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Analysis of Fault Detection in Analog Circuits Using WSF-SKC Optimized SVM Technique

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Abstract- Many industrial applications and control systems depend heavily on analogue electrical circuitry. The conventional method of diagnosing such circuit faults can be time-consuming and erroneous, which might have a severe impact on the industrial output. The fault detection and analysing of analogue circuits with intelligent effective model is proposed in this work. The suggested technique primarily consists of two main stages one is extraction of features and the other is classification of faults. The analysis is performed on the response of frequency in analogue circuits. For extracting features particle swarm optimization (PSO) is utilized. The PSO is used to evaluate the fitness function of Wilks A-Statistic Filters sallen-key circuit (WSF-SKC). With fault characteristics retrieved using the particle swarm approach that are carefully selected, the fault classes may be separated more quickly. To categorise different failures in a benchmark circuit, a Support Vector Machine (SVM) classifier is built. Utilising firefly optimisation, the classifier is improved. Different fault codes were tested in experiments for defect detection and identification. The findings of the experiment indicate that this proposed technique can significantly increase the accuracy of fault diagnosis. The accuracy obtained for WS-LPF is 99.95%, WS-HPF is 99.97 and WS-BPF is 99.90% respectively.

Keywords- Frequency response, Sallen Key circuit, PSO, Firefly Algorithm, SVM

I. INTRODUCTION

A fault is seen as a mistake that may have unfavourable implications and the condition of the device or system is abnormal. If the system or equipment cannot return to a stable operational condition, it is said to be defective. Analysis of a system's or device's symptoms, which are frequently interpreted as departures from typical parameters, is the first step in fault identification. The system's typical operating condition must be understood to identify aberrant operations as said in [1]. Numerous consumer and industrial applications employ electronic systems. Due to the numerous and diverse components employed in these circuits, modern electronic systems continue to expand in complexity [2]. Identifying the defect physically by analysing each circuit's element is a costly and time-consuming approach because of how complicated electrical circuits are. It is crucial for productivity, cost, and time loss that electronic system faults are fixed as quickly as feasible. Both analogue and digital circuits make up modern electrical systems. The faults in the digital systems have a well-organized components structure of the circuits which makes the process easy to identify as said in [3]. Finding the problem, nevertheless, can be challenging in analogue electronic circuits because of the dependence of signal which is given as input, tolerances of the components, and the constantly changing behaviour of these systems by author in [4].

Based on prior knowledge of the system's condition, in [5] the author suggested about the modelling of systems with the help of artificial intelligence. To effectively mimic the system behaviours, machine learning algorithms often required a substantial quantity of historical data. Using discrete Volterra series and an optimum coefficient, in [6] author describes a fault detection system for analogue circuits. In the analogue circuits the features are extracted from the fault data based on different locations for which tests are conducted.

A defect diagnostic module is created utilising these characteristics and a condensed closest neighbour method. With an accuracy of 89.4%, low pass filter circuit is been tested and diagnosis is performed. The author in [7] presents a fault-driven test-based support vector machine classifier-based fault diagnostic method for analogue circuits. The SVM classifier is trained with the characteristics retrieved from the utilized circuit depending on the failure of elements obtained from the response of the output the fault condition to be located and identified. 90% accuracy is achieved for problem location is observed while the device is working LPF circuit which is analogue. A sparse auto-encoder and the module in neural network are suggested in [8] for fault detection in energy-efficient circuits. The resultant signal of the circuit is examined for characteristics using the autoencoder approach under both normal and abnormal operating situations. A neural network classifier algorithm is trained using these characteristics to find out the defects located in electronics devices. When recognising the issue

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with rectifier circuit in a three-phase, the system has a 90% accuracy rate.

An attribute extraction method for defect identification in analogue circuits is suggested by author in [9]. The properties like information entropy, maximum value and spectrum energy are extracted by using the decomposition method like wavelet packets. Fault data dimensions and normal data dimension are gathered from the circuits are been reduced by the application of feature reduction. The replicate selection technique is used to classify data to identify the defect. The low-pass filter circuit fault diagnostic test results revealed 99% accuracy. The author in [10] uses a neural network model to evaluate analogue circuits. When a known supply signal is provided, the characteristics are retrieved from the circuit current signal. To create test data for the quadratic filtering circuitry system evaluation, Monte Carlo analysis is employed. In [11] the author presents a deep neural network that uses wavelet information taken from the output signal to identify faults in analogue circuits. Having 96% reliability, the system has been tested on a band-elimination filtering circuitry. In [12] author suggests using an SVM classifier to categorise faults in analogue circuits. One of the techniques i.e., wavelet analysis is utilized for extracting the data from the circuitry and used for extracting the failures in frequency response circuits. A high-pass filter circuit fault is located using an SVM classifier. In [13] a similar technique is suggested utilising SVM that has been optimised by cuckoo search optimisation. Based on frequency response data, an SVM classifier is also utilised to diagnose faults in analogue circuits. The SVM classifier's evaluation findings reveal an accuracy rate of 98.7%.

In this paper, to improve the rate of accuracy and perfection of identifying the faults two end optimization process is performed. One is features optimization while performing the feature extraction process for defect detection in analogue circuits with respect to study of wilks statistic sallen key filter circuit. The other optimization process is performed at classification stage to improve the rate of identification of faults in analogue circuits. The paper organized as follows, section 2 provides a deep discussion of the proposed model i.e., the process of feature extraction and classification. The experimental findings are evaluated in section 3. Finally, conclusion of proposed model in section 4.

II. METHODOLOGY

The input signal is examined in the suggested model. Following testing, Wilks A-statistic feature vectors are used to process the extraction of features under SKC. Utilising PSO, the features have been optimised. These characteristics are supplied into the SVM for categorization. The firefly optimisation approach is used to improve the classifier. Fig.1 depicts the suggested model, which is detailed in the section following.

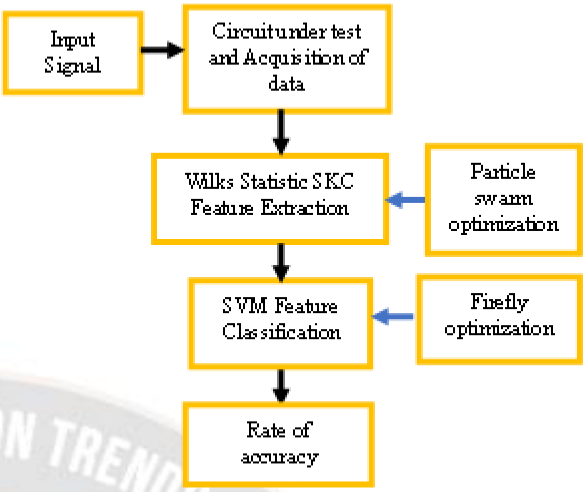

Figure 1. Block Diagram of Proposed Model

A. Wilks A-Statistic Sallen-Key Circuit

To assess the variables' ability to discriminate across different classes of samples, the Wilks statistic was established in the multivariate statistical analysis. For detecting faults in analogue circuitry, a wilks statistic features extraction and selection of features process is performed in this study. The feature vectors are evaluated and the variables are selected depending on the wilks statistic and is given in equation (1)

$$\wedge_{(m)} = \frac{|W|}{|T|} = \frac{|W|}{|B+W|} \tag{1}$$

$\wedge_{(m)}$ has a range of [0, 1] in accordance with the parameters W and B are represented as sum of square matrix within the class of samples selected and deviations within the samples selected. T is termed as total deviation within the samples selected.

$$W = \sum_{i=1}^{g} \sum_{j=1}^{k_i} (x_{ij} - \overline{x}_\iota)(x_{ij} - \overline{x}_\iota)^T \tag{2}$$

$$B = \sum_{i=1}^{g} k_i \, (\overline{x}_\iota - \overline{x})(\overline{x}_\iota - \overline{x})^T \tag{3}$$

The total fault samples classes are termed as 'g', for the i^{th} fault the sample feature vector is represented as k_i, and the feature vector of j^{th} for i^{th} fault is termed as x_{ij}. The mean of the sample vector features of i^{th} class is x_i and the overall mean is termed as x.

The common frequency spectrum equation for a the second-order LPF is:

$$H_{LP} = \frac{K}{-\left(\frac{f}{fc}\right)^2 + \frac{jf}{Qfc} + 1} \tag{4}$$

Here the term 'fc' is the frequency distributed at corner and Factor of quality nis termed as Q. If $f \ll f_c$ then $H_{LP} = k$ in this case the signal passing the circuit is multiplied by the gain factor K. If $f = f_c$ then $H_{LP} = -jKQ$ in this case the signal passing the circuit is upgraded by the quality factor Q. If $f \gg f_c$ then $H_{LP} = -k\left(\frac{fc}{f}\right)^2$ in this case the signal passing the circuit is attenuated w.r.t the square of frequency parameter ratio. If the attenuation hiked by a power factor '2' then the

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equation (4) is termed as second order LPF. The low pass SKC is shown in Fig.2.

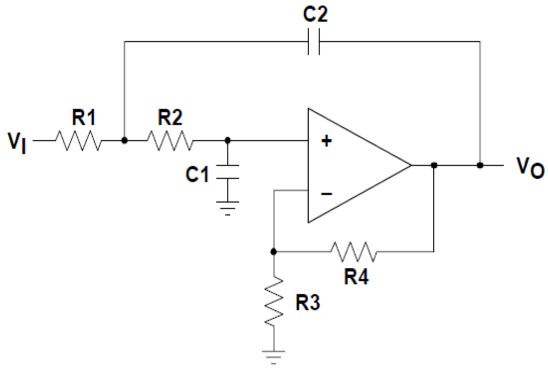

Figure 2. Low-Pass Sallen-Key Circuit

The transfer function of ideal low pass sallen key filter is,

$$Z1 = R1, Z2 = R2, Z3 = \frac{1}{sC1},$$

$$Z4 = \frac{1}{sC2}, and\ K = 1 + \frac{R4}{R3}$$

$$\frac{Vo}{Vi}(lp) = \frac{k}{s^2(R1R2C1C2)+s(R1C1+R2C1+R1C2(1-k))+1} \quad (5)$$

The high pass SKC and band pass SKC diagrams are shown in Fig.3 and Fig.4

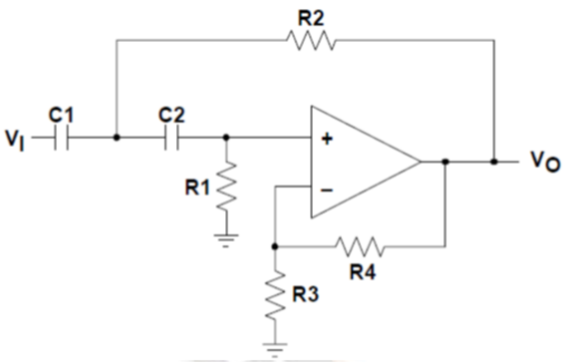

Figure 3. High pass Sallen-key circuit

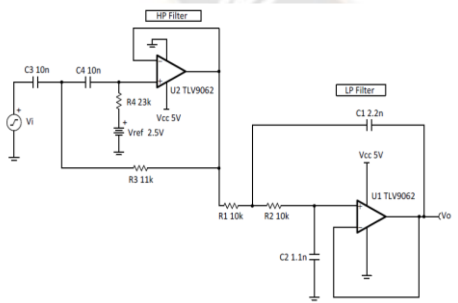

Figure 4. Band pass Sallen-key circuit

B. Particle Swarm Optimization Algorithm

This algorithm is introduced in the year 1995 by the author in [15] and was motivated by the soaring bird foraging habit. The PSO algorithm's main goal is to find the optimum solution through knowledge sharing and group participation.

$$v_i^{k+1} = \omega(k)v_i^k + c_1r_1(p_i - x_i^k) + c_2r_2(p_g - x_i^k) \quad (6)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (7)$$

A massless particle having the velocity and position characteristics of a bird in a group of population and this process is existing in the form of PSO. Every particle tries to obtain the best position in the search space The current best position of the particle is share with other particle so that the position of particle will be updated w.r.t to the velocity of the particle**.** The velocity and position of particle are evaluated using equation (6) and (7) given below.

Finally, by sharing the update new position among the particle the global best solution will be obtained at the end of specified iterations.

For every iteration one fitness function is evaluated and is used to compute the fitness value of the particle. After identifying the two extreme points the speed and location of particle is identified using the above equations 6 and equation 7.

The velocity and position of i^{th} particle at k^{th} is termed as v_i^{k+1} and x_i^{k+1} respectively. Here c_1 and $\boldsymbol{c_2}$ termed as factor of learning, the best position of the i^{th} particle is termed as p_i and the optimized global best position is given as p_g,the random numbers are given as r_1 and r_2. The range varies of these numbers vary from 0 to 1 and the inertia factor is termed as $\omega(k)$.

The PSO algorithm's capacity for global optimisation is strong if the value of ω is high. In contrast, the PSO algorithm's capacity for local optimisation is great if the value of ω is low. The value of ω is continuously updated depending on the performance monitoring function of suggested optimization technique is to suit in the real time applications. The method regularly used in these analogue frequency circuits (AFC) is linear decrement weight (LDW) methodology and is given as,

$$\omega = \frac{(\omega_{ini} - \omega_{end})(G_k - k)}{G_k} + \omega_{end} \quad (8)$$

From equation 8, the term G_k is the iterations with maximum in number, inertia weight at initial stage is termed as ω_{ini}, while iter_max the inertia weight is said to be ω_{end}.

The straight forward implementation nature of PSO helps in obtaining higher rate of accuracy in results.

C. Feature extraction process using PSO

Analogue circuit fault diagnosis is primarily concerned with locating of the faults in the input signal. The faults feature in the analogue circuits can be identified using frequency response signals rather than time response signals. The information of the signal in time domain i.e., signal sources and interferences are often designed, where as in frequency domain there is loss of data due to its frequency distribution.

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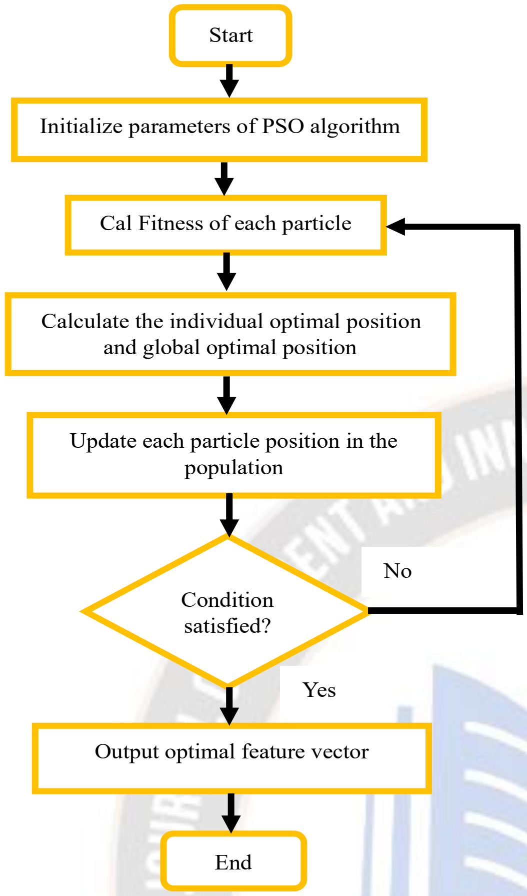

Figure 5. Process flow for extraction of features

The data in frequency domain need to be rearranged into compact form for data analysis. To overcome the problem features vectors are extracted that are present in the signal with frequency response. Additionally, the feature vector's variables' units vary, which leads to various normalisation standards for every variable.

The approach chosen in this work in extracting of features using PSO technique along with WSL-SKC. By using the suggested model, the feature vectors are extracted from the frequency response analogue circuits. This approach described above does not use the conventional frequency characteristics of the analogue circuit. In contrast, the PSO method optimises the feature vector's variables within the range specified for the frequency. We offer a generic technique for building the vectors related with the frequency response. The features vectors of the wilks- statistic SKC is considered as the fitness function and is used in PSO technique. The feature vectors achieved will impact the process of classification, to achieve best position of particles the fitness function is supposed to evaluate. The process of initiating the PSO and obtaining the best optimal output is shown in Fig.5. The PSO parameters are initialized and fitness for each particle is calculated and find the best optimal position by updating the positions until global best solution is obtained. The following are the precise phases of the vector feature selection approach involved in 6-stages:

Stage1: Set up the PSO algorithm's variables, such as the particle's position and speed, the ideal range, iterations to be performed, and the size of the population of swarms.
Stage2: Map each particle's bidirectional location to the feature vector's changeable number sequence. Using equations from (1) to (5) for evaluating the fitness value, determine the Wilks -statistic for vector features for the population of swarms
Stage3: Compute the global ideal location of the population as well as particles individual position
Stage4: the position of particle needs to be updated in the population initiated using equations (7) and (8).
Stage5: satisfying the end condition else repeat stage2 to stage4.
Stage6: Because of extracting the features, output the feature vector that corresponds to the global optimum location.

D. Fault Classification Process using FA-SVM

In SVM kernels play important role and shows the impact on the process of classification. In this phase, the Firefly Algorithm (FA) is used to determine the SVM's ideal hyperparameters, and the training sample set S is utilized to develop the classification approach of the SVM.

During the process of proposed FA optimization, the kernel parameters of SVM is transformed to 2D position for the selected population of fireflies. In this process the fitness function selected is from the sample set 'S' and obtaining the maximum value of fitness function. Fig.6 depicts the step-by-step procedure for creating the FA-SVM classifier for diagnosing analogue circuit faults. The fireflies are initialised and the fitness function for each firefly is evaluated. The brightness concept is considered by which the flies get attracted and update the position until obtaining the global best solution. The following are the precise methods for building the FA-SVM classifier for diagnosing analogue circuit faults:

Stage1: Set the FA settings, such as the range of senses, intensity of light, and attraction, as well as population of firefly and iterations.
Stage2: kernel parameter of SVM is mapped to each firefly's two-dimensional location, and the training sample set's diagnostic accuracy is chosen as the fitness value. Then figure out each firefly's fitness value.
Stage3: Each firefly looks for the firefly that is the brightest in its field of vision.
Stage4: the position of every firefly needs to be updated among the population
Stage5: satisfying the end condition else repeat stage2 to stage4.
Stage6: Optimized results are achieved for the parameters of kernel function utilized in SVM
Step 7: By training the sample set S, create a defect diagnostic classifier based on the optimisation findings.

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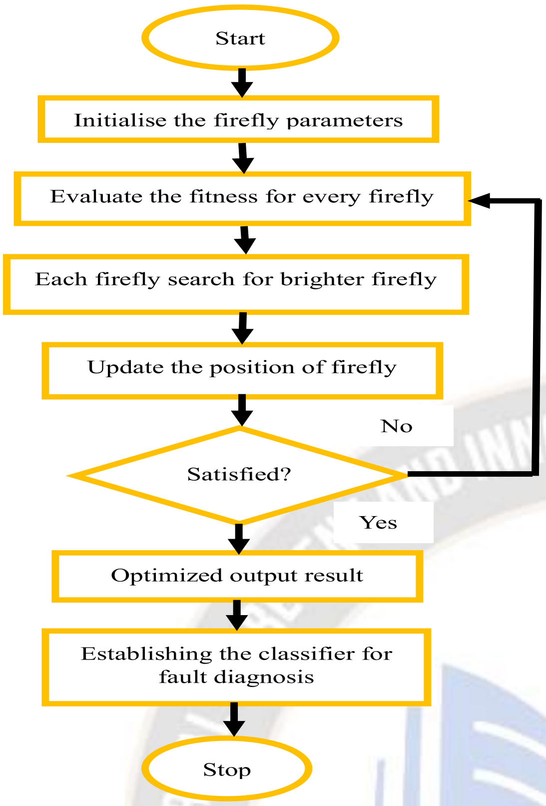

Figure 6. Process of classification using FA-SVM

III. Experimental Finding

A Sallen-Key filter circuits such as low pass (LP), high pass (HP) and band pass (BP) is utilised as the experimental circuits to test the efficacy of the suggested analogue circuit defect diagnostic approach based on FA-SVM employing frequency characteristics. The likelihood of a single-fault condition occurring in an analogue circuit is far higher than the likelihood of a double-fault condition. The same technique can be used for both single and double faults conditions. Therefore, the fault diagnostic technique indicated above is evaluated using the single-fault situation of two test networks.

Fig. 2 depicts the first functional Sallen-Key low pass filter circuit. C1, C2, R1, R2, R3, and R4, are deemed important components based on the sensitivity assessment of the circuit's elements. The value of the component in the circuit should not get deviated more than 50%, if value is higher than 50% the component in the circuit is said to be defective and fault is present.

Table I. Faults values of the proposed SKC- LP

$Fault\ Code$	$Fault\ Class$	$Nominal\ Value$	$Fault\ Value$
$F0$	NF	…..	…..
$F1$	$C1\uparrow$	1nF	2nF
$F2$	$C1\downarrow$	1nF	0.5nF
$F3$	$C2\uparrow$	1nF	2nF
$F4$	$C2\downarrow$	1nF	0.5nF
$F5$	$R1\uparrow$	1kΩ	2kΩ
$F6$	$R1\downarrow$	1kΩ	0.5kΩ
$F7$	$R2\uparrow$	1kΩ	2kΩ
$F8$	$R2\downarrow$	1kΩ	0.5kΩ
$F9$	$R3\uparrow$	2kΩ	3kΩ
$F10$	$R3\downarrow$	2kΩ	0.5kΩ
$F11$	$R4\uparrow$	1kΩ	2kΩ
$F12$	$R4\downarrow$	1kΩ	0.5kΩ

As a result, 12 separate fault classes are formed by processing the incorrect frequency responses, $C1\uparrow, C1\downarrow, C2\uparrow, C2\downarrow, R2\uparrow, R2\downarrow, R3\uparrow, R3, R4\uparrow, R4\downarrow, R5\uparrow, R5\downarrow, and\ no-fault\ (NF)$, the upper arrow indicates higher value of component compared to actual value and down arrow indicates low values than the actual value. Table I displays each component in the circuit's fault code, fault class, nominal value, and fault value. For the analysis of alternating current (AC) a 10V amplitude level sweep signal is considered in the analogue circuit fault diagnostic system. The output of the circuit with frequency response is obtained when the values of the capacitors and resistors are adjusted according to the tolerance range.

Table II. Faults values of the proposed SKC- HPF

$Fault\ Code$	$Fault\ Class$	$Nominal\ Value$	$Fault\ Value$
$F0$	NF	…..	…..
$F1$	$C1\uparrow$	1nF	1.5nF
$F2$	$C1\downarrow$	1nF	0.8nF
$F3$	$C2\uparrow$	1nF	1.4nF
$F4$	$C2\downarrow$	1nF	0.86nF
$F5$	$R1\uparrow$	1kΩ	1.45kΩ
$F6$	$R1\downarrow$	1kΩ	0.54kΩ
$F7$	$R2\uparrow$	1kΩ	1.5kΩ
$F8$	$R2\downarrow$	1kΩ	0.75kΩ
$F9$	$R3\uparrow$	2kΩ	2.3kΩ
$F10$	$R3\downarrow$	2kΩ	1.6kΩ
$F11$	$R4\uparrow$	1kΩ	1.7kΩ
$F12$	$R4\downarrow$	1kΩ	0.8kΩ

Table III. Faults values of the proposed SKC- BPF

$Fault\ Code$	$Fault\ Class$	$Nominal\ Value$	$Fault\ Value$
$F0$	NF	…..	…..
$F1$	$C1\uparrow$	2.2nF	2.5nF
$F2$	$C1\downarrow$	2.2nF	2nF
$F3$	$C2\uparrow$	1.1nF	1.4nF

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$F4$	$\underline{\boldsymbol{C2} \downarrow}$	1.1nF	0.8nF
$F5$	$R1 \uparrow$	10kΩ	10.4kΩ
$F6$	$R1 \downarrow$	10kΩ	9.72kΩ
$F7$	$R2 \uparrow$	10kΩ	10.3kΩ
$F8$	$R2 \downarrow$	10kΩ	9.82kΩ
$F9$	$R3 \uparrow$	11kΩ	11.5kΩ
$F10$	$R3 \downarrow$	11kΩ	10.7kΩ
$F11$	$R4 \uparrow$	23kΩ	23.7kΩ
$F12$	$R4 \downarrow$	23kΩ	23.6kΩ

The dataset utilized for classification is created by considering 100 samples for every defect class. The sample set 'S' is divided randomly for the purpose of testing and training in SVM classification process. The sample set 'S' is given with an assumption of 'k' class of faults need to be identified and is given as $S = \{S_1, S_2, \ldots\ldots, S_k\}$. Data utilized for training and testing in the ratio of 70:30. The test results are evaluated using the matlab software tool. The SKC response using different filters in frequency domain is shown in Fig.5 which is a no-fault simulation results obtained while performing simulation in matlab.

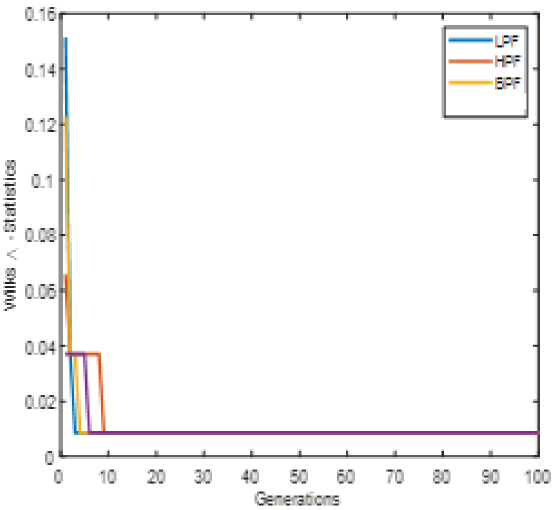

Figure 5. Convergence curve using different filters

The experimental circuit's useful frequency range may be calculated from Fig. 5 to be between 0.1 kHz and 1000 kHz. Using the PSO feature extraction technique suggested in this work, the feature vector variables are chosen within this range. Experience has led to the selection of 3 as the feature vector dimension, 10 as the particle population size, 100 as the maximum number of iterations, and 0.1 to 1000 kHz as the optimisation range.

The kernel function which is evaluated using the SVM-FA for the diagnosis of faults is constructed for the circuitry evaluation. The faults and its values using the Low-Pass Sallen-Key Circuit is tabulated in Table III and IV

Table III. Identification of Fault class for WS-Low pass filter

$Fault\ Class$	$Rate\ of\ Accuracy$ (%)
$F4$	99.20
$Others$	100
$Average$	99.95

From table III it is observed that fault class F4 have lower accuracy rate when compared to others. Here one of the test data of F4 fault class is incorrectly identified as other faults class like F2 or F7 or F9.

Table IV. Accuracy obtained using for WS-Lowpass filter

Method	**Accuracy (%)**
SALLEN – KEY with SVM	98.90
PSO – SALLEN – KEY with SVM	99.919
SALLEN – KEY with FA – SVM	99.925
PSO – SALLEN with FA – SVM	99.95

The overall accuracy in identifying the fault class using the proposed model is shown in table V and the accuracy values obtained using different methods on WS-High pass filter is shown in below table VI.

Table V. Identification of Fault class for WS-High pass filter

$Fault\ Class$	$Rate\ of\ Accuracy$ (%)
$F4$	99.54
$Others$	100
$Average$	99.97

Table VI. Accuracy obtained using for WS-High pass filter

Method	**Accuracy (%)**
SALLEN – KEY with SVM	98.91
PSO – SALLEN – KEY with SVM	99.923
SALLEN – KEY with FA – SVM	99.934
PSO – SALLEN with FA – SVM	99.971

The accuracy values obtained using WS-Band pass filter is shown in below table VII and VIII

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Table VII. Identification of Fault class for WS-Band pass filter

Fault Class	*Rate of Accuracy* (%)
*F*5	99.14
*F*8	99.25
Others	100
Average	99.905

Table VIII. Accuracy obtained using for WS-Bandpass filter

Method	**Accuracy (%)**
SALLEN – KEY with SVM	98.87
PSO – SALLEN – KEY with SVM	99.885
SALLEN – KEY with FA – SVM	99.89
PSO – SALLEN with FA – SVM	99.905

To account for the component tolerance impact, we only employed two adjustable resistors and one adjustable capacitor in our experiment. Additionally, an adjustable fault-free component's parameter value is selected at random within 10% of its nominal value.

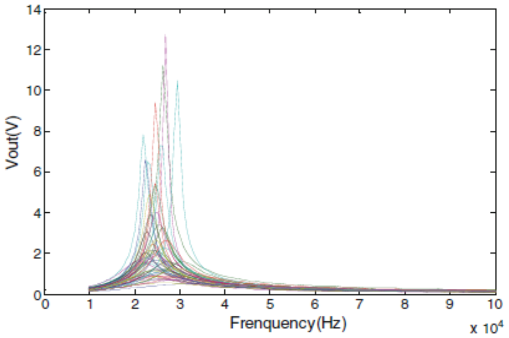

Figure6. Response of SK-BPF w.r.t to 10% tolerance effect

Finally, the proposed model accuracy values are compared with other existing methods and are tabulated in table IX

Tabel X. Comparison of accuracy results using different exiting techniques

Method	**Accuracy (%)**
Wavelet coefficient for extracting features [16]	93.1
Kurtosis and Entropy model [17]	98.6
Lifting wavelet model [18]	99.2
Proposed Model	99.905

IV. CONCLUSION

A unique approach is created for the extraction of features and classification of faults stages to address the problems with fault detection for analogue circuits. Wilks' -statistic, one of the key metrics for determining variables in multivariate statistics, may assess the variable discriminatory capacity. Therefore, the Wilks -statistic is employed as the foundation for the extraction and choice of features and is utilized for diagnosis of faults in the analogue circuits with frequency response. PSO combined with WSF-SKC is utilized for the process of extracting the features. The approach is tested on low pass, high pass and band pass filters. The suggested extraction of features approach may ideally choose a collection of unit homogeneous feature vectors without superfluous data. The faults identification is done when the kernel function parameter in SVM is optimized using the FA. The fault detection approach developed in this study has a diagnostic accuracy of 99.97% for the SKC when FA-SVM optimisation techniques are used. The approach suggested in this project has benefits over other ways. The results of the experiments demonstrate that the suggested approach enhances the analogue circuit's dependability and maintainability and offers a superb remedy for the problem of diagnosing analogue circuit faults. Further, the PSO technique can be combined with many other techniques like neural networks, fuzzy logic systems to achieve a solution for the specific problem.

CONFLICT OF INTREST

The authors declare no conflict of interest

AUTHOR CONTRIBUTIONS

R. Gurunadh conducted the research work, collected the data, and wrote the paper. Dr. K. Babulu supervised the work and approved the final version.

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