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PERFORMANCE ANALYSIS OF MODEL FOR FAULT DIAGNOSIS IN RADIATION-HARDENED MEMORIES USING SVDD-PSO

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Abstract. *Radiation-hardened memories are extensively used in critical commercial applications such as nuclear power plants, industrial systems, and space missions for reliable data storage and retention. While numerous algorithms have been proposed for diagnosing faults in these memories, most focus less on fault optimization. To address this gap, this paper presents a performance analysis of a fault diagnosis model based on the Support Vector Data Description–Particle Swarm Optimization (SVDD-PSO) algorithm for fault optimization. The proposed fault diagnosis model is designed using specific parameters tailored for radiation-hardened memories. The results demonstrate that the methodology achieves higher accuracy, optimal fitness value, and reduced time penalty when diagnosing fault samples. The model's performance is further evaluated using logistic regression, with a Receiver Operating Characteristic (ROC) curve accuracy of 96%, reflecting a balanced trade-off between the true positive rate (TPR) and false positive rate (FPR). The higher TPR and lower FPR confirm that the proposed model is well-suited for fault diagnosis in radiation-hardened memory systems.*

Key words: *Fault Diagnosis Model, Particle Swarm optimization, Radiation Hardened Memories, Support Vector Data Description.*

1. INTRODUCTION

Nowadays, memories play an integral role to process data over time in embedded systems. Static & Dynamic memories are generally used in embedded systems that are assembled with advanced technology. These memories are club with the IoT network. IoT (Internet of Things) is linked with the number of devices. Hence, complexity of networks increases with certain issues including security, authenticity, dependability, and

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scalability [1-2]. In commercial applications like in industries, military, nuclear power and space applications these memories are suitable due to its high density.

These memories may suffer from sensitivities to total ionize single event & prompt dose effect. Components in memories are not designed for harsh space environments as they contain several large customized memory-based arrays in the individual RAM cells and latches [3-4]. Radiation-hardened memories [5] are the magneto resistance RAM or MRAM and non-volatile conductor memories [6]. These memories can resist damage due to high levels of ionizing radiation which is caused due to particle radiation and high level of EM radiation energy [7]. There are certain issues regarding radiation memories as the high levels of ionizing radiation will create some special design challenges [8]. A certain type of fault will be generated like a single charge particle in which it will lose lots of electrons which will cause electronic noise and signal spikes [9].

So, for diagnosis this issue a fault model is designed which will detect the fault in memory on the basis of memories parameters [10]. These faults can be optimized with the help of different optimization technique like Genetic Algorithms, Artificial Bee Colony, Particle Swam optimization, Ant Colony Optimization, Squirrel search Algorithm, and Cuckoo Search Algorithm. But in this paper we have use SVDD-PSO optimization because is provide better accuracy and optimal value for fault model as compare to other fault optimization techniques [11].

The SVDD-PSO model's performance is limited by its dependency on parameter selection and convergence speed in complex fault scenarios. Additionally, its scalability for large-scale memory systems and multi-fault detection requires further investigation.

The model can be improved by incorporating adaptive parameter tuning, hybrid meta-heuristic techniques, and dynamic threshold mechanisms. Additionally, integrating IoT-based real-time monitoring and enhancing scalability for multi-fault detection in large memory systems can further optimize performance.

This paper is categorized into following sections. Section 1 provides an introduction to the basic features and use of Radiation Hardened Memories. Section 2 describes the Conventional SVDD and PSO algorithms. Section 3 explains the hybrid SVDD-PSO Algorithm with the help of a flow chart. Section 4 describes the proposed model for analysis of SVDD-PSO. Section 5 provides the Optimized fault diagnosis in Memories using SVDD-PSO. Section 6 shows the results and discussion with the help of a comparative study. Section 7 describes the conclusions and future scope of the analysis.

2. CONVENTIONAL SVDD AND PSO ALGORITHM

Support vector data description is a machine-learning method for single-class classification and outer detection [12-13]. It deals with a huge amount of data and finds a hyper sphere in the feature space that encloses the normal instances, while minimizing the volume of the hyper sphere [14]. This characteristic makes SVDD be used in optimal fault detection. The basic structure of this algorithm is consisting of Kernel parameter Kf and error correcting penalty coefficient Ec [15]. The radial base function kernel measures the similarity based on the Euclidean distance between data points. It is commonly used and is suitable for capturing non-linear relationships; the lower the value Kf more accurate the system will be. Error-correcting penalty coefficient Ec is determined by the upper boundary condition of the Lagrange multiplier [15].This algorithm is defined as data with dimension (d) for $X \in Rd$.

$$XjIxj \in \mathrm{Rd} \tag{1}$$

where j = 1,2,3.....n (known trained data set sample)

The data set requires finding the minimum hyper sphere with a centre C and radius R in high-dimension system F with nonlinear sampling and this system includes all the data set. The main objective of the SVDD method is to reduce the radius R of the system at the same time also reduce the singular value by adding relaxation variable εj to manage the trade-off between the volume of the sphere and the error rate, with the help of the Ec error penalty coefficient. Now for the Quadratic system,

$$\min F(R,c,j) = R^2 + E_C \sum_{j}^{n} \varepsilon_J \tag{2}$$

$$\| xj - c \|^2 \leq R^2 + \varepsilon j \tag{3}$$

Equations (1) and (2) are solved through the Lagrange function for optimization of the problem.

$$\angle(R,c,\alpha_j,\lambda_j,\varepsilon_j) = R^2 + E_c \sum_{j=1}^{n} \varepsilon_j \sum_{j=1}^{n} \varepsilon_j \lambda_j - \alpha_j (R^2 + \varepsilon_j) - \| x_j - c \|^2 \tag{4}$$

Here, αj, and λj are the Lagrange multiplier. After solving the above equation (4), assuming the partial derivative result is 0, then Using equation (5) and (6), in dual from we can be obtained equation 2.

$$\sum_{j=1}^{n} \alpha_j = 1 \;\&\; c = \sum_{j}^{n} \alpha_j \chi_j \tag{5}$$

$$\mathrm{E_c} \lambda_j - \alpha_{j=0} \text{ for } (0 \leq \alpha_j \leq E_c) \tag{6}$$

$$max \alpha_j \angle(R,c,\varepsilon_j,\alpha_j,\lambda_j) = \sum_{j=1}^{n} \alpha_j \mathrm{K}(\chi_j \chi_j) - \sum_{j=1}^{n} \sum_{k=1}^{n} \alpha_j \alpha_k \mathrm{K}(\chi_j,\chi_k) \tag{7}$$

With the help of Mercer’s theorem equation (3) is modified into equation (7), which satisfies the KKT (Karush Kuhn tucker) optimization condition, solving the above equation (8)

$$\begin{aligned} &\left\| \chi_{\mathrm{j}} - c \right\|^2 < R^2 \text{ for } \alpha j = 0 \\ &\left\| \chi_{\mathrm{j}} - c \right\|^2 = R^2 \text{ for } (0 < \alpha_j < E_c) \\ &\left\| \chi_{\mathrm{j}} - c \right\|^2 > R^2 \text{ for } \left(\alpha_j = E_c \right) \end{aligned} \tag{8}$$

We get these three conditions for αj, now to calculate the distance function centre to the test point is D2(x). F(x) defines whether the sample is in range or not, if F(x)≥0 then the sample is in range otherwise not.

$$D^2(\chi) = K(\chi_j, \chi_k) - 2\sum_{j=1}^{n} \alpha_j K(\chi_j, \chi_k) + \sum_{j=1}^{n} \sum_{k=1}^{n} \alpha_j \alpha_k K(\chi_j, \chi_k) \tag{9}$$

$$F(\chi) = \mathrm{sgn}(R^2 - \| \chi_j - c \|^2) = \mathrm{sgn}(R^2 - D^2(\chi)) \tag{10}$$

2.2. PSO (Particle Swarm Optimization)

Particle Swarm Optimization is a population-based optimizing technique that was designed by Kennedy & Eberhart in 1995[15]. This algorithm is inspired by Swarm intelligence like fish schooling, and bird flocking behavior. In PSO inertia weight is the most important parameter as it controls the momentum of the particle by weighing the contribution of the previous velocity.PSO is a computation method to find the optimal solution for the specific parameter given by the system by fulfilling all the design requirements and considering the best solution in terms of optimization. Radiation-hardened memories are prone to various types of faults, including Stuck-At Faults (SAF), Coupling Faults (CF), and Transition Faults (TF), each of which can compromise data integrity and system reliability. SAFs occur when a memory cell is stuck at a constant logical value (0 or 1), preventing it from changing states, which leads to incorrect data storage. Coupling Faults arise when the state of one memory cell influences the state of another, often due to interference in densely packed memory arrays. Transition Faults, on the other hand, involve the failure of a memory cell to transition between logic states within the required time frame, resulting in delayed or incorrect data processing [16-17]. The Particle Swarm Optimization (PSO) algorithm plays a crucial role in optimizing fault detection for these fault types by searching for optimal diagnostic parameters in multi-dimensional solution spaces [18]. For SAFs, PSO identifies patterns in voltage and current responses to detect stuck cells accurately. In the case of CFs, the algorithm optimizes detection thresholds to account for cell-to-cell interactions, minimizing false positives. For TFs, PSO adjusts timing parameters to distinguish between normal and faulty transitions, ensuring high detection accuracy with minimal time penalty [19-20]. By leveraging PSO, the fault diagnosis model achieves improved accuracy, faster convergence, and better scalability for radiation-hardened memory systems. To make SVDD method optimal a PSO algorithm is inculpated into the SVDD to optimize its parameters. A generalized algorithm for PSO:

Step 1: Initialize the particle position with a uniformly distributed random vector xj for upper bounded and lower bounded conditions, where j is the number of particles *j*=1,2, 3, ……… *n*.
Step 2: Initialize the particle's best-known position to its initial best position. Pj←xj, if f(Pj) ≤f (Pg), then update the particle best position Pg ←Pjhere, Pj Particle best position and Pg is in the Global best position.
Step 3: Initialize the particle velocity vj for boundary condition (-|ub-lb|, |ub-lb)|
Step 4: Update the dimension of each particle, random numbers r1 and r2 between (0,1) and correction factor C1,C2 .
Step 5: Calculate the velocity

$$v_j + 1 = \omega_j v_j + C1r1(Pb_j - \chi_j) + C_2 r_2 (p_g - \chi_j) \tag{11}$$

Step 6 Update the particle's best-known position.

$$\chi_j + 1 = \chi_j + \nu_j + 1 \tag{12}$$

Step7: If f(Pj) < f(Pg) then g ← Pj is the best particle position.

Now, the fitness function of the system is calculated using leave one out method which is a cross-validation technique used to achieve the display of SVDD [20], by training the model on all data points except one and then testing it on the left-out data point. This process is repeated for each data point in the dataset, and the overall performance is evaluated shown in equation (13)

$$\mathrm{P(f)} = \frac{1}{\mathrm{n}} \sum_{j=1}^{n} \angle(f_k(\chi_k \gamma_k)) \tag{13}$$

Where,

f_k: Classifier of data sample for training $n - 1$,

$f_k(\chi_k)$: Result of sample data,

$f_k(\gamma_k)$: Actual Classification.

3. HYBRID SVDD-PSO ALGORITHM

Fig. 1 shows the Flow of the SVDD-PSO algorithm process [21-22], this algorithm uses a particle swarm's optimization algorithm which is summed up with the SVDD model to provide the sample data set parameter optimization with the Kernel function.

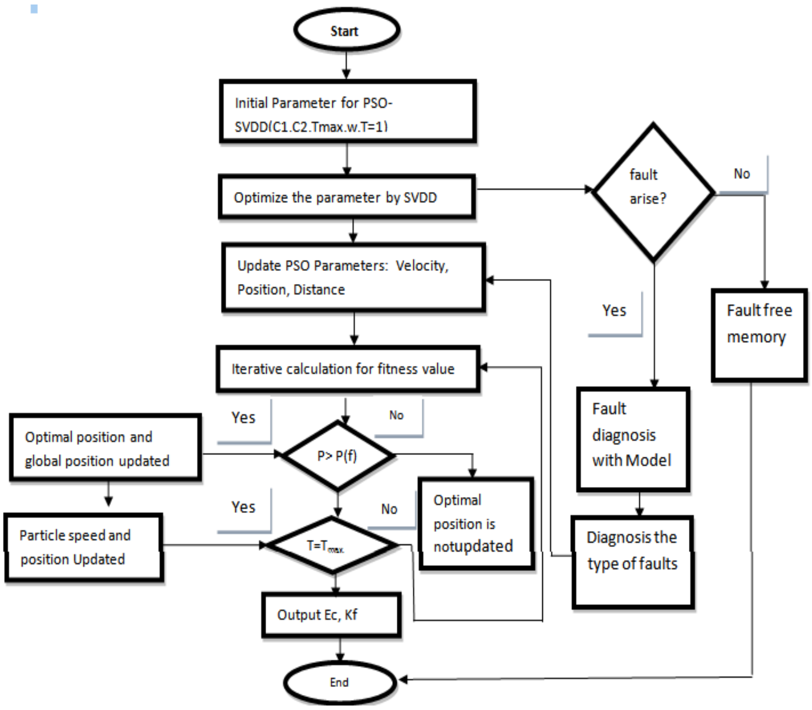

Fig.1 Flow of SVDD-PSO algorithm process

Step 1: Initialize the input parameter for SVDD-PSO like correction factor C1=C2=1.5, maximum number of iteration Tmax=64, inertia weight w=1.
Step 2: Optimize the parameter kernel function Kf and Ec Error correcting penalty coefficient are taken as the combination of iterative PSO optimization variable in the SVDD model and update fault diagnostic model if the fault arises. If nofault arises then system memories are fault free.
Step 3: Update PSO-SVDD Parameters: initial Velocity, initial Position distance using equation (10).
Step 4: Iterative calculation for fitness value P(f) using equation (14) for each particle.
Step 5: Update global optimal location, update Velocity (vj + 1) using equation (12), Update Position (xj + 1) using equation 13.
Step 6: check whether the output reaches the optimal parameter combination of the SVDD model if not then repeat step 4.
Step 7: Using the optimal values of parameter in the SVDD model.

4. Proposed Model for the Analysis of SVDD-PSO

Fig. 2 shows the proposed work state of the art; an analysis of radiation hardens memories for fault detection is conducted with the help of the optimization technique, SVDD-PSO (Support vector data description- Particle swarm optimization). Results show that the SVDD-PSO provides better optimal fitness function 12 as compare to other optimization techniques.

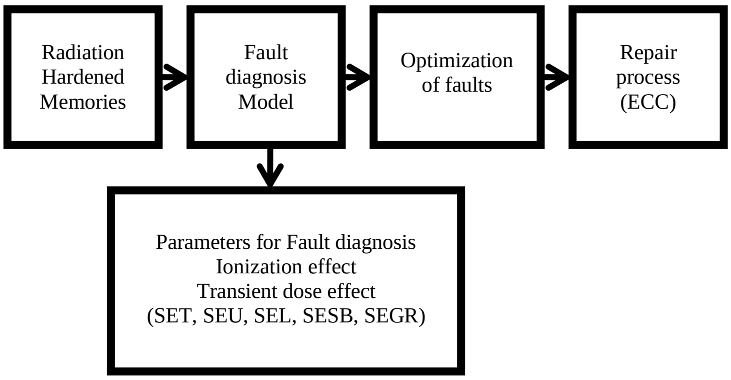

Fig. 2 Proposed Work Architecture

We have considered a memory of size 512 (8*8*8) for fault detection and to find the optimal solution for the faults that arises. Once the fault arises then finding which fault will be repair first. With the help of fault diagnosis model, several faults will be generated like stuck at fault, transition fault, address decoder fault, and other types of coupling faults based on radiation harden memory effect like ionization effect, Transient dose effect, System generated EMP Effects, Digital damage (SET). There are some other effects also which is part of the transient dose effect in radiation-hardened memories:

Single event Upset (SEU): In this high energy particle striking a memory cell which causes a flip in the state of the memory cell from 1 to 0. This type of fault in memory is called transition fault.

Single Event Functional Interrupt (SEFI): This effect occurs when a single event interrupts the memory cell's normal operation. This type of fault in memory is called Stuck at fault.

Single Event Transient (SET): These faults arise when there is temporary fluctuation in the memory cell caused by high energy particles, which leads to invalid data. These faults can be stuck at fault or transition fault.

We have considered 8*8*8 memory size with 64 faults as shown in Table 1. These faults are obtained by the fault diagnosis model parameters as shown in table 2. In this model, we have considered certain fault parameters based on which these fault are obtained. We have analyzed only stuck at fault in this paper using the SVDD-PSO method. Once the faults are identified and optimized then these faults are repaired using Error correcting code techniques [21-23].

Table 1 Stuck at faults in Memory

S.No.	Fault type	Memory size	Faults arise	Banks
1	Stuck at faults	8*8*8(512 cell)	64	32 32

Table 2 Fault Parameters

S.No	Fault Parameters	Types of faults occurs
1	Single event Upset	SAF, TF
2	Single Event Functional Interrupt	SAF
3	Digital damage	TF,SAF
4	Ionization effect	Address decoder and Coupling faults

5. Optimized Fault Diagnosis in Memories Using SVDD-PSO

An 8*8*8=512 cell memory size is considered within the fault diagnosis model. Table 1 shows 64 faults are extracted from the fault's characteristic parameters. These faults are divided into two banks of 32-bit size. We have assumed three cases of fault arise as shown in table 3. Case 1 for the total faults arises, Case 2 for upper half bank faults arises and Case 3 for lower half bank faults arises. The fitness function for three cases are measured using equation (14) and (15), Gaussian noise function is used for the absolute value of a random variable replace by a uniform random variable for the fault fitness function.

$$\text{Fitness} = (\chi * 100)^2 + (\gamma * 100)^2 \tag{14}$$

$$\text{Fun} = @(\chi)\chi(1) * \exp(\text{-norm}(\chi) * 2) \tag{15}$$

Table 3 Cases of Fault Position

Cases	Lower Bound Condition	Upper Bound Condition	Faults position
Case 1(Total faults, 64)	1,2,3,4,5,6	59,60,61,62,63, 64	2,5,10,16,28,32,38 42,48,52,59,62
Case 2(Upper half faults, 32)	1,2,3,4,5,6	27,28,29,30, 31,32	2,5,10,11,12,15,20,2 4 26,27,28,32
Case 3(lower half faults, 32)	33,34,37,38,39,40	45,48,52,58,60 62	33,34,37,38,39,40,45 ,48,52,58,60,62

6. Results and Discussion

A three case of the fault data set shown in Table 1 as input to the SVDD-PSO model; all data faults point is below the threshold level range in each case as shown in Fig. 3 to Fig. 5. The distance between these fault data points is calculated using equation (9). In these figures, 5 sets of faults are inputs into the SVDD-PSO model, and 4 sets of faults are below the threshold level which indicates that they met the fault diagnosis Model parameters.

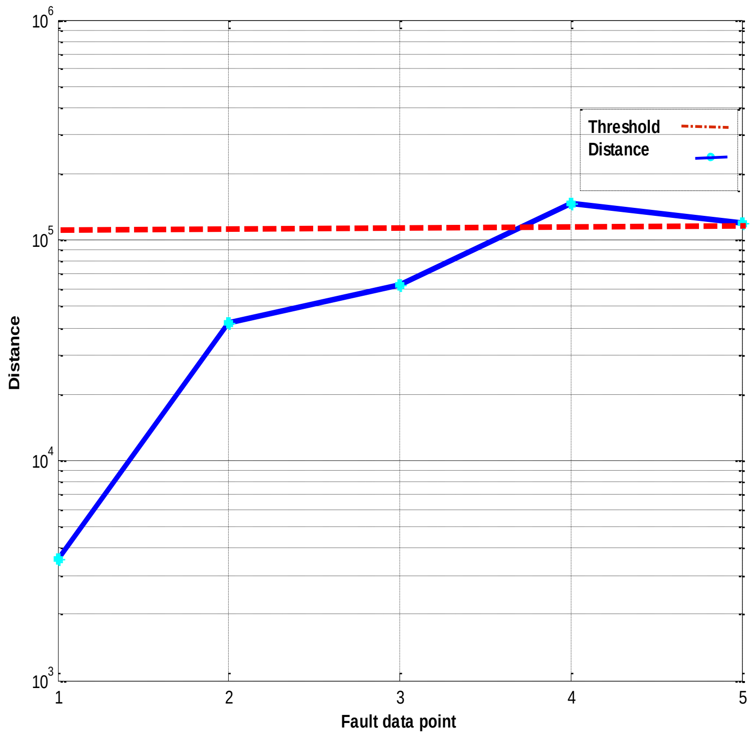

Fig. 3 Case 1(Total Faults, 64)

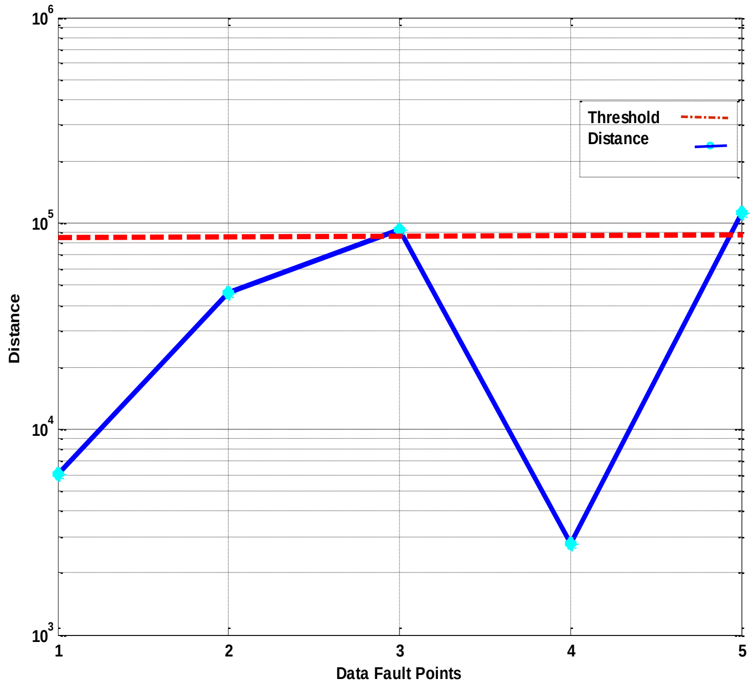

Fig. 4 Case 2(Upper Half Faults,32)

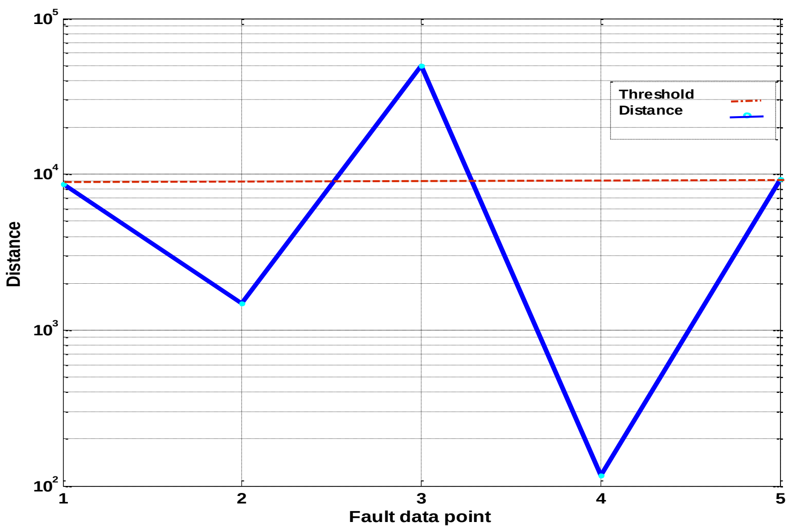

Fig. 5 Case 3(Lower Half Faults, 32)

Fig. 6 shows the comparison between three optimization techniques used for finding the value of fitness function. Particle swarm optimization, Squirrel search Algorithm-support vector data Description and support vector data Description – Particle swarm optimization. As from table 4 shows that the SVDD-PSO better fitness function than the other two algorithms.

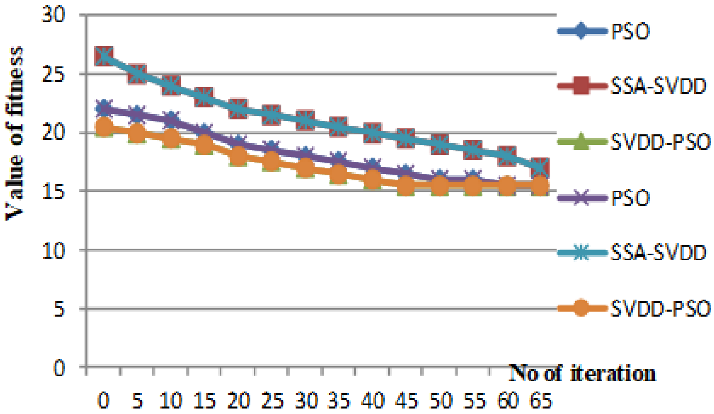

Fig. 6 Value of Fitness Function w.r.t no. Of Iteration

A SVDD-PSO Model performance is also evaluated with help logistic regression. Fig. 7 show the ROC Receiver operating characterize curve which provides the tradeoff between TPR and FPR for the model using the threshold Probability [24-26].

Table 4 Algorithms Used

S.No.	Algorithm Used	Value of fitness
1	PSO	26.5
2	SSA-SVDD	22
3	SVDD-PSO	20

TPR is the True positive rate which is ratio of true positive data to the sum of true positive and false negative where FPR is the false positive rate which is the ratio of false positive data to the sum of false positive data and true negative data as shown in equation (16) and (17).

$$\text{TPR} = \frac{TruePositive}{TruePositive + FalseNegative} \tag{17}$$

$$\text{TPR} = \frac{FalsePositive}{FalsePositive + TrueNegative} \tag{18}$$

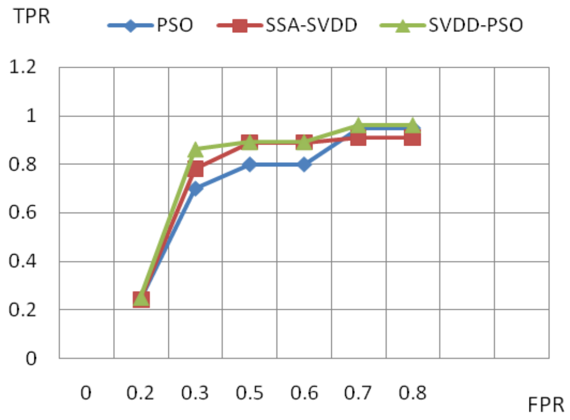

Fig. 7 ROC between TPR and FPR

From Fig. 7 ROC (Receiver operating characterize curve) of the system model is 96% which is a tradeoff between true positive rate and false positive rate for the SVDD-PSO model using the threshold Probability. A proposed Model shows higher TPR and lower FPR rate, which show that the model is fit for the fault diagnosis for radiations harden memories.

7. Conclusions

In this work, present a novel fault diagnosis and repair methodology for radiation-hardened memories using the SVDD-PSO (Support Vector Data Description - Particle Swarm Optimization) algorithm is proposed to optimize fault diagnosis and repair processes in radiation-hardened memories. A fault diagnosis model is designed using key parameters based on the characteristics of these memories. Five sets of faults are input into the SVDD-PSO model, out of which four sets fall below the threshold level, indicating that they meet the fault diagnosis model's parameters. The results demonstrate that the proposed model achieves better accuracy and an optimal fitness value with a reduced time penalty. Additionally, the model's performance is evaluated using logistic regression, and the Receiver Operating Characteristic (ROC) curve of the system shows a 96% accuracy rate, reflecting a balanced trade-off between the true positive rate (TPR) and the false positive rate (FPR). The proposed model exhibits a higher TPR and lower FPR, indicating its suitability for fault diagnosis in radiation-hardened memories. Overall, the results confirm that the proposed methodology provides improved accuracy and optimal fault detection with minimal time overhead, making it an effective solution for fault diagnosis and repair in radiation-hardened memory systems.

Future work can explore integrating hybrid meta-heuristic algorithms and adaptive threshold mechanisms to enhance fault detection accuracy and convergence speed. Additionally, expanding the model for IoT-based real-time fault monitoring and energy-efficient optimization in embedded systems is recommended.

REFERENCES

[1] A. A. Sadawi, M. S. Hassan and M. Ndiaye, "A Survey on the Integration of BlockchainWith IoT to Enhance Performance and Eliminate Challenges", *IEEE Access*, vol. 9, pp. 54478-54497, 2021.
[2] S. Lee, H. Choi, T. Kim, H. -S. Park and J. K. Choi, "A Novel Energy-Conscious Access Point (eAP) System with Cross-Layer Design in Wi-Fi Networks for Reliable IoT Services", *IEEE Access*, vol. 10, pp. 61228-61248, 2022.
[3] A. K. Shukla, S. Dhull, A. Nisar, S. Soni, N. Bindal and B. K. Kaushik, "Novel Radiation Hardened SOT-MRAM Read Circuit for Multi-Node Upset Tolerance", *IEEE Open J. Nanotechnol.*, vol. 3, pp. 78-84, 2022.
[4] M. J. Marinella, "Radiation Effects in Advanced and Emerging Nonvolatile Memories", *IEEE Trans. Nucl. Sci.*, vol. 68, no. 5, pp. 546-572, 2021.
[5] T. Li et al., "Investigation on Transient Ionizing Radiation Effects in a 4-Mb SRAM with Dual Supply Voltages", *IEEE Trans. Nucl. Sci.*, vol. 69, no. 3, pp. 340-348, 2022.
[6] G. Z. Liu et al., "Reliable and Radiation-Hardened Push-Pull pFlash Cell for Reconfigured FPGAs", *IEEE Trans. Device Mater. Reliab.*, vol. 21, no. 1, pp. 87-95, 2021.
[7] A. A. Keshavarz, T. A. Fischer, W. R. Dawes and C. F. Hawkins, "Computer Simulation of Ionizing Radiation Burnout in Power MOSFETs", *IEEE Trans. Nucl. Sci.*, vol. 35, no. 6, pp. 1422-1427, 1998.
[8] J. E. Schroeder, A. Ochoa and P. V. Dressendorfer, "Latch-Up Elimination in Bulk CMOS LSI Circuits", *IEEE Trans. Nucl. Sci.*, vol. 27, no. 6, pp. 1735-1738, 1980.
[9] N. F. Haddad, R. D. Brown, S. Doyle and S. J. Wright, "Radiation Hardened Memories for Space Applications", In Proceedings of the 2001 IEEE Aerospace Conference Proceedings, Big Sky, MT, USA, 2001, pp. 2281-2288.
[10] J. M. Benedetto, P. H. Eaton, D. G. Mavis, M. Gadlage and T. Turflinger, "Digital Single Event Transient Trends With Technology Node Scaling", *IEEE Trans. Nucl. Sci.*, vol. 53, no. 6, pp. 3462-3465, 2006.
[11] E. Xu, Y. Li, L. Peng, M. Yang and Y. Liu, "An Unknown Fault Identification Method Based on PSO-SVDD in the IoT Environment", *Alexandria Eng. J.*, vol. 60, no. 4, pp. 4047-4056, 2021.
[12] B. Tran, B. Xue and M. Zhang, "A New Representation in PSO for Discretization-Based Feature Selection", *IEEE Trans. Cybern.*, vol. 48, no. 6, pp. 1733-1746, 2018.
[13] M.-C. Chen, C.-C. Hsu, B. Malhotra and M. Kumar Tiwari, "An Efficient ICA-DW-SVDD Fault Detection and Diagnosis Method for Non-Gaussian Processes", *Int. J. Prod. Res.*, vol. 54, no. 17, pp. 5208-5218, 2016.
[14] J. L. Fernandez-Martinez and E. Garcia-Gonzalo, "Stochastic Stability Analysis of the Linear Continuous and Discrete PSO Models", *IEEE Trans. Evol. Comput.*, vol. 15, no. 3, pp. 405-423, June 2011.
[15] H. Y. Teh, K. I. -K. Wang and A. W. Kempa-Liehr, "Expect the Unexpected: Unsupervised Feature Selection for Automated Sensor Anomaly Detection," *IEEE Sensors J.*, vol. 21, no. 16, pp. 18033-18046, 2021.
[16] V. Mathur, A. K. Pundir, R. K. Gupta and S. K. Singh, "Recrudesce: IoT-Based Embedded Memories Algorithms and Self-healing Mechanism", In Proceedings of Congress on Control, Robotics, and Mechatronics (CRM 2023), vol 364. Springer, Singapore, 2024.
[17] V. Mathur, A. K. Pundir, S. Singh, S. K. Singh, "An Insight into Algorithms and Self Repair Mechanism for Embedded Memories Testing", In Proceedings of the Flexible Electronics for Electric Vehicles (FLEXEV 2022) in *Lecture Notes in Electrical Engineering*, vol 1065, p. 48, Springer, Singapore, 2024.
[18] G. Noarov, R. Ramalingam, A. Roth, and S. Xie, "High-Dimensional Unbiased Prediction for Sequential Decision Making," presented at the *Optimization for Machine Learning Conference (OPT 2023)*, 2023.
[19] E. Gyamfi and A. D. Jurcut, "Novel Online Network Intrusion Detection System for Industrial IoT Based on OI-SVDD and AS-ELM," *IEEE Internet of Things J.*, vol. 10, no. 5, pp. 3827-3839, 2023.
[20] D. Zhang, W. Xiang and Q. Cao, "Application of Incremental Support Vector Regression Based on Optimal Training Subset and Improved Particle Swarm Optimization Algorithm in Real-Time Sensor Fault Diagnosis", vol. 51, pp. 3323-3338, 2021.
[21] D. Wenliao, G. Zhiqiang, W. Liangwen, L. Ansheng and W. Zhiyang, "Intelligent Fault Diagnosis of Plunger Pump in Truck Crane Based on a Hybrid Fault Diagnosis Scheme", In Proceeding of the 11th World Congress on Intelligent Control and Automation, Shenyang, China, 2014, pp. 5361-5365.
[22] R. Singh and B. Bhushan, "Data-Driven Technique-Based Fault-Tolerant Control for Pitch and Yaw Motion in Unmanned Helicopters", *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1-11, 2021.
[23] A. Amar, V. T. Alaparthy and S. D. Morgera, "A Machine Learning Based Intrusion Detection System for Mobile Internet of Things", *Sensors*, vol. 20, no. 2, pp. 461-465, 2020.
[24] V. Mathur, S. Singh and A. Pundir, "An investigation of augment March C - algorithm using IoT: heuristic approach", *Comput. Technol.*, vol. 29, no. 4, pp. 110-121, 2024.
[25] A. Bin Queyam, R. Kumar Meena, S. Kumar Pahuja and D. Singh, "An IoT Based Multi-Parameter Data Acquisition System for Efficient Bio-Telemonitoring of Pregnant Women at Home", In Proceedings of the 2018 8th International Conference on Cloud Computing, Data Science and Engineering (Confluence), Noida, India, 2018, pp. 14-15.
[26] M. J. Marinella, "Radiation Effects in Advanced and Emerging Nonvolatile Memories", *IEEE Trans. Nucl. Sci.*, vol. 68, no. 5, pp. 546-572, 2021.