Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 4, August 2025, pp. 2889~2898
ISSN: 2302-9285, DOI: 10.11591/eei.v14i4.9058

Surface-mount device design cycle time reduction using hybrid predictive modeling and optimization algorithm

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Article Info

Article history:

Received Jul 26, 2024
Revised Mar 21, 2025
Accepted May 27, 2025

Keywords:

Convolutional neural networks
Design optimization
Hybrid algorithm approach
Monte Carlo simulation
Predictive modeling
Simulated annealing

ABSTRACT

This study develops a hybrid predictive and optimization model for surface-mount device (SMD) design, addressing the extended design cycle times in the semiconductor industry caused by high computational demands. Challenges are tackled effectively through integration of convolutional neural network (CNN) for high-accuracy predictions and simulated annealing (SA) algorithm for optimization of SMD physical parameters. CNN model that trained on Monte Carlo simulation (MCS) data, achieved a predictive accuracy of 99.91% in forecasting SMD design errors. Concurrently, SA algorithm refined design parameters and substantially reducing error rates to nearly zero after 800 iterations. Our results indicate that combining predictive modeling with an optimization algorithm significantly enhances SMD design efficiency, providing a robust tool for mitigating time-to-market risks in semiconductor manufacturing.

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1. INTRODUCTION

In the rapidly evolving field of electronics manufacturing, surface-mount device (SMD) technology plays a crucial role in enhancing device miniaturization. While previous research has explored various aspects of SMD design optimization, there remains a significant gap in effectively integrating predictive modeling with optimization techniques to reduce design cycle times. Most existing studies focus on either enhancing predictive accuracy or optimizing the manufacturing process separately. They often fall short of providing a holistic approach that combines both elements to tackle the complexities of SMD designs, particularly under varying manufacturing conditions [1]. One of the critical challenges in SMD manufacturing is the high rate of dimensional and placement errors, which lead to considerable yield losses. Traditional design methods, predominantly reliant on trial-and-error, often fail to manage the intricate interactions among various design parameters influenced by stochastic variables in the production environment [2], [3].

Recent advancements in Monte Carlo simulations (MCS) provide a solution that goes beyond trial-and-error methods. Yet, this method posts a new challenge to design cycle time which is often extended due to the reliance on significant computational resources for simulation. This research primarily addresses the reduction of design cycle times, highlighting the importance of an advanced predictive approach that leverages MCS data. This approach streamlines the design process by avoiding multiple simulation runs that lead to high computational loads, as illustrated in Figure 1.

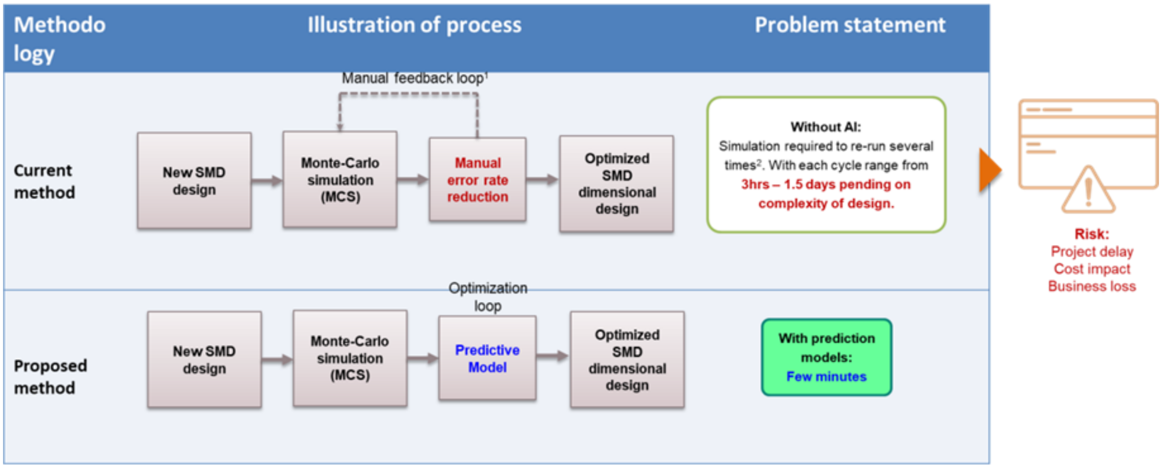


Figure 1. Illustration on how predictive model benefits in SMD design cycle

While MCS provides detailed insights into complex systems by exploring a range of possible outcomes [4], [5] and predictive models such as convolutional neural network (CNN) excel in pattern recognition, particularly in analyzing visual and spatial data [6]. However, the integration of these technologies in SMD design optimization remains underexplored.

This research proposes a novel integration of MCS data with a best performing predictive model to develop a predictive framework for SMD design. This approach is then further enhanced by hybridize simulated annealing (SA) optimization algorithm, which refines the design parameters iteratively based on the predictions from models, aiming to minimize errors effectively. This synergy enables the predictive model to handle complex, multi-dimensional data sets and allows for dynamic optimization of design parameters, significantly reducing computational load and time requirements. The result is a more streamlined and cost-efficient SMD design process that improves product reliability and significantly reduces time-to-market [7].

2. METHOD

This research adopts a methodological framework designed to develop and evaluate a predictive and optimization model for SMD design, utilizing MCS data. The methodology is divided into several key phases; each aimed at addressing specific aspects of the model development and ensuring the reliability and effectiveness of the final outputs. Flowchart of research activities are demonstrated in Figure 2.

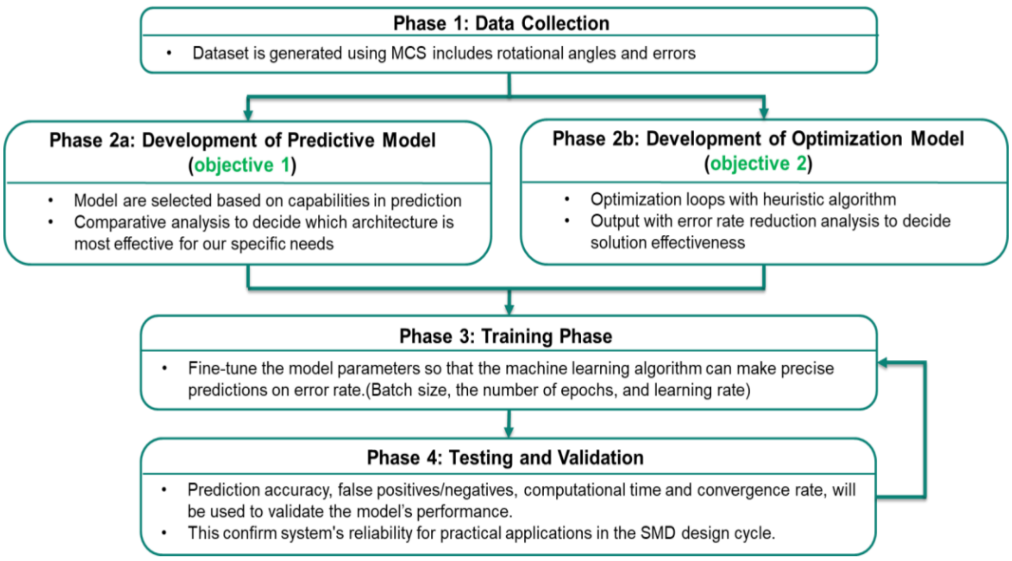


Figure 2. Flowchart of research activities

Phase 1 involves generating MCS data to simulate a diverse array of SMD design scenarios focusing on dimensional parameters. This data generation is crucial as it allows for the exploration of potential outcomes and variabilities under different manufacturing conditions. The generated data serves as the foundation for training the predictive model and provides critical insights for testing and refining the optimization algorithms. This dataset ensures that the models are trained in realistic scenarios that mirror the complexities encountered in actual manufacturing environments.

Phases 2 and 3 of the research involves the development, evaluation, and selection of several predictive models alongside an optimization algorithm to determine the most effective approach for SMD design optimization. Multiple predictive models are included in this evaluation. CNN is employed for its superior capability in recognizing patterns and spatial hierarchies crucial in predicting dimensional failures in SMD designs. Random forest (RF) is utilized for its robustness and effectiveness in handling tabular data with numerous features. Additional models, such as RF with synthetic minority over-sampling technique (SMOTE), hybrid CNN+RF, and genetic algorithm (GA) are also considered to compare their predictive accuracy and computational efficiency against each other. These models are trained on the same MCS-generated dataset to learn the correlation between input parameters and failure rates. This comparative analysis is critical to identify which model most effectively predicts SMD design failures while managing computational resources efficiently by evaluating its predictive accuracy, precision, recall, and F1-score. SA optimization algorithm works with model’s predictions to refine and optimize design parameters continuously through iterations. The SA algorithm's parameters, such as cooling schedule and stopping criteria, are meticulously calibrated to balance exploration and exploitation phases, thereby optimizing the SMD manufacturing process in terms of cost and performance. This hybrid approach facilitates a continuous loop of prediction and optimization, reducing design cycle times and improving efficiency.

In Phase 4, the integrated models undergo rigorous evaluation to ensure robust performance. The SA algorithm optimizes design parameters to minimize errors and improve efficiency, with performance metrics like accuracy and convergence rates critically assessed. This phase confirms the models' reliability and practical applicability in the SMD design cycle, ensuring their readiness for deployment in semiconductor manufacturing. This thorough description of the processes involving data preparation, model development, and validation ensures a robust and replicable framework of methodology, with detailed algorithms and techniques included.

3. RESULTS AND DISCUSSION

In this study, two objectives were set to develop predictive modeling and optimization processes in SMD design. Objective 1 focused on developing a predictive model capable of accurately forecasting dimensional failures in SMD designs. This was achieved through the utilization of machine learning and deep learning algorithms trained on MCS data, aimed at handling the complexities of dimensional parameters. Objective 2 aimed to refine these predictions using optimization algorithms that could minimize errors and enhance design efficiency. The success of these objectives was determined through a detailed evaluation of each model's performance to assess their effectiveness.

Predictive models, particularly the CNN demonstrated remarkable accuracy, achieving a predictive accuracy of 99.91% and a recall of 100%, which significantly correlates with reduced dimensional errors in SMD designs. This high level of performance underscores the capability of deep learning in extracting and learning complex patterns from high-dimensional data, much more efficiently than traditional methods. Comparatively, while models like RF and RF with SMOTE also showed robust performance, they did not achieve the precision or recall rates of the CNN, highlighting the superiority of deep learning in this application.

For objective 1, multiple models’ performance was meticulously evaluated using several key metrics, which are important for understanding its effectiveness. The following metrics were considered [8]:
Precision is ratio of correctly predicted positive observations to total predicted positives (1):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

Recall is ratio of correctly predicted positive observations to all observations in actual class (2):

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

F1-score is the harmonic mean of precision and recall (3):

$$\text{F1} - \text{score} = 2 \text{ x } \frac{\text{Precision X Recall}}{\text{Precision+Recall}} \tag{3}$$

This score balances precision and recall, particularly useful in situations where an equal importance to false positives and false negatives is essential.

3.1. Evaluation of multiple predictive models

To provide a comprehensive overview of the comparative analysis of various predictive models used in the study, detailed performance reviews for multiple algorithms are included in Table 1: RF, RF with SMOTE, neural network (NN) with Tanh activation, CNN, a combined approach of CNN and RF, and GA. This will further explain the selection process for the model that best addresses the complexity associated with dimensional data of SMD designs through algorithm performance review and comparison.

Table 1. The performance of multiple models trained using MCS data

Models	Accuracy (%)	Precision (%)	Recall (%)	Run time, min *(approximate)*
RF	99.83	97	95	10
RF (SMOTE)	99.72	90	99	10
NN (Tanh)	99.89	96	99	20
CNN	99.91	97	100	20
CNN+RF	99.83	97	95	20
GA	99.79	95.29 *(F1 score on true)*		50

3.1.1. Random forest

The RF model demonstrated strong performance with an accuracy of 99.83%, precision of 97%, and recall of 95%. This ensemble method, which creates multiple decision trees and aggregates their results, provides a robust mechanism against overfitting and is effective in handling various types of data. However, its slightly lower recall compared to other models suggests the need for enhancement when very high sensitivity is required.

3.1.2. Random forest with synthetic minority over-sampling technique

To address the imbalance in the dataset, SMOTE was applied before running the RF algorithm. This approach improved the recall significantly, reaching 99%, which indicates its effectiveness in identifying nearly all positives. However, the precision dropped to 90%, suggesting a trade-off between identifying all relevant instances and maintaining accuracy in predictions.

3.1.3. Neural network with Tanh activation

NN model with Tanh activation showed improved overall accuracy (99.89%) and matched the high recall (99%) achieved by RF with SMOTE, while maintaining better precision at 96%. This model benefits from deep learning capabilities to capture complex, non-linear relationships in the data, making it highly effective for precise and sensitive detection tasks.

3.1.4. Convolutional neural network

CNN model excelled with the highest accuracy of 99.91% and a recall of 100%, showcasing its superior capability in feature extraction from high-dimensional spatial data. This model's deep learning structure is particularly adept at processing data with inherent spatial hierarchies, such as those found in SMD designs, which makes it extremely reliable for predictive tasks in manufacturing settings.

3.1.5. Convolutional neural network+random forest combined approach

Combining CNN and RF aimed to leverage the strengths of both models—CNN's capability in handling spatial data and RF's robustness in generalization. However, this approach did not significantly outperform the standalone CNN model in terms of accuracy or recall, suggesting that the complexity of combining these models might not provide additional benefits over using CNN alone in this context.

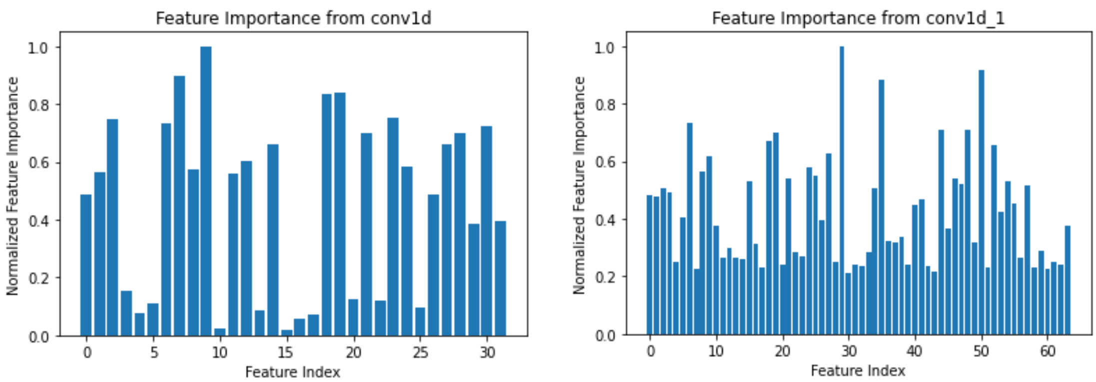
3.1.6. Genetic algorithm

GA was explored for its ability to optimize solutions in complex search spaces without the constraints of traditional methods. While it showed good overall performance with an accuracy of 99.79% and a balanced F1-score, the computational cost and time required were significantly higher. The GA's strength lies in its flexibility and effectiveness in optimizing a wide range of parameters but may not be the most efficient choice for predictive modeling when compared to neural network-based models.

3.1.7. Discussion on model selection

The choice of the CNN model was informed by its outstanding performance metrics particularly its perfect recall rate and highest accuracy. These characteristics are crucial for predictive models in manufacturing, where the cost of missing a defect (false negatives) is high. The discussion also highlighted the trade-offs involved with other models. While RF with SMOTE and the standalone NN with Tanh activation offered high recall, they did not achieve the balance of high accuracy and precision provided by CNN. The combined CNN+RF approach and the GA did not demonstrate sufficient advantages in performance to justify their complexity and computational expense in this specific application.

The model selection process highlights the superior performance of CNN in predictive modeling for SMD designs. Figure 3 shows the hierarchical features of learning ability of CNN. Detailed in Figure 3(a), the CNN model's architecture leverages multiple convolutional layers with increasing filter sizes (32 and 64), employing rectified linear unit (ReLU) activation functions and MaxPooling1D layers to enhance the extraction and robustness of features. This design allows the CNN to adeptly capture complex patterns and hierarchical features from the input data, surpassing the capabilities of conventional models that often rely on manual feature engineering [6]. The effectiveness of this approach is evidenced by significant feature importance as seen in the convolutional layers' outputs, indicating a deeper understanding of critical patterns that influence predictions as shown in Figure 3(b).



(a) (b)

Figure 3. Normalized feature importance; (a) from 1st convolutional layer "conv1d" and (b) from 2nd convolutional layer "conv1d_1"

Recent research [9] has highlighted the limitations of manual feature engineering and the advantages of CNN's automated feature extraction in achieving high accuracy and generalization in complex scenarios such as SMD design. Results in Table 1, Figures 3(a) and (b) also demonstrate the outcome on integration of dense layers' post-convolution in CNN model that promotes feature interactions, thereby making it the optimal choice as predictive models in this study. A significant limitation of this study is the absence of extensive real-world validation [10]. While the models and algorithms were initially tested using synthetic data and simulations, they have not been rigorously validated in actual manufacturing settings.

3.2. Optimization model with hybrid algorithm approach

This section focuses on the second objective of the study: application of a predictive model for design optimization with hybrid algorithm approach. The integration of SA optimization algorithm with the predictive outputs of the CNN model refined design parameters effectively, minimizing error rates to nearly zero after 800 iterations. This synergy between predictive accuracy and optimization technique successfully streamlined the design process. Comparing this study's results with existing studies, we found that our integrated approach of using CNN with SA does not compromise on performance. Unlike some methods that may achieve high accuracy but falter in real-world applications due to overfitting or underestimation of complex interactions. For instance, studies utilizing only traditional machine learning algorithms often report high accuracy but lack the dynamic adaptability provided by our hybrid method [11]. Our method benefits from the precision of CNN without negatively affecting the operational efficiency of the optimization process, making it particularly effective in high-stakes semiconductor manufacturing environments where error margins are incredibly low.

3.2.1. Hybrid-based model

Splitting the prediction process into two stages to focus on specific aspects of the problem-solving process, offers several strategic and technical advantages [11]. Here's a detailed look at the structure of such approach in the context of this project in flow chart, involving predictive model and heuristic models for predicting error rates in SMD device assembly. Figure 4 shows the benefits of a hybrid model approach in optimizing SMD manufacturing processes, utilizing a trained CNN and heuristic algorithms. In Phase 2a, CNN is tasked with extracting complex patterns from high-dimensional data, enhancing predictive capabilities that can be scaled and deployed across various manufacturing settings. In Phase 2b, a heuristic hybrid model is applied, enhancing the system's adaptability and allowing for dynamic adjustments based on real-time feedback, thereby fine-tuning the outputs generated by CNN. The hybrid model approach leverages the precision of deep learning to make accurate predictions while using heuristics to adjust dimensions, ensuring optimal assembly configurations and minimizing potential conflicts in manufacturing setups.

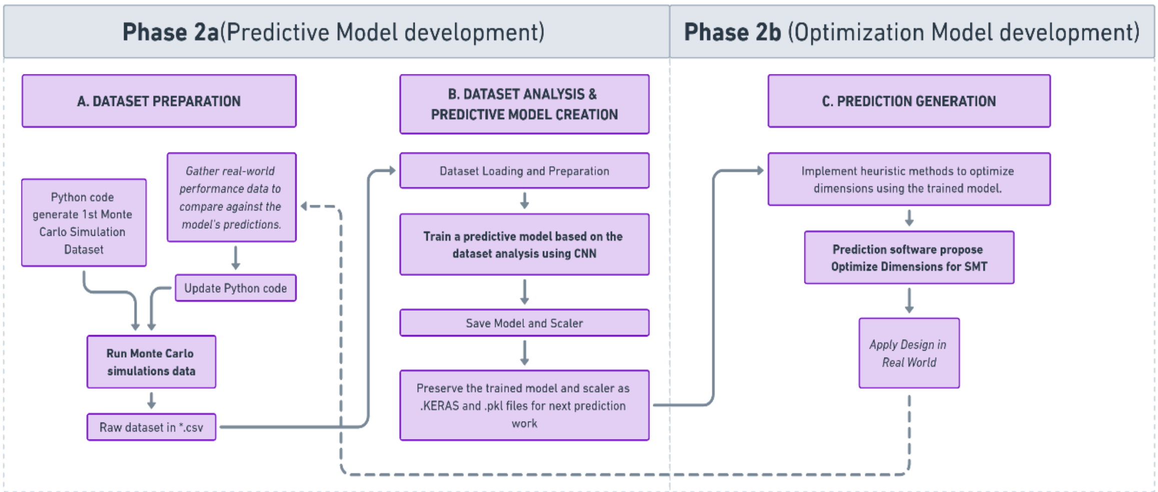


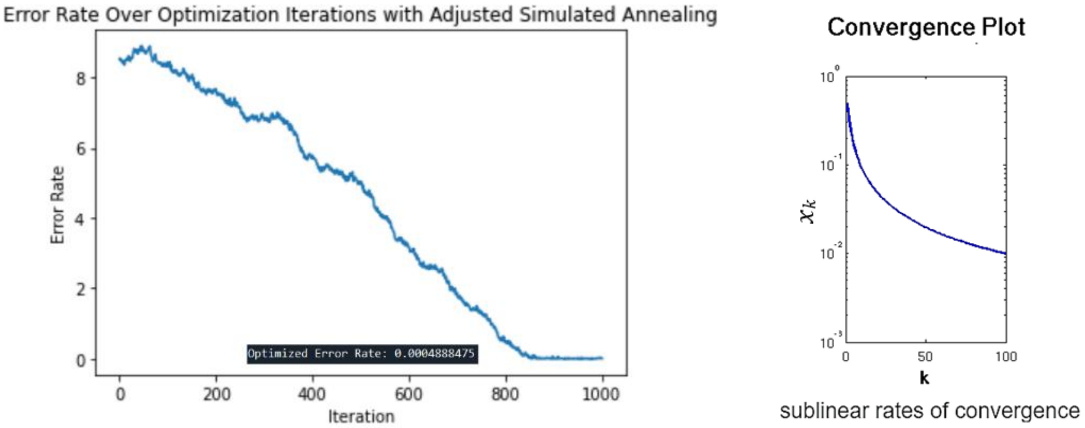
Figure 4. Flowchart illustrating hybrid model

3.2.2. Heuristic optimization algorithm: simulated annealing

This study employs a probabilistic heuristic optimization technique: SA, to find the global optimum of a given function. This technique is different from other formal heuristic algorithms such as ES, or ant colony optimization (ACO) in that it employs a controlled random search that mimics the annealing process in metallurgy [12]. Application of SA optimization technique in refining the design parameters for SMD assembly involves a controlled cooling process that enables the system to explore the solution space effectively without getting trapped in local minimum. This method is beneficial to prevent underfitting and overfitting and also the ability in handling complex, multi-dimensional optimization problems typical in manufacturing scenarios [13].

The process begins with the initialization of a solution and iteratively generates new solutions, adjusting parameters slightly and evaluating their fitness as shown in Figure 5(a). If a new solution shows improved fitness, it is accepted; otherwise, it might still be accepted with a probability dependent on the difference in fitness and the system's temperature, helping to escape potential local minima. In the optimization process, careful attention was given to avoid overfitting by using technique of early stopping based on validation performance [14]. The use of a cooling schedule in SA also helped in preventing the model from overfitting by gradually reducing the acceptance of worse solutions, thus focusing on genuine improvements.

In Figure 5, the graph shows a fluctuating trend indicating model is exploring the solution space and making adjustments to the proposed dimensions. This kind of fluctuation is typical in optimization processes, especially when using heuristic methods [15]. Model could now effectively learn from the data and propose dimension adjustments that progressively minimized the error rate, as depicted in the error rate trend graph. The result chart as shown in Figure 5(a) illustrates the error rate trend over iterations, highlighting the earliest convergence point at iteration approximately 700-850. This point marks the model's initial significant improvement, where error rate sharply drops, indicating the identification of a near-optimal solution early in the process as shown in Figure 5(b).



(a) (b)

Figure 5. Heuristic optimization model; (a) linear functions and (b) illustration of convergence plot

Simulated testing showed a decrease in dimensional conflicts from 1.2% down to <0.01%, highlighting the model's effectiveness. Descending line that stabilizes or flattens out suggests that the optimization process effectively reducing error rate over time. If line reaches a plateau means model may have found an optimal or near-optimal set of parameters. While line with many spikes observed, particularly toward later iterations indicates that the optimization process is still exploring the parameter space and is affected by the randomness inherent in heuristic methods [16]. The convergence pattern observed in SA is characterized by initial rapid improvements that taper off as the system temperature lowers, illustrating a sublinear convergence rate [17]. This pattern is indicative of the algorithm's effectiveness in refining search parameters progressively, ensuring that the solution is not only optimal or near-optimal but also stable, minimizing the risk of overfitting by avoiding too steep optimizations that might fit noise instead of the signal. Mathematically, sublinear convergence occurs when the sequence of iterates x_k approaches the optimal solution x^* such that the error at the k-th iteration $\|x_k - x^*\|$is bounded by a function that decreases to zero slower than $1/k$. Formally, for a given tolerance ϵ, there exists a scalar C>0 such that the error at iteration k satisfies [18].

$$\| X_k - X^* \| \leq \frac{C}{k^\alpha} \text{ for some } 0 < \alpha < 1 \quad (4)$$

Here, α represents the rate of convergence. For sublinear rates, this would be any value between 0 and 1. If error plot $\|x_k - x^*\|$ over iterations k, a curve will be observed that drops quickly at first and then gradually flattens out. In the context of a heuristic optimization model like the one discussed, sublinear convergence implies that the algorithm makes rapid progress initially, but as it moves closer to the optimum [19], the rate of improvement decreases. This behavior is often observed in practice due to the increasing difficulty of finding better solutions as one approaches the optimal set of parameters effectively allowing the system to explore a broader solution space initially and then gradually focusing on the area around the global optimum as the temperature decreases [20]. This cooling schedule helps in balancing exploration and exploitation, thus optimizing the convergence pattern [21]. The gradual temperature reduction mimics the cooling of materials, minimizing defects and optimizing energy within the system, which is critical in achieving a fine-tuned model that is robust and generalizable [22], [23]. The success of these models in practical settings provides a valuable framework for ongoing advancements in the field, suggesting that the integration of advanced predictive models with robust optimization techniques can substantially reduce design cycle times in semiconductor manufacturing [24]-[26].

4. CONCLUSION

This study establishes an advancement in the field of semiconductor manufacturing by successfully integrating predictive model, CNN and heuristic optimization algorithm, SA within the SMD design process. Utilization of CNN not only enhances predictive accuracy which surpasses existing methods but also demonstrates remarkable scalability across varied manufacturing settings. This achievement confirms our hypothesis that predictive models and optimization algorithm can drastically improve the efficiency of SMD design. The approach minimized error rates to almost negligible levels, thereby streamlining design cycle times significantly by avoiding multiple simulations. Such improvements have practical implications towards real-world scenario offering a robust and duplicable framework. Future research could extend these findings by exploring more complex datasets and broader manufacturing scenarios. Integrating advanced architectures such as reinforcement learning could provide deeper insights into complex situational decision-making, further enhancing the applicability of the outcome in this study. Additionally, ensuring the ethical deployment of these AI-driven systems and maintaining stringent data governance will be essential. This will not only uphold accountability and transparency but also harness the full potential of smart manufacturing solutions, promoting innovation while adhering to rigorous standards. The results pave the way for a transformative approach in the manufacturing sector, suggesting that the synthesis of predictive and optimization models can significantly enhance design efficiencies. As industries increasingly shift towards automation, the integration of such advanced technologies will likely play a pivotal role in shaping the future of manufacturing.

ACKNOWLEDGEMENTS

The authors would like to thank the Universiti Teknikal Malaysia Melaka (UTeM) for their invaluable support.

FUNDING INFORMATION

The authors express their gratitude to the Universiti Teknikal Malaysia Melaka (UTeM) for its financial support of this research. This funding has contributed to covering publication costs and providing research facilities.

AUTHOR CONTRIBUTIONS STATEMENT

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Ummi Raba'ah Hashim	✓		✓				✓			✓		✓		✓
Mohd Hilmi Hasan				✓	✓		✓			✓	✓		✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data will be made available on request.

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