Classification Of PEC Detect Using Hybrid Technique

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Abstract--- **In aircraft fuselage, multilayer structures are used mostly and detect the defect in this structure by using eddy current testing. Compared to conventional eddy current pulse excitation eddy current is most important. These methods are used for flaw detection and defect characteristics. Lift off effect and interlayer air gaps are main thing in eddy current defect characteristics. In this work proposed a hybrid approach to predict or reduce this defect using genetic algorithm with Library support vector machine. In this work three phases are implemented that are feature extraction, normalization and classification. In feature extraction dimensionally reduction are done by using Independent component analysis and classification are handled by hybrid approach of Genetic algorithm with Library Support Vector Machine (GA-LIBSVM). From the result observed that the proposed method proves the better accuracy of 96.66 compared to existing method of SVM as 90.32. The proposed framework used the data from GMR data theory.**

I. INTRODUCTION

Data mining is a recently emerging field, connecting the three worlds of Databases, Artificial Intelligence and Statistics. The information age has enabled many organizations to gather large volumes of data. However, the usefulness of this data is negligible if "meaningful information" or "knowledge" cannot be extracted from it. Data mining, otherwise known as knowledge discovery, attempts to answer this need. In contrast to standard statistical methods, data mining techniques search for interesting information without demanding a priori hypotheses. As a field, it has introduced new concepts and algorithms such as association rule learning. It has also applied known machine-learning algorithms such as inductive-rule learning (e.g., by decision trees) to the setting where very large databases are involved. Data mining techniques are used in business and research and are becoming more and more popular with time.

Eddy currents are generated when time varying magnetic fields are applied to conducting materials satisfying Faraday's law [1]. These currents flow in such a way that secondary magnetic fields are produced to oppose the applied (primary) magnetic field satisfying Lenz's law [1]. Pulsed eddy currents (PEC) have favorable advantages over conventional eddy currents (CEC). They are a result to the sum of a continuum of odd number harmonics of the fundamental sinusoidal waveform frequency of the pulse [3, 4]. Therefore, a transient response obtained from the pulsed eddy current system contains many frequencies. Because of the skin effect [5, 6], the depth to which eddy currents penetrate the tested specimen depends on the frequency of applied field in CEC. However, skin effect depends on the duty cycle period of the probing pulse in PEC [5]. Therefore using PEC allows the inspection of various specimen depths with just one pulse as opposed to the multiple frequency scans required for CEC.

Pulsed eddy current (PEC) testing employs pulses as excitation so that the greater amount of frequencies in a response is able to reflect richer information at many depths [7]. Based on analysis of the response waveform in the time domain, the lift-off intersection point where the transient signal is insensitive to variations in the lift-off height can be selected to suppress lift-off effects [8, 9], but the lift-off intersection point greatly relies on the probe's structure and specimen's conductivity, which may weaken the probe's generality. More effects will be implemented on post processing. With the goal of decreasing the lift-off effect, time frequency domain analysis [10] was also proposed to separate the lift-off effect from influence caused by metal loss and interlayer gap variations.

II. RELATED WORK

In eddy current applications, the distance between the pick-up coil and the specimen is referred to as lift-off. Variations in this parameter tend to affect the time delay to the peak of the received signal in the reference subtracted signal [11]. A crossing point for varying steps of lift-off with all other parameters kept constant was first observed by Waidelich and Haung [12]

Giguere et al [13] and Lefebvre et al [14] have reported on the successful use of the crossing point phenomenon in eliminating lift-off effects in PEC evaluation of conducting specimen. They were able to extract the thickness of a material independent of lift-off by time gating the signals around the time of the lift-off point of intersection. Safizadeh et al [15] however observed that the crossing point actually varied and they considered other aspects of the signal to separate effects due to lift-off and thickness.

III. METHODOLOGY

In propose system current pulse eddy current defect classification is very much useful for aircraft. The two main properties of pulse eddy current are lift – off effect and interlayer air gaps. In proposed work, Independent component analysis (ICA) and hybrid method of Genetic algorithm with Library SVM (LibSVM) are investigated for defect automated classification under different interlayer gaps and lift-off effects.
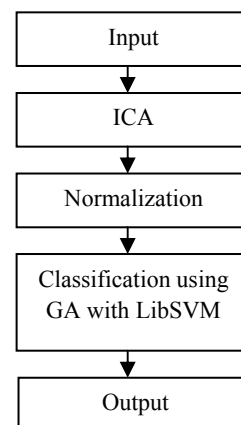

Figure 1: Block Diagram for Proposed System

Data's are collected from the GMR dataset. Then the data's are dimensionally reduced using Independent Component Analysis (ICA) method then it is normalized and given into classification using hybrid method of Genetic algorithm (GA) with Library Support Vector Method (LibSVM).

A. Independent component analysis

Several ICA algorithms have been proposed so far, which are different in objective functions (or contrast functions) for statistical independence and how to derive ICA algorithms [16, 17 and 18].

Algorithm for Independent Component Analysis
Pseudo-code for estimating the independent components S of the original data X, and for decomposing X in terms of the estimated components $\hat{S}$.

Step 1: $X_0 = X - \hat{X}$

Step 2: $\sum_{k \times k} = V\Lambda V^T$

Step 3: $R_{K \times K} = \sqrt{\Lambda^{-1}} V^T$

Step 4: $Y_0 = RX_0, \text{cov}(Y_0) = I_k$

Step 5: Apply the ICA code to estimate the p independent components $\hat{S}_{p \times n}$ and the corresponding mixing matrix $\hat{B}_{k \times p}$ such that $\hat{Y}_0 = \hat{B}\hat{S}$

Step 6: $\hat{X}_0 = R^{-1}\hat{Y}_0 = R^{-1}\hat{B}\hat{S}$

Step 7: $\hat{X} = \hat{X}_0 + \hat{X} = R^{-1}\hat{B}\hat{S} + \hat{X} = \hat{A}\hat{S} + \hat{X}$ where $\hat{A}_{k \times n} = R^{-1}\hat{B}$

In general, estimated independent components obtained by using these algorithms are different each other. However, it is difficult to discuss which algorithms are most appropriate for feature extraction of characters in the present circumstances. Hence, in the followings, we shall adopt Fast ICA algorithm proposed by Hyvarinen and Oja [19] from its convergence speed.

Suppose that we observe a m-dimensional zero mean input signal at time t, $v(t) = \{v_1, \ldots, v_m\}'$ where ' means the transposition of matrices and vectors. Then the n-dimensional whitening signal, x (t), is given by the following equation:

$$x(t) = Mv(t) = D^{-1/2}E'v(t) \qquad (1)$$

Where M means a $n \times m(n \leq m)$ whitening matrix that is given by a matrix of eigenvalues, D, and a matrix of eigenvectors, E. Here, assume that v (t) is composed of n statistically independent signals, $s(t) = \{s_1(t), \ldots, s_n(t)\}'$. Then, the following linear transformation from x(t) to s(t) exists:

$$s(t) = Wx(t) \qquad (2)$$

$W = \{w_1, \ldots, w_n\}'$ is often called a separating matrix, and it can be acquired through the training of a two-layer feed forward neural network. This neural network has n outputs denoted as $\hat{s}(t) = \{\hat{s}_1(t), \ldots, \hat{s}_n(t)\}'$ and the ith row vector, $w_i'(i = 1, \ldots, n)$, ofW corresponds to a weight vector from inputs to the ith output $\hat{s}_i$.

The term 'independent' is used here according to the following definition in statistics:

$$p[s_1(t), \ldots, s_n(t)] = \prod_{i=1}^{n} pi[s_i(t)] \qquad (3)$$

Where $p[.]$ is a probability density function. Since the above probability density function is not preliminary unknown, suitable objective functions should be devised such that neural outputs, $\hat{s}_i$ are satisfied with Eq. (3) as much as possible, that

$\tilde{s}(t) \approx s(t)$. Karhunen and Oja have proposed the following objective function [10], J(.), to be maximized in terms of output signals $\hat{S}$:

$$J(\hat{s}) = \sum_{i=1}^{n} \left| E\{s_i^{\sim 4}\} - 3\left[E\{s_i^{\cdot 2}\}\right]^2 \right| \qquad (4)$$

Where E{.} means expectation. As well known, Eq.(4) corresponds to the fourth-order cumulants of $\tilde{s}_i(t)$ called kurtosis. Learning algorithms for a separation matrix, W, are derived from the gradient of Eq. (4). In the followings, we adopt Fast ICA algorithm proposed by Hyvarinen & Oja in which fixed points of the gradient are obtained on-line.

B. Normalization:

Since the quantities of the feature vector may be quite different, a normalization process is required to standardize all the features to the same level. Normalizing the standard deviation and mean of data permits the network to treat each input as equally essential over its range of values. We have used the function 'mapstd' to normalize the inputs and targets so that they will have zero mean and unity standard deviation.

C. Classification using Hybrid Method:

Classification is done by using Genetic algorithm with Library Support Vector Machine.

i. Genetic algorithm:

The genetic algorithm is a well-known meta-heuristic algorithm, following the natural evolution processes. Haupt and Haupt [20] stated that like any other meta-heuristic algorithm, GAs do not guarantee to find the optimal solution.
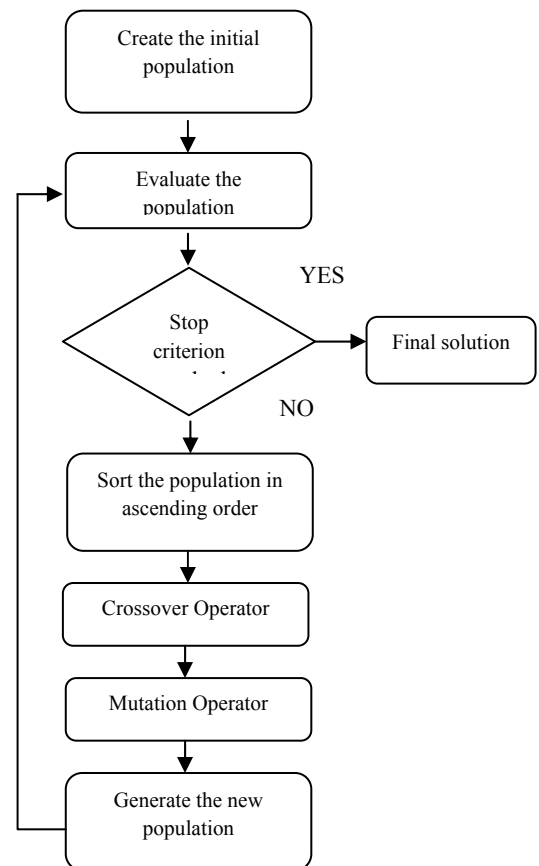

Figure 2: Block Diagram for Genetic Algorithm

The GAs commence by defining optimization variables, objective functions, and control parameters [21]. Usually, GAs receive works on an initial population involving the individual solutions represented by ''chromosomes'', which are strings include all the genes (i.e. variables) involved in a possible solution. The chromosomes are evaluated based on the ''objective function'', which is the desired objective of the problem

In any iteration of the GA, some of the current individuals are replaced with new generated offspring. ''Crossover rate'' is defined as ratio of the number of offspring produced in any iteration to the population size. A pair of individuals from the current population is selected as the parents of a pair of offspring. Highly fitted individuals, relative to the whole population, have a higher chance to be selected as parents in next generation, while less fitted individuals have a correspondingly low probability of being selected [22].
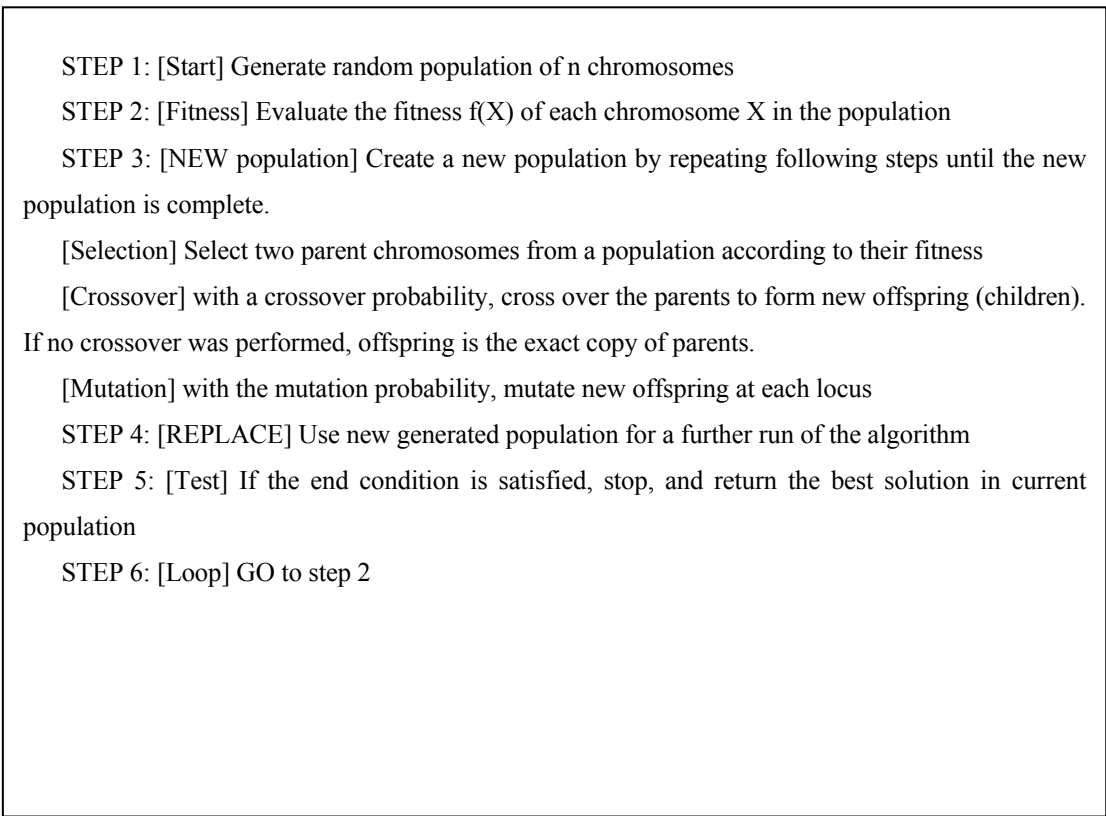
GAs are good at taking larger, potentially huge, search spaces and navigating them looking for optimal combinations of things and solutions which we might not find in a life time. GAs is very different from most of the traditional optimization methods. Genetic algorithms need design space to be converted into genetic space. So, Genetic algorithms work with a coding of variables. The advantage of working with a coding of variable space is that coding discretizes the search space even though the function may be continuous. A more striking difference between GAs and most of the traditional optimization method is that GA uses a population of points at one time in contrast to the single point approach by traditional optimization methods. This means that GA processes a number of designs at the same time

ii. *Library Support Vector Machine (LIBSVM)*

The figure 2 illustrates the flowchart for proposed framework. LIBSVM is a library for Support Vector Machines (SVMs). The goal is to easily apply SVM to their applications. LIBSVM has gained wide popularity in machine learning and many other areas. In this work, we present implementation of LIBSVM. Issues such as solving SVM optimization problems theoretical convergence multiclass classification probability estimates and parameter selection. A typical use of LIBSVM involves two steps: first, training a data set to obtain a model and second, using the model to predict information of a testing data set. For SVC and SVR, LIBSVM can also output probability estimates.

This is same as SVM technique; where in training SVM the m by 1 vector of training labels (type must be double) is taken.
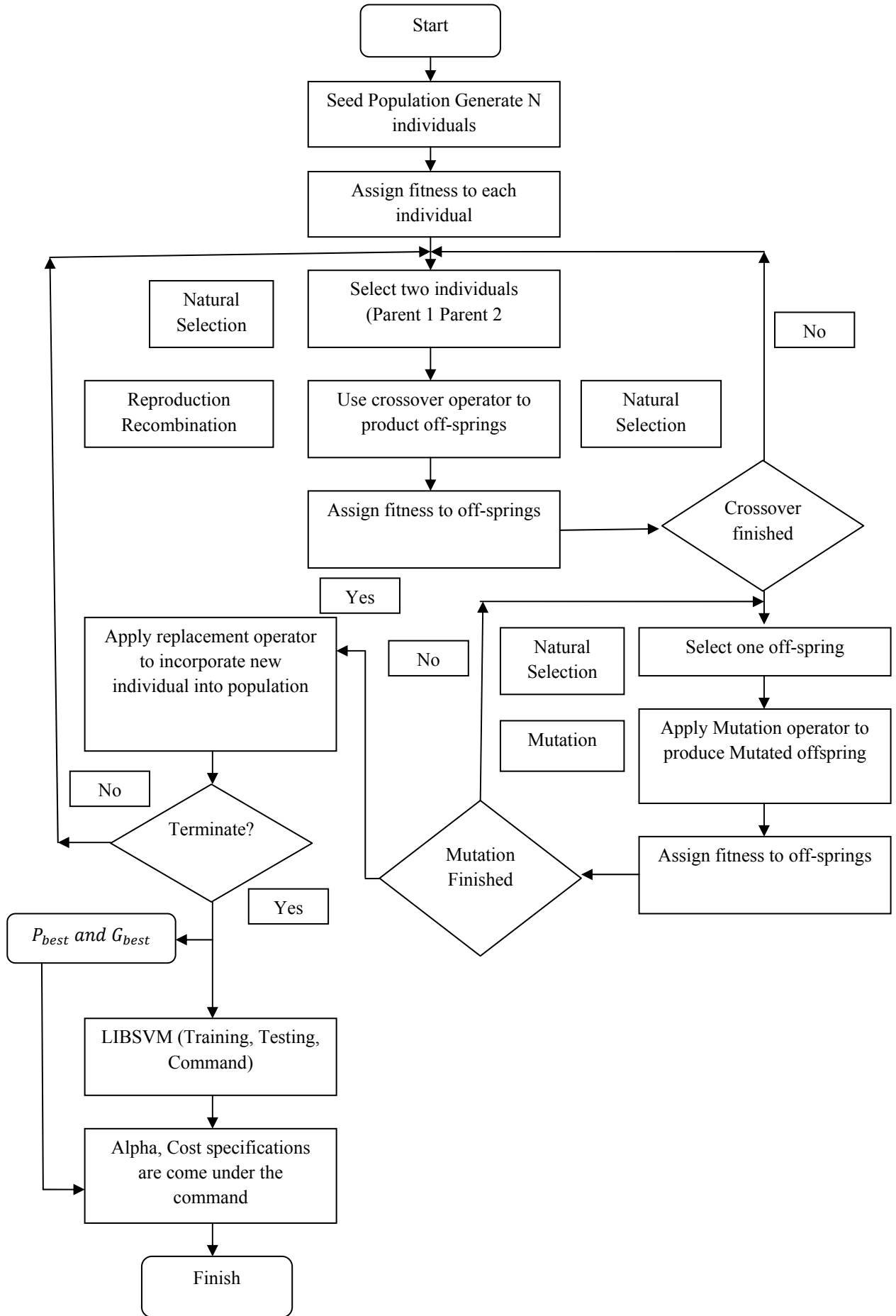

STEP 1: [Start] Generate random population of n chromosomes

STEP 2: [Fitness] Evaluate the fitness f(X) of each chromosome X in the population

STEP 3: [NEW population] Create a new population by repeating following steps until the new population is complete.

[Selection] Select two parent chromosomes from a population according to their fitness

[Crossover] with a crossover probability, cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.

[Mutation] with the mutation probability, mutate new offspring at each locus

STEP 4: [REPLACE] Use new generated population for a further run of the algorithm

STEP 5: [Test] If the end condition is satisfied, stop, and return the best solution in current population

STEP 6: [Loop] GO to step 2

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                          ┌──────────────┐
                          │    Start     │
                          └──────────────┘
                                 │
                    ┌────────────────────────┐
                    │ Seed Population Generate N │
                    │       individuals        │
                    └────────────────────────┘
                                 │
                    ┌────────────────────────┐
                    │  Assign fitness to each  │
                    │       individual         │
                    └────────────────────────┘
```

Start

Seed Population Generate N individuals

Assign fitness to each individual

Natural Selection

Select two individuals (Parent 1 Parent 2

No

Reproduction Recombination

Use crossover operator to product off-springs

Natural Selection

Assign fitness to off-springs

Crossover finished

Yes

Apply replacement operator to incorporate new individual into population

Natural Selection

Select one off-spring

No

Mutation

Apply Mutation operator to produce Mutated offspring

No

Terminate?

Mutation Finished

Assign fitness to off-springs

Yes

P_{best} and G_{best}

LIBSVM (Training, Testing, Command)

Alpha, Cost specifications are come under the command

Finish

Figure 3: Flow Chart for Proposed Work

IV. EXPERIMENTAL RESULT

In this section, the artificial defects in two-layer specimen with various interlayer air gaps and lift-offs are automated classified with the proposed method. The experimental results are evaluated using MATLB. The proposed method of ICA with LIBSVM is compared with the existing method of PCA with SVM.
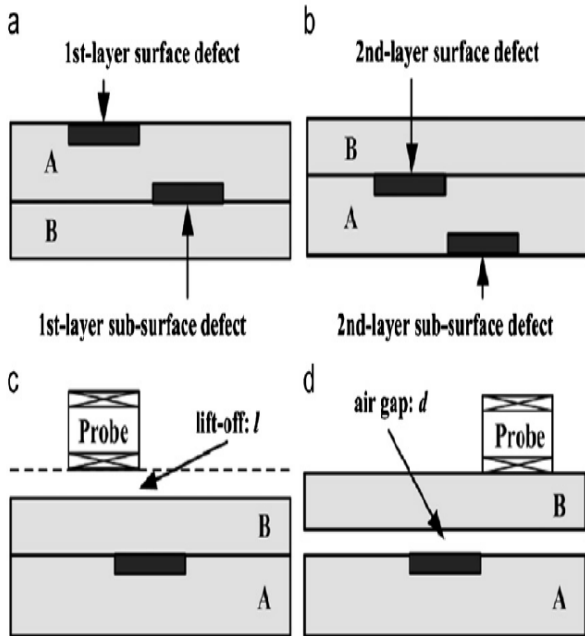
Figure 4: Schematic of two-layer specimen.

The specimen can provide four sets of defects:1st-layer surface defects and1st-layer sub-surface defects shown in Figure 4 (a), 2nd-layer surface defects and 2nd-layer sub-surface defects in Figure 4 (b)., the distance l between the probe and specimen is used to simulate the various lift-offs is shown in figure 4 (c). Distance d between two plates in Figure 4 (d) is used to simulate the inter layer air gaps
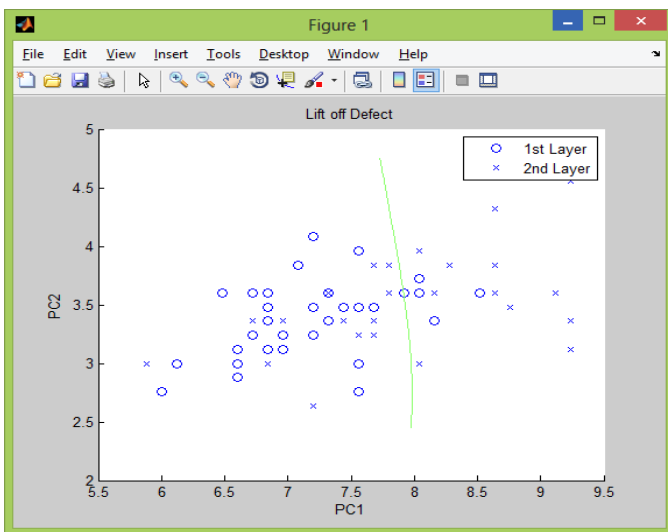
Figure 5: Classification results of 1st-layer surface and 2nd layer for lift-offs
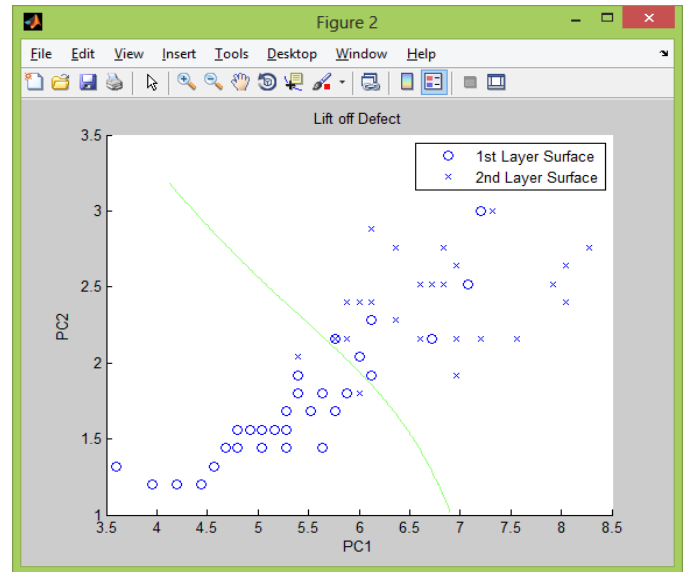
Figure 6: Classification results of 1st-layer surface and 2nd layer surface
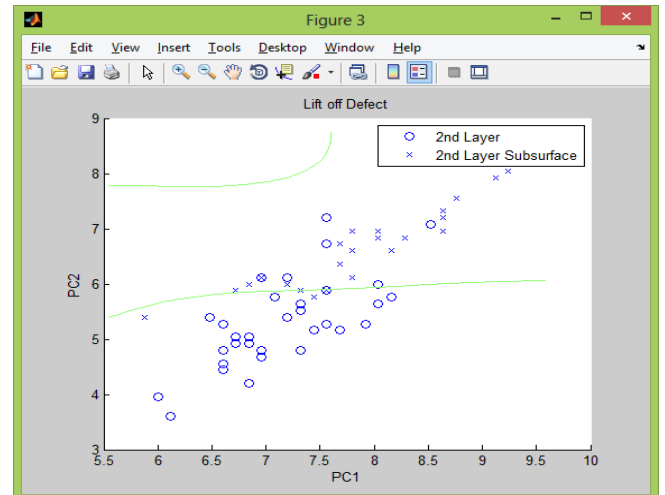
Figure 7: Classification results of 1st-layer and 2nd layer subsurface
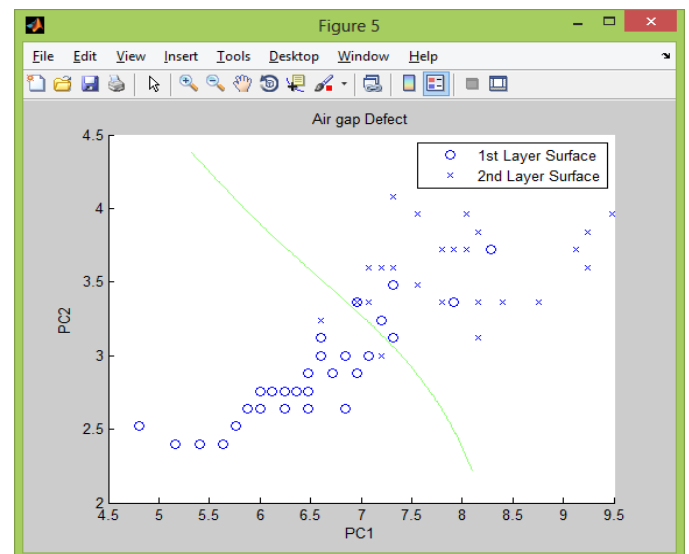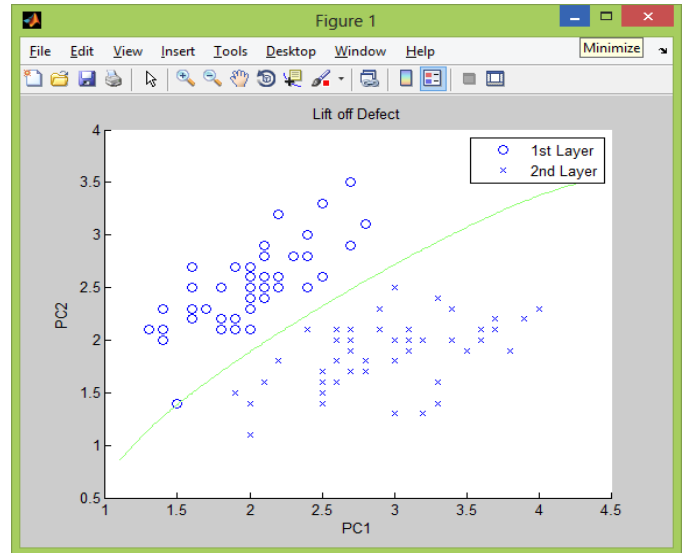

Figure 8: Classification results of 1st-layer and 2nd layer
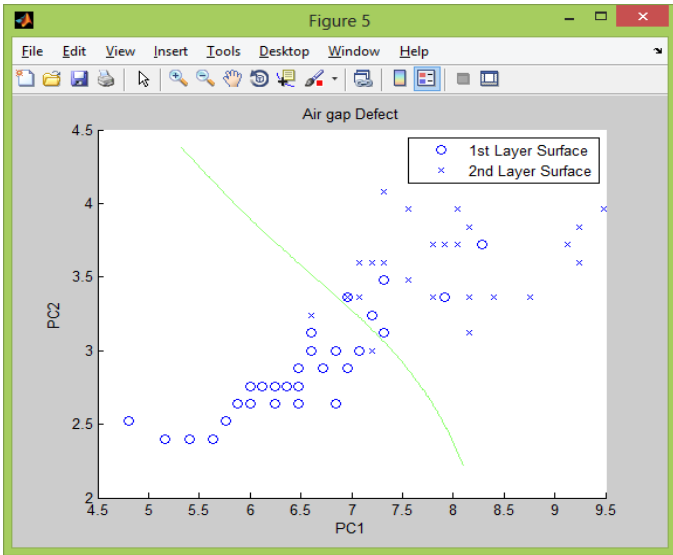
Figure 9: Classification results of 1st-layer and 2nd layer surface
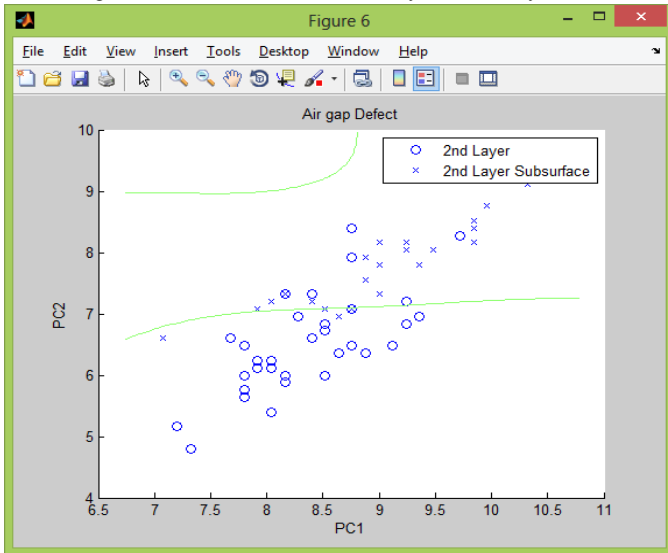
Figure 10: Classification results of 2nd layer and 2nd layer subsurface

The figure 5 illustrates the classification result of 1st layer and 2nd layer for lift-off. The defects in two-layer specimen with various lift-offs and the constant air gap are classified. Figure 6 shows the classification result of 1st layer and 2nd layer surface for lift-off. Figure 7 gives the classification result of 1st layer and 2nd layer subsurface for lift-off defect. The differential time responses DT of all defects are used to generate the new features through the conventional PCA-based method and the first two PCs are used to classify the defects through the SVM-based method. Figure 8 shows the classification results of 1st-layer and 2nd-layer defects. Figure 9 shows the classification results of 1st-layer surface and 2nd-layer surface. Figure 10 illustrates the shows the classification results of 2nd layer surface and 2nd-layer subsurface.

To overcome these and prove better accuracy by proposed system of ICA with LIBSVM.

Figure 11: Classification Results of 1st Layer and 2nd Layer
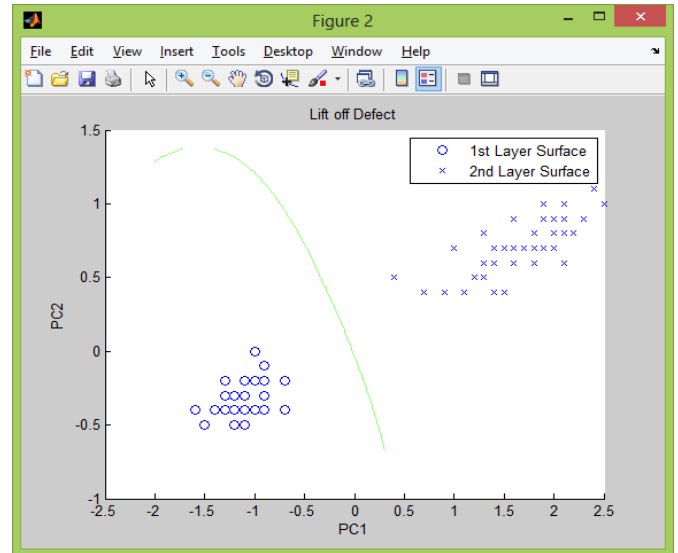

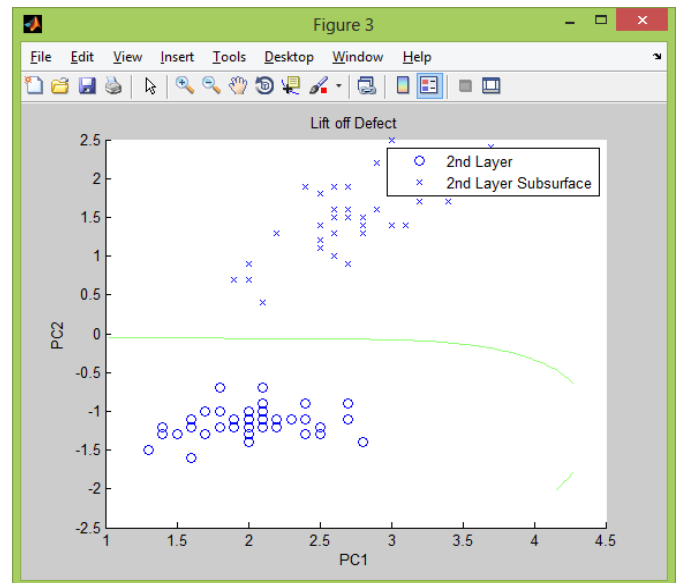Figure 12: Classification results of 1st layer surface and 2nd layer surface

Figure 13: Classification results of 2nd layer surface and 2nd layer subsurface
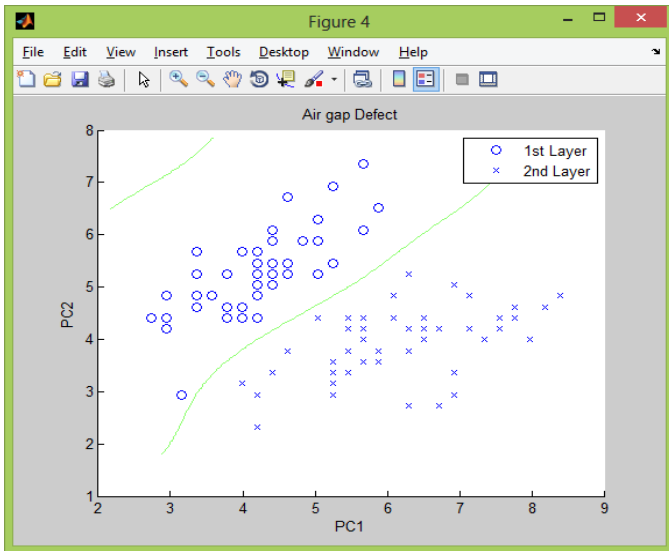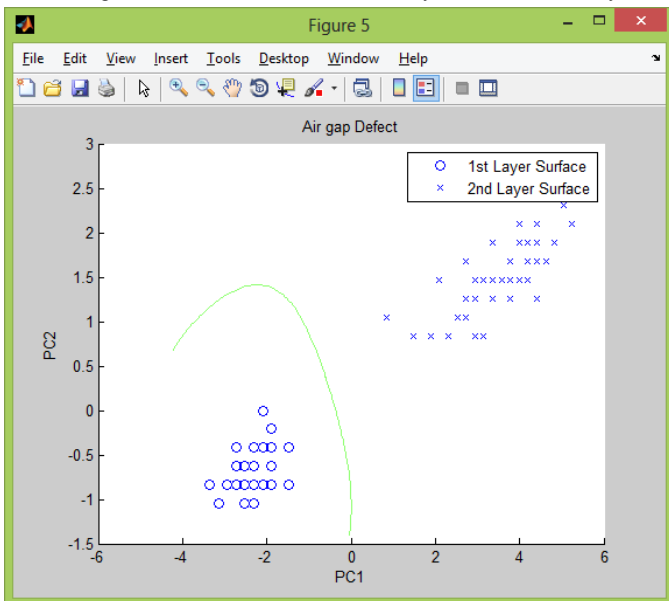
Figure 14: Classification results of 1st layer surface and 2nd layer

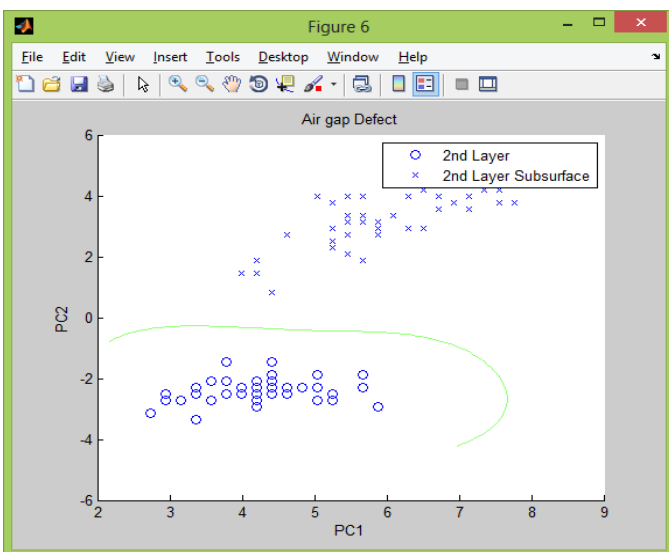Figure 15: Classification results of 1st layer surface and 2nd layer surface

Figure 16: Classification results of 2nd layer surface and 2nd layer subsurface

The figure 11 illustrates the classification results of 1st layer and 2nd layer for defection lift-offs of proposed method of ICA is used for dimensionally reduction and the classification is obtained by using GA-LIBSVM. Figure 12 illustrates the classification results of 1st layer surface and 2nd layer surface for defection lift-offs. Figure 13 illustrates the classification results of 2nd layer surface and 2nd layer surface for defection lift-offs. Figure 14 illustrates the classification results of 1st layer surface and 2nd layer for air gap defection. Figure 15 illustrates the classification results of 1st layer surface and 2nd layer surface for air gap defection. Figure 16 illustrates the classification results of 1st layer surface and 2nd layer subsurface for air gap defection.
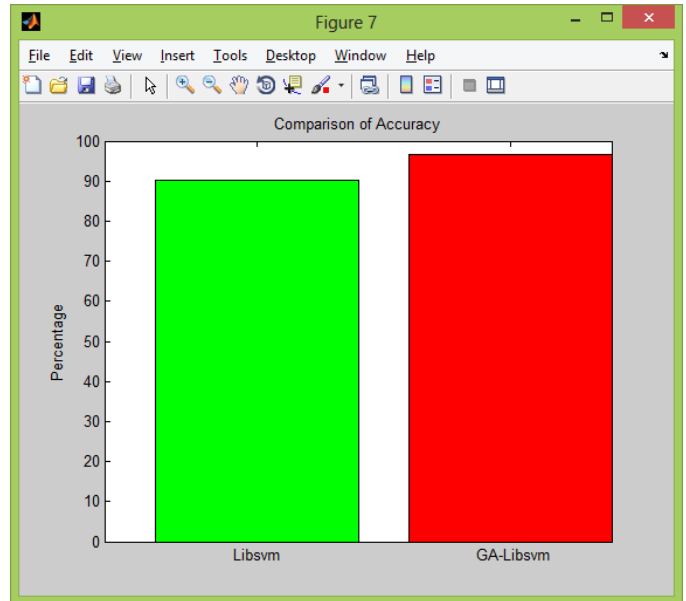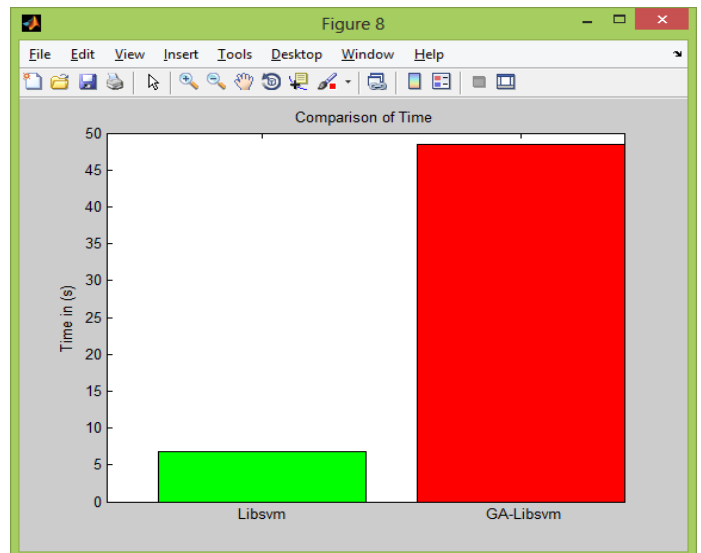

Figure 17: Comparison of Accuracy

Figure 18: Comparison of Time

The figure 17 and 18 illustrates the comparison of accuracy and time between the proposed methods of ICA with GA_LIBSVM. From the figure clearly observes that the proposed method proves the better result than the existing method. That the proposed method gives the accuracy of 96.66% with 984.53s and the existing method provides the accuracy of 90.32% with 6.8s.

TABLE I COMPARISON BETWEEN EXISTING AND PROPOSED SYSTEM

SPECIMEN	EXISTING	PROPOSED	ACCURACY		PARAMETER SPECIFICATION	
The specimen can provide four set of defects: 1st layer surface defects, 1st layer sub surface defects, 2nd layer surface defects and 2nd layer sub-surfaces defects	Existing methods are done by using Principal component Analysis (PCA) with Support Vector Machine (SVM). Defect classification with various air gaps and air liftoffs	Proposed methods are done by using Independent component Analysis (ICA) with Genetic Algorithm library Support Vector Machine (LIBSVM). Defect classification with various air gaps and air liftoffs.	By Comparing both two defects accuracy can be calculated. A measure of a predictive model that reflects the proportionate number of times that the model is correct when applied to data. Accuracy is calculated from the equation $$Accuracy = \frac{TN + TP}{TN + FP + FN + TP}$$		It specifies the algorithm used for proposed and existing for lift off and air gap.	
With liftoff the defects can be classified	The defects in two layer specimens with various liftoffs from 0mm to 1.4 mm and the air gap 0mm are classified	The defects in two layer specimens with various liftoffs from 0mm to 1.4 mm and the air gap 0mm are classified.	Where TN is the number of true negative cases FP is the number of false positive cases			
With air gap the defects can be classified	The interlayer gaps d in two-layer specimen vary from 0mm to 1.4mm and the liftoff l is constant at 0mm.	The interlayer gaps d in two-layer specimen vary from 0mm to 1.4mm and the liftoff l is constant at 0mm.	FN is the number of false negative cases TP is the number of true positive cases			
For liftoff 1) 1st layer 2ND LAYER	The defect in two layer specimen with various lift off and the constant air gap are classified.	The classification results of 1st layer and 2nd layer for defection lift-offs of proposed method of ICA is used for dimensionally reduction and the classification is obtained by using GA-LSVM	Existing	Proposed	Existing	Proposed
			Accuracy is calculated from the above equation for PCA with SVM	Accuracy is calculated from the above equation for ICA with GA-LIBSVM	PCA with SVM	ICA with LIBSVM
2) 2nd layer 2nd layer sub surface	The defect in two layer specimen with various lift-offs and constant air gap are classified. The results are obtained using PCA and	The classification results of 2nd layer and 2nd layer sub surface for detection lift-offs proposed method of ICA is used for dimensionally	Existing	Proposed	Existing	Proposed

SPECIMEN	EXISTING	PROPOSED	ACCURACY		PARAMETER SPECIFICATION	
	SVM. This defect is much better than previous defect	reduction and the classification is obtained by using GA-LIBSVM. The accuracy is much better than the existing method	Accuracy is calculated from the above equation for PCA with SVM	Accuracy is calculated from the above equation for ICA with GA-LIBSVM	PCA with SVM	ICA with LIBSVM
For air gap 1st layer 2nd layer	The differential time responses DT of all defects are used to generate the new features through the conventional PCA based method and the first two PCs are used to classify the defects through the SVM based method	The classification results of 1st layer and 2nd layer for air gap defection of proposed method of ICA is used for dimensionally reduction and the classification is obtained by using GA-LIBSVM. The accuracy is much better than the existing method	Existing	Proposed	Existing	Proposed
			Accuracy is calculated from the above equation for PCA with SVM	Accuracy is calculated from the above equation for ICA with GA-LIBSVM	PCA with SVM	ICA with LIBSVM
2nd layer surface 2nd layer surface	The differential time responses DT of all defects are used to generate the new features through the conventional PCA based method and the first two PCs are used to classify the defects through the SVM based method	The classification results of 1st layer and 2nd layer for air gap defection of proposed method of ICA is used for dimensionally reduction and the classification is obtained by using GA-LIBSVM. The accuracy is much better than the existing method.	Existing	Proposed	Existing	Proposed
			Accuracy is calculated from the above equation for PCA with SVM	Accuracy is calculated from the above equation for ICA with GA-LIBSVM	PCA with SVM	ICA with LIBSVM
Overall maximum values for both Existing and Proposed for Accuracy and Time	The maximum values of defects air gap and liftoff with PCA and LIBSVM are denoted in accuracy and time	The maximum values of defects air gap and liftoff with ICA and GA-LIBSVM are denoted in accuracy and time.	Overall Existing Accuracy	Overall proposed Accuracy	Overall existing time	Overall proposed time
			90	96.6	7	48

Table 1 provides the overall comparison between the existing and proposed system. From the comparison table clearly observed that the proposed system provides the better result.

Table II COMPARISON OF ACCURACY AND TIME FOR EXISTING LIFT OFF

LAYERS	ACCURACY	TIME(s)
1st layer 2nd layer	83.33	4
1st layer surface 2nd layer surface	90	4
2nd layer surface 2nd layer sub surface.	90	3

Table III COMPARISON OF ACCURACY AND TIME FOR EXISTING AIR GAP

Layers	Accuracy	Time
1st layer 2nd layer	90	3
1st layer surface 2nd layer surface	90	4
2nd layer surface 2nd layer sub surface.	93.33	3

Table IV COMPARISON OF ACCURACY AND TIME FOR PROPOSED LIFTOFF

LAYERS	ACCURACY	TIME
1st layer 2nd layer	90	15
1st layer surface 2nd layer surface	93.33	18
2nd layer surface 2nd layer sub surface.	96.66	15

Table V COMPARISON OF ACCURACY AND TIME FOR PROPOSED AIR GAP

LAYERS	ACCURACY	TIME(s)
1st layer 2nd layer	93.33	10
1st layer surface 2nd layer surface	96.66	12
2nd layer surface 2nd layer sub surface.	96.66	12

Table VI COMPARISON OF ACCURACY FOR LIFT OFF BEFORE NORMALIZATION

LAYERS	Existing	Proposed
1st layer 2nd layer	80	83.33
1st layer surface 2nd layer surface	76.66	80
2nd layer surface 2nd layer sub surface.	80	836.66

Table VII COMPARISON OF ACCURACY FOR AIR GAP BEFORE NORMALIZATION

LAYERS	Existing	Proposed
1st layer 2nd layer	73.33	76.66
1st layer surface 2nd layer surface	73.33	80
2nd layer surface 2nd layer sub surface.	76.66	80

Table 1 to 7 provides the comparison table for proposed and existing accuracy and time for lift off and air gap and results obtained before normalization.
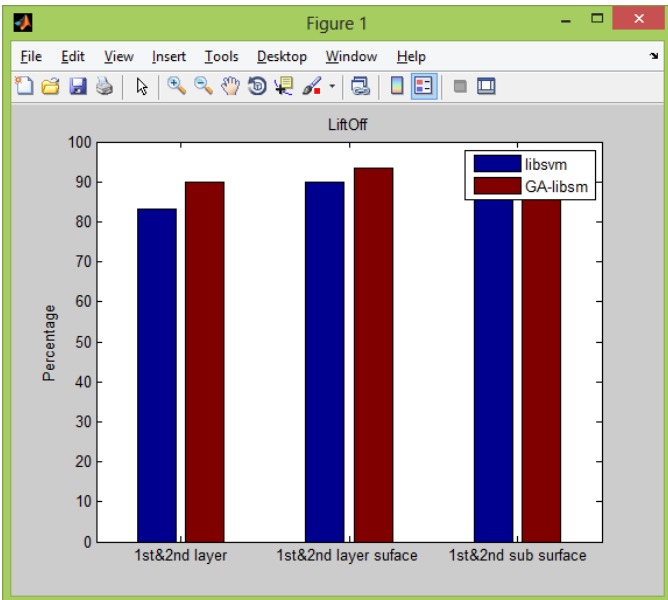
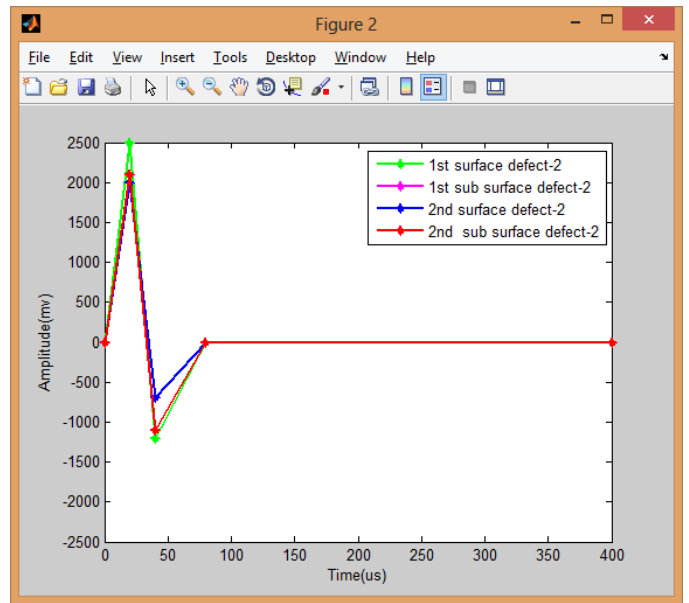Figure 18: Comparison of Accuracy for lift off for all layers.

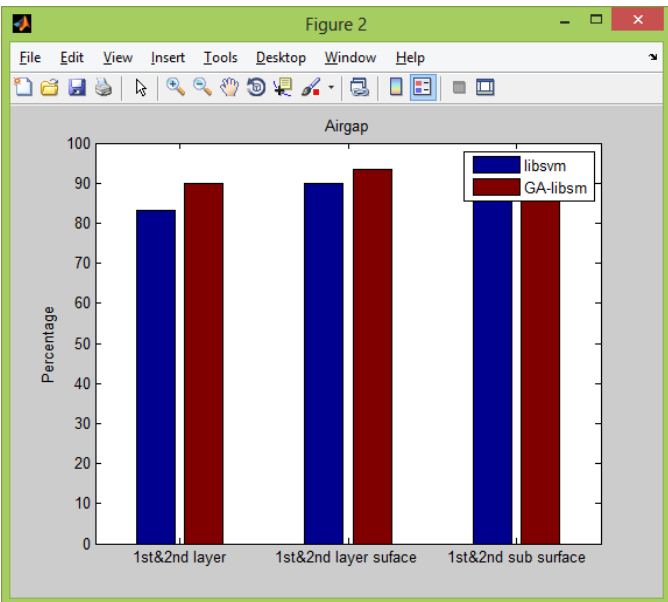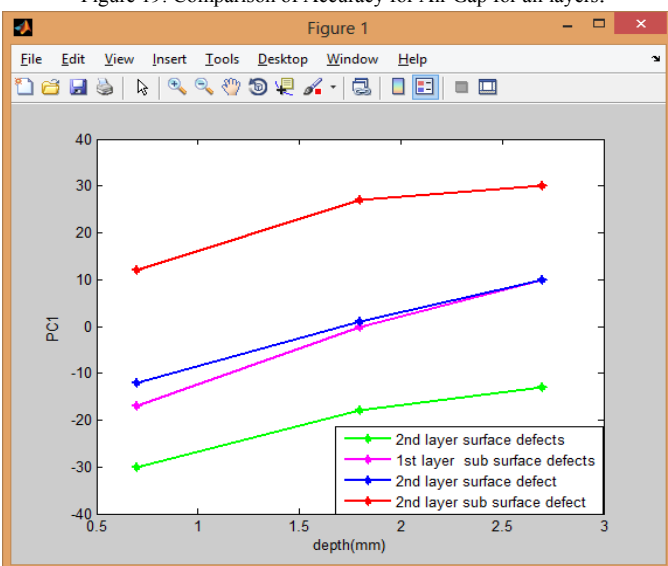Figure 21: Comparison of Amplitude for layers

Figure 18 illustrates the accuracy for lift off of all the layers between LIBSVM and Genetic Algorithm with LIBSVM. From the figure clearly observed that the combination of GA with LIBSVM provides the better result. Figure 19 illustrates the accuracy for Air Gap of all the layers between LIBSVM and Genetic Algorithm with LIBSVM. From the figure clearly observed that the combination of GA with LIBSVM provides the better result. Fi9gure 20 and 21 illustrates the comparison of layers and their amplitudes.

V. CONCLUSION

In this work, defect automated classification in aircraft multiply structure is investigated through pulsed eddy current with the help of ICA and GA-LIBSVM. Defects in two-layer. The PEC technique with the help of ICA and GA-LIBSVM can build the model for defect automated classification in two-layer structures. The defects on different layers can be classified satisfactorily using the proposed method.

This hybrid approach is very useful and accurately defect the lift-off and air gaps. In Genetic Algorithm, three steps are followed that are selection, crossover and mutation. In mutation part that pbest and gbest are produced and it is given to the command of alpha and cost specification of LIBSVM. From the experiment result proves that the proposed method classify best and give accuracy as a better one than existing one.

Figure 19: Comparison of Accuracy for Air Gap for all layers.

Figure 20: Comparison of layers depth

REFERENCES

[1] R. A. Serway and J. W. Jewett. Physics for scientists and Engineers, with modern physics, pages 967–1002. Thomson Brooks/Cole, New York, USA, 6th edition, 2000.

[2] N. Mohan, T. M. Undeland, and W. P. Robbins. Power Electronics, Converters, Applications and Designs. John Wiley and Sons, Inc, New York, USA, 2nd edition, 1995.

[3] E. Kreyszig. Advanced Engineering Mathematics, pages 431–485. Wiley International Edition, New York, USA, second edition, 1967.

[4] C. Tia, J. H. Rose, and J. C. Moulder. Thickness and conductivity of metallic layers from pulsed eddy current measurements. Review of scientific Instruments, 67(11):3965–3972, November 1996.

[5] A. Krawcyzk and J. A. Tegopoulos. Numerical Modelling of Eddy Currents, pages 1–42. Clarendon Press-oxford, 1993.

[6] A. Sophian, G.Y. Tian, D. Taylor, J. Rudlin, Design of a pulsed eddy current sensorfor detection of defects in aircraft lap-joints, Sensors and Actuators A: Physical101 (2002) 92–98

[7] Grossinger, R., Kupferlinga, M., Kasperkovitz, P., et al., Eddy Currents in Pulsed Field Measurements, J. Magn. Magn. Mater., 2002, vol. 242, pp. 911–914.

[8] Giguere, S., Dubois JMS. Pulsed Eddy Current: Finding Corrosion Independently of Transducer Lift-Off, Rev. Prog. Quant. Nondestr. Eval. , 2001, vol. 19, pp. 49–56.

[9] Giguee, S., Lephine, B.A., and Dubois, J.M.S., Pulsed Eddy Current Technology: Characterizing Material Loss with Gap and Lift-Off Variations, Res. Nondestruct. Eval. , 2001, vol. 13, pp. 119–129.

[10] Safizadeh, M.S., Lepine, B.A., Forsyth, D.S., and Fahr, A., Time Frequency Analysis of Pulsed Eddy Current Signals, J. Nondestruct. Eval. , 2001, vol. 22, pp. 73–86.

[11] D. L. Waidelich. Pulsed Eddy Currents. 'Research Techniques in Non-destructive Testing, Academic press', pages 383–416, 1970.

[12] D. L. Waidelech and C. R. Lahmeyer. The testing of thick sheets of metal using Pulsed Eddy Currents. Technical report, University of Missouri Colombia, Missouri 65211, USA, 1979.

[13] J. R. S. Giguere and J. M. S. Dubios. Pulsed Eddy Current: Finding corrosion independently of transducer lift-off. Review of progress in QNDE, 19:449–456, 2002.

[14] J. H. V. Lefebvre and J. M. S. Dubois. Lift-off Point of Intercept (LOI) Behaviour. 31st Review of progress in QNDE, 17, Summer 2001.

[15] M. S. Safizadeh, B. A. Lepine, D. S. Forsyth, and A. Fahr. Time frequency analysis of pulsed Eddy Current signals. Journal of Nondestructive Evaluation, 20(2):73–87, June 2001.

[16] Lambers, H and Poorter, H. "Inherent variation in growth rate between higher plants: A search for physiological causes and ecological consequences. Advances in Ecological Research 23, 187-261.

[17] Corn leaf analysis and interpretative Guidelines, Olsen's Agricultural Laboratory, Inc, 2008.

[18] J. A. Silva and R. Uchida, "Essential Nutrients for Plant Growth: Nutrient Functions and Deficiency Symptoms", College of Tropical Agriculture and Human Resources, University of Hawaii at Manoa, 2000.

[19] A. Hyvarinen and E. Oja "A fast fixed-point algorithm for independent component analysis", Neural Computation, 9, 1483-1492, 1997.

[20] R.L. Haupt, S.E. Haupt, Practical Genetic Algorithms, John Wiley and Sons Inc., New Jersey, 2004.

[21] A. Sokolov, D. Whitley, Unbiased tournament selection, in: The Conference on Genetic and Evolutionary Computation, GECCO'05, ACM, Washington DC, 2005, pp. 1131–1138.

[22] S. Sivanandam, S. Deepa, Introduction to Genetic Algorithms, Springer-Verlag, Berlin, 2008.