In-Process Tool Condition Monitoring in Compliant Abrasive Belt Grinding Process Using Support Vector Machine and Genetic Algorithm

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Abstract

Industrial interest in tool condition monitoring for compliant coated abrasives has significantly augmented in recent years as unlike other abrasive machining processes the grains are not regenerated. Tool life is a significant criterion in coated abrasive machining since deterioration of abrasive grains increases the surface irregularity and adversely affects the finishing quality. Predicting tool life in real time for coated abrasives not only helps to optimise the utilisation of the tool's life cycle but also secures the surface quality of finished components. This paper describes the evolution of the abrasive grain degradation in the belt tool with process time and also the development of Support Vector Machine (SVM) and Genetic Algorithm (GA) based predictive classification model for in-process sensing of abrasive belt wear for robotized abrasive belt grinding process. With this tool condition monitoring predicting system, the effectiveness of the belt and the surface integrity of the material is secure. The analysis of sensor signals generated by the accelerometer, Acoustic Emission (AE) sensor and force sensor during machining is proposed as a technique for detecting belt tool life states. Various time and frequency domain features are extracted from sensor signals obtained from the accelerometer, acoustic sensor and force sensor mounted on the belt grinding setup. The time and frequency domain features extracted from the signals are simultaneously optimised to obtain a subset with fewer input features using a GA. The classification accuracy of the k-Nearest Neighbour (kNN) technique is used as the fitness function for the GA. The subset features extracted from the signals are used to train the SVM in MATLAB. An experimental investigation using four different conditions of tool states is introduced to the SVM and GA for the prediction and classification. By the experimental results, this research proves that the proposed SVM based in-process tool condition monitoring model has a high accuracy rate for predicting abrasive belt condition states.

Keywords: Abrasive belt grinding; GA; Tool wear; Condition monitoring; SVM;

1. Introduction

Coated abrasive tools in the form of a disk, flap wheel and belt are widely used in the industry for tertiary finishing operations. An important aspect of the coated abrasive tools is their compliance as illustrated in the Fig. 1. The tool deforms in conformity with the surface of work coupon due to a polymer backing when it comes in contact without modifying its nominal shape and at the same time achieving required material removal.

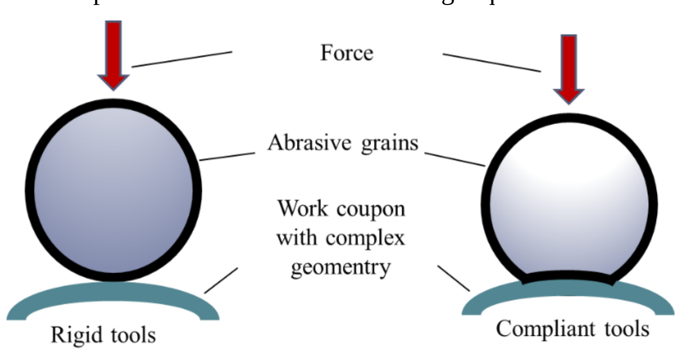

Fig. 1. Comparison of contact characteristics of rigid and compliant tools.

Abrasive belt grinding is a two-body abrasive compliant machining process used to improve the surface finish of components. The belt grinding system consists of thermosetting polyurethane elastomer contact wheel that can be deformed to assist the coated abrasive belt to fasten around it which functions as cutting edge that makes it be a compliant tool. In recent years, belt grinding system consisting of a robot arm and coated belt grinding abrasive tool, has emerged as a finishing process for machining surfaces with complicated geometry like turbine blades. Like any other abrasive machining, grinding belt topography features such as grain distance, grit size, and wear rate impacts the final ground surface quality [1]. The life cycle of a coated abrasive belt tool vitiates due to continuing grain wear resulting to tool failure. As the abrasive belt tool approaches the end of its life, the degradation in the surface quality of the machined workpiece is quite apparent. Many aspects of the interactions between cutting tool, workpiece, and material removal during compliant belt grinding are not fully understood due to high nonlinearity of the process. The granularity of the abrasive grain is dominant among all process parameters for material removal in belt grinding process [2]. The pre-planned tool replacement methodologies are no longer suitable in belt grinding process as the machining conditions vary extensively. The decrease in the material removal rate due to belt wear was compensated by increasing the abrasive belt speed and decreasing the workpiece feed rate [3]. A linear mathematical model was proposed which stated that the overall material removal rate is proportional to belt wear factor [4]. A reliable real-time monitoring system could allow ideal exploitation and identification of the tool life states and avert these problems.

The idea of tool life monitoring has earned vital importance in any manufacturing industry. This is mainly due to the conversion of the manufacturing stations from physically operated production machines to highly automated robotic manufacturing cells. Thus, there is an immense need for tool life monitoring systems to confirm the best performance of the unsupervised machining stations. Sensing techniques for tool condition monitoring are classified into two categories namely direct sensors and indirect sensors [5]. Direct methods have the benefit of delivering a direct and accurate evaluation of the tool's state but are constrained to in-cycle deployment because cutting edges are mostly unreachable during machining. However in the case of indirect methods, process parameters such as temperature, vibration, cutting forces, AE, etc. are calculated successively, and tool states are assessed based on reliable signal patterns which can be correlated to tool wear states.In the case of unsupervised machining stations, an appendage of sensor capabilities can extremely reduce downtime and augment product quality. Experiments have been performed to study effects of tool wear on cutting force signals when drilling copper alloy to achieve on-line drill wear monitoring [6]. The correlation between flank wear and average tangential cutting force coefficient were used with cutting parameters such as cutting speed, depth of cut and feed per tooth to evaluate tool wear for milling [7]. A time series modelling technique was developed to extract features such as autoregressive parameters, the power of the AE signal and AR residual signals for monitoring coated carbide tool conditions based on AE signals obtained during machining of C-60 steel and were found that these features were sensitive to wear rate [8]. These works on tool wear monitoring were focused on time series and frequency domain analysis. Wherein, an upper limit is set among the normal and abnormal states of the tool. Conversely, the threshold value changes with time and cutting environment which makes these techniques in-accurate. For increasing the performance, more novel logics, such as pattern recognition and statistical techniques have been developed in the region of tool wear assessment. A neural network-based sensor fusion model for estimation of the average flank wear of the primary cutting edge based on features isolated from the fused data of some machining zone signals such as cutting forces, spindle vibration, spindle current, and sound pressure level has also been investigated [9]. A new modelling outline for tool wear monitoring in using Hidden Markov Models (HMMs) based on feature vectors extracted from the vibration signals calculated in turning operation of AISI 8620 steel has also been proposed [10]. The exact moment at which abrasive grinding wheel wears to accomplish the dressing process was determined by vibration and AE sensor [11]. A virtual verification system for grinding wheel condition monitoring by use of a neural network and fuzzy logic was developed by blending vibration, AE and grinding forces sensor outputs [12]. AE and force signals have been used for classifying the tool conditions into four distinct classes namely sharp tool, used tool, chip noise, and tool breakage using pattern recognition [13]. Most of the previous research work on tool wear monitoring was on hard tools with defined cutting edges and rigid grinding tools using sensors and decision-making algorithm as listed in Table 1. Tool condition monitoring has not been concentrated on the compliant tools, to bridge this gap the proposed research tries to develop a methodology for condition monitoring and predicting tool wear in compliant belt grinding process.

Though not much work has been explored in tool wear of coated belt abrasive tools, other works on coated abrasive tools provide some insight.A real-time complimentary multi-sensor integration system to predict surface roughness of the work coupon in belt grinding process based on contact conditions was developed using SVM based classification algorithm [14]. A removal control method for the belt grinding process through the optimised dynamic parameters of the robot was proposed using an adaptive model based on statistic machine learning [15]. The changes of grinding force and metal removal rate with time in coated Abrasive belt grinding are caused principally by the formation and increase of the worn flat area on grain tips [16]. The influence of abrasive grain's wear and contact conditions on surface texture in belt finishing process and concluded that material removal rate changes based on the wear level of active grains and becomes stable after the effective contact duration [17]. There have been studies on the influence of the effects and the interactions of the belt finishing parameters such as abrasive film parameters, cutting parameters on the surface texture. The study proved that amid the parameters of belt finishing, the granulometry of abrasive films is the highly significant parameter on surface finish and quality [18].

Table 1. Major research efforts in tool wear monitoring.

Process	Year	Investigators	Sensors used	Decision-making techniques
Milling	1994	S. Kakade et al. [19]	AE	Statistical analysis
	1995	S. C. LIN and R. J. YANG [20]	Force	Statistical analysis
	2000	S.L. Chen and Y.W. Jen [21]	Force, vibration	Neural network
	2007	Ghosh N et al. [22]	Force, vibration, Current, and Sound pressure	Backpropagation neural network
	2009	M. Malekian et al. [23]	Force, vibration, and AE	Neuro-fuzzy method
	2010	Jun-Hong Zhou et al.[24]	AE and force	Auto-Regressive Moving Average (ARMA)/ Dominant Feature Identification (DFI)
	2017	B. Cuka and D.W. Kim [25]	Force, vibration, current, and microphone	Fuzzy logic
	2017	Dazhong Wu et al. [26]	Force, vibration, and AE	Random Forests
Turning	2000	D.E. Dimla and P.M. Lister [27]	Force, accelerometer	Time series and frequency analysis
	2008	Alonso and Salgado [28]	Accelerometer	Singular Spectrum Analysis (SSA) and cluster analysis
	1999	Ghasempoor [29]	Force	Neural network
	2002	L.Wang et al.[30]	Accelerometer	Hidden Markov models (HMMs)
	2010	Agustin Gajate [31]	Force, vibration, and AE	Neuro-fuzzy
Drilling	1995	S.C. Lin and C.J. Ting [32]	Force and power	Statistical analysis
	2000	X. Li et al. [33]	Accelerometer	Neural network model with fuzzy logic (FNN)
	2001	H. M. Ertunc et al. [34]	Force and power	HMMs
	2005	C. Sanjay et al. [35]	Force	Backpropagation neural networks
Broaching	2007	D. Shi and N. N. Gindy [36]	Force, strain sensor and accelerometer	SVM and Principal Component Analysis (PCA)
Grinding	1992	E. Brinksmeier and F. Werner [37]	Optical sensor	Statistical analysis
	2001	Pawel Lezanski [12]	Force, vibration, and AE	Neural network and fuzzy logic
	2007	T.Warren Liao et al.[38]	AE	Adaptive genetic clustering algorithm

These studies on belt grinding process emphasise on the impact of tool condition monitoring in the effectiveness of the machining process and surface finish. As tool grain wear has a direct influence on the uniform material removal, monitoring such coated abrasive tool condition in real time helps in quality control of surface in finished components. This research tries to predict the belt cycle time in compliant belt grinding process virtually in real time with the help of smart sensors using the machine learning based classification technique such as SVM. This kind of metrology adds value for the whole manufacturing process. The paper is organised as follows: an overview of Abrasive belt grinding process and the problem statement is presented in Section 1, followed by a brief outline of belt grinding process, SVM and GA in Section 2. The machining conditions, experimental setup and relationship of belt wear on material removal rate and surface roughness is discussed in Section 3. Methodology and complementary based multi-sensor integration approach for belt condition monitoring are reported in Section 4. Results of the feature selection, optimisation and classification accuracy using SVM and GA is summarised in Section 5. Finally, the conclusions of this research work are reviewed in Section 6.

2. Theoretical basis

2.1. Abrasive belt grinding process

Abrasive belt grinding is a modification of the traditional grinding process which has emerged as a finishing process for machining surfaces with intricate shapes and contours. The belt grinding setup is made up of coated abrasive belt and is fastened around at least two rotating rubber contact wheels which make it be a compliant tool as illustrated in Fig. 2. The soft contact rubber wheel enables this machining process very appropriate to manufacture free-form surfaces due to its capability to adapt to the workpiece surface [39]. The material is removed from a semi-finished component by the interaction of tiny coated abrasive particles with the surface. The contact area between the workpiece and the belt surface varies on the force applied on the work coupon and Young's modulus of the contacting elastic wheel as shown in Fig. 2. The final surface quality of the belt grinded process is impacted by components such as grinding belt topography features and cutting parameters.

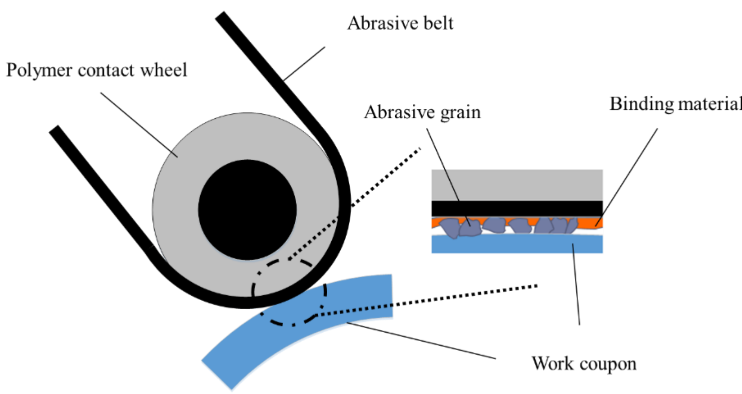

Fig. 2. Principle of belt grinding process.

Hamann [4] had proposed a linear mathematical model as shown in Eq. (1) which states that the overall material removal rate r is either relative or inversely proportional to parameters such as C_A (constant of the grinding process), K_A (combination constant of resistance factor of the work coupon and grinding ability factor of the belt), k_t (belt wear factor), V_b (grinding rate), V_w (feed-in rate), L_w (machining width) and F_A (normal force).

$$r = C_A.K_A.k_t.\frac{V_b}{V_w.L_w}.F_A \tag{1}$$

This proposed equation states that material removal in the workpiece that is machined depends on the belt wear factor (k_t). Therefore, it is evident that material removal is directly proportional to the topography of the grains in the belt surface which serves as an undefined cutting-edge determining the depth of penetration during machining. The material removal intensifies when the number of the interaction of the abrasive grains per unit time gets maximised [3]. A newer belt tool exhibits a greater ability to achieve higher cutting depth which results in a higher removal material and than the older. It is a significant disadvantage to use a tool until breakage occurs, as it affects the quality of the surface severely [40]. The process of wear and breakdown of abrasive belt simultaneously decreases material removal rate and weakens the surface accurateness of workpieces. In general, understanding the stages of tool wear and predicting belt tool life in real-time helps to allow optimum utilisation of the tool's life cycle and optimal performance of automated manufacturing process.

2.2. Support Vector Machine

Classification efficiency of SVM with other classifiers like Decision Tree, Naïve Bayes, Bayes Net were compared and proposed that SVM has better classification proficiency than the others for tool condition monitoring [41]. Support Vector Machine are ideal for solving nonlinear classification problems using kernel trick which has been explained in this section.

For linearly separable data a hyperplane $f(\mathbf{x}) = 0$ can be determined as,

$$f(\mathbf{x}) = \mathbf{w}^{\mathbf{T}}\mathbf{x} + b = \sum_{j=1}^{n} \mathbf{w_j x_j} + b = 0 \tag{2}$$

where $\mathbf{w}$ is an n-dimensional vector and b is a scalar which determine the optimal parting hyper-plane that leaves maximum margin from both the classes. In-case of non-linear classification a, Kernel trick is used. Kernel trick converts the data into a higher dimensional feature space to formulate it possible to implement linear separation. SVM using a non-linear kernel function $\phi : \mathcal{X} \to \mathcal{F}$ transforms data from the input space $\mathcal{X}$ to a feature space $\mathcal{F}$. In the space $\mathcal{F}$ the discriminant function is:

$$f(\mathbf{x}) = \mathbf{w}^{\mathbf{T}}\phi(\mathbf{x}) + b \tag{3}$$

Linear classification can be derived from the non-linear SVM by absolutely mapping the input data $\mathbf{x}$ into the feature space and training the SVM for the mapped features $\phi(\mathbf{x})$ as shown in Fig. 3. The weight vector can be articulated as a linear combination of the training examples, i.e.$\mathbf{w} = \sum_{i=1}^{n} \alpha_i \mathbf{x_i}$ hence Eq. 3 takes the form:

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i \mathbf{x_i}^T \mathbf{x} + b \tag{4}$$

In the feature space, $\mathcal{F}$ this expression takes shape:

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i \phi(\mathbf{x_i})^{\mathbf{T}} \phi(\mathbf{x_j}) + b \tag{5}$$

Nonlinear SVMs can then be trained by swapping the inner products in Eq. 5 with the analogous kernel $K(\mathbf{x_i}, \mathbf{x_j})$.

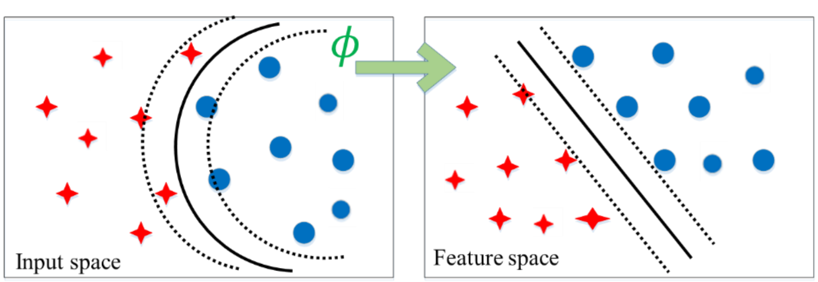

Fig. 3. Mapping the input space to feature space using kernel trick.

$$K(\mathbf{x_i}, \mathbf{x_j}) = \phi(\mathbf{x_i})^{\mathbf{T}} \phi(\mathbf{x_j}) \tag{6}$$

The resultant classifier for the non-linear SVM is then denoted in terms of the kernel function as:

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i \, K(\mathbf{x_i}, \mathbf{x_j}) + b \tag{7}$$

In the field of tool condition monitoring, several tool wear classification and assessment techniques have been proposed so far using SVM [36, 42]. This research tries to predict the tool condition of coated abrasive compliant belt in real time during machining process with the help of smart sensors.

2.3. Genetic Algorithm

Classification accuracy of the predictive system is affected by too many features as some features may be redundant and non-informative. The high-dimensional feature set can negatively affect classification accuracy as well as affect the performance during real monitoring. Genetic Algorithm has been established to be a very adaptive and competent means of feature selection [43]. The operations in a GA are iterative processes manipulating one population to generate a new population via genetic functional such as crossover and mutation. The chromosome design, fitness function affect the feature selection using the GA. Genetic Algorithm generates consecutive populations of another solution that are represented by a chromosome. Fitness function evaluates the attribute of a solution in the evaluation step. The crossover and mutation functions are the main operators that randomly impact the fitness value. Fig. 4 illustrates the genetic operators of crossover and mutation and GA evolutionary process.

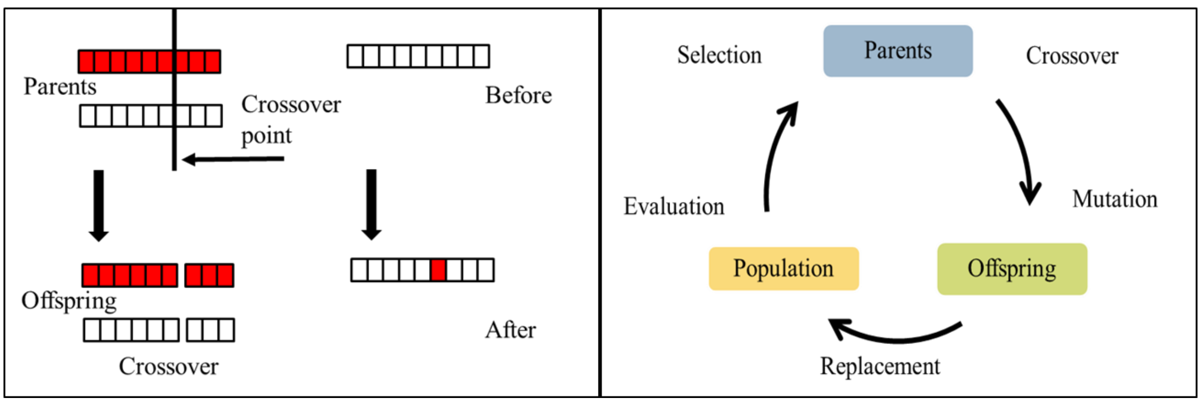

Fig. 4. Crossover, mutation operation, and evolutionary cycle in Genetic Algorithm.

Chromosomes are picked for reproduction by estimating the fitness value. Offspring swaps the old population using the elitism and take shape into a new population of the next generation. The righter chromosomes have a high probability to be selected into the mixing pool using the roulette wheel or the tournament selection methods. The evolutionary process operates many generations until termination condition satisfy. Genetic Algorithm finds the best possible subset of features from feature space after a series of iterative computations until acceptable results are obtained.

3. Experimental conditions

3.1. Belt Structure and evolution of belt tool states

The Fig. 5 shows a cross-section of an abrasive belt, which includes a backing material, a base coat and an abrasive grain type. Choice of the abrasive belt for tertiary finishing is primarily dependent on the type of backing material, grit size, abrasive material used and bonding. Abrasive belts of grit size 60 (medium coarser) made up aluminium oxide grain, and canvas as the backing material of width of 10 mm is chosen for experimental trials in this research work. Table 2 describes the four belts used for the experiments and their respective time of usage. Belts that have four different process runtime are compared visually to study the evolution of grain wear on the belt surface with cycle run time. Taly-Surf non-contact laser profilometer was used to profile an area of about 5mm X 5mm. Based on the visual analysis of 3D laser profile reading as shown Fig. 6, it is evident that the grains wither considerably from the backing material relative to the lifetime of a belt tool

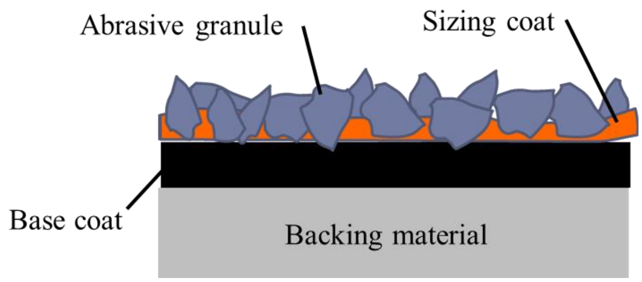

Fig. 5. Cross section of an abrasive belt.

Table 2. Belts conditions used for experimental trials and their respective time of usage.

Belt No	Short forms of the prepared belts	Amount of usage time (minutes)
1	New belt	0
2	Belt after 5 minutes of cycle time	5
3	Belt after 15 minutes of cycle time	15
4	Worn out belt	30

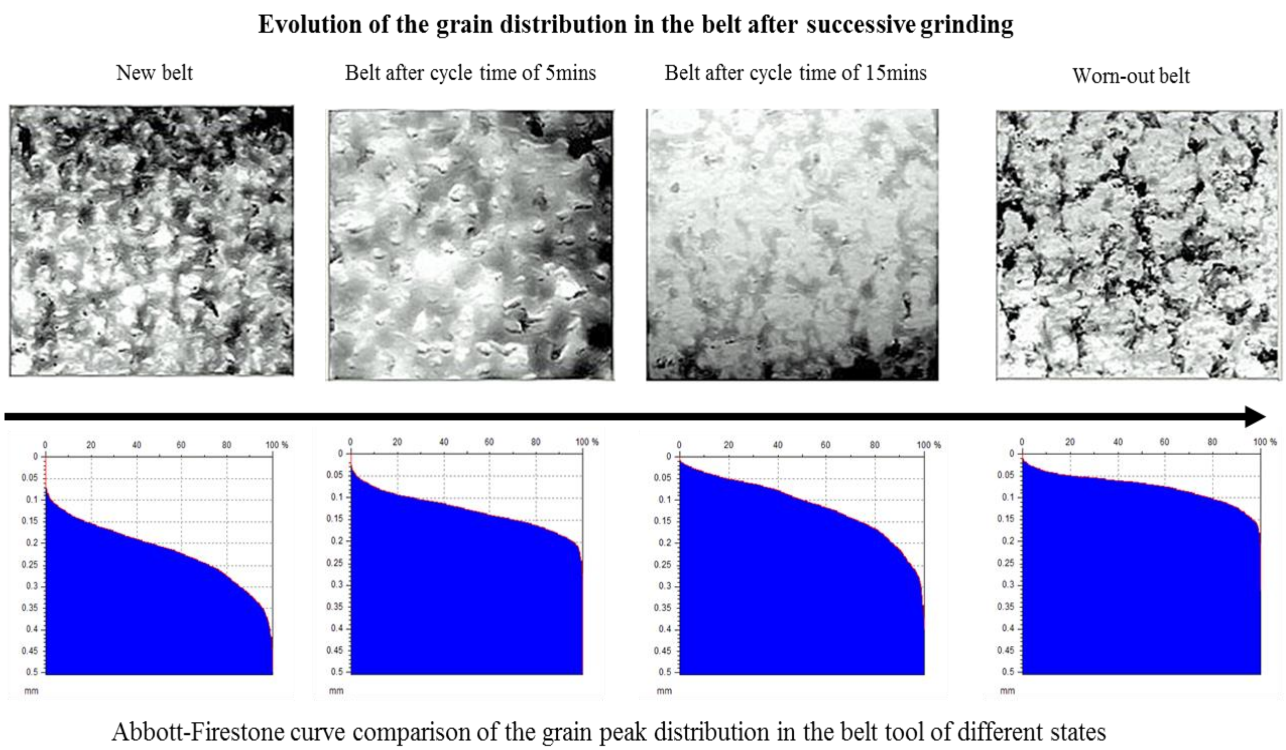

Fig. 6. 3-D laser profile scan of the grain structure evolution and Abbott-Firestone (material ratio curve) comparison of the granularity distribution in the belt tool of different states.

To be consistent in defining the four belt wear states feed rate, grinding speed and force were kept constant as shown in Table 3 with only varying the cycle time during the belt preparation for the experimental trials. The belt states are defined using Abbott- firestone curve which gives a clear idea about the granularity of the abrasives. As shown in Fig. 6, it is evident that the grains become extinct from the backing material relative to the cycle time of a belt tool.

3.2. Experimental setup

An electric belt grinder is customised with fixture design such that it is used as a belt grinding tool as shown in Fig. 7. The electric belt grinder is an electrically-powered abrasive belt tool that runs at 11,000 rpm at unloading condition and can drive belts with dimensions about 8" to 3/4" wide x 18" long. ABB 6660-205-193 type robot was used to perform the experimental trials. A constant contact force of 20N throughout the abrasive belt finishing process in the normal direction (z-axis) was imparted. Force compensation is achieved by using force sensor (ATI force sensor) attached to the end effector of the robotic arm of ABB 6660 robot. ABB Robot Studio executes tool path planning. Toolpath planning has five different zones as shown in Fig. 8. Zone A and Zone B are when the abrasive belt tool arrives at the machining region; point C is the zone where real machining happens in force control mode, point D is the end of grinding process and zone E is where the abrasive belt tool moves away from the grinding region. Table 3 shows the experimental conditions used in this research. Contact wheel of the belt grinder is normally kept to the surface for maintaining uniform material removal, and mild steel workpiece of same roughness is used throughout machining trials. Experiments are carried out in dry condition.

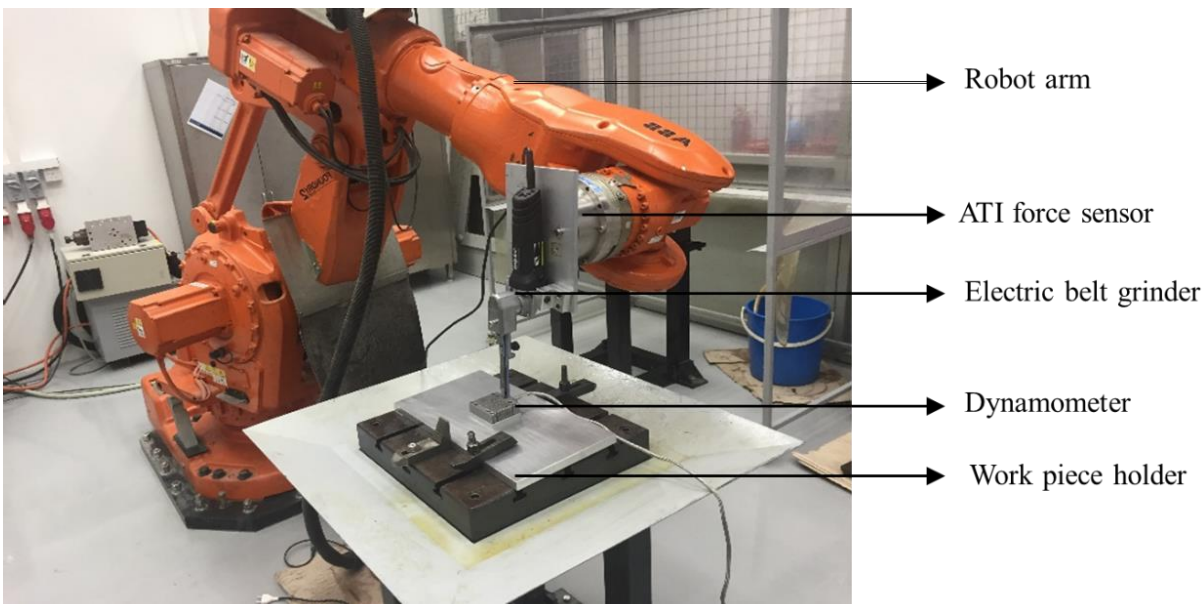

Fig. 7. Experimental setup for compliant abrasive belt machining.

Table 3. Experimental condition.

Parameters	Values
Abrasive belt	Aluminium oxide-60 grit size
Grinding method	Constant force of 20N using ABB robot studio
Grinding speed	11,000 RPM, 50 mm/sec
Workpiece	Mild steel (size 135 mm X 90 mm X 20 mm)
Contact wheel	Diameter:16 mm, Rubber: Hardness 80 Shore A

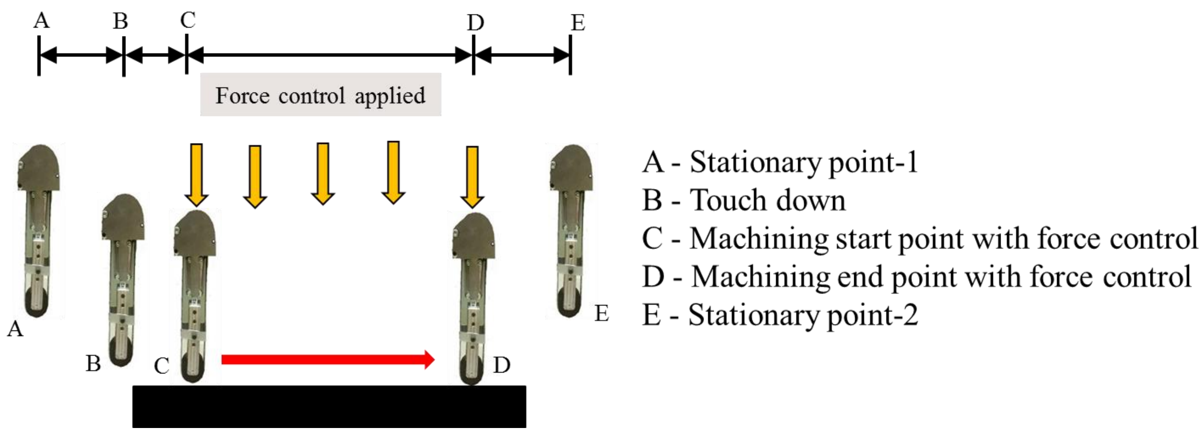

Fig. 8. Toolpath planning in force control mode by ABB Robot Studio.

3.3. Relation between the belt wear and material removal rate

Extraction of the 2D profile from the Taly-scan profilometer across the tool path in mild steel workpiece after machining with different four tool states and same machining condition gives information about how the material removal rate varies with tool wear condition. Fig. 9 shows that new belt that has higher grain density and sharp peaks has a higher material removal rate compared to the belts that have experienced gradual wear. This trend of material removal emphasises the importance of the belt tool condition monitoring

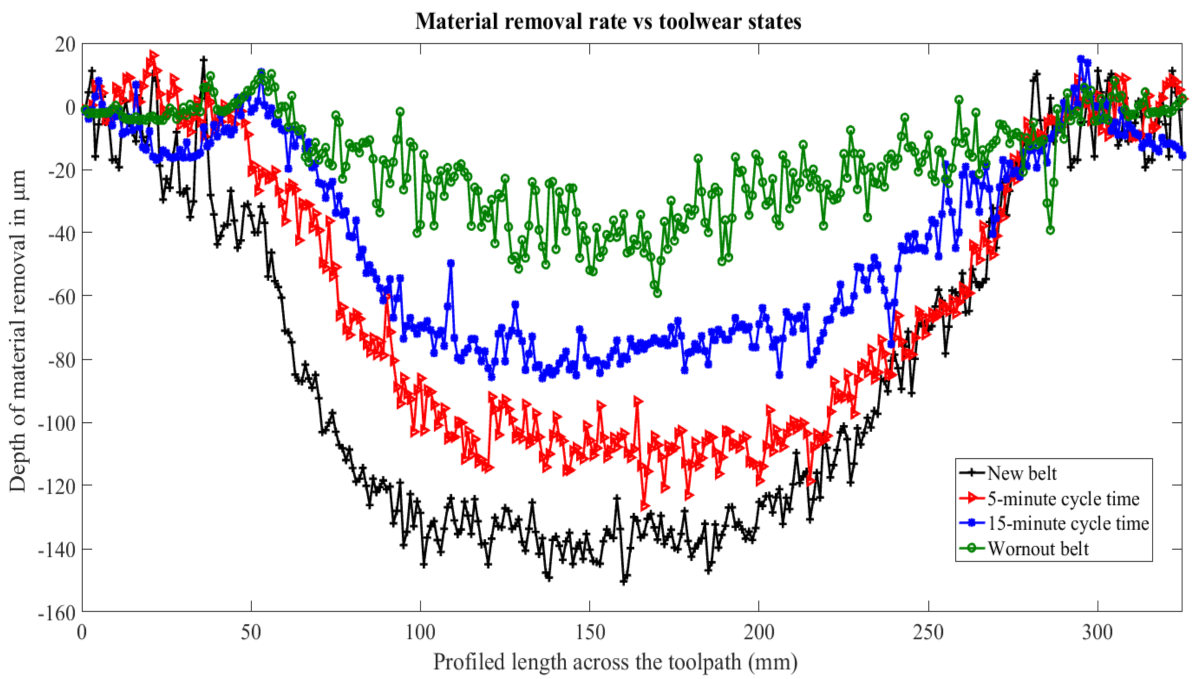

Fig. 9. Comparison between material removal using belt grinder for different belt tool states of grit size 60.

3.4. Relation between the belt wear and surface roughness

Analysing the surface roughness across the machined path in mild steel workpiece after machining with different four tool states and same machining condition gives information about how the surface roughness varies with tool wear condition. Comparison on surface roughness (R_a) generated when machined with belts having a different cycle time is given by Fig. 10. Fig. 10 shows that surface roughness (R_a) of workpieces various considerably on the gradual wear of the belt. This trend of surface quality highlights the importance of the belt tool condition monitoring. In the manufacturing industry that replacement of the belt is still based on operator experience developing. Predicting the tool condition in coated abrasive compliant belt machining process in real time by virtual verification adds value for the whole manufacturing process.

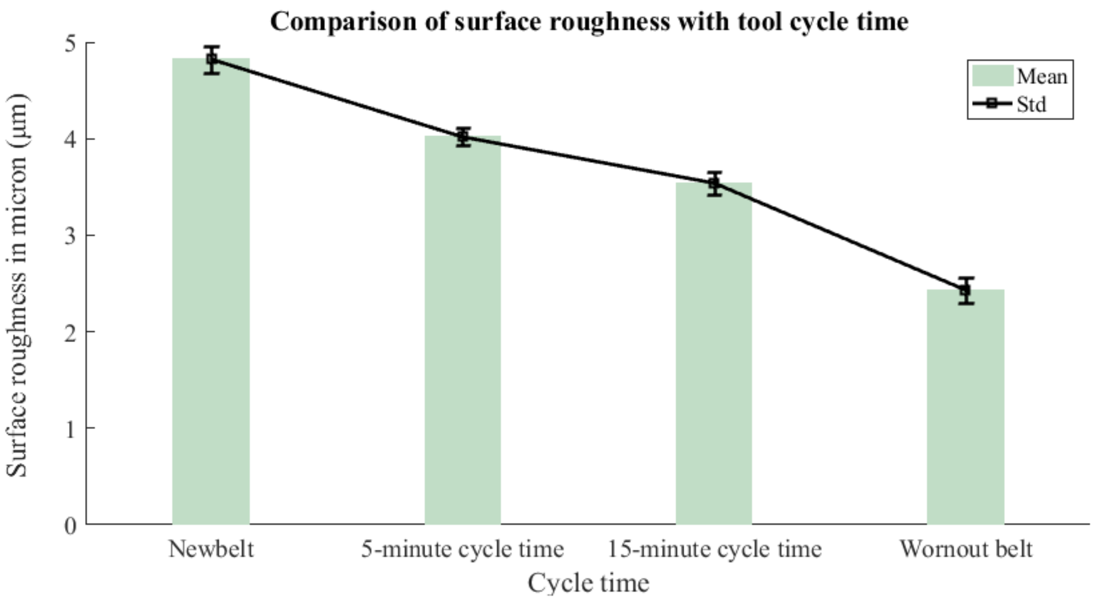

Fig. 10. Comparison between surface roughness (Ra) generated along the grinded path from 8 locations on the mild steel coupon during machining with each belt tool state of grit size 60.

4. Belt tool condition monitoring

4.1. Methodology

Mild steel with a planar surface of the same initial roughness of 2 µm is machined with the abrasive belt of four different tool wear states as mentioned in Table 2 with the same machining condition as stated in Table 3. The signatures during machining with four tool wear states are captured using the appropriate sensors placed. The raw sensor data comprises fixed-width sliding windows (10% of data acquisition rate readings/window). From each window, a vector of 27 independent features from time domain and frequency domain are extracted at 2 kHz in force sensor, accelerometer sensor and 1Mhz in the acoustic sensor as shown in Table 4. Redundant data and insignificant features are eliminated by using GA based on kNN classifier. On optimisation, a new feature subset is introduced into supervised learning classification algorithm based on quadratic–SVM with the four different tool condition states as the classifiers in MATLAB classification learner toolbox. As a supervised method, SVM takes advantage of prior knowledge of tool wear states and constructs a hyperplane as the decision surface so that the periphery of the separation between different tool state is extended. Once the model is trained with 70% of training subset data, the remaining 30% testing subset features are extracted from four different tool condition states with the same machining condition and are assumed to come from real time environment. These subset features are passed into the classification model developed and trained using SVM to check the robustness of the model. Schematic flow of the methodology is described in Fig. 11. In this work, the quadratic kernel function is used for mapping data onto a high-dimensional feature space where the linear classification can be derived from the non-linear.

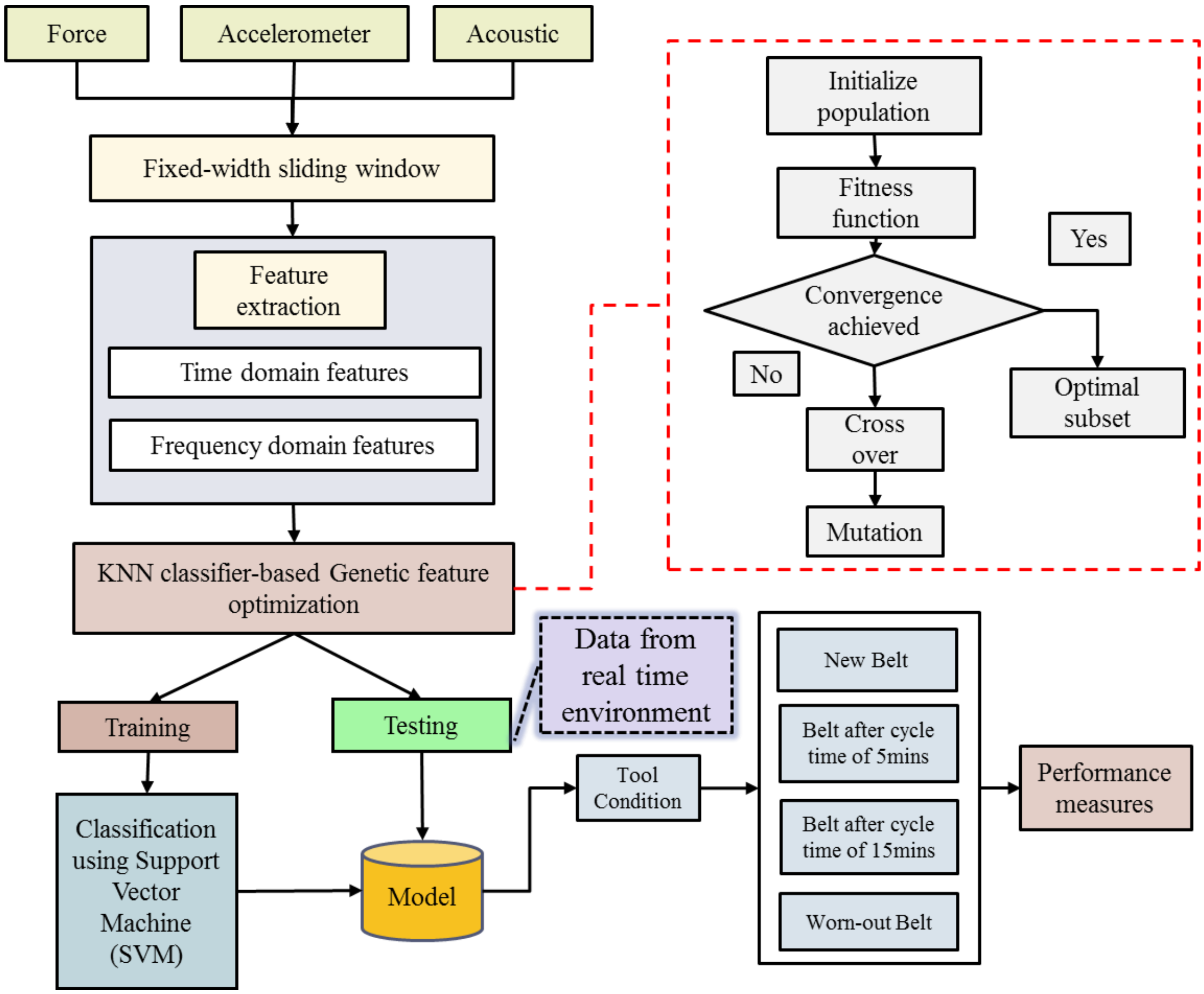

Fig. 11. Methodology flow to predict tool wear state using SVM and GA.

Table 4. Time and frequency domain features extracted from the sensor signatures for tool condition monitoring.

Feature No	Feature name
1	Mean value
2	Root Mean Square (RMS)
3-5	Autocorrelation (Height of the main peak, height and position of the second peak)
6	Kurtosis
7	Skewness
8	Crest factor
9	Band-power
10	Standard deviation
11-22	Spectral peak features (Height and position of first six peaks)
23-27	Spectral power (Features in 5 adjacent and pre-defined frequency bands)

4.2. Complementary based multi-sensor integration system

The use of multiple sensors is specifically necessary for applications where the prerequisite is that the system intermingles with and operates in a dynamic environment [44]. In-process sensors can be exercised strategically for machining process automation and have the ability to predict the process state based on sensory feedback. The way by which various sensors are incorporated into the operation of the system is usually a major factor in the overall design of an intelligent system [45]. Correlation between the cutting force, acceleration and AE signatures on the material removal and surface roughness phenomenon can be used to predict tool wear states. Spontaneously released transient elastic energy from elastic or plastic shear stress due to material removal or material deformation occurring at high frequencies can be captured using AE sensor. Surface quality is intensely related to cutting force which is one of the crucial characteristic parameters to monitor during grinding processes using force sensor. Dynamic contact behaviour between tool and material in the abrasive processes can be quantified using the accelerometer. Correlation between tool vibration based on contact conditions can be used to verify the state of the tool during grinding. AE, force and accelerometer sensors show greater sensitivity at ultra-precision machining regime which is a typical characteristic of any abrasive machining process [46, 47].

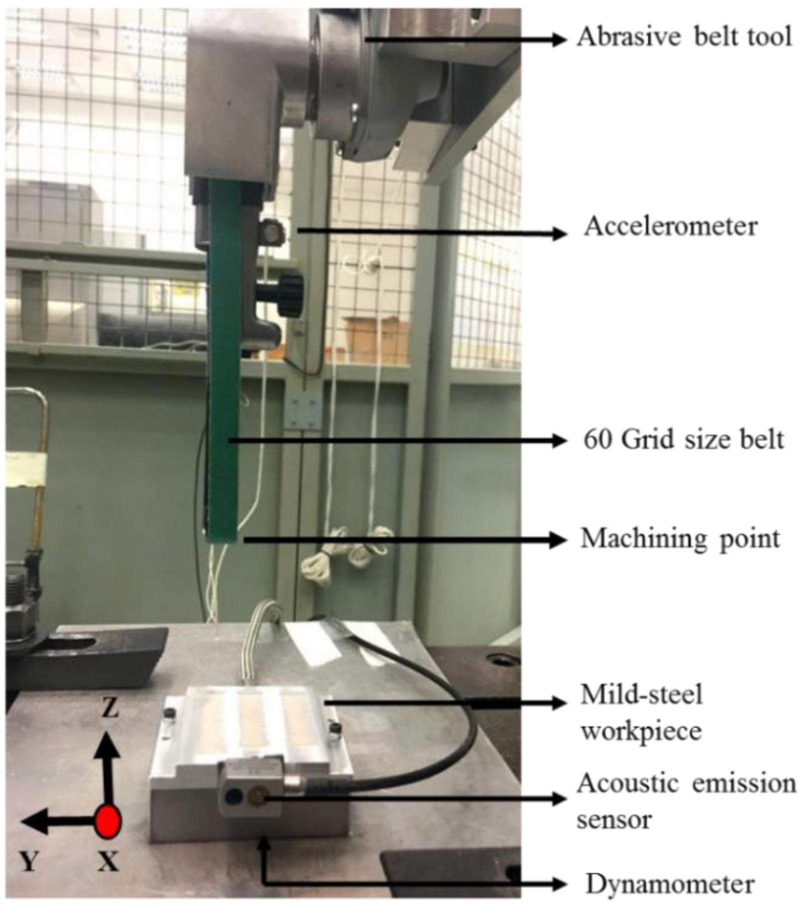

Fig. 12. Integrated sensor system for belt tool condition monitoring.

Complimentary multi-sensor integration system incorporating force, accelerometer and AE has been proposed as a strategy to estimate the values of physical variables being measured to give a complete picture of the tool condition state of abrasive belt grinding process which is difficult to understand. Kistler 8763A500 triaxial accelerometer sensor is placed near the tension arm of the electric belt grinder to obtain data on tool vibration during machining. Accelerometer, force and AE sensor signatures on contact of the belt grinder with the work coupon are shown in Fig. 13, Fig. 14 and Fig. 15.

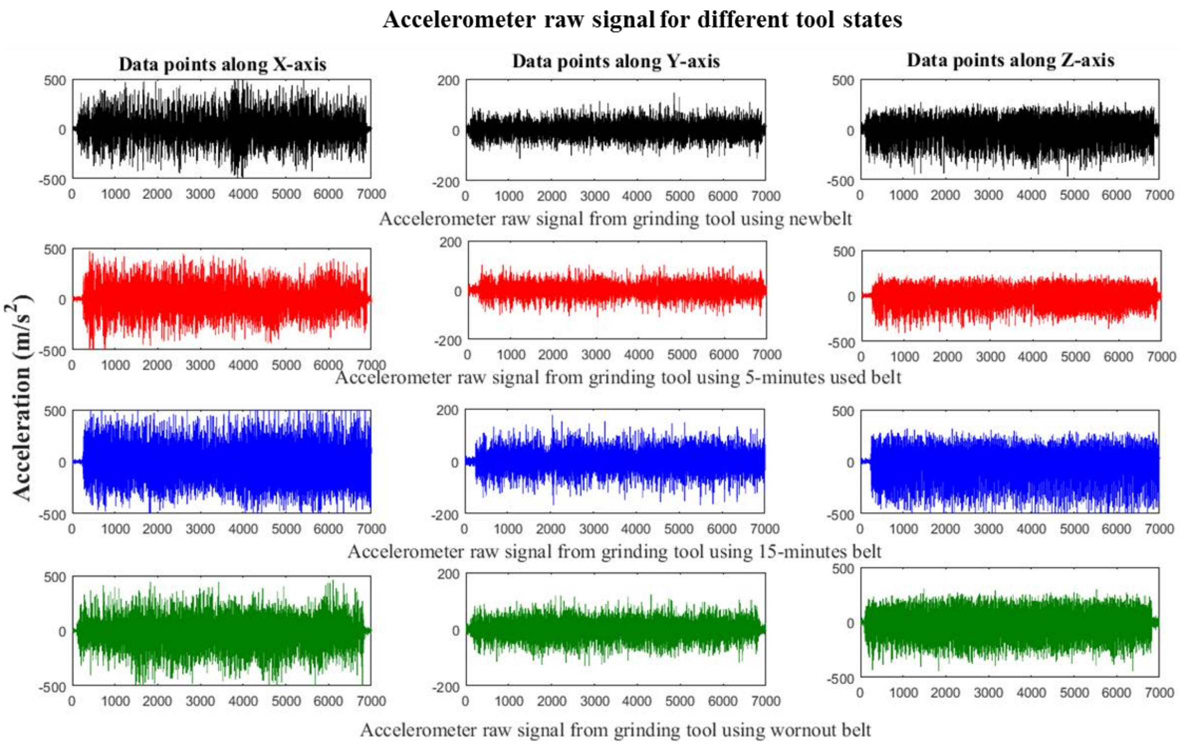

Fig. 13. Accelerometer raw signal from grinding tool for different tool states.

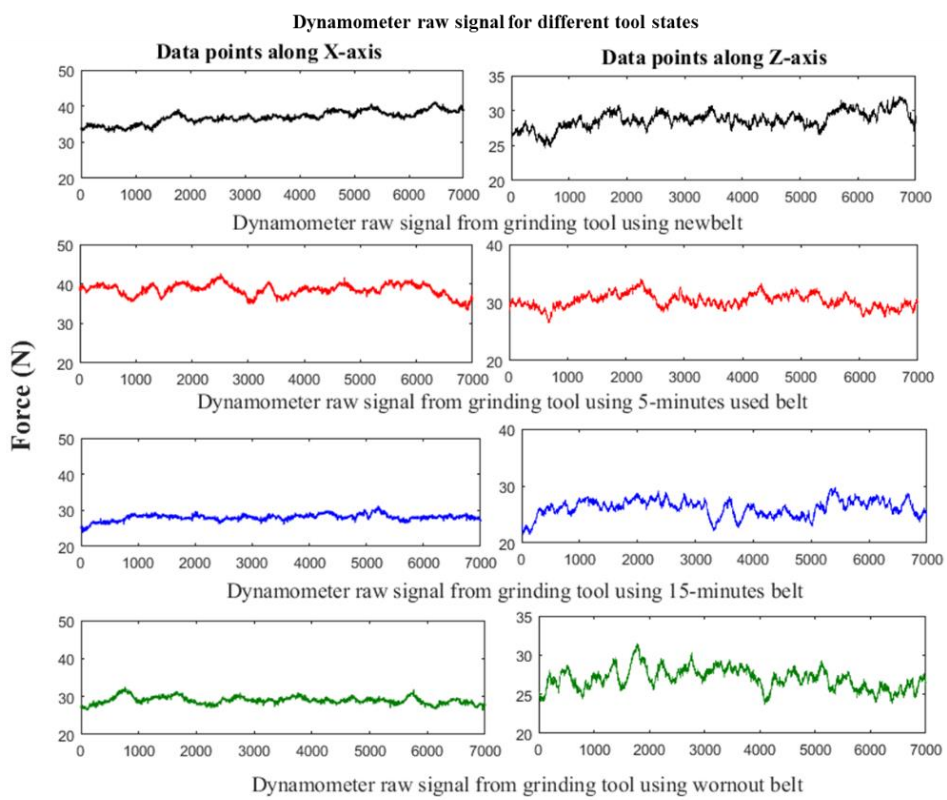

Fig. 14. Dynamometer raw signal for different tool states during belt grinding process.

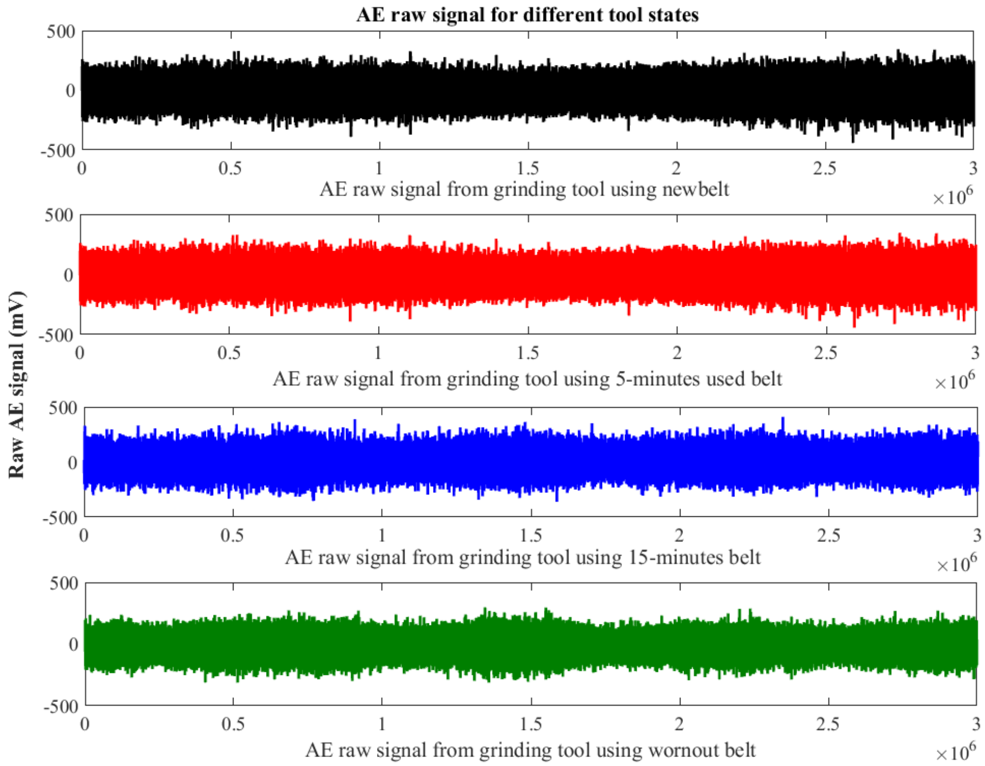

Fig. 15. AE raw signal for different tool states during belt grinding process.

The accelerometer has been put on the tool in such a way that it does not interrupt the belt transmission. AE sensor is located nearby to the machining zone in the mild steel workpiece with good acoustic coupling facing the machining direction. Fig. 12 shows overall setup and sensor placement. LabVIEW environment is used to acquire the signal from AE and accelerometer whereas, in the case of the dynamometer, Data Acquisition (DAQ) device supported by DEWESoft platform is used to acquire and post-process normal and tangential force signals. An in-situ tool condition monitoring system based on LabVIEW platform has been developed consisting of a Kistler 9254 three component dynamometer on which the mild steel workpiece is mounted, Kistler 8763A500 triaxial accelerometer and Kistler Piezotron® AE sensor.

5. Result and analysis

5.1. Feature extraction

Experiments are carried out with four tool wear conditions and data from all the three sensors is recorded. The sensor signatures from the dynamometer suggest that forces along x (along with the direction of the tool path) and z (normal to the workpiece) axis show significance compared to force along the y-axis (which is perpendicular to the pass). In the case of the accelerometer, all the signatures from three axes showed significance. However, the noise component in accelerometer mounted on to the running tool is eliminated using Butterworth-bandstop filter. Once the required preprocessing of the signal is done, features are extracted from the force, acceleration, and AE sensor. The use of sensitive features is a major factor in condition monitoring and prognosis [48]. Tax et al. The time domain features such as RMS, peak value, kurtosis, and crest factor can be used to detect damage in the rolling bearing [49]. The absolute deviation was used to measure the statistical dispersion to analyse changes in the signal during the cutting time and compared the changes with the tool wear [50]. Features such as mean value, the coefficient of variation and skewness of AE signals were used to classify coated tool into three classes with realistic accuracy [51]. A high-frequency resonance technique obtained the spectrum of the envelope signal for diagnosing bearing fault detection [52]. AE-based condition monitoring has some advantages over vibration-based condition monitoring and is more sensitive in tracking the progression of any defect [53].

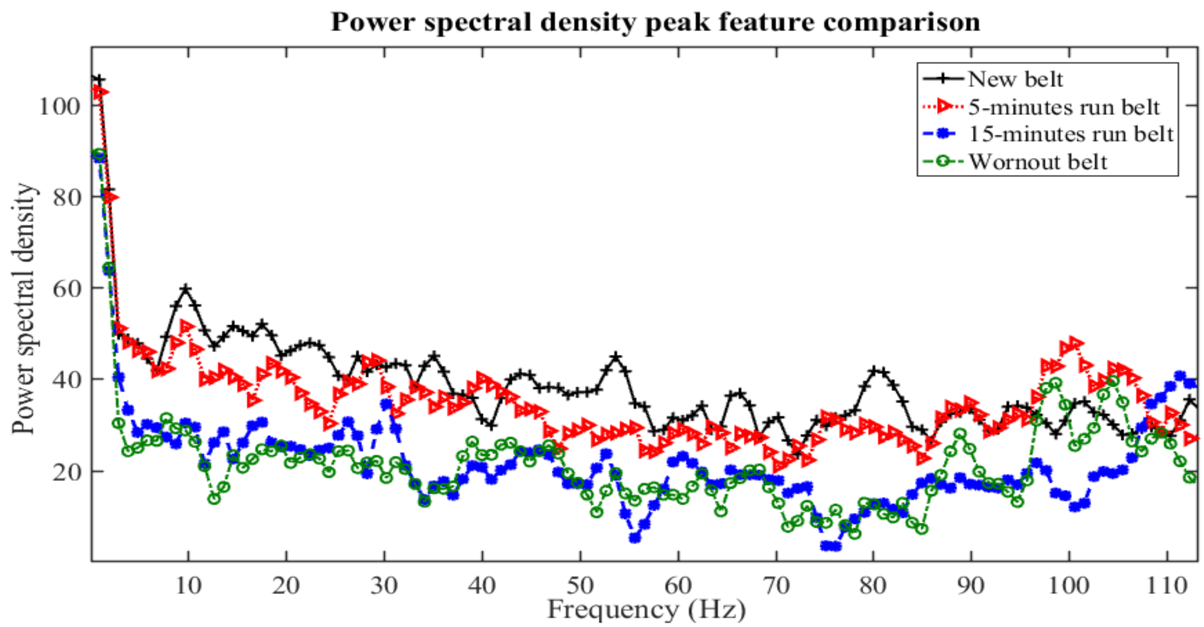

Fig. 16. Comparison between spectral peak features for different tool states from force sensor in the x-direction.

Power spectral density comparison plot of the force sensor in Fig. 16 demonstrates the variation in height and position of the first six highest peaks during machining with an abrasive belt of different tool wear states. Auto-correlation comparison plot of accelerometer signature in Fig. 17 shows features such as the height of main peak as well as height and position of the second peak are distinct during machining with belt tools of different usage time. Fig. 18 demonstrates the variation between power spectral features at different frequency bands for various tool wear states from AE sensor.

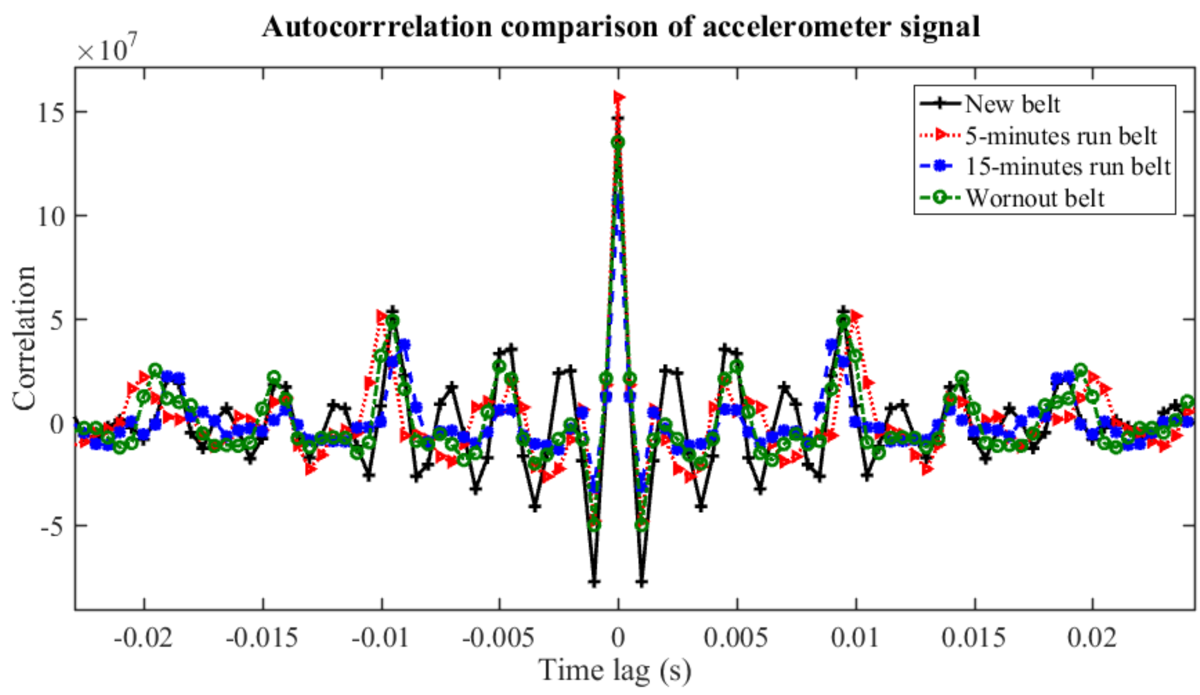

Fig. 17. Comparison between auto-correlation features for various tool states from accelerometer sensor in the z-direction.

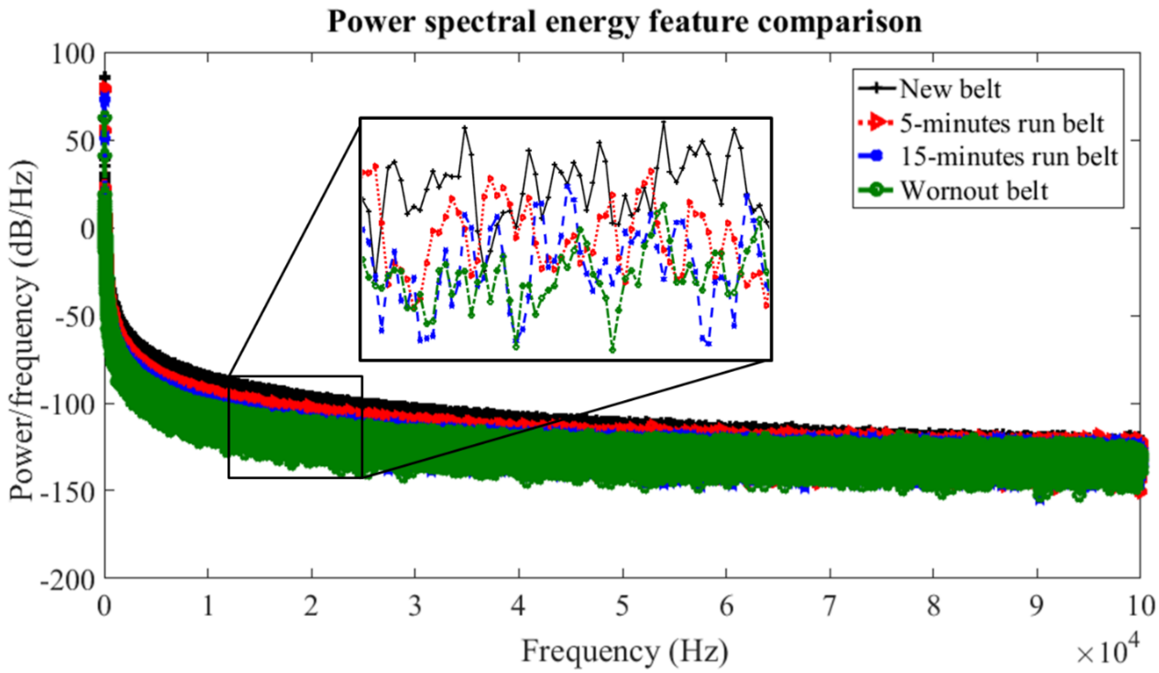

Fig. 18. Comparison between power spectral energy features at different frequency bands for various tool wear states from AE sensor.

These distinct features from sensor data are exploited to predict tool condition states in this research. Distinct time domain and frequency domain features can be used to classify between four different tool cycle life in real time when such features are captured and identified. Welch's based spectral density extraction approach is used throughout this research work to extract information from a signal such position and value of peak frequencies. Periodogram is also utilised in this work for computing distribution of the energy features of the signal over the predefined frequency band. The choice of signal features is usually based on a priori knowledge of the nature of the signals to be classified. A total of 27 individual features from time domain and frequency as discussed in Table 4 from each sensor channel is used for predicting belt tool condition monitoring. Data are extracted from 6 channel comprising an AE sensor, 3-axes of accelerometer and 2-axes of dynamometer which accounts for higher feature space of 162 features (27 features per channel).

5.2. Genetic Algorithm (GA)-feature subset selection

Classification accuracy of the recognition system reduces and time required for learning a classification function increases when the features space is higher as some of the features may be redundant and non-informative [54]. Feature selection is used to detect a powerfully predictive subset of fields and is primarily a multi-objective problem with two main objectives of minimising both classification error and the number of features. Feature subset selection is to pick a subset of the original features to be used for the subsequent process, thus reducing the number of features used in classification without conceding on accuracy.Table 5 indicates the chromosome design, fitness function, and system architecture configuration of the GA-based feature selection implemented using the MATLAB in this research. Classification accuracy, the number of identified features, and the feature cost are the three decisive factor used to create a fitness function. The fitness function gives numerical values which are used in ranking the given chromosomes in the population. Consequently, for the chromosome with superior classification accuracy, a small number of features, and low total feature cost fitness value will be higher. The kNN based fitness function is used in GA to minimise classification error and reduce the number of features. The best fitness and mean fitness should be close in value as the GA reaches the termination condition which is also evidenced by the GA simulation diagrams as shown in Fig. 19. The best and mean fitness value, using the kNN classification error for feature set were 0.00206801 and 0.00207715. The kNN algorithm resolves classification problem by taking into account the hamming distance in the feature space thereby lowering the features from 162 to 26 as illustrated in Fig. 20.

Table 5. Parameters used in GA simulation.

GA parameter	Value
Creation function	Creation uniform
Fitness function	kNN-based classification error
Number of generations	100
Crossover arithmetic	Arithmetic crossover
Crossover probability	0.8
Mutation probability	0.1
Elite count	15
Mutation	Mutation adapt feasible

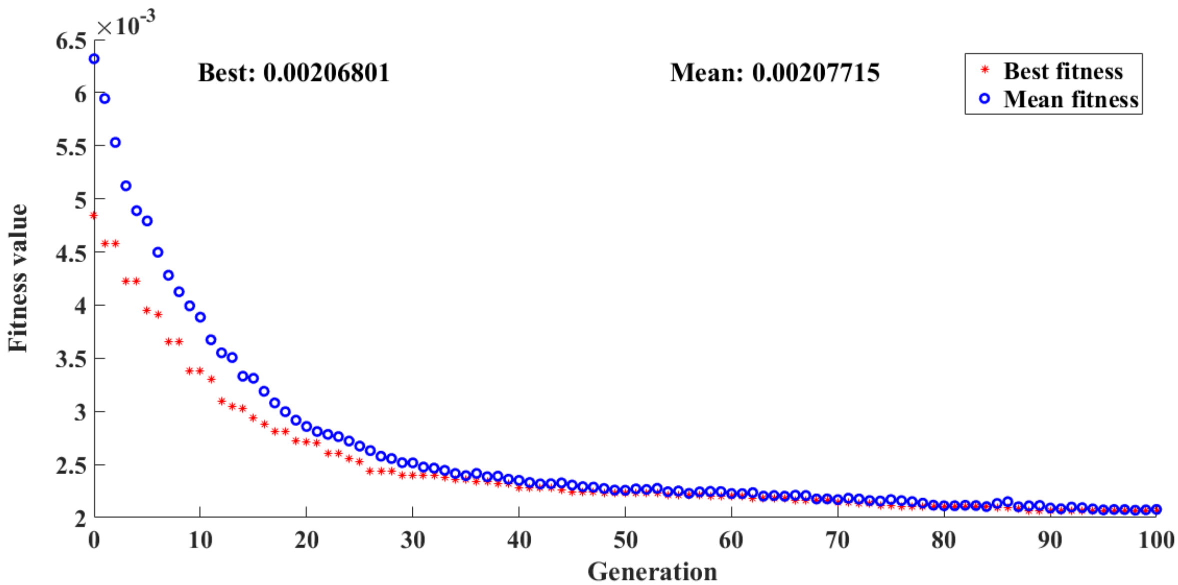

Fig. 19. Proximity between best and mean fitness in GA simulation diagram.

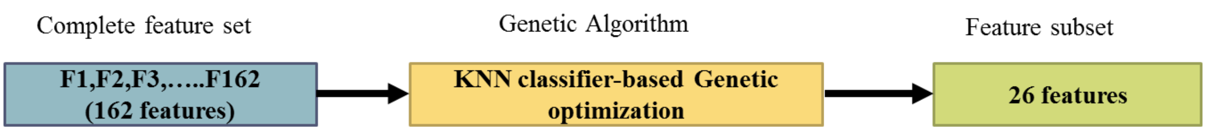

Fig. 20. Feature subset selection.

Though kNN classifier-based GA was used to reduce the feature space in this research other suitable feature reduction techniques can also be applied to get different possible feature set and it is to be noted that best feature set for one classifier may not be best for a different classifier [55]. Fig. 21 reveals that the correlation between band power and skewness features varies depending on the tool wear states, i.e., the topography of the abrasive belt. Such interpretation of the feature space hints us with the possibility of classifying the tool wear states and predict the condition of the belt in real-time.

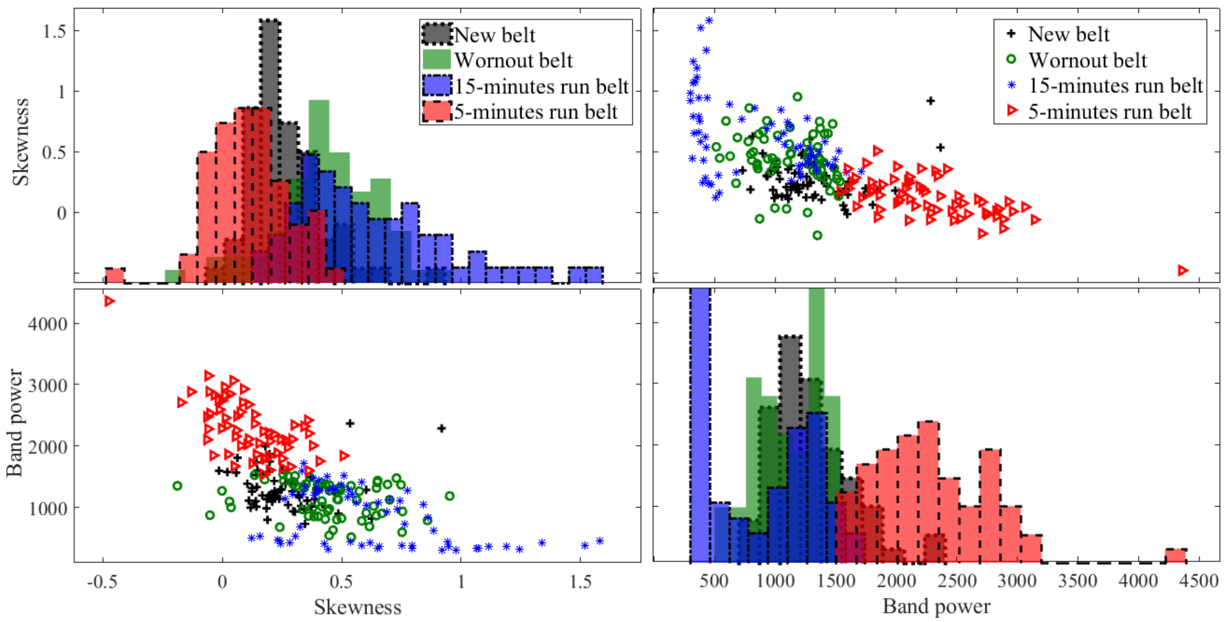

Fig. 21. Relationship and distribution between skewness and band power feature acquired for four different tool-wear states.

5.3. SVM-tool states classification

The performance-testing experiment is designed to test the predictive ability of classification models with a new subset of 26 features obtained from GA-based kNN classifier under same machining conditions. Classification of the tool wear states by the classifiers consists of two main parts: training data and testing data. Hence, among data sets 70% data is selected stochastically for the training and 30% for testing the developed models. Five predictive models using k-NN, Naive Bayes, SVM, Artificial neural network and Bagged Trees were developed and compared. The performance of the five algorithms considered depends primarily on their respective parameter configuration. The set of training parameters for each classifier used in this research are discussed in Table 6.

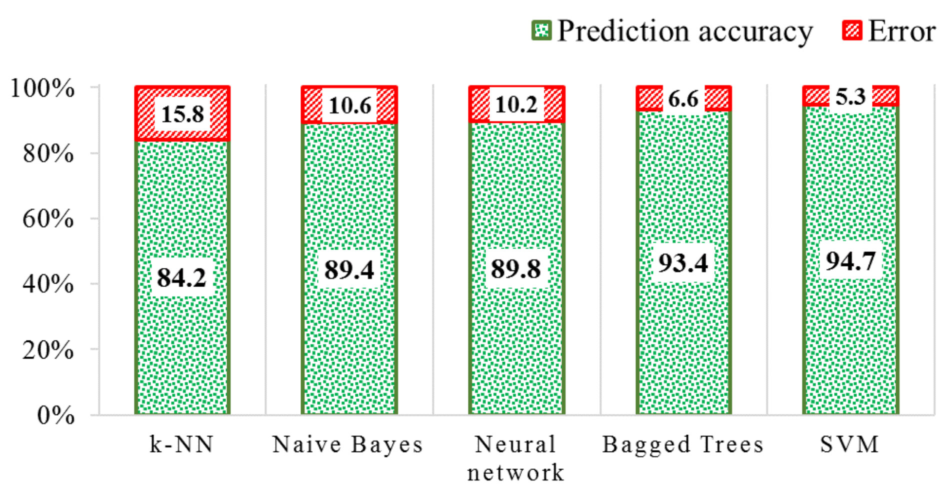

Fig. 22. Prediction accuracy of individual classifiers.

Table 6. Training parameters of the classifiers for predicting tool wear states.

Classifier Type	Parameters	Values
SVM	Validation method	Hold-out validation
	SVM kernel function	Quadratic
	Kernel scale	Automatic
	Features	26 Subset features
	Multiclass method	One-vs-One
	Standardize data	True
	Prediction speed	~3200 observations/sec
	Training time	0.568 secs
kNN	Classifier	Cosine KNN
	Number of neighbours	10
	Distance metric	Cosine
	Distance weight	Equal
	Prediction speed	~8200 obs/sec
	Training time	0.2232 secs
ANN	Number of neurons	30
	Output layer	4
	Training method	Backpropagation
	Performance	Cross-entropy
	Epoch	25 iterations
	Training time	0.3699 secs
Naive Bayes	Distribution Names	Normal (Gaussian) distribution
	Predictors	Categorical
	Class probability	0.250
	Training time	0.4017 secs
Bagged Trees	Classifier	Complex Tree
	Maximum number of splits	100
	Split criterion	Gini's diversity
	Surrogate decision splits	Off
	Prediction speed	~7100 obs/sec
	Training time	0.83391 secs

The training parameters of the classifiers chosen were based on empirical rules and their performance was evaluated based on prediction accuracy. It is to be noted that the training parameters of the classifiers can be further optimised based on training time and prediction accuracy which will be a part of our future work. We observed quadratic kernel-based SVM having prediction accuracy higher than the other classifiers with the set of parameters considered as shown in the Fig. 22. Fig. 23 shows 4-by-4 confusion matrices obtained with the quadratic-SVM model.

The quadratic SVM kernel function maps data onto a high-dimensional feature space where the linear classification is derived from the nonlinear with different abrasive belt tool condition as classifiers. The accuracy of prediction of quadratic-SVM was 94.7% with errors occurring due to misclassification between the 15-minute used belt and wornout belt. As can be seen, there is a clear separation between different abrasive belt tool condition classifiers and the fraction of samples misclassified of the developed SVM model is small as shown in the Fig. 24.

True class	New belt	5-minutes used belt	15-minutes used belt	Wornout belt
New belt	100%			
5-minutes used belt		100%		
15-minutes used belt			94%	14%
Wornout belt			6%	86%
Positive predicted value	100%	100%	94%	86%
False discovery rate			6%	14%

Predicted class

Fig. 23. Confusion matrix of the quadratic-SVM classifier model with a prediction accuracy of 94.7%.

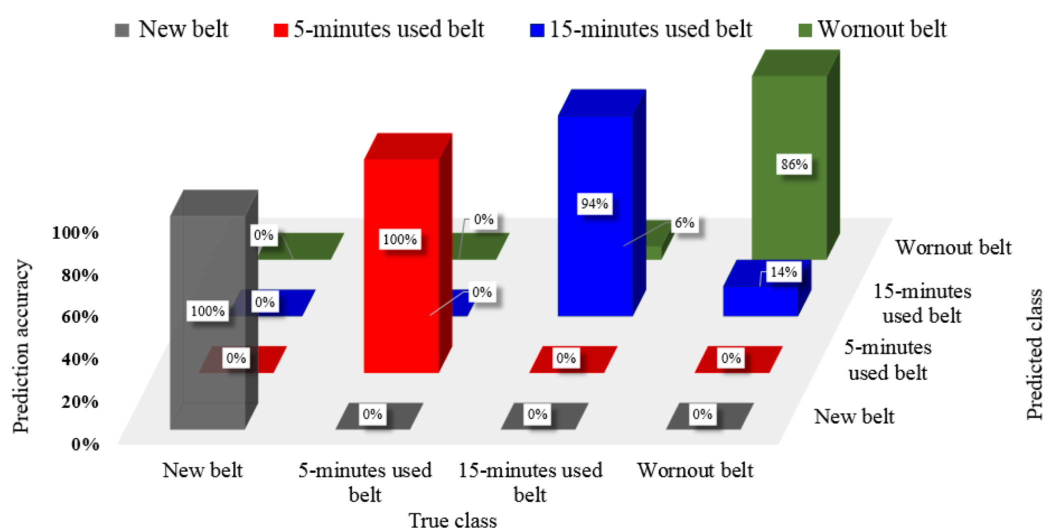

Fig. 24. Classification and misclassification of the developed SVM model.

6. Conclusion

A methodology is developed out of this work for condition monitoring and predicting tool wear in compliant tools as most of the research work previously were on hard cutting tools with defined cutting edges and rigid grinding tools. Principally, the key aim of the proposed research is to determine whether a belt tool is underutilised or overused and is due for replacement. Four different belt tool state condition is prepared, and experimental trials are carried out using a customised belt grinding tool mounted on ABB 6660 robot.

- Firstly, the evolution of the belt tool with process time is visually analysed and found that grains wither considerably from the backing material with process time which alters the material removal rate and surface accuracy.
- A parallel multi-sensor integration system comprising of force, accelerometer and the acoustic sensor whose signals carry the best information about the state of the belt wear has been developed and investigated in this work for belt tool condition monitoring.
- Two main kinds of waveform data analysis such as time-domain and frequency domain are used to extract features that can correlate with tool wear condition.
- Genetic Algorithm based on kNN classifier is used to reduce feature space from 162 features to 26 features.
- Finally, quadratic-SVM classifiers are utilised to perform the multi-classification of belt tool conditions with the prediction accuracy of 94.7%.

The current study demonstrated a methodology which could effectively monitor belt tool state and reduce the irregularities during finishing operations and has potential practical application in industry. However, we have presumed that the material of the workpiece and grinding parameters are fixed, which is not normally true and varies between industries. Therefore, further work will include more grinding input factors and optimised feature space with classifier combination, to formulate this system more robust for subsequent realisation.

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