Hybrid Modeling-Based Density Peak Clustering for Functional Test-Cost Reduction

1st Lei Zhang
AHU-IAI AI Joint Laboratory,
Anhui University
Institute of Artificial Intelligence,
Hefei Comprehensive National Science Center
Hefei, China
wa22201150@stu.ahu.edu.cn

2rd Yun-Bo Zhao
Department of Automation, USTC
Institute of Artificial Intelligence,
Hefei Comprehensive National Science Center
Institute of Advanced Technology, USTC
Hefei, China
ybzhao@ustc.edu.cn

3th Yu Kang
Department of Automation, USTC
Institute of Artificial Intelligence,
Hefei Comprehensive National Science Center
Institute of Advanced Technology, USTC
Hefei, China
kangduyu@ustc.edu.cn

4nd Kangcheng Wang
Institute of Artificial Intelligence,
Hefei Comprehensive National Science Center
AHU-IAI AI Joint Laboratory,
Anhui University
Hefei, China
kcwang@iai.ustc.edu.cn

5th Peng Bai
Department of Automation, USTC
Hefei, China
baipeng@lenovo.com

2025 37th Chinese Control and Decision Conference (CCDC) | 979-8-3315-1056-5/25/$31.00 ©2025 IEEE | DOI: 10.1109/CCDC65474.2025.11090410

***Abstract*—As the complexity of integrated circuits increases, so does the cost of the functional testing processes necessary to ensure the quality of electronic products. Reducing testing costs has become an urgent priority for electronic manufacturers. This article proposes a density peak clustering algorithm based on a hybrid mechanism-data modeling approach. A fault tree is employed to analyze the functional testing process of a motherboard, and the analyzed mechanistic information is effectively integrated with data information. This hybrid information is utilized to enhance the calculation of local density and relative distance within the density peak clustering algorithm. The enhanced density peak clustering algorithm is applied to cluster board-level functional testing items and to develop an optimized testing strategy. Compared to the classic density peak clustering algorithm, the proposed method reduces the average total testing cost of the board-level functional test by 26.90%.**

***Index Terms*—Mechanism-data hybrid modeling, density peak clustering, functional testing, cost reduction.**

I. Introduction

Functional testing is a crucial process for ensuring product quality in manufacturing by assessing the functionality of electronic components. It is widely utilized in different types of electronic manufacturing lines [1]. As the complexity of integrated circuits increases, the costs associated with functional testing are also on the rise [2]. Consequently, reducing the expenses related to functional testing has become an urgent need for electronic manufacturers [3].

This work was supported by the Key Research and Development Program of Anhui (No. 202104a05020064), (Corresponding authors: Yu Kang, Kangcheng Wang).

In real-world production, functional testing is typically divided into two categories: board-level and system-level functional testing. This approach helps reduce rework costs by testing the motherboard of the product in advance [4]. Board-level testing generally employs a selective testing strategy, meaning that only a portion of the board and certain testing items are assessed [5]. Since the board-level functional testing strategy directly influences testing duration and the rework costs associated with defective motherboards or final products, which in turn affects the overall cost of testing, developing an efficient testing strategy is crucial for cost reduction [6].

Test selection and test ordering are two common methods for designing functional testing strategies. The former effectively reduces the testing costs of the board by evaluating only a portion of the testing items [7], while the latter can only reduce the testing costs of defective boards by altering the order of the testing items [8]. Consequently, test selection can significantly lower testing costs compared to test ordering, particularly in processes with a high yield [9]. Recent studies indicate that test selection has emerged as the predominant strategy for various circuits [10, 11].

Current test selection strategies typically evaluate whether a testing item is assessed individually, without considering the similarities among testing items. Since the corresponding modules of these testing items are located on the same board, and some modules are often interrelated, the testing results for these items tend to be similar. By employing clustering algorithms to group testing items based on their similarities, we can effectively leverage this relationship when selecting items from these clusters. Some studies have utilized clustering algorithms to achieve feature selection [12–14]. However, these clustering algorithms have limitations, including the need to artificially specify the number of clusters and their limited effectiveness in clustering non-clustered data. The density peak clustering (DPC) algorithm [15] has significantly improved upon classic clustering methods in various aspects. It does not require the pre-specification of the number of clusters and has lower demands regarding data distribution. Consequently, DPC has been widely studied and applied in recent years [16, 17]. However, current DPC algorithms and their enhanced versions primarily perform direct clustering on the collected data, failing to fully exploit the mechanistic information of the underlying processes. As a result, they tend to overfit in practical applications, necessitating further investigation.

Based on the analysis presented above, this article proposes an enhanced DPC algorithm that utilizes a mechanism-data hybrid modeling approach. Additionally, it develops a test selection method based on the enhanced algorithm to reduce the costs associated with functional testing. A fault tree is employed to identify the mechanistic information of the board-level functional testing process. This information is then effectively integrated with the process data to enhance the calculation of local density and relative distance for the DPC algorithm. The improved DPC algorithm is subsequently used to cluster functional testing items and determine the board-level functional testing strategy. The effectiveness of the enhanced algorithm and the developed strategy is validated using simulation data that closely resembles actual data.

The rest of the article is organized as follows: Section II introduces a DPC algorithm based on a hybrid mechanism-data modeling approach and outlines a test selection method based on the improved DPC algorithm. Section III conducts simulation experiments designed to verify the effectiveness of the proposed method. The article concludes with a summary.

II. METHOD

In this section, the calculation of local density and relative distance in the DPC algorithm has been enhanced by integrating data correlation and mechanism correlation.

A. Hybrid Modeling

In this subsection, we quantitatively analyze the data and mechanistic information from relevant industrial processes and incorporate it into a hybrid similarity.

Firstly, the Jaccard similarity coefficient is used to quantitatively analyze the correlation between data sets. The Jaccard similarity coefficient focuses only on the consistency of features between individuals compared to other correlation methods. For sets A and B, the Jaccard similarity coefficient represents the ratio of the number of elements in their intersection to the number of elements in their union. A larger Jaccard coefficient indicates a higher degree of similarity between the samples. The Jaccard coefficient is calculated as follows:

$$R_d = \frac{|A \cap B|}{|A \cup B|} \tag{1}$$

where R_d denotes the data correlation between sets A and B, $|A \cap B|$ denotes the number of elements in the intersection of sets A and B, and $|A \cup B|$ denotes the number of elements in the union of sets A and B.

The fault tree is used to quantitatively analyze the mechanism correlation. In fault tree analysis, events are categorized as top events, intermediate events, and basic events according to their causal relationships. Top events refer to the undesired failure states of the system. Basic events are those for which it is either impossible or unnecessary to further investigate the cause of the failure. Intermediate events are the factors that lead to the occurrence of the top event, aside from the basic events. If a basic event occurs multiple times within the fault tree and influences several intermediate events, it is considered a common cause, leading to a correlation between intermediate events. Different intermediate events correspond to different sets of basic events. The mechanism correlation is defined as the ratio of the number of elements in the intersection of various sets of basic events to the number of elements in the union of those sets, which can be calculated as follows:

$$R_m = \frac{Q_s}{Q_a} \tag{2}$$

where Q_s denotes the number of elements in the intersection of various sets of basic events, and Q_a denotes the number of elements in the union of these sets.

Later, R'_d and R'_m are derived by normalizing the data correlation and mechanism correlation of the research attribute, respectively. The hybrid correlation of the research attribute is then calculated using the following formula:

$$R_{jk} = \frac{R'_d + R'_m}{2}, \quad j,k = 1,...,m \tag{3}$$

where j and k denote the indices of the research attributes, and m represents the total number of research attributes.

B. Revised DPC

In this subsection, the computation methods for local density ρ and relative distance δ in the density peak clustering algorithm have been enhanced based on the correlation metrics obtained from hybrid modeling. This improvement aims to enhance the effectiveness of clustering on manufacturing data.

The computation method for the local density ρ_j of the attribute M_j has been improved. To highlight the differences in the local density of research attributes, a Gaussian kernel function is utilized to calculate the local density of samples, rather than merely counting the number of samples within the truncation distance. The local density is calculated using the following formula:

$$\rho_j = \sum_{k \neq j} \exp\left[-\left(d_{jk} \cdot d_c^{-1}\right)^2\right] \tag{4}$$

where d_c denotes the truncation distance and d_{jk} denotes the distance between two samples.

In cluster analysis, a smaller distance d_{jk} indicates a greater similarity between samples. The greater the likelihood that research attributes with higher similarity will be grouped into the same cluster. The hybrid correlation R_{jk} denotes the similarity of research attributes using both data and mechanistic information. A higher hybrid correlation among research attributes signifies greater similarity, which is inversely proportional to the distance between samples. Therefore, the hybrid correlation R_{jk} is used to calculate the distance d_{jk} between samples. The computation method for the local density ρ_j of the attribute M_j can be enhanced as follows:

$$\rho_j = \sum_{k \neq j} \exp\left[-\left(R_{jk}^{-1} \cdot d_c^{-1}\right)^2\right] \tag{5}$$

The computational method for calculating the relative distance δ_j of the attribute M_j has been enhanced. If a data point is the one with the highest local density, its relative distance is defined as the distance to the data point that is furthest from it. Conversely, if the data point does not have the highest local density, the relative distance will be determined by the distance to the nearest data point that has a higher local density. The relative distance is calculated as follows:

$$\delta_j = \begin{cases} \max\limits_k\{d_{jk}\}, & \rho_j > \rho_k \text{ for } \forall k \\ \min\limits_k\{d_{jk} | \rho_k > \rho_j\}, & \text{otherwise} \end{cases} \tag{6}$$

In calculating relative distance, the hybrid correlation R_{jk} is utilized to assess the distance d_{jk}. Therefore, the method for calculating relative distance can be improved as follows:

$$\delta_j = \begin{cases} \max\limits_k\{R_{jk}^{-1}\}, & \rho_j > \rho_k \text{ for } \forall k \\ \min\limits_k\{R_{jk}^{-1} | \rho_k > \rho_j\}, & \text{otherwise} \end{cases} \tag{7}$$

The derived local density and relative distance of each research attribute are combined as follows:

$$D = \{(\rho_1, \delta_1), ..., (\rho_m, \delta_m)\} \tag{8}$$

All samples are subsequently projected onto a coordinate system to generate a decision map, where the horizontal and vertical coordinates are represented by ρ and δ, respectively. The decision values are then calculated as follows:

$$\gamma_j = \rho_j \cdot \delta_j \tag{9}$$

Select the half of the samples with larger γ_i values to serve as candidate points for the clustering centers.

Due to uncertainty regarding the number of clustering centers and their impact on clustering, the silhouette coefficient (SC) is used to evaluate the effectiveness of clustering produced by various clustering centers as follows:

$$\mathrm{SC} = \frac{1}{m} \sum_{j=1}^{m} \frac{b_j - a_j}{\max(a_j, b_j)} \tag{10}$$

where a_j denotes the average distance from the attribute M_j to all other samples within the same clustering group, and b_j denotes the average distance from the attribute M_j to all other samples in different clustering groups.

Enumerate all combinations of candidate points for clustering centers. For each combination, the remaining points are grouped in descending order of local density into the cluster associated with the nearest neighbor that has a higher local density. Then, the silhouette coefficient of each cluster is calculated. The clustering result that yields the highest silhouette coefficient is selected as the final clustering result, and the corresponding clustering centers are the final clustering centers.

C. DPC-Based Functional Test Selection

In this subsection, the revised DPC algorithm, which integrates the correlations of data and mechanism, is applied in the functional testing process to develop a testing strategy.

The test results of testing items contain only faulty or good results (0 or 1); therefore, the formula of Jaccard similarity coefficient is materialized into binary data of the functional test. It classifies test samples based on whether the testing items have passed the functional test. The data correlation metric is calculated as the ratio of samples with identical test results to the total number of samples, as represented by the following formula:

$$R_d = \frac{Q_{00} + Q_{11}}{Q_{00} + Q_{10} + Q_{01} + Q_{11}} \tag{11}$$

where Q_{00} denotes the number of samples in which both items failed the functional test, Q_{10} and Q_{01} denote the number of samples in which one item failed while the other passed the test, and Q_{11} denotes the number of samples in which both items passed the test.

The mechanism correlation between testing items is evaluated based on the mechanistic information of the motherboard components. To quantitatively analyze the mechanism correlation of functional testing items, this article utilizes a fault tree tailored to the functional testing of a typical laptop motherboard [18]. In the fault tree, the failure of the motherboard is identified as the top event, the failures of the testing items are categorized as intermediate events, and the causes of the testing items' failures are classified as basic events. The indices of the basic events corresponding to the intermediate events are presented in Table I.

The $\mathrm{M_j}$ in Table I denotes the jth intermediate event, and the occurrence of $\mathrm{M_j}$ indicates the failure of the jth testing item. The sets of basic events are derived through fault tree analysis. The detailed procedures for conducting the fault tree analysis were outlined in Ref. [18]. The mechanism correlation for each testing item is calculated using Eq. (2).

The correlations of data and mechanism are normalized separately, and the hybrid correlation is calculated by Eq. (3).

The improved DPC algorithm computes the local density and relative distance of all test items. Subsequently, a clustering decision map is generated, and the decision values for all test item samples are calculated to identify potential clustering center candidates. Various combinations of candidate test items are selected, and the remaining test item samples are assigned to obtain the clustering results. Following this, the corresponding silhouette coefficient values are calculated. The clustering results associated with the maximum silhouette coefficient value are chosen as the final clustering results.

TABLE I
THE INDICES OF BASIC EVENTS CORRESPONDING TO INTERMEDIATE EVENTS

Symbol	Intermediate events	Indices of basic events
M_1	WWAN failure	$\{1, \cdots, 12\}$
M_2	Keyboard failure	$\{3, \cdots, 8, 10, 13\}$
M_3	Fan failure	$\{3, \cdots, 8, 10, 21\}$
M_4	G-sensor failure	$\{3, \cdots, 8, 10, 22\}$
M_5	Lid failure	$\{3, \cdots, 8, 10, 23\}$
M_6	Trackpad failure	$\{3, \cdots, 8, 10, 24\}$
M_7	Trackpoint failure	$\{3, \cdots, 8, 10, 25\}$
M_8	HDMI failure	$\{3, \cdots, 12, 14, 15\}$
M_9	LVDS failure	$\{3, \cdots, 12, 26, 27\}$
M_{10}	Fingerprint failure	$\{3, \cdots, 12, 16, 17\}$
M_{11}	Camera failure	$\{3, \cdots, 12, 17, 28\}$
M_{12}	Panel failure	$\{3, \cdots, 12, 18, 19\}$
M_{13}	Bluetooth failure	$\{3, \cdots, 12, 17, 20\}$
M_{14}	WLAN failure	$\{2, \cdots, 12\}$
M_{15}	Speaker failure	$\{3, \cdots, 12, 29, 31, 32\}$
M_{16}	Microphone failure	$\{3, \cdots, 12, 30, 31, 32\}$

The clustering center testing item is selected as a testing item, while all other testing items are excluded to determine the testing strategy $\boldsymbol{S} \in \{0, 1\}^m$, where $S_j = 1$ if the jth item is the clustering center, while $S_j = 0$ otherwise. Specifically, $S_j = 1$ denotes that the jth item is a tested functional item, whereas $S_j = 0$ indicates that the jth item is a non-testing functional item.

The flowchart illustrating the proposed hybrid modeling-based density peak clustering for reducing functional test costs is presented in Fig. 1.

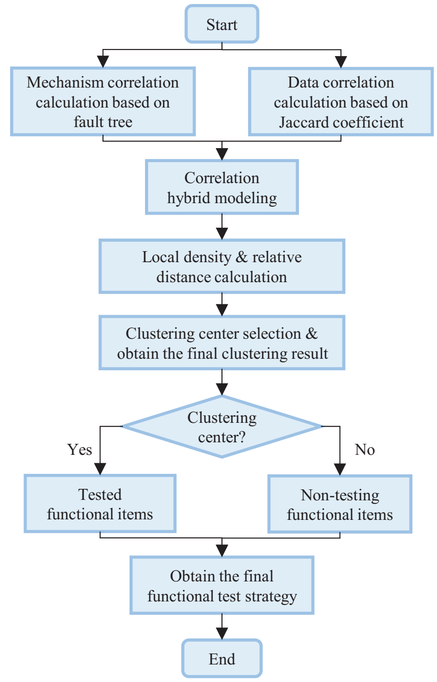

Fig. 1. The flowchart illustrating hybrid modeling-based DPC for reducing functional testing costs

D. Evaluation Criterion

This article employs the false negative rate, average testing time, and average testing cost as evaluation criteria. These criteria reflect the ability to intercept false negative boards, time efficiency, and the overall cost of testing strategies.

The false negative rate under the testing strategy $\boldsymbol{S}$ can be determined through the following statistical analysis: If the test results for the item yield a value of 0, the board will be classified as a detected defective board. The formula for determining whether the ith motherboard is classified as a detected defective board is as follows:

$$T_i = \begin{cases} 1, & T_{ij} = 0, j \in U(\boldsymbol{S}) \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where T_{ij} represents the functional test result of the jth test item on the ith motherboard, and $U(\boldsymbol{S})$ denotes the set of test items involved in the functional test according to the test strategy $\boldsymbol{S}$. The total number of defective boards identified under the test strategy $\boldsymbol{S}$ can be determined by counting the number of defective boards detected among all motherboards, as calculated by the following formula:

$$N_d(\boldsymbol{S}) = \sum_{i=1}^{N} T_i \tag{13}$$

where N is the number of motherboards involved in the functional test.

The number of false negative boards under the test strategy $\boldsymbol{S}$ can be determined by subtracting the number of detected defective boards from the total number of defective boards. This can be calculated as follows:

$$N_m(\boldsymbol{S}) = N_e - N_d(\boldsymbol{S}) \tag{14}$$

where N_e denotes the total number of defective boards.

The ratio of undetected defective motherboards to the total number of defective motherboards is referred to as the false negative rate, which can be calculated as follows:

$$P_m(\boldsymbol{S}) = \frac{N_m(\boldsymbol{S})}{N_e} \tag{15}$$

The average rework cost associated with the test strategy $\boldsymbol{S}$ can be calculated as follows:

$$C_r(\boldsymbol{S}) = \frac{C_r^0 N_m(\boldsymbol{S})}{N} \tag{16}$$

where the rework cost refers to the rework time, C_r^0 denotes the average rework time per defective board.

The average testing time is the mean of the testing time for each board, calculated as follows:

$$C_t(\boldsymbol{S}) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j \in U(\boldsymbol{S})} (C_t^0)_{ij} \tag{17}$$

where $U(\boldsymbol{S})$ denotes the set of testing items under $\boldsymbol{S}$, and $(C_t^0)_{ij}$ denotes the testing time of the jth testing item on the ith board.

The average testing cost is the sum of the average rework cost and the average testing time. It is calculated as follows:

$$C_p(\boldsymbol{S}) = C_r(\boldsymbol{S}) + C_t(\boldsymbol{S}) \tag{18}$$

Based on the above formulas, the evaluation criteria of each testing strategy are calculated and compared to verify the effectiveness of the proposed method.

III. Simulation Study

A. Data Generation

In this section, the effectiveness of the proposed method will be evaluated through simulation experiments. The defect rate of a testing item refers to the probability of failure during board-level functional testing. To safeguard the commercial confidentiality of the laptop motherboard manufacturer, this simulation experiment does not display the actual defect rates and testing times of the test items. Subsequently, a series of binary values (0 or 1) is generated as the simulation testing results based on the defect rates of the testing items, where a result of 0 indicates a failure of the testing item, and a result of 1 indicates that the testing item is functioning properly.

The simulation testing dataset, which contains the testing results of 16 items across 1×10^6 motherboards (including 112 defective motherboards), was generated based on the aforementioned steps. The defect rate and testing time for each testing item in the simulation testing dataset is presented in Table II.

TABLE II
THE DEFECT RATE AND TESTING TIME OF EACH TESTING ITEM IN BOARD-LEVEL FUNCTIONAL TESTING

Testing items	Defect rate ($\times 10^{-3}$)	Testing time (s)
WWAN test	0.55	5.72
Keyboard test	0.36	0.13
Fan test	0.56	19.13
G-sensor test	0.31	16.61
Lid test	0.47	17.56
Trackpad test	0.57	3.78
Trackpoint test	0.34	6.33
HDMI test	0.69	3.12
LVDS test	0.93	9.69
Fingerprint test	0.86	9.50
Camera test	1.08	0.26
Panel test	0.87	0.11
Bluetooth test	1.07	8.57
WLAN test	1.12	2.18
Speaker test	0.96	3.78
Microphone test	0.97	5.17

B. Ablation Study

Apart from the revised algorithm of the proposed method, the study also includes three additional experiments corresponding to three ablation algorithms: one is the DPC algorithm based solely on the distance metric of data correlation (Data-DPC), another is the DPC algorithm based solely on the distance metric of mechanism correlation (Mechanism-DPC), and the third is the classic DPC algorithm based on the Euclidean distance metric of yield and test time (Classic-DPC). The revised DPC algorithm of the proposed method is the DPC algorithm based on the distance metric of hybrid correlation (Hybrid-DPC).

The four DPC algorithms, which utilize different distance metrics, are employed to complete the correlation measure and clustering of the functional testing items in the input simulation test data set. The testing strategy is then established based on the results of this clustering.

The optimal clustering results for each algorithm are presented in Table III. This table includes various numbered arrays that correspond to the clustering groups of different testing items, with the first item number in each group representing the item number of the clustering center. The test strategies and evaluation criteria for the different algorithms are detailed in Table IV and Table V, respectively.

C. Result Analysis

The results corresponding to the evaluation indicators for each clustering algorithm are presented in Table V. The Hybrid-DPC algorithm demonstrates superior performance compared to all other algorithms across all criteria. This indicates that the testing strategy developed by the Hybrid-DPC algorithm is more effective in identifying defective motherboards and reducing testing time, ultimately resulting in a significant reduction in total testing costs.

The Mechanism-DPC algorithm has the same number of false negative boards as the Hybrid-DPC algorithm; however, it incurs significantly longer testing times (as shown in Table V), resulting in a higher overall testing cost.

The Classic-DPC algorithm exhibits the highest number of false negative boards among all algorithms, followed by the Data-DPC algorithm. The Data-DPC algorithm also has a notably shorter testing time, which contributes to lower overall testing costs. Among all algorithms, the Classic-DPC algorithm not only has the highest number of false negative boards but also the longest testing time, resulting in a total testing cost that is higher than that of the other algorithms.

The analysis above demonstrates that the Data-DPC algorithm and the Mechanism-DPC algorithm effectively reduce testing time and the number of false negative boards by incorporating data and mechanistic information from the testing process, respectively. As a result, they achieve a total testing cost that is lower than that of the Classic-DPC algorithm. Additionally, the Hybrid-DPC algorithm decreases both testing time and the number of false negative boards by simultaneously integrating process data and mechanistic information, leading to an even greater reduction in overall testing costs.

IV. Conclusion

This article proposes an enhanced density peak clustering algorithm based on mechanism-data hybrid modeling. It introduces a test selection method aimed at reducing the costs associated with functional testing. A fault tree is employed to analyze the mechanistic information of the board-level

TABLE III
THE OPTIMAL CLUSTERING RESULTS FOR VARIOUS CLUSTERING ALGORITHMS

Clustering algorithm	Optimal clustering results
Hybrid-DPC	[**1**], [**3**, 2, 4, 5, 7], [**6**], [**8**], [**9**, 10, 11, 13, 14], [**12**], [**15**], [**16**]
Data-DPC	[**2**], [**4**], [**5**, 1, 3, 6, 8], [**7**], [**9**, 11, 13, 14, 15, 16], [**10**], [**12**]
Mechanism-DPC	[**2**], [**3**], [**4**], [**5**], [**6**], [**7**], [**15**, 1, 8, 9, 10, 11, 12, 13, 14, 16]
Classic-DPC	[**1**], [**2**], [**4**, 12, 13, 14, 16], [**5**], [**6**], [**7**, 11, 15], [**8**, 3, 9, 10]

TABLE IV
TESTING STRATEGIES DERIVED FROM VARIOUS CLUSTERING ALGORITHMS

Clustering algorithm	Number of functional testing items															
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Hybrid-DPC	1	0	1	0	0	1	0	1	1	0	0	1	0	0	1	1
Data-DPC	0	1	0	1	1	0	1	0	1	1	0	1	0	0	0	0
Mechanism-DPC	0	1	1	1	1	1	1	0	0	0	0	0	0	0	1	0
Classic-DPC	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0

TABLE V
EVALUATION CRITERIA FOR VARIOUS CLUSTERING ALGORITHMS

Clustering algorithm	False negative rate		Average testing time		Average testing cost	
	Value	Relative change	Value	Relative change	Value	Relative change
Hybrid-DPC	**0.1250**	\	**48.5141**	\	**49.0181**	\
Data-DPC	0.1875	33.3333%	54.5087	10.9975%	55.2647	11.3031%
Mechanism-DPC	**0.1250**	0.0000%	65.0135	25.3784%	65.5175	25.1832%
Classic-DPC	0.3829	67.4419%	65.5114	25.9456%	67.0594	26.9035%

functional testing process, which is then integrated with process data to enhance the calculation of local density and relative distance within the density peak clustering algorithm. The enhanced clustering algorithm is utilized to categorize functional testing items and develop a board-level testing strategy. Compared to the classic DPC algorithm, the proposed method reduces the average total testing cost of the board-level functional test by 26.90%.

REFERENCES

[1] D. Piumatti, S. Borlo, M. S. Reorda, and I. R. Bojoi, "Assessing the effectiveness of different test approaches for power devices in a PCB," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 9, no. 3, pp. 3671–3685, Jun. 2021.

[2] P. Bai, K. Wang, Y.-B. Zhao, Y. Kang, and W. Fang, "Functional test-cost reduction based on optimization modeling and congestion control," in *2024 14th Asian Control Conference (ASCC)*, Jul. 2024, pp. 1–6.

[3] I. Pomeranz, "Functional design-for-testability for functional test sequences," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, pp. 1–8, 2024.

[4] P. Bai, Y. Kang, K. Wang, Y. Zhao, and S. Dong, "Modelling and optimizing motherboard functional testing in laptop manufacturing," *Journal of Systems Science & Complexity*, vol. 37, no. 6, pp. 2406–2423, Sep. 2024.

[5] E. Afacan, N. Lourenço, R. Martins, and G. Dündar, "Review: Machine learning techniques in analog/RF integrated circuit design, synthesis, layout, and test," *Integration*, vol. 77, pp. 113–130, Mar. 2021.

[6] I. Pomeranz, "Partitioning functional test sequences into multicycle functional broadside tests," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. 29, no. 1, pp. 89–99, Jan. 2021.

[7] S. Hałgas, "Soft fault diagnosis in linear circuits: Test selection and non-iterative identification procedure," *Measurement*, vol. 217, p. 113061, Aug. 2023.

[8] W. Zhan and L. Zhang, "Reordering method of test set based on vector eigenvalues using critical area estimation," *Integration*, vol. 96, p. 102169, May 2024.

[9] R. Pan, Z. Zhang, X. Li, K. Chakrabarty, and X. Gu, "Black-box test-cost reduction based on Bayesian network models," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 40, no. 2, pp. 386–399, Feb. 2021.

[10] M. Liu, R. Pan, F. Ye, X. Li, K. Chakrabarty, and X. Gu, "Fine-grained adaptive testing based on quality prediction," *ACM Transactions on Design Automation of Electronic Systems*, vol. 25, no. 5, pp. 1–25, Jul. 2020.

[11] Y. Li, X. Wang, N. Lu, and B. Jiang, "Conditional joint distribution-based test selection for fault detection and isolation," *IEEE Transactions on Cybernetics*, vol. 52, no. 12, pp. 13 168–13 180, Dec. 2022.

[12] P. Zhou, J. Chen, M. Fan, L. Du, Y.-D. Shen, and X. Li, "Unsupervised feature selection for balanced clustering," *Knowledge-Based Systems*, vol. 193, p. 105417, Apr. 2020.

[13] M. Capo, A. Perez, and J. A. Lozano, "A cheap feature selection approach for the k-means algorithm," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 5, pp. 2195–2208, May 2021.

[14] X.-F. Song, Y. Zhang, D.-W. Gong, and X.-Z. Gao, "A fast hybrid feature selection based on correlation-guided clustering and particle swarm optimization for high-dimensional data," *IEEE Transactions on Cybernetics*, vol. 52, no. 9, pp. 9573–9586, Sep. 2022.

[15] Y. Wang, J. Qian, M. Hassan, X. Zhang, T. Zhang, C. Yang, X. Zhou, and F. Jia, "Density peak clustering algorithms: A review on the decade 2014–2023," *Expert Systems with Applications*, vol. 238, p. 121860, Mar. 2024.

[16] W. Guo, W. Wang, S. Zhao, Y. Niu, Z. Zhang, and X. Liu, "Density peak clustering with connectivity estimation," *Knowledge-Based Systems*, vol. 243, p. 108501, May 2022.

[17] X. Fang, Z. Xu, H. Ji, B. Wang, and Z. Huang, "A grid-based density peaks clustering algorithm," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 4, pp. 5476–5484, Apr. 2023.

[18] Y. Li, K. Wang, Y. Kang, Y. Zhao, and P. Bai, "Board-level functional test selection based on fault tree analysis," in *2023 6th International Symposium on Autonomous Systems (ISAS)*, vol. 5. IEEE, Jun. 2023, pp. 1–6.