Multi-Component Fault Diagnosis of Self Aligning Troughing Roller (SATR) in Belt Conveyor System using Decision Tree – a Statistical Approach

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Self-Aligning Troughing Roller (SATR) is one of the critical components in belt conveyor; it is a very critical component in riding the belt conveyor in fault free condition. SATR arrangement has a long roll to support the given belt and handle maximum load per cross-section. SATR has machine elements like ball bearing, central shaft and the external shell. In belt conveyor system certain faults such as bearing fault (BF), central shaft fault (SF), combined bearing flaw and central shaft fault (BF& SF) occur frequently. Fault diagnosis in SATR essentially forms a classification problem. A prototype setup has been designed and fabricated; Different faults such as bearing fault (BF), central shaft fault (SF), combined bearing flaw and central shaft fault (BF& SF) are introduced one at a time and the corresponding vibration signals have been acquired from the setup . Followed by this step a set if statistical parameters were computed which forms the feature set and classified using Artificial Neural Network (ANN) algorithms and decision tree algorithms. At the outset, decision tree algorithm shows superior performance in terms of classification accuracy. The whole effort is to bring out the best number of features for maximum efficiency. A tenfold cross validation was performed to validate the results.

Keywords: *Self Aligning Troughing Roller (SATR), Belt conveyor system (BCS), Decision Tree, Statistical features, Confusion matrix.)*

1. INTRODUCTION

Self Aligning Troughing Roller (SATR) may fail due to the following: multi dimensional forces, inadequate lubrication, culpable sealing, uneven loading and improper training of conveyor belt. The critical elements that regularly come up with failures in SATR are groove ball bearing and the central shaft. The malfunction of these parts straight away influences the efficiency of the SATR which can foil the proper functioning of belt conveyor system. In these circumstances, to keep away from overwhelming damage of the belt conveyor, a failure prediction system is a major requirement. A failure detecting system is devised with frequently occurring faults. The various conditions for this research are SATR running in Fault Free condition (FFC), SATR with bearing fault condition (BFC), SATR with central shaft fault (CSF), SATR with bearing fault and central shaft fault (BFC & CSF). The malfunction of these components affects the functioning of SATR which in turn lead to under- performance of the belt conveyor system. The conventional and FFT methods work well when signals are static. However, the components of SATR generate vibration signals with significant variation i.e. a very complex signal. From the complex signal, descriptive statistical features were extracted. One cannot assure that the all the features are always useful. Some unwanted features have to be removed. Selection of these features is based on their impact in fault prediction, which is the consequent stage of SATR condition monitoring. Apart from this, a good quality fault diagnose tool has to be utilized for classification. At present there are a fair number of classification algorithms, each having their own pros and cons. Entropy based algorithms are best suited for these types of applications. It can be found that in condition monitoring, the classification correctness differs among algorithms. Thus, it is necessary to find a pertinent algorithm which can be used to assess the condition monitoring of SATR. Decision tree algorithm is one such algorithm whose performance for SATR condition monitoring is not prominently reported in the literature. Hence, the statistical approach for feature extraction and classification using decision tree algorithm is considered in the present study. Also the results are compared with ANN algorithms.

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2. RELATED WORK

Ashkan Moosavian *et al.*, (2015) proposed a vibration based analysis to identify piston scuffing fault. It is reviewed that the vibration signals were analyzed in time-domain, frequency-domain and time–frequency domain. Continuous wavelet transform (CWT) was used to obtain time–frequency representations[1]. Whereas XinXia *et al.*, (2015) reviewed the Volterra series is widely employed in the fault diagnosis of rotor-bearing system to prevent dangerous accidents and improve economic efficiency. The results indicate that the method performs good capability on the identification of Volterra series of rotor-bearing system, and the proposed method can further improve the accuracy of fault diagnosis [2]. Bostjan Dolenc *et al.*, (2015) assessed a method for the diagnosis of distributed bearing faults employing vibration analysis. The vibration patterns generated were modeled by incorporating the geometrical imperfections of the bearing components. It is concluded that the features extracted from vibrations in fault-free, localized and distributed fault conditions form clearly separable clusters, thus enabling diagnosis [3]. Mitchell Yuwono *et al.*, (2015) discussed an advanced signal processing technique for detecting the source of defects in rotating elements such as bearing. This paper proposed an automatic bearing defect diagnosis method based which has achieved distinguished results [4]. V. Muralidharan *et al.*, (2013) proposed a novel methodology for selection of wavelets for fault diagnosis application using J48 algorithm. In this paper, wavelet features using different families of wavelets were extracted from the vibration signals and the features were classified using decision tree algorithm. It was proved that the J48 algorithm was one of the best algorithms in combination with the wavelet features. Also, an attempt has been made to realize the fault diagnosis capability of fuzzy logic and rough sets. Certain rules have been framed with rough sets and classified using fuzzy engine. The result was promising one and the techniques were well appreciated [5, 6]. Gys van Zyl *et al.*, (2013) analyzed the failure analysis of conveyor pulley shaft in service. Various methods of analysis were carried out to determine the failure root cause and contribution factors. Investigation methods included visual examination, optical and scanning electron microscope analysis, chemical analysis of the material and mechanical tests which finally revealed that shaft failed due to fatigue [7]. V.Muralidharan *et al.*, (2014) investigated how continuous monitoring of mono block centrifugal pump is essential in order to reduce the unnecessary break downs. At the outset, vibration based approaches are widely used to carry out the condition monitoring tasks. Particularly fuzzy logic, support vector machine (SVM) and artificial neural networks were employed for continuous monitoring and fault diagnosis. Further the paper dealt with five classical states of monoblock pump viz., normal, cavitations, bearing fault, impeller fault, impeller and bearing fault together, were simulated on mono-block centrifugal pump. Set of features have been extracted using different wavelets and classified using SVM algorithm. Finally it was concluded that feature extraction using wavelets and SVM algorithm for classification were effective for fault diagnosis of mono-block centrifugal pump [8]. Raymond Sterlinga *et al.*, [2014] relates two model based diagnostics methodologies ,the quantitative (continuous) model based diagnosis and qualitative model based diagnosis (QMBD) that can be used to detect and diagnose various faults that occur in Air Handling Units. Comparative results of both methodologies on an air handling unit were presented and thoroughly discussed using as a benchmark[9]. M.S. Safizadeh *et al.*, (2014) presented a new method for bearing fault diagnosis using the fusion of two primary sensors: an accelerometer and a load cell. A logical program has been used to decide about the condition of the ball bearing. The test results obtained from experiments demonstrate that the load cell is powerful to detect the healthy ball bearings from the defected ones, and the accelerometer is useful to detect the location of fault. The proposed method was applied to three cases of bearing fault detection and the results were compared with the results of conventional methods using individual sensors. It was finally concluded that the results show the benefits of the proposed method for improving fault detection and diagnosis accuracy [10]. M. Liang *et al.*, (2014) proposed an intelligent bearing fault detection method based on a calculus enhanced energy operator (CEEO). The main purpose is to extract the bearing fault signature in the presence of strong noise and multiple vibration interferences without prior information of the resonance excited by the bearing fault. It put forward a new parameter-free and filter-free technique in the form of enhanced energy operator to boost bearing fault detestability. The main theoretical contributions of this include the enhancement of the traditional energy operator technique by improving signal-to-noise and signal-to-interference ratios and the efficient implementation of the calculus enhanced energy operator for bearing fault detection .The simulation studies have shown that the CEEO method outperforms the conventional energy operator and the enveloping methods in handling both noise and interferences. It was suggested that it is versatile, unlike the traditional high frequency resonance techniques and does not require the resonance information and eliminates the filtering process. Hence, it can be directly applied for bearing fault detection. This paper claims that the performance of this method has also been examined using our experimental data and found to be satisfactory [11]. Gabriel Fedorko *et al.*, (2013) presented a detailed analysis of the belt conveyor damage through test specimen and found heavy destructive damage of its internal structure which gradually passes through the layer and it ends at the border of the bottom cover layer. Reflections about possible internal damage of the test specimen preceded this conclusion during the measurement. These reflections resulted from the analysis of measured and graphic displayed data, where the damage was assumed based on the significant faults of curves. Further, it concluded that if the damage of the conveyor belt is caused during its operation and left unidentified on time, and the conveyor belt is still under operation. However, by the effect of tension forces and transported material load the belt is exposed to the formation of destructive processes, which will destroy its internal structure. The internal destructive line will grow until the moment when the value of conveyor belt strength will be less than the sum of tension forces and the other forces affecting on the conveyor belt, it causes failure of the conveyor belt [12]. Farid Bettine et al., (2018) predicted the machining accuracy of a Five-axis Machine tool which is a vital process in precision manufacturing providing a kinematic error solution in five axes Machine. This solution is found on Artificial Neural

Network (ANN) for trochoidal milling machining strategy. The proposed a multi-layer perception (MLP) model to find the inverse kinematics solution for a Five-axis Machine. The results shows numerical study of trochoidal strategy to make sure a control of radial engagement [13]. M. Demetgul *et al.*, (2014) presented performances of multiple generic methods. The Diffusion Map (DM), Local Linear Embedding (LLE) and Auto Encoder (AE) algorithms are employed for feature extraction. Encoded signals were classified by using the Gustafson–Kessel (GK) and K-medoids algorithms [14]. V Muralidharan *et al.*, (2012) made a comparative study between Naive Bayes classifier and bayes net classifier for fault diagnosis of monoblock centrifugal pump. The algorithms were based on conditional probability and literature related to applications of these algorithms are only a few. The comparative study concludes that the bayes net algorithms perform better than its counterpart. However, bayesnet algorithm demands strong domain expertise and hence the diagnosis can only be made by a relatively skilled persons [15]. V. Sugumaran *et al.*, (2011) presented the effect of number of features in the classification performance of bearing dataset. Two different types of features such as statistical features and histogram features have been taken and analyzed with the same classification algorithm. Finally, it was concluded that seven features were the optimum number of features for the bearing dataset [16]. Shunkun Yang *et al.*, (2017) performed a FMEA based fault diagnosis for a software system. Initially FMEA based approach was followed and F-CBR method was promoted. A model for Baysian network was formulated through F-CBR by the corresponding failure spectra [17]. Tarek Ameid *et al.*, (2017), presented a fault diagnosis approach for an induction motor with closed loop. The adjacent bar was considered as a faulty condition in this study. The faulty conditions were analysed through Fast Fourier Transform (FFT) and other detections of the data [18]. A. Krishnakumari *et al.*, (2017) presented a work which is based on fault diagnosis of gears using vibration signals. Similarly, a fuzzy inference engine was also made and the representative data points were tested [19]. Though remarkable quantity of research works have been through in the area of fault diagnosis, the fact is very few literatures reported the enhancement of the algorithms. From this it is clear that over a span of more than a decade, it is hard to find an article which discusses that the fault diagnosis of the carrying Self aligning carrying idler which plays a very important role in belt conveyor systems. The gap in this research forms the basis for the present study. Hence this study was taken up to analyse the possible faults that can occur so that the breakdown of the system can be avoided. In this paper, statistical features are used to classify the faults with decision tree algorithm, ANN and to find the best number of features.f

The paper hereafter is organized as follows: section 3 illustrates the experimental setup followed by section 4 examines the feature extraction procedure and section 5 presents the feature selection and classification using decision tree in detail. Further, the results and discussion are presented in section 6 followed by the conclusion in section 7. The paper is concluded with the references in section 8. Self aligning troughing roller fault diagnosis consists of several steps viz., fabrication of conveyor experimental setup with different fault conditions, signal acquisition, signal conditioning, feature extraction (Statistical features in this case), and feature classification. Refer Figure 1, for the step by step procedure of the process.

3. EXPERIMENTAL SETUP

From the figure 1, the entire flow of the process can be clearly understood. Each step is explained in the subsequent sections of the paper. Initially, the conveyor system is allowed to run with all components of SATR working at good condition (Good). The vibration signals were captured in this condition. Then, slowly, the faults considered in this study such as SATR with bearing fault (BF), SATR with shaft fault (SF), and SATR with shaft and bearing fault (SF & BF) were introduced one by one and the respective vibration signals were acquired.

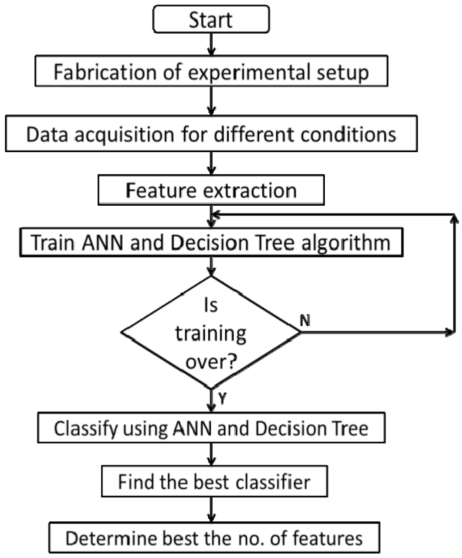

Figure.1. Flow chart for fault diagnosis of Self Aligning Troughing Roller

3.1 Experimental Setup.

Figure 2 shows SATR vibration analysis experimental setup. The investigational setting was made with the high precision MEMS accelerometer with the sensitivity of 10 Mv/g and a frequency range of 0 -2000 Hz (3dB) suitable for vibration monitoring. The accelerometer was hermetically mounted at the SATR stringer support considering the accelerometer mounting technique which is very ideal for vibration extraction. The accelerometer was connected to the signal-conditioning unit (DACTRAN FFT analyzer), where the signal goes through the charge amplifier and an Analogue-to-Digital Converter (ADC). The vibration signal in digital form was fed to the computer through a USB port. The signal was then read from the memory and replayed and processed to extract different features. Once the signal acquisition has been completed, then the signals are trimmed off to ensure the uniform length of the signal for all the conditions of the conveyor system.

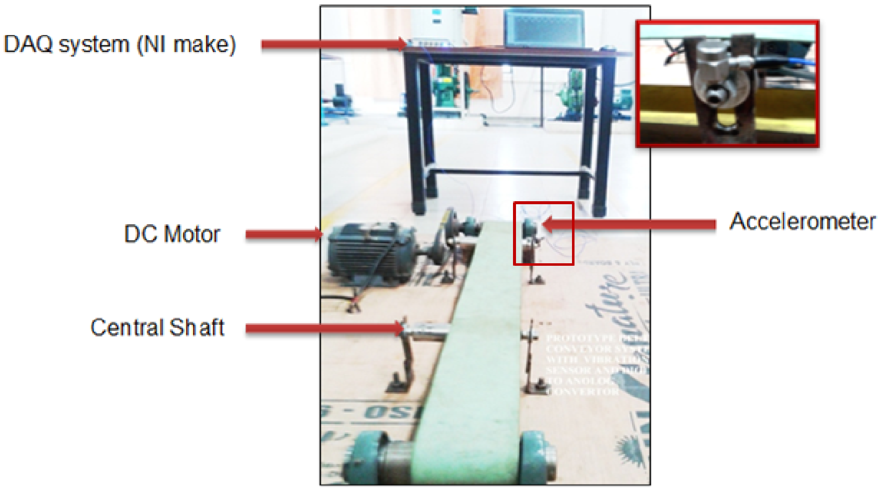

Figure 2. SATR experimental setup

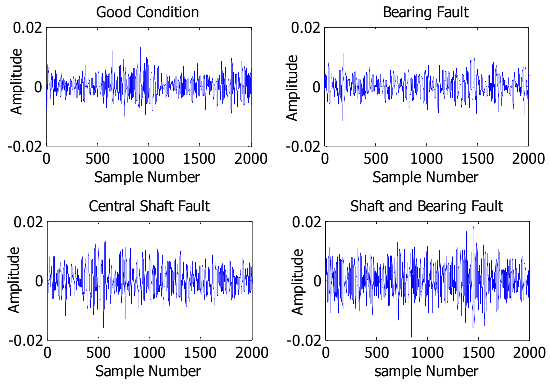

Figure 3. Time domain plots of different fault conditions of SATR

Table 1.Shaft diameter readings

S.No	Dia. of shaft before grinding in mm	Dia. of shaft after grinding in mm	Side
1	10.01	9.88	left Side 1
2	10.00	9.90	
3	10.00	9.98	Right Side 2
4	99.99	9.99	

Refer Figure.3 for the representative time domain plots for various conditions of the SATR. One set of shaft and bearing is prefabricated with faults as per dimensions given in Table 1. The roller Bearing (Model No KG6200Z) was prefabricated with a fault to acquire the vibration signals. The outer ring and the inner ring of thickness 5 mm and 3 mm respectively are ground for 4 mm and 2.5 mm respectively for developing faults. Refer Table 2 for the bearing dimensions.

Table 2. Bearing outer ring thickness readings

S.No.	Dia. of Roller bearing before grinding in mm	Dia. of shat after grinding in mm
1	4.50	4.0
2	4.51	3.90

4. FEATURE EXTRACTION

Statistical analysis of the signal gives various parameters which may be useful in discriminating the faults in the setup. The various parameters are mean, median, mode, standard error, standard deviation, kurtosis, skewness, minimum value, maximum value, sample variance and range. The features are explained one by one in sequence.

i. Mean : It is the simple average of the entire signal. It is expressed mathematically as

$$Mean = \frac{Sum}{n} \tag{1}$$

where n – Total number of instances

ii. Median: Median is the numerical value separating the higher half of a data sample, a population, or a probability distribution, from the lower half. In other words, choosing a middle value from the series provided the numbers are arranged in ascending order.

iii. Mode: Mode is the value that appears most often in a set of data. The mode of a discrete probability distribution is the value x at which its probability mass function takes its maximum value.

iv. Standard Error: Standard error is a measure of the amount of error in the prediction of y for an individual x in the regression, where x and y are the sample means and ‘n’ is the sample size.

v. Standard deviation: Standard deviation shows how much variation or dispersion from the average exists

vi. Kurtosis: Kurtosis indicates the flatness or the spikiness of the signal

vii. Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean. Positive skewness indicates distribution with an asymmetric tail extending towards more positive values

viii. Minimum value: It signifies the possible minimum value in the distribution.

ix. Maximum value: It signifies the possible maximum value in the distribution.

x. Sample variance: The sample variance is the second sample central moment

xi. Range: It defines the difference between the maximum value and the minimum value

In this stage, eleven common features were extracted from the vibration signals through simple macro in order to see quantitatively the difference between good and faulty conditions. The formulas used for features are presented in section 4. The features are selected based on their physical meaning as to how much they contribute in discriminating the faults in SATR. By analyzing the pool of eleven features one by one, the impotent features can be neglected easily. From the feature set, one can easily say that the features such as minimum value, maximum value, range and sample variance are not considered due to the following reasons.

(i) Minimum value gives the information that the least value present in the signal. It will not help in any way to discriminate the faults
(ii) Maximum value gives the information that the highest value present in the signal which will not be of any use in classifying the faults
(iii) Range is the difference between maximum value and minimum value which will not help in discriminating the faults
(iv) Sample variance is the amount of difference from the mean value and is represented by standard deviation

4.1 Artificial Neural Network

Artificial Neural Network (ANN) is a technique which is modeled with biological neurons and nervous systems. It has an ability to learn and interpret the signals which are fed as inputs. The general framework for the ANN is that it has an input layer where the inputs are given and the outputs are taken via output layer. It has got hidden layers between input and output layers. The input signals are learned and interpreted by means of an activation functions which are associated with every hidden layers. Usually, the processing is being performed by multilayer perceptrons.

4.2 Multi-Layer Perceptron (MLP)

This is an important class of neural networks, namely the feed forward networks. Typically, the network consists of a set of input parameters that constitute the input layer. MLPs have been applied to solve some difficult and diverse problems by training them in a supervised manner with back-propagation algorithm. Each neuron in the hidden and output layer consists of an activation function, which is generally a non-linear function. The weights of the network to be trained are initialized to small random values. The weights are updated through an iterative learning process known as 'Error Back Propagation (BP) algorithm'. Error Back Propagation process consists of two passes through the different layers of the network; a forward pass in which input patterns are presented to the input layer of the network and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights if the networks are all fixed. The error value is then calculated, which is the mean square error (MSE) given by eqn (4) and eqn (5)

$$E_{tot} = \frac{1}{n}\sum_{n=1}^{n} E_n \tag{2}$$

where $$E_{tot} = \frac{1}{n}\sum_{n=1}^{m}\left(\zeta_k^n - O_k^n\right) \tag{3}$$

where m is the number of neurons in the output layer, and ζ_n^k is the k th component of the desired or target vector and O_k^n is the k th component of the output vector. The training process is carried out until the total error reaches an acceptable level (threshold). If $E_{tot} < E_{min}$ the training process is stopped and the final weights are stored, which is used in the testing phase for determining the performance of the developed network

4.3 J48 algorithm

Data mining techniques are being increasingly used in many modern organizations to retrieve valuable knowledge structures from databases, including vibration data. An important knowledge structure that can result from data mining activities is the decision tree (DT) that is used for the classification of future events. Decision trees are typically built recursively, following a top-down approach. The acronym TDIDT, which stands for Top-Down Induction on Decision Trees, refers to this kind of algorithm. A standard tree induced with C5.0 (or possibly ID3 or C4.5) consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a leaf; and each node involves one attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute. J48 algorithm (a WEKA implementation of C4.5 algorithm) is a widely used one to construct decision trees. Decision tree algorithm (J48) has two phases: building and pruning. The building phase is also called as the 'growing phase'.

5. RESULTS AND DISCUSSION

In section 3, feature extraction using statistical methods has been discussed. There were total of eleven features suggested for classification. From the physical meanings of the features, seven features were considered. The features were taken in order one by one and classified using ANN and J48 algorithm. The respective classification accuracies were noted down for both the algorithms. Figure 4 shows the comparative analysis of ANN and J48 algorithm for individual features taken one by one.

From Figure 4, it is clear that J48 algorithms are superior in performance when compared to ANN. Though ANN is good when less number of features are considered, overall performance is good for J48 algorithm. The trend of the curve for j48 improves from lower value to higher value. i.e. when the number of features go higher and higher the performance gets improved. When all the seven features are considered it yields a classification accuracy of 89.1%. Even though it sounds good, the computation time and degree of complexity is more.

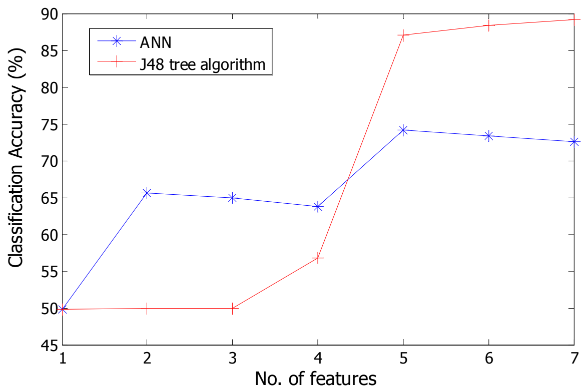

Figure 4. Comparative plot between ANN and J48 algorithm

Hence, one should find a solution to achieve the same performance with lesser efforts in terms of less complexity and less computational effort. One possible solution for this issue is to go for dimensionality reduction. It means that to select only useful features and discard the unwanted features. This step can be performed using decision tree. A set of seven features which were considered earlier is given as input and the output is presented in the form of decision tree as shown in Figure 5.

The first number in the parenthesis indicates the number of data points that can be classified using that feature set. The second number indicates the number of samples against this action. If the first number is very small compared to the total number of samples, then the corresponding features can be considered as outliers and hence ignored. The decision tree suggests only four features among seven with which the entire classification process is carried out. It means that the four features such as standard error, standard deviation, kurtosis and Skewness are the prominent features and possess the highest fault discriminating capability. The other three features such as standard variance, median and mode can be ignored as there is no significant change in the performance in their absence. The selected four features could fetch a classification accuracy of 89.5 % with J48 algorithm and 67.8% with ANN. The reason for decrease in performance with ANN is due to when more number of features are considered more hidden layers will be introduced and weightages are assigned to them. Whereas the number of features is less, the hidden nodes will be less and ultimately ANN fails to achieve more accuracy as it works based on the trial and error methods. For the classification and 10 fold cross validation, J48 algorithm was used. Table 3 shows the confusion matrix for classification using J48 algorithm with four features.

From the confusion matrix (Table 3), one can understand that 250 samples were considered for each condition of SATR. All the diagonal elements of the confusion matrix represent the number of correctly classified data points and the non-diagonal elements represent the incorrectly classified data points.

In this manner, the classification accuracies are established. In this case, 146 good condition data points have been correctly classified and the remaining 46 points indicate they fit in to bearing fault (BF) and 58 fit into combined shaft and bearing fault (SF&BF). Similarly, 199 data points of shaft fault have been correctly classified and 34 were misclassified as good and 17 as combined shaft and bearing fault (SF&BF). In this way, the confusion matrix can be interpreted and classification accuracy was found to be 89.5%. The results obtained are specific to this particular dataset. Classification accuracy of 89.5% does not assure similar performance for all feature datasets. However, one can expect classification accuracy close to 90%. In general, the classification accuracy is very high compared ANN. Hence, the decision tree algorithm and statistical features can be very much suited for fault diagnosis of SATR in a belt conveyor system.

Table 3. Confusion Matrix

	Good	SF	BF	SF&BF
Good	146	0	46	58
SF	34	199	0	17
BF	0	0	250	0
SF&BF	0	17	1	232

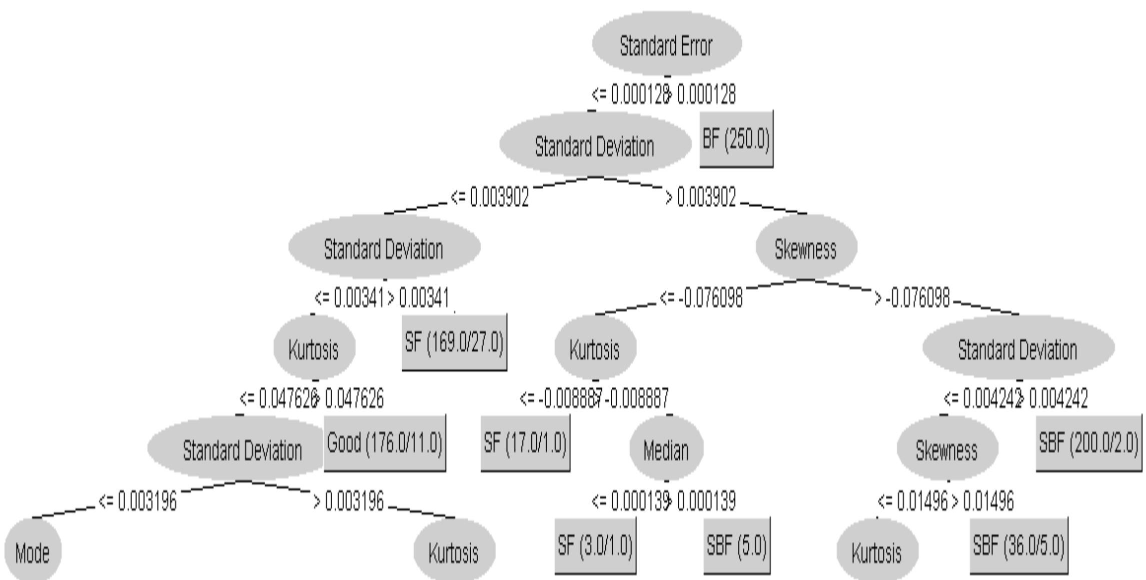

Figure 5 Decision Tree

6. CONCLUSION

From the current analysis it is evident that fault diagnosis of SATR in a belt conveyor system has extensive scope for further application and research. The vibration signals were acquired using NSIC data acquisition system. The acquired data was preprocessed for extracting the statistical features. The features were classified with decision tree algorithm and ANN. It was concluded that the classification accuracy with decision tree was found to be 89.5 % and that of ANN 67.5 %. Then, the best number of features was identified using decision tree in order to overcome the computational complexity and time consumption. Since the data was acquired at a specific working condition, this end result may not be comprehensive for all the cases. Aiming at the shortcomings of the conventional failure analysis method for SATR, the methodology adopted would definitely serve as a guideline for the future research in this area. As a whole, classification accuracy of 89.50% is a significant one in this application; one can conclude that the statistical features and decision tree algorithms are a good option for fault diagnosis of SATR in a belt conveyor system.

REFERENCES

[1] Moosavian A., Najafi G., Ghobadian B., Mirsalim M., Jafari S.M., Sharghi P.: Piston scuffing fault and its identification in an IC engine by vibration analysis, Applied Acoustics, No. 102, pp:40-48, 2016.

[2] Xia X., Zhou J., Xiao J., Xiao H.:A novel identification method of Volterra series in rotor-bearing system for fault diagnosis,Mechanical systems and signal processing,No. 66, pp:557-567, 2016.

[3] Dolenc B., Boškoski P., Juričić D.:Distributed bearing fault diagnosis based on vibration analysis,Mechanical Systems and Signal Processing, No.66, pp:521-532, 2016.

[4] Yuwono M., Qin Y., Zhou J., Guo Y., Celler B.G., Su S.W.:Automatic bearing fault diagnosis using particle swarm clustering and Hidden Markov Model,Engineering Applications of Artificial Intelligence, No. 47, pp:88-100,2016.

[5] Muralidharan V., Sugumaran V.:Selection of discrete wavelets for fault diagnosis of monoblock centrifugal pump using the J48 algorithm,Applied Artificial Intelligence, No. 27 (1), pp:1-19, 2013.

[6] Muralidharan V., Sugumaran V.:Rough set based rule learning and fuzzy classification of wavelet features for fault diagnosis of monoblock centrifugal pum, Measurement, No. 46 (9), pp:3057-3063,2013.

[7] Van Zyl G., Al-Sahli A.:Failure analysis of conveyor pulley shaft, Case Studies in Engineering Failure Analysis, No.1 (2), pp:144-155,2013.

[8] Muralidharan V., Sugumaran V. Indira V.: Fault diagnosis of monoblock centrifugal pump using SVM.Engineering Science and Technology, an International Journal, No.17 (3), pp:152-157,2014.

[9] Sterling R., Provan G., Febres J., O'Sullivan D., Struss., Keane M.M. :Model-based fault detection and diagnosis of air handling units, A comparison of methodologies, Energy Procedia,No.62, pp:686-693, 2014.

[10] Safizadeh M., Latifi S.:Using multi-sensor data fusion for vibration fault diagnosis of rolling element bearings by accelerometer and load cell, Information Fusion, No.18, pp:1-8, 2014.

[11] Liang M., Faghidi H.:Intelligent bearing fault detection by enhanced energy operator,Expert Systems with Applications, No.41 (16), pp:7223-7234, 2014.

[12] Fedorko G., Molnar V., Marasova D., Grincova A., Dovica M., Zivcak J., Toth T., Husakova N.:Failure analysis of belt conveyor damage caused by the falling material. Part II: Application of computer metrotomography, Engineering Failure Analysis, No. 34, pp:431-442, 2013.

[13] Farid Bettine ., Hacene Ameddah ., Rabah Manaa.: A Neural Network Approach for Predicting Kinematic Errors Solutions for Trochoidal Machining in the Matsuura MX-330 Five-Axis Machine, FME Transactions (2018) 46, 453-462 453.

[14] Demetgul M., Yildiz K., Taskin S., Tansel I., Yazicioglu O.:Fault diagnosis on material handling system using feature selection and data mining techniques, Measurement, No.55, pp:15-24, 2014.

[15] Muralidharan V., Sugumaran V.:A comparative study of Naive Bayes classifier and Bayes net classifier for fault diagnosis of monoblock centrifugal pump using wavelet analysis,Applied Soft Computing, No. 12 (8), pp:2023-2029, 2012.

[16] Sugumran V., Ramachandran K.:Effect of number of features on classification of roller bearing faults using SVM and PSVM, Expert Systems with Applications, No. 38 (4), pp:4088-4096, 2011.

[17] Yang S. et al.:Optimized fault diagnosis based on FMEA-style CBR and BN for embedded software system,The International Journal of Advanced Manufacturing Technology, 2017

[18] Ameid T., Menacer A., Talhaoui H., Harzelli I.:Broken rotor bar fault diagnosis using fast Fourier transform applied to field-oriented control induction machine: simulation and experimental study, The International Journal of Advanced Manufacturing Technology,2017

[19] Krishnakumari A., Elayaperumal A., Saravanan M., Arvindan C.:Fault diagnostics of spur gear using decision tree and fuzzy classifier, The International Journal of Advanced Manufacturing Technology, No.89 (9), pp:3487-3494, 2017.

NOMENCLATURE

K*	a distance function
p	probability function on
U*,	probability of all paths
m	number of neurons in the output layer
E_n	Error Back Propagation (BP) algorithm'

Hz	Frequency
N	sample size
n	Total number of instances
m	number of neurons in the output layer
E_n	Error Back Propagation (BP) algorithm’
Hz	Frequency
BF	Bearing Fault
SF	Shaft Fault
BF& SF	Bearing and Shaft fault

Greek Symbols

ζ_k^n	kth component of the desired or target output vector
O_k^n	kth component of the output vector.
$\bar{x}$	population mean

Superscripts

k	Consecutive function
n	Sequential function order

ВИШЕКОМПОНЕНТНА ДИЈАГНОЗА ОТКАЗА САМОИЗРАВНАВАЈУЋЕГ ВАЉАЈУЋЕГ ВАЉКА (САТР) У СИСТЕМУ ТРАНС-ПОРТНИХ ТРАКА ПОМОЋУ СТАБЛА ОДЛУЧИВАЊА – СТАТИСТИЧКИ ПРИСТУП

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САТР је једна од главних компонената код функционисања транспортних трака у условима без отказа. САТР мора да подржава траку и носи максимално оптерећење по попречном пресеку. Ваљак САТР се састоји од машинских елемената као што су куглични лежај, централно вратило и спољашња постељица.
Међутим, често се дешавају откази рада лежаја, централног вратила, и истовремено лежаја и централног вратила. Направљен је пројекат и израђен је прототип ваљка. Отказ рада наведених машинских елемената увођен је један по један и добијени су одговарајући сигнали вибрација.
Следећи корак је израчунавање скупа статистичких параметара, чиме се формира скуп карактеристика и класификација помоћу алгоритама АНН и алгоритама стабла одлучивања.
Алгоритам стабла одлучивања већ на почетку показује супериорне перформансе у погледу прецизности класификације. Циљ рада је да се добије највећи одговарајући број карактеристика да би се постигла максимална ефикасност. Провера резултата је обављена десетоструком унакрсном валидацијом.