Multiple Fault Diagnosis of Motorcycles based on Acoustic Approach

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Abstract

Several models have been proposed for fault detection and diagnosis in motorcycles based on acoustic signals. Motorcycles produce sound signals with varying temporal and spectral properties under different working conditions. These sounds can be the source of information for automatic diagnosis of faults. However, these models are not capable of assessing multiple faults. This paper attempts to diagnose multiple faults in motorcycles using two-stage approach. During first stage the model identifies the vehicle is healthy or faulty. If vehicle is observed as faulty, the second stage identifies the major faults present. The distribution of energies, in the first five subbands of wavelet packet decomposition is used as features. A two-stage ANN classifier is deployed for recognition of faults in the fused fault signatures. The recognition accuracy is over 78% when trained with individual fault signatures and over 88% when trained with combined signatures.

1. Introduction

Two-wheelers growth is mainly going to come from the rural areas where consumers look for versatility and ruggedness at affordable rates. While in urban areas, increasing congestion within cities and the lack of parking space plays into the consumer's mentality to choose a two wheeler. The fuel efficiency offered by a two wheeler is another bonus to the price minded Indian consumer. Society of Indian Automobile Manufacturers (SIAM) has forecast the two-wheeler segment to register a growth of 6% to 8% by 2013-14 [1]. Normally motorcycles turn faulty due to improper usage, wear and tear and for other inherent defects. Apparently these sound patterns characterize the defects and form fault signature. They fall under the category of non-speech signals and are different from the one produced during speech. Fault diagnosis based on sound is difficult since the sound patterns change with variations in speed, health condition, road condition, surrounding environment and the like. Despite these variations, the sound patterns give a clue of the fault. Expert mechanics take test rides to assess the condition of the motorcycle.

The literature survey is carried out to know the state-of-the-art in application of signal processing to automobile industry and other allied areas. The studied literature is organized into four parts: general applications of signal processing for fault diagnosis [2-8], engine fault diagnosis [9-14], gearbox fault diagnosis [15-17], and multiple-fault diagnosis applications [18-22].

Condition monitoring application uses features such as magnitude of the signal, natural logarithm of the magnitude and MFCC [2]. The extracted features are used as input to various pattern classifiers. A structure for monitoring the state of a turbocharger and supervising the air pressure in vehicle wheels is demonstrated [3]. A multi-resolution wavelet analysis is related with a neural network for the fault analysis of industrial robots [4]. A Wavelet Transform (WT) based Artificial Neural Network (ANN) input data pre-processing scheme is outlined for localized gear tooth defect recognition [5]. Daubechies DB-20 mean-square dilation WTs of the data are used as inputs to ANNs for pattern recognition. A denoising method based on the wavelet technique for feature sound extraction for diagnosis of machines is illustrated [6]. A fault diagnosis method for rolling bearing is presented to compare the fault recognition alternatives for induction machines according to the information required for the diagnosis, the number and relevance of the faults, the speed to anticipate a fault and the accuracy in the diagnosis [7]. A fault diagnosis method for rolling bearing is based on the integration of improved wavelet packet, frequency energy analysis and Hilbert marginal spectrum [8].

A case-based reasoning (CBR) approach is used for engine fault detection [9]. A wavelet transform is applied to the acoustic signal analysis in order to identify the sound sources of a diesel engine [10]. The contour maps measured from the front sound of a diesel engine, indicate that the oil sump and timing gear cover are the main sound sources of the engine front. An empirical mode decomposition (EMD) and wavelet packet backpropagation neural network is used for engine fault diagnosis [11]. The mechanisms of engine front noise generation and the corresponding countermeasures of a diesel engine using sound intensity method are discussed [12]. A fault detection system for motorcycles based on acoustic signals is presented [13]. The approach employs 1D central contour moments, their invariants, of wavelet subbands and DTW classifier. A mechanical fault diagnosis system for a scooter engine platform is developed which uses continuous wavelet transform and artificial neural network [14].

A system for recognition of the vibration signals of a gearbox employs adaptive wavelet filter [15]. An approach decomposes the vibration signals into a finite number of intrinsic mode functions and then establishes the autoregressive (AR) model of each intrinsic mode function (IMF) component and finally generates the corresponding autoregressive parameters [16]. The AR and IMF features are used as input to the support vector machine (SVM) classifier. Fault diagnosis system for Massey Ferguson gearbox is devised using root mean square (RMS) and power spectral density (PSD) [17].

A fault recognition methodology is recommended for broken rotor bar fault recognition and diagnostics in terms of its multiple signature processing features [18]. A model based on PCA and neural network are employed for the multi-fault diagnosis of sensor systems [19]. A method for detecting localized bearing defects based on wavelet transform is presented [20]. A technique for gear multi-fault diagnosis is devised based on the integration of wavelet transform, autoregressive (AR) model and principal component analysis (PCA) [21]. A fault detection and diagnosis (FDD) method for unmanned ground vehicles (UGVs) operating in multi agent systems uses the hierarchical FDD method consisting of three layered software agents [22]. All software agents interact with each other to detect a fault and diagnose its characteristics.

The multi-fault diagnosis resembles the way mechanics diagnose the faults. The acquired sound samples of engine and exhaust are fused to form the combined fault signatures. Energy distributions in the approximation coefficients of wavelet packet subbands are used as features and Artificial Neural Network (ANN) is used as recognizer. It is observed from the output of the recognizer that the predominant values correspond to the respective individual faults.

The actual contribution of the proposed work is development of a methodology for the source localization of multiple faults. To the best of our knowledge, no reported work attempts to recognize the presence of multiple faults in motorcycles based on the produced sounds. The novelty of the proposed approach lies in analyzing and interpreting the outputs of the ANN classifier indicating the presence of multiple faults. Use of energy distribution in wavelet packet subbands was limited to vehicle classification in the reported works.

The remainder of the paper is organized into four sections. Section 2 gives a review of literature. Section 3 discusses the proposed methodology with a brief on tools and techniques. The experimental results are elaborated in Section 4. Finally, Section 5 concludes the work.

2. Review of literature

Existing works concentrate on recognition and fault diagnosis of machinery, vehicles, engines and gearbox. Variants of wavelets, fuzzy technology and variants of ANN are deployed. Since the existing works employ different databases, recording environments and denoising schemes, it is difficult to compare the findings of our work with the reported works. Our work is more suitable for real-world implementation since it classifies the sound signals recorded in noisy environment.

3. Proposed methodology

Acquired sound signals are segmented prior to feature extraction. The distribution of energies among the approximation and detailed coefficients of wavelet packet subbands are explored as features. The feature vectors are formed by extracting the features from the first five subbands. The extracted features are input to ANN classifier for fault detection in the first stage and identifying the combination of the faults in the second stage. Figure 1 depicts the overview of the methodology. The methodology works in two stages, fault detection and identification. Both the stages use the same features and classifier. The decision vector of the first stage is input to the second stage along with the feature vectors. The decision vector helps in considering only the relevant samples for the next stage.

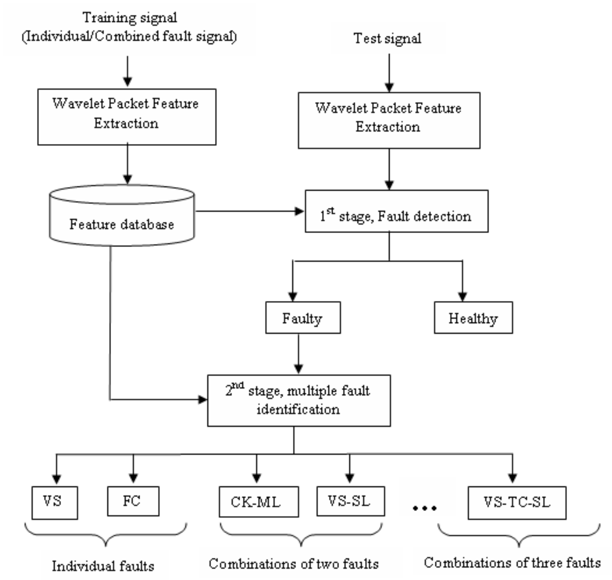

Figure 1 *Block diagram of the approach*

Following subsections discuss the substages of the proposed approach for two-stage and multiple fault diagnosis.

3.1 Acquisition of sound samples

The sound signals of the motorcycles are recorded using Sony ICD-PX720 digital voice recorder. The sampling frequency of 44.1 kHz with 16-bit quantization is used. Recording is carried out under the supervision of expert mechanics. The recording environment has disturbances from human speech, other vehicles being serviced, air-compressor and auto-repair tools. Recorder is held closer to the engine to minimize the influence of disturbances. An expert mechanic controls the start of the engine and throttle simultaneously.

3.2 Segmentation

Acquired sound samples are segmented into samples of one-second each for uniformity in processing. The portion of the signal of duration one-second, beginning from local maxima in the first 50 ms span is considered as a segment.

3.3 Wavelet packet feature extraction

Combined fault signature in the time-domain is transformed to time-frequency domain using Daubechies DB4 wavelets. For n levels of decomposition, the WPD produces 2n different sets of coefficients (or nodes) as opposed to (n +1) sets for the DWT.

The energy in the approximation coefficients of the wavelet packet decomposition exhibits good separability for different faults. The percentage energy values of the first five subbands form the feature vector, later used for classification. The faults are chosen in combinations of engine and exhaust subsystems. The separability analysis of the features is carried out and the results of comparison of energies are presented. Figure 2 shows the separability of the energy distribution for the fault signatures considered in this study.

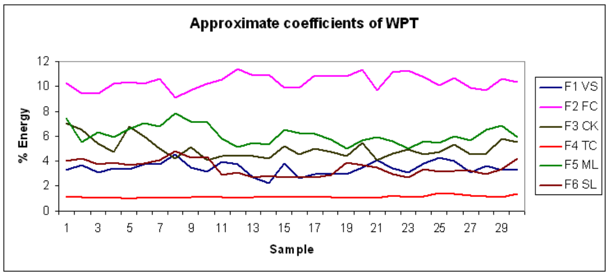

Figure 2 a *Percentage energy in approximation coefficients*

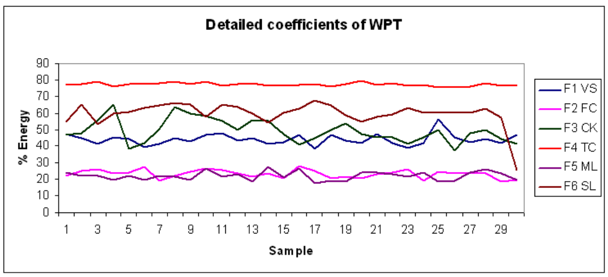

Figure 2.b *Percentage energy in detailed coefficients*

From Figure 2, it is evident that the separability among different faults is clear. But for some samples, the energy distribution is interleaved, leaving scope for confusion. Hence, ANN classifier is felt suitable for this work, since it can be employed in problems where the class boundaries are not clear. The features are extracted from the samples recorded from the cluttered environment because of which the developed methodology has potential of adaptation for real-world applications.

Fusion of fault signatures

Let F1 belong to engine subsystem and F2 belong to exhaust subsystem. The signatures of these faults are superimposed to synthesize the combined engine and exhaust subsystem's fault. The *wfusmat* of MATLAB is used to fuse the signals with 'mean' method. The 'mean' method fuses the time-domain signals by averaging the corresponding sample values. The spectra of the original signals and the combined fault signature are shown in Figure 3. The combined fault signature resembles the spectral traces of the individual fault signatures, in the normalized frequency domain.

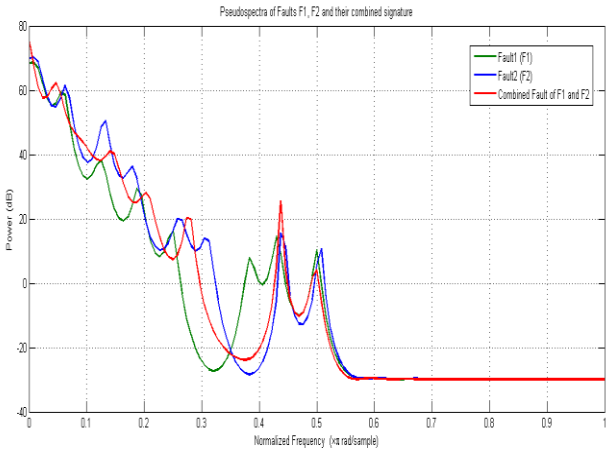

Figure 3 *Spectra of individual and combined fault signals*

3.4 Artificial Neural Network

Despite the advancements in biologically inspired computing techniques, ANNs are still accepted for classification problems with scope for approximation. Figure 4 outlines the architecture of the two-stage neural network. If two or more predominant values are observed on the output of the second stage, it indicates presence of multiple faults in the input fault signature. The positions of the predominant outputs correspond to the presence of the respective faults in the input combined fault signature.

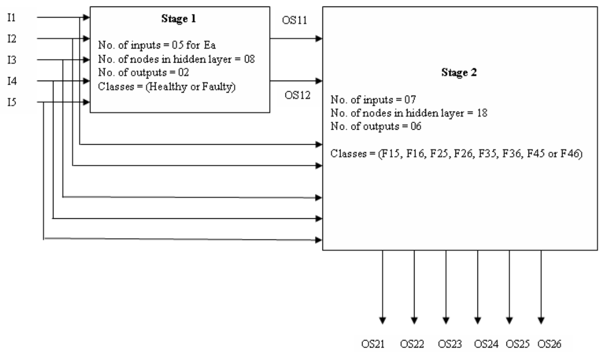

Figure 4 *Two-stage ANN architecture*

The neural network has five nodes in the input layer, eight in the hidden layer and two in the output layer, for the first stage. Similarly the number of nodes in the hidden layer, for second stage is empirically found to 18. The second stage yields six outputs indicating the presence of either individual or combination of two or three faults, belonging to either engine or exhaust subsystem.

4. Results and discussion

If the faults are attended in time it can be repaired and major breakdown can be avoided. Majority of the faults are due to problems in engines and some due to minor problems in exhaust. A brief description of the faults under consideration is given under:

Valve setting (VS): Any deviation of crank angle in valve opening/closing timing causes variation in peak combustion chamber pressures, leading to change in sound.

Faulty crank (FC): Any wear in the journal bearings and bushing areas will lead to increase in vibrations and noise produced by the engine.

Cylinder kit (CK): Wear in the cylinder and the piston creates a clearance between them, which results into escaping of the burnt gases. This causes drop in power output of the engine and change of sound.

Timing chain (TC): Loose chain vibrates and alters the valve setting, resulting in change in sound.

Muffler leakage (ML): The reactive gases in the residual exhaust, which are at high temperature, mixed with water vapor, lead to corrosion reactions and minute holes. These holes in the muffler change the firing sound produced by an engine.

Silencer leakage (SL): If there is a hole inside the silencer filter pipe or the damaged gasket, it causes silencer leakage.

Motorcycles manufactured by Hero Honda (Now Hero Motocorp), Honda motors, TVS Motors, Bajaj are considered. Faulty sample database includes the sound samples synthesized by combining the engine subsystem faults, namely, VS, FC, TC, CK and exhaust subsystem faults, namely, ML and SL. The subband energies of the healthy and faulty motorcycles differ, mainly due to the uneven cycles of operation of the engine in presence of a fault. Further, the faults related to exhaust system result in drastic change in sound. ANN classifier is used for classification in both the stages. The two-bit output of ANN indicates whether the test input is of healthy or faulty motorcycle. The outputs of the samples classified as faulty are combined with the feature inputs to form the input vector for the next stage. The second stage generates a six-bit output indicating the combination of the fault.

Stage 1: Fault detection

The features generated from the energy distribution in approximation coefficients of the first five subbands of wavelet packet decomposition are input to the classifier. An ANN with five inputs, eight hidden layer neurons and two outputs is used. The outputs of the ANN indicate whether the input feature vector corresponds to healthy or faulty motorcycle. Table 1 shows the fault detection results for the first stage.

Table 1 Results *of first stage of classification*

Total number of test samples		**Output**	**Target**	
Healthy	**Faulty**		**Healthy**	**Faulty**
60	60	Healthy	60	0
		Faulty	0	60
120	120	Healthy	120	0
		Faulty	1	119
180	180	Healthy	180	0
		Faulty	1	179
433	433	Healthy	433	0
		Faulty	1	432

Stage 2: Fault source localization in presence of multiple faults

The second stage ANN attempts to recognize the combinations of two and three faults. Input to the second stage classifier is formed by augmenting the five input feature vectors with the decision vector of the first stage. The samples identified as faulty are classified into F1 (VS), F2 (CK), F3 (FC), F4 (TC), F5 (ML) and F6 (SL). Table 2 shows the classification performance for the second stage of classification process.

Table 2 *Results of second stage of classification for individual faults*

From the Tables 1 and 2, it is evident that for smaller sample sets the classification accuracy will be approximately 100%. Classification performance suffers for larger data sets. Table 3 summarizes the classification performance for each stage.

Table 3 *Summary of classification for each stage for detection of individual faults*

No. of samples	**Target**						
	Output	**F1 (VS)**	**F2 (FC)**	**F3 (CK)**	**F4 (TC)**	**F5 (ML)**	**F6 (SL)**
85	F1	85	0	5	2	0	0
83	F2	0	82	0	0	0	1
69	F3	0	0	64	0	0	1
82	F4	0	0	0	80	0	0
56	F5	0	0	0	0	55	0
57	F6	0	1	0	0	1	54

Since the classification performance is appreciable for sample sets of size 30 each with six fault types, the work can be implemented in service stations of moderate sizes, where around 100 vehicles are serviced everyday.

The sound signal database contains 433 sound samples in total. It has 85 samples of valve setting fault, 83 samples of faulty crank, 69 samples of cylinder kit problem, 83 samples of timing chain setting fault, 56 samples of muffler leakage, and 57 samples of silencer leakage. Samples used for testing are chosen randomly.

The features extracted from the individual fault signals are used for training. The combined fault signatures are input to the ANN with five inputs. The predominant outputs of the ANN are observed to know the presence of a fault or combination of faults. For the combined fault signatures, such predominant outputs can be observed at two or three positions corresponding to the faults present in the combined signature. The results for the combination of VS and ML faults are given in Table 4.

Table 4 *Obtained outputs for some of the test samples with combined VS and ML faults*

No. of input samples	Classification accuracy							
	Stage 1		Stage 2					
	Healthy	Faulty	F1	F2	F3	F4	F5	F6
140	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
280	1.00	0.99	0.70	0.85	0.95	0.95	1.00	0.90
420	1.00	0.99	0.90	1.00	1.00	0.97	1.00	0.96
866	1.00	0.99	1.00	0.98	0.86	0.97	0.98	0.95

Test samples	Faults					
	VS	FC	CK	TC	ML	SL
TS1	**1.0000**	0.0050	0.0025	0.0000	**0.8621**	0.0000
TS2	**0.9959**	0.0168	0.0406	0.0000	**0.9425**	0.0000
TS3	**1.0000**	0.0086	0.0233	0.0000	**0.9329**	0.0000
TS4	0.0521	0.0250	**0.9988**	0.0000	**0.9415**	0.0000
TS5	**0.5000**	0.0087	0.0048	0.0000	**0.4935**	0.0000
TS6	**0.9914**	0.0044	0.0005	0.0000	**1.0000**	0.0000
TS7	**0.9133**	0.0051	0.0031	0.0000	**0.8122**	0.0000
TS8	**0.9089**	0.0408	0.0006	0.0000	**0.6554**	0.0000
TS9	**0.9093**	0.0409	0.0001	0.0000	**0.9441**	0.0000
TS10	**1.0000**	**0.0108**	0.0000	0.0000	0.0000	0.0000

The number of test samples used is 10. The number of cases wherein both the faults correctly detected is 8. In case of test samples TS4 and TS10, one of the two faults is correctly detected. In all the cases the ANN either indicates the presence of a single fault or both the faults in the combination. There are no cases wherein both faults go undetected.

The next experiment uses the combined fault signatures for training and the classifier is tested with combined fault signatures. This experiment is motivated by the way human experts analyse the sound patterns from faults. Normally, they diagnose the combined faults based on their experience of handling the combined faults but not the individual fault signature. When they hear the sound signatures of multiple faults, they remember the peculiarity of the sound generated. Later in case of another vehicle producing the same pattern, they will recall the sound they heard while testing for the same combination earlier. In this experiment the ANN is trained with fused signals and tested with the disjoint sets of randomly chosen fused signals. The results are summarized in Table 5.

Table 5 *ANN trained with combined fault signatures and tested with combined signals*

Combination	No. of samples used for testing	No. of correctly classified samples	No. of misclassified samples	Misclassified as
VS ML	10	10	0	-
VS SL	10	7	3	2 CKSL; 1TCSL
FC ML	10	9	1	1 VSML
FC SL	10	8	2	1 VSSL; 1 VSML
CK ML	10	10	0	-
CK SL	10	8	2	1 TCSL; 1 VSSL
TC ML	10	9	1	1 CKML
TC SL	10	10	0	-
Total	80	71	9	

When the ANN is trained and tested with the combined fault signatures, 71 samples out of 80 are recognized, as evident from Table 6. Only one case of total misclassification is observed during experimentation. There are few instances of incorrect recognition of single faults. The experiment resulted in an accuracy of 88.75% for recognition of both the faults. The accuracy of recognition of at least one fault is 98.75%, resulting in a total error of 1.25%, which is quite admissible for practical situations. The increase in classification accuracy can be attributed to the training of ANN classifier similar to the diagnosis by human experts.

Further the fault signatures are tested for the presence of three faults. The faults from engine and exhaust subsystems are combined by choosing at least one from each. For e.g., VS-TC-ML combination includes two faults from engine subsystem and one from exhaust. Table 6 summarizes the results of combinations of three faults.

The total number of samples used for testing is 160. The accuracy of correct recognition is 100% for recognition of at least one fault. At least two faults were recognized with an accuracy of 82.50%. The accuracy resulted for the correct recognition of all the three faults is 30.63%. The results show that for some of the combinations like VS-ML-SL and TC-ML-SL, the recognition performance is over 90%, and for other combinations the results are not satisfactory. This is attributed to the decrease in SNR due to superimposition effects.

Table 6 *Classification results for combinations of three faults*

Combination	Recognition of 3 faults	Recognition of 2 faults	Recognition of 1 fault	Recognition of no fault
VS – CK – SL	4	6	0	0
VS– CK – ML	0	9	1	0
VS – SL – ML	10	0	0	0
TC – SL – ML	9	1	0	0
FC – TC – SL	3	2	5	0
FC – TC – ML	2	0	8	0
FC – SL – ML	2	8	0	0
CK – ML – SL	3	7	0	0
CK– FC – ML	2	8	0	0
CK – FC – SL	1	9	0	0
VS – TC – ML	2	5	3	0
VS – FC – ML	2	8	0	0
VS – FC – SL	2	8	0	0
VS – TC - SL	4	4	2	0
CK – TC - ML	3	0	7	0
CK – TC - SL	0	8	2	0
Total	49	83	28	0

Discussion

Working in stages helps the mechanics to assess the faults stepwise and take suitable repair measures. Normally, a naïve mechanic detects a fault and after acquiring more experience, he will be able to localize the source of a fault. The work is an attempt to automate these traits of experts. The automation requires a feature extraction and classification of the sound patterns of diseased motorcycles. Since there is a scope for approximation due to noisy signals ANN classifier is found suitable for the problem in hand. We have used the energy distribution among the wavelet packet subbands as features, since the distribution is unique to individual fault types. The proposed approach yields 100% classification accuracy when 10 samples of each type of fault are used. The approach is suitable for small or medium garages and service stations.

Separability analysis of the features reveals that the selected features are suitable of classifying the faults without denoising. However, the automotive experts opine that the simultaneous presence of three faults is a rare case. In spite of this, a test is carried out on the fused signatures of three faults. Summarized results reveal that the system successfully recognizes the presence of at least two faults with an accuracy of over 82%. From the experimentation, it is observed that misclassification of the faults is within the same subsystem and not across the subsystems.

The work carried out opens up several issues such as enhancement of classification performance for combinations of three or more faults, assessment of influence of denoising, intra-subsystem multiple fault recognition and the like.

6. Conclusion

The investigation successfully classifies the motorcycles into healthy and faulty in the first stage, and identified the fault source (individual or combined), in the second stage. Minimum classification accuracy of 85% is observed when uneven number of samples is used. The features are derived from wavelet packet energy of the sound signals. The ANN classifier has given the classification accuracy of 76.25% for combinations of two faults. The accuracy is increased to 88.25% when the ANN is trained and tested with the combined fault signatures. In case of combination of three faults, the recognition accuracy is 100% for recognition of at least one fault among the faults in the combination. Recognition accuracy for detection of two faults in a combined signature having three faults is 82.5%. The present work leaves scope for further exploration of fault source localization within the same subsystem.

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