PPV of vibration signals with the sensor-dependent signal fusion and decision fusion. Thus, it is concluded that the multi-layered integration has exem–plary results among all the formerly stated corres–pondence in the fault-identification of multiple parts in rotational machinery running under variable speed condition.

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NOMENCLATURE

w	Weight vector
x_i, x_j	Input feature vector
b	Bias
$\|\|\cdot\|\|$	Euclidean norm
σ	Free parameter
yi	Output
$d(x, y)$	Distance between training and target data points
k	Number of closest data points
Σ	Summation
$z(t)$	Complexity behaviour of multicomponent signals
$a_i(t)$	Amplitude
$\Phi_i(t)$	Phase of each single component signal
Ω	Frame of discernment
bel	Belief function
pl	plausibility function
u	conflict coefficient
$m_i(\theta)$	Model classifier's basic probability allocation
θ_1, θ_2	null and alternate hypotheses
W_i	Weightage of each basis model
$R(d_1)$ $R(d_2)$	Prediction results of two classifiers

Abbreviation and acronyms

D-S theory	Dempster Shafer's theory
ML	Machine learning

SVM-RBF	Support vector machine-Radial Basis function
KNN	K-nearest neighbours
SCM	Structural causal model
WVM	weighted voting method
CM	Condition monitoring
DAC	Data acquisition
STFT	Short-Time Fourier transform
WT	Wavelet Transform
TFA	Time-Frequency Analysis
GDT	Generalized Demodulation Transform
AI	Artificial Intelligence
DT	Decision Tree
ANN	Artificial Neural Network
LDA	Linear discriminant analysis
QDA	Quadratic discriminant analysis
MLP	Multilayer perceptron
BN	Bayesian Network
HT	Hilbert Transform
TFR	Time-Frequency representation
IMF	Intrinsic mode functions
EMD	Empirical mode decomposition
IF	Instantaneous frequency
PPV	Positive Predictive Value
FDR	False Discovery rate
BPA	Basic Probability allocation
ASS	advantage state sets
DAG	directed acyclic graph

ЗНАЧАЈ ФУЗИЈЕ НА ВИШЕ НИВОА У ДИЈАГНОСТИЦИ ВИШЕКОМПОНЕНТНИХ ГРЕШАКА У УСЛОВИМА ПРОМЕНЉИВЕ БРЗИНЕ У РОТАЦИОНИМ МАШИНАМА

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Већина добро познатих изазовних ефеката идентификације вишеструких дефеката у ротационој машини када је брзина променљива, славно су прегледани од стране многих истраживача. Међутим, различите логике фузије су еволуирале у серији покушаја истраживања, али није посвећена велика пажња у испитивању сигнала нестабилне брзине. Решавајући ову празнину у литератури, овај рад се фокусира на вишеслојну стратегију фузије уз помоћ сензорно-центричне интеграције карактеристика. и Демпстер Схаферова (Д-С) теорија доказа за откривање вишеструких кварова у лежајевима, вратилима и зупчаницима ротационих машина под условом варијације брзине. Примарно, тренутна фреквенција и омотач добијених вибрација и звучних сигнала сложених делова система се процењују и уносе у машинско учење (МЛ) као што је машина за подршку векторима (СВМ) и К-најближи суседи (КНН) која верификује перформансе класификације. Исправност правила комбинације Д-С се приписује упоређивањем са резултатима друге познате фузије засноване на одлукама, као што су структурни каузални модел (СЦМ) и метод пондерисаног гласања (ВВМ). Ово осветљава ефекат наметања ДС теорије за комбиновање МЛ резултата интегрисаних вибрацијских и звучних сигнала који је симболизован као агрегација на више нивоа са тачношћу од 85,76%. Да би се више осветлила ова предложена метода, откривено је и верификовано дубоко истраживање о погрешно класификованим класама осовине за сигнале вибрације помоћу СВМ-РБФ-а за једностепену и вишестепену фузију. Ово даје обећавајуће резултате за вишестепени приступ фузији у дијагностици кварова ротационих машина при различитим брзинама.