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Review and Perspectives

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AI-assisted Design for Reliability: Review and Perspectives

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Abstract

The demand for rapid advancement in AI, mobile and automotive markets is pushing the boundaries of electronic packaging, including heterogeneous integration, high-power packages, and large-die packaging. Against this backdrop, machine learning technologies emerge as dynamic tools for correlation building and classification, revolutionizing the traditional approaches to design, manufacturing, and testing in electronic packaging, as well as the Design for Reliability (DfR) methodologies.

This paper reviews the most recent AI-assisted approach for electronic packaging and then focuses on the AI-assisted DfR (AI-DfR) approaches. Our examination reveals that AI methods have been adapted to meet the specific needs of electronic packaging. The industry's anticipation for AI-DfR stems from its potential to address prevailing reliability design challenges, yet its multidisciplinary essence poses hurdles to swift progress. This review proposes future directions for AI-DfR's development, spotlighting critical areas such as the quality and efficiency of finite element modeling, design and optimization of training models, selection of AI models, and maintenance and value enhancement strategies.

Keywords: Electronic Packaging: Design, Machine learning, AI model, Manufacturing, Testing and Reliability, Design for reliability

1. Introduction

Electronic packaging plays a pivotal role in semiconductor applications, facilitating electrical connectivity, thermal management, and mechanical stability. The selection of materials for electronic packaging encompasses a wide array of choices, including plastics, metals, and composites. On the other hand, the manufacturing yield requirement is high to maintain the industry's profitability. This diversity introduces complex, multidisciplinary challenges across design, manufacturing, and testing/reliability of electronic packaging.

Recent advancements in packaging designs—such as fan-out, panel-level packaging, chiplet, high-power packaging (IGBT), and large-die packaging—cater to emerging markets like electric automotive and artificial intelligence (AI). These innovations bring forth new failure mechanisms, presenting fresh research challenges. Alongside traditional physics-based methodologies, the surge in data-driven strategies, notably machine learning, marks a significant shift. Initially focused on correlating input/output vectors and classifying datasets, the expansion of computational capabilities and accessibility of open-source algorithms have propelled the adoption of machine learning in tackling electronic packaging engineering challenges.

Except for the existing physics-driven approaches, data-driven approaches are booming, and machine learning techniques are one of them. The machine learning techniques were initially aimed at the correlation building between input/output vectors and the dataset classification. The continuous improvement of the computation power pushes the growth of machine learning. Moreover, thanks to the open-source algorithm, many machine learning subroutines are available to both academia and industry, which promotes the application of machine learning to the engineering challenges of electronic packaging applications.

Moreover, this paper focuses on the concept of AI-Assisted Design for Reliability (AI-DfR), an approach defined to address specific failure mechanisms within electronic packaging. Traditionally, numerical methods like finite element methods (FEM) have been the go-to strategy for analyzing failure mechanisms, especially when experimental validation proves to be prohibitively expensive. However, FEM's complexity limits its accessibility to only a handful of experts within any given organization. Furthermore, the high computational cost of complex FEM problems is too great for practical use.

To democratize the design process and extend the capabilities of FEM-based analyses, AI-DfR proposes the integration of machine learning models as viable alternatives to FEM. Such models are meticulously trained using datasets predominantly derived from FEM simulations. This strategic approach ensures that once the machine learning model is operational, individuals without extensive FEM expertise can make reliability predictions with a degree of accuracy comparable to that of seasoned FEM users. It's important to note that this AI-DfR method is particularly relevant for tackling select failure mechanisms where traditional FEM applications are deemed necessary but challenging due to their complexity or the specialized knowledge required.

Furthermore, this paper focuses on the AI-assisted design for reliability (AI-DfR), and it is defined as follows.

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Given a failure mechanism of the packaging family, numerical approaches, such as FEM, are always applied when the obtaining of the experiment results is costly. To broaden the FEM-based design capabilities of the organization, researchers applied a machine learning model to replace the FEM. Note that such a machine learning model should be trained against the database that is generated mainly by the FEM. Once this machine learning model is available, the non-FEM user can perform the reliability predictions as accurately as the experienced FEM user.

A two-step approach is applied in this paper. First, most recent research papers are collected from a few well-known electronic packaging journals and conferences, including Microelectronic Reliability, IEEE Access, IEEE Transactions on Components, Packaging and Manufacturing Technology (CPMT), ASME Electronic Packaging, Electronic Components and Technology Conference (ECTC), International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems (EuroSimE). Approximately 50 highly relevant papers are collected, and the trend of the machine learning application to electronic packaging can be captured. Subsequently, we identify key global research entities in AI-DfR, spanning both academia and industry, to examine their contributions toward addressing electronic packaging reliability challenges. This includes an in-depth analysis of motivations, methodologies, and outcomes, laying the groundwork for future AI-DfR explorations.

The organization of this paper is as follows: The second chapter elucidates the application of AI in the realm of electronic packaging. An examination of seminal AI-DfR research initiatives and their approaches to common reliability failure mechanisms is presented next. Finally, we project future directions for AI-DfR and conclude with a summary of our findings.

2. Applied Machine Learning in Electronic Packaging

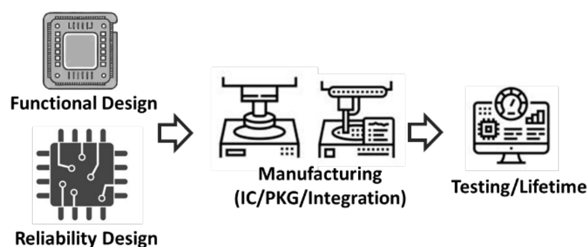

Fig. 1 The overview of possible AI application in the electronic packaging domain

Fig. 1 presents a comprehensive overview of AI-assisted methodologies in the electronic packaging sector, encompassing AI-DfR technologies, and design, manufacturing, and testing phases. Unique motivations drive each area, employ distinct approaches, and yield specific outcomes.

2.1 Functional Design

In scenarios where circuits exhibit nonlinear responses due to high frequency and power, traditional theoretical methods falter. Challenging operational conditions further complicate functional design, where both theoretical models and simulations often fall short. AI models come into play, establishing connections between design parameters, operational conditions, and performance outcomes.

The application of circuit design is diverse: Faraji et al. utilized a recurrent neural network (RNN) to model the time-domain characteristics of nonlinear circuits and components[1]. Güzel and Çolak employed multi-layer neural networks to forecast the current-voltage characteristics of Schottky diodes under low temperatures [2]. Ender et al. adopted a reinforcement learning (RL) strategy to devise a reliable switching scheme for the deterministic switching of perpendicularly magnetized spin-orbit torque magnetoresistive memory cells [3]. Additionally, Son et al. used an RL approach to design an optimal 3-D cross-point (X-Point) array structure with considerations for signal integrity issues[4]. Guo et al. implemented a convolutional neural network (CNN) technique for radio frequency (RF) trace design [5]. Polo-López et al. used Fruit fly Optimization Algorithm (FOA) for the design of waveguide devices [6]. Zhang et al. employed a transfer learning-based deep neural network (TL-DNN) to link performance parameters with geometric parameters, utilizing an in-house electromagnetic solver to create these databases [7], as shown in Fig. 2(a). Chu and Ho used Latin Hypercube Sampling (LHS) to systematically create a database for training an ANN for ultra low-k chip design [8].

For application-driven IC/electronic AI-assisted design methods: Santikellur et al. proposed a shared page-aware machine learning-assisted method for predicting and enhancing multi-level cell NAND flash memory performance[9]. Zhang et al. used neural networks for designing bonding wire arrays for high power and high-frequency packaging[10],, depicted in Fig. 2(b). A LightGBM machine learning model was introduced to substitute the conventional thermoelectric coupling model for IGBT junction temperature, thereby reducing the reliance of IGBT reliability evaluation results on IGBT model parameters[11]. Zhao et al. applied neural network techniques for high-speed link simulation[12]. Wang analyzed wireless power transfer efficiency and represented it through an AI model [13]. Huai et al. utilized support vector machine and decision tree algorithms to identify wire bond lift-off in power electronics manufacturing[14].

Machine learning models have been particularly instrumental in incorporating the impact of the user environment, such as high radiation effects, into the design. Allegro et al. investigated the radiation impact on devices and represented it with an AI model[13]. Laurini et al. examined neutron radiation soft-error effects on two

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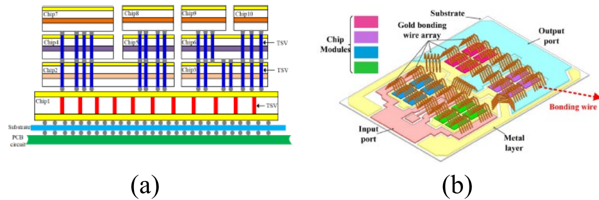
different hardware architectures for edge computing systems[15]. Huang et al. applied a deep neural network method for the routing of heterogeneous integration BGA substrates[16].

AI models have been pivotal in various aspects of functional design, from predicting multi-level cell NAND flash memory performance to designing high-power packaging and high-frequency bonding wire arrays. These models demonstrate AI's capability to address time-dependent circuit responses and layout characteristics effectively. Neural network based approaches are often detected in this sector.



(a) (b)

Fig. 2 Function design that applied AI model

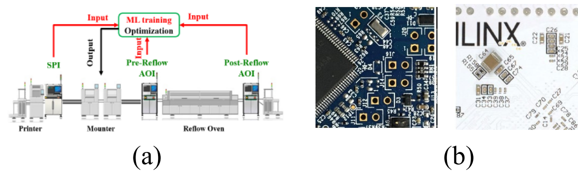
2.2 Manufacturing

AI-assisted manufacturing highlights two major trends: fine-tuning machine parameters for new productions and capturing failures through instant online inspection. Notable applications include: Choi et al. applied multivariate kernel density estimation (MKDE) for the end-point detection of plasma etching [17]. The yield of the pick-and-place is crucial to the whole surface mounting process. He et al. applied an AI-assisted framework for the machine setting when a new product was introduced[18]. Lai et al. established a machine learning model based on the database generated by computational fluid dynamics (CFD) and applied the machine learning model to obtain the optimal reflow recipe[19], illustrated by Fig. 3(a).

Vision-based object positioning is very important in the electronic industry for assembly and inspection tasks. Many methods have been proposed to tackle the problem, either by traditional machine vision or by deep learning (DL) techniques. Ling et al. applied YOLOv8 for the PCB component detection[20], as illustrated by Fig. 3(b). Noroozi et al. applied YOLOR[21].

The solder quality control is important in the surface mounting process. Liao et al. applied ConvNeXt-YOLOX to detect printed circuit board assembly solder joint defects. Ulger et al. applied α-skew Jensen–Shannon divergence (α-JS) for solder joint inspective, and α-JS performed better than YOLACT. Pahwa et al. applied 3D deep learning to analyze the shape of the solder after reflow[22].

Solorzano and Tasi applied reinforcement learning techniques to adapt to environmental changes [23]. Nashrudin et al. applied neural networks, linear regression, and decision forest methods for the prediction of the void after the no-flow underfill process [24].



(a) (b)

Fig. 3 Manufacturing that applied AI model

AI models, particularly advanced neural network based image recognition techniques, have significantly contributed to enhancing surface mount technology processes, including device positioning and solder joint quality control. These advancements underscore AI's role in improving manufacturing efficiency and quality.

2.3 Testing and Reliability

The testing of the semiconductors reveals manufacturing issues and delivers better products to customers. Hence, machine learning technologies are mostly applied to fast and accurately analyze the testing image together with other instrument. For example, Pareek et al. developed a deep learning driven thermal failure analysis system based on infrared thermography[25].

Remaining useful lifetime (RUL) remains an interesting topic in reliability. However, the prediction of a product failure during field usage is a scientific challenge due to multiple potential failure physics, loading conditions, material/interfacial inconsistency, manufacturing conditions and user profiles. Hence, using the physical-driven approach makes it challenging to capture failure probability characteristics precisely, and data-driven approaches have been introduced. Without a clear correlation to failure physics, the training database must be primarily generated experimentally.

Since 2018, Ahmadia et al. proposed to apply machine learning techniques to detect the IC/packaging failure from the sliced X-ray images[26]. Weiss applied AI-based inspection method to detect the defects in components[27]. Tee et al. applied CNN method, including VGG and ResNet50 to detect the failure of delayered IC image[28].

Phoulady et al. proposed a synthetic data augmentation workflow that generates virtual defective parts, effectively overcoming the data scarcity problem and enabling the creation of large datasets at a low cost[29].

Modern CMOS technologies such as FDSOI are affected by severe aging effects that do not only depend on physical issues related to nanoscale technologies, but also on the circuit environment and its run-time activity. To predict the aging behavior of circuits in FDSOI 28 nm technology with respect to bato operation conditions and workload, machine learning polynomial regression is applied [30].

Djedidi et al. applied auto-regressive neural network model using the operation temperature as the input to model the RUL of the system on chip (SoC) [31]. Bu et al. applied long short-team memory (LSTM) method for the negative bias temperature instability of SOI pMOSFETs using LSTM method[32]. Cheng et al applied attention-

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LSTM method for the prediction of the RUL of electrical connectors[33]. Wang et al. applied Pearson correlation stacking (P-stacking) machine learning algorithm and LSTM to perform IGBT lifetime prediction. Liu et al. predicted IGBT junction temperature using cuckoo search-based extreme learning machine[34].

Lee and Kwon trended the impedance response of solder joint degradation with supported vector machine (SVM) using early stage impedance measurements [35]. Cremer et al. uses a Decision Tree (DT) learning for predicting the reliability of the IEEE 68-bus system [36].

The life cycle of lithium-ion polymer batteries has been modeled by ANN and support vector machine by Zhou et al[37] and Ding et al[38].

Yuan et al. investigated the AI model that can represent the excited spectrum of LED modules [39], and then developed a transfer learning based adaptive surrogate modeling on predicting the lumen depreciation of the LEDs with individual differences [40, 41]. Milor and Ghosh applied the NN to calibrate the hydrostatic stress equation for experimental data [42].

The research group headed by Wunderle has been conducting doing a lot of work on the use of AI in testing and reliability in the microelectronics field. Meszmer et al. looked into delamination and cracking in piezo-resitive stress sensors under thermal shock, introduced in [43] and later expanded on in [44]. They make a comparison between Single and Multi-Layer Feed Forward, (SLFF) and (MLFF), Convolutional and Recurrent Neural Networks, (CNN) and (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). The gated-RNNs, LSTM and GRU, performed best, but they also required significantly more training time. However, due to a lack of data the models could not do cross predictions, i.e. training from one sensor and predicting the other. This problem was addressed in [45] by increasing the dataset from [44] with a factor of 8 by exploiting the symmetries in the time series.

Pareek et al. developed a non-destructive failure analysis method using infrared thermography. First introduced in [add5] and expanded upon in [46]. They compared Pulse Phase Thermography (PPT), Thermographic Signal Reconstruction (TSR), Principal Component Thermography (PCT) and a combination of TSR and PCT. The combination of TSR and PCT yielded the best performance. Initial results for augmenting the data with FEM were given, which was further developed in [25].

A surrogate CNN model for predicting the alignment errors of the lens stack in LiDAR sensors was proposed by Meszmer et al. [47]. The data is generated from a digital twin, to which noise was added using a Monte Carlo approach to simulate real world conditions. The validation loss was always lower than the training loss for the test set, resulting in an ”unknown fit”. While the method is promising further research is required.

3. AI-assisted Design for Reliability (AI-DfR)

AI-DfR integrates AI models, trained using databases from sophisticated numerical methods, enabling engineers to make expert-level predictions with limited knowledge.

This approach has gained traction within the industry, with leading companies developing proprietary methodologies. Specifically, Sinha et al. from IBM have pioneered AI-DfR since 2021 to predict the solder joint fatigue life for wafer-level chip-scaled packages (WLCSP) through a neural network approach [48]. Similarly, Raghavan et al. from IBM have utilized AI-DfR for warpage analysis to determine the optimal copper percentage distribution in substrates [49]. Pan et al. from Micron have implemented an artificial neural network-based AI-DfR method to assess solder joint reliability for BGA packages in Micron's advanced 232-layer NAND memory. Furthermore, Wu et al. from ASE have explored the potential of neural networks in predicting the warpage of fan-out wafer level packaging [50].

This section aims to delve into three crucial failure mechanisms: solder joint fatigue, warpage, and multi-physical performance degradation, which are significant areas of demand within the industry.

In summary, image recognition and signal processing techniques remain the key methods in the testing and reliability sector. However, considering that each product is different and the product's preference evolves over time, time-dependent and product-oriented AI modeling techniques have emerged. Moreover, this AI model potentially becomes part of a complex system's prognostic health management (PHM) framework.

3.1 Solder joint fatigue

As one of the primary failure mechanisms in electronic packaging, solder joint fatigue is often mentioned in the research. One of the reasons is that the reliability test to evaluate solder joint fatigue is very time-consuming, and the results highly depend on the packaging design, manufacturing, and field application.

Solder joint fatigue, a leading failure mechanism, is notoriously time-consuming to test, with outcomes heavily dependent on design, manufacturing, and application conditions. The Finite Element (FE) method, traditionally employed to assess solder joint fatigue failure risks, has been limited to experts due to its complexity. AI's advent allows non-experts to predict solder lifetime, paralleling expert evaluations accurately.

To investigate the AI-DfR techniques for solder joint fatigue, the BGA type, especially WLCSP, under the thermal cycling loading, is often chosen as the carrier due to the lifetime of BGA and WLCSP being controlled mainly by the solder joint fatigue failure mechanism.

Chiang's research group has been at the forefront of advancing solder joint fatigue prediction for decades. Since 2019, Chou et al. have applied ANNs for solder joint lifetime prediction, incorporating grid search techniques to mitigate the instability caused by initial guesses of neural network parameters [51]. Subsequently, many machine learning techniques have been adopted, surpassing

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traditional neural network approaches. These include random forest [52, 53], extra tree [54], ensemble learning [55], PSO [56], kernel ridge regression(KRR)[57], k-nearest neighborhood [58, 59], polynomial regression [60], nonsupervised- supervised mixed method [61] and support vector machine [62]. The FE-based database for training these models has expanded from 564 data points in 2019[51] to over 9,000 by 2023 [62], illustrating Chiang's group's extensive contribution to applying AI-DfR methodologies for solder joint fatigue. Moreover, the efficiency and accuracy of different AI have been summarized in Panigrahy et al [57].

Table 1 The efficiency and accuracy of AI model for solder joint fatigue analysis [57]

Method	Mean/Max Error (Training)	Mean/Max Error (Testing)	Dataset count	CPU time (s)
ANN	5/28	--	576	151
ANN	3/20	--	1296	235
RNN	6/36	--	576	173
RNN	3/27	--	1296	698
SVR	10/68	13/55	576	0.093
SVR	7.3/46	8/30	1296	6
KRR	8.4/57	12.2/39	576	0.093
KRR	5.3/40	5.6/24	1296	0.422
kNN	18.9/83	--	576	0.03
kNN	11.4/28	--	1296	0.034
RF	12/56	36/133	576	3.5
RF	6.3/28	26.3/103	1296	4

Chen et al. developed an ANN model trained against a database generated by FE for the WLCSP's solder joint fatigue lifetime, achieving more than 90% accuracy using the backpropagation algorithm and incorporating a creep material model for the solder joint [63].

Yuan and Lee explored the minimum data required to effectively train an AI-DfR model for solder joint fatigue prediction, highlighting the crucial role of data distribution [64]. Yuan et al. utilized a genetic algorithm to minimize the impact of the initial guesses on neural network parameters [65].

Villalba and Vandevelde linked 15 design parameters to the plastic strain of the BGA solder joint, setting a 15% allowable difference. This process led to the creation of an FE-based database, segmented into parts for training, validation (to address overfitting), and testing. They observed that SVM performed comparably to ANN, while random forest and polynomial methods were less effective [66].

Yao et al. extended AI-DfR to the prediction of solder joint lifetime for fan-out WLCSPs, employing a physics-based ANN. This dual ANN system, one for material parameters and another for mechanical analysis, calculates equivalent strain, von Mises stress, and warpage based on material coefficients and geomaterial characteristics [67, 68]. This methodology has been further adapted to power electronics with significant industry participation [69].

Yi and Jones uses a feed forward NN for projecting solder joint reliability using data acquired from previous researchers [70].

Samavatian et al. [71] developed a Conventional ANN (CANN) into their newly proposed Correlation-Driven Neural Network (CDNN) for predicting both solder joint fatigue as well as creep. Using a large amount of FEM and experimental data for public sources combined with their own data, allowed for predicting the useful lifetime for different compositions, thermal loading and solder joint geometries. In a subsequent paper[add1] Samavatian et al. expanded on the CDNN method with a self-healing dataset to create the Iterative CDNN (ICDNN). The self-healing dataset works by identifying the gaps in the dataset used for CDNN, and filling the bounds of the parameter space with FEM simulations. The model is then trained to predict the useful lifetime of the solder joint, which are in turn used to fill the gaps in the dataset as long as the predictions differs no more than 5% from its neighbours. This process is iterated until the dataset is filled in, which lead to an error reduction of a factor of 3, but a sixfold increase of training time.

The effort required for creep-based fatigue predictions using FE is substantial. To adapt these predictions for complex printed circuit board assemblies, Tauscher et al. applied an AI model to correlate a local model of the solder joint with its lifetime. This method, utilizing only linear global FE, reduces the computational demands of conventional non-linear FE modeling by employing a surrogate local solder joint model [72], offering a promising approach for assessing the solder joint fatigue reliability in heterogeneous integration, shown in Fig. 4.

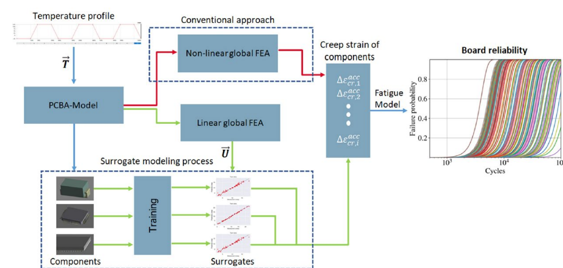

Fig. 4 The surrogate process as a replacement for nonlinear global FEA[72]

Shan et al.introduced a Particle Swarm Optimization (PSO) algorithm for thermal optimization in microsystems in [73] and [74]. The connection between Through-Silicon Via (TSV) design and performance was identified by a

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Back Propagation Neural Network (BPNN). Then PSO was used to optimize for peak bump and TSV temperature, as well as maximum stress and deformation.

Li et al. used PSO for TSV arrays with performance constraints. A Genetic Algorithm BPNN is used to map the relationship between design and performance, then PSO was used for multifield cooptimization of the design parameters [75].

Mao et al. consider packaging on PCB condition and build AI model to obtain the von Mises stress, equivalent plastic strain and energy density in solder joints and PCB warpage[76].

3.2 Warpage

The prediction of warpage in flip chip (FC) packaging has been thoroughly investigated by Selvanayagam et al., revealing that the complexity of the substrate layout and varying copper content significantly affects warpage outcomes. They developed an ANN model with a single layer to correlate nine equivalent CTEs to warpage, established by an FE-based database. The Markov Chain Monte Carlo (MCMC) method was introduced to approximate the equivalent material CTE, demonstrating the parameter's sensitivity to warpage [77-79]. Furthermore, the optimal metal density, resulting in minimal warpage, was identified using an inverse ANN model combined with MCMC and PSO [80-83], as well as tensor train decomposition techniques [84, 85], illustrating an AI-assisted data and physics-driven design framework for low warpage package design in Fig. 5.

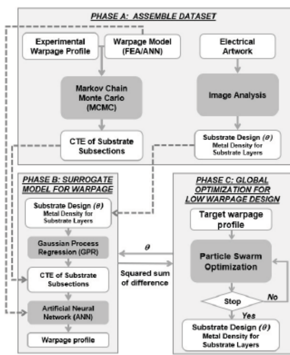

Figure 1. AI-assisted data and physics driven design framework for low warpage package design.

Fig. 5 AI-assisted data and physics driven design framework for low warpage package design [80].

Shu et al. applied the extra tree to predict the warpage of the panel-level packaging [54].

3.3 Multi-physical Performance Degradation

Prisacaru et al. propose the concept of a virtual twin for electronic packaging by a combination of the FEM and NN to study the delamination growth inside the packaging where several automotive products are introduced [86].

4. The Perspectives of the AI-DfR

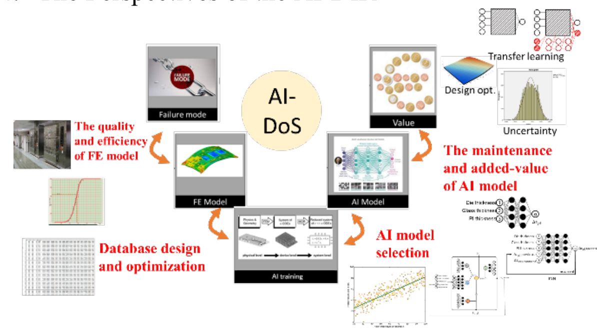

Fig. 6 The future perspectives of AI-DfR

Fig. 6 showcases a potential development trend for the future of AI-DfR, highlighting its process from FE model creation and database generation to AI model training and application. As AI-DfR garners high expectations from the industry, several potential research directions are proposed, identifying four main trends:

4.1 The quality and efficiency of FE model

The training database for AI-DfR is derived from FE models, making the quality and efficiency of these models crucial for successful AI-DfR applications. Several aspects need to be considered, including the material model and its coefficients, the predicting capability of the model and the improvement of the FE model.

Nonlinear material models and their coefficients significantly affect FE prediction quality. Thus, a robust method for efficiently extracting coefficients from experimental results for nonlinear, time-, and temperature-dependent material models is essential. Yuan et al. have introduced a neural network-based method, equation-informed neural networks (EINN), for this purpose [87, 88].

Validation of the FE model should extend beyond a single experimental result, with a comprehensive set of experiments providing a more reliable training database and AI-DfR model. This validation process also aids in understanding the correlation between FE predictions and experimental outcomes.

Regarding database design, striking a balance between the FE model's efficiency and accuracy is pivotal. Techniques like equivalent replacement and multiple point constraints (MPC) can minimize computational efforts. Furthermore, employing 2D assumptions may be feasible when the outcomes of 3D and 2D analyses are comparable.

4.2 Database design and optimization

In principle, AI models generally perform better with more training data. However, generating extensive FE results is time-consuming, raising questions about the practicality of this approach in real-world applications. Hence, developing database design methods that structurally analyze the statistical distribution of input parameters' response domain is critical. Efforts by pioneering researchers in dataset design and optimization

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have laid the groundwork for future advancements in this area [52, 55, 62].

Different approaches are available for database design and optimization. The most straightforward method for design is to augment an existing database with FEM results as shown in [25]. More advanced method for augmentation is the self-healing database introduced in [43] and using symmetries in [45]. For optimization the LHS algorithm from [8] shows promise. The LHS stars with a random set a sample points, and sequentially adding new samples according to the steepest descent algorithm. This means it only adds data with the highest impact on performance to the database. The LHS algorithm has been further developed by Iordanis in [89].

4.3 AI model selection and training procedure optimation

Selecting an AI model requires careful consideration of the FE model's quality and efficiency, as well as the training database's design. Although there's no one-size-fits-all guideline for AI model selection based on failure mechanisms, time-dependent processes like solder joint fatigue in WLCSP suggest that sequential neural network architectures (e.g., RNN, LSTM) might outperform ANNs.

Despite this, evidence from numerous studies suggests ANNs often yield the best results. However, as the database size increases, so does the training time for neural network-based architectures, unlike non-parametric AI models such as random forests, SVMs, KRR, and k-nearest neighbors. Additionally, the training parameters of the AI model can affect learning efficiency, making review tables like Table 1 invaluable for tuning various parameters.

4.4 The maintenance of the AI model and its value extension

Significant efforts, including FEM building, database generating, AI model training, are required to to achieve precious AI-DfR model. The maintenance of the AI model should be considered when the new parameters are introduced, and new design levels are set. Proper transfer learning techniques are needed, to update the AI-DfR model efficiently based on previously obtained models and new datasets.

On the other hand, the application of these AI-DfR should be further developed. For instance, Selvanayagam et al. applied the AI-DfR model to obtain the equivalent material properties of PCB, but also used the same AI-DfR model to perform the warpage optimization[81]. Since AI model is a light-computation with high prediction accuracy, it is reasonable to predict the reliability response under manufacturing instabilities by Monte Carlo approach. An attempt was made in [47], which showed mixed results. More research is needed to asses the usefulness of this approach.

5. Conclusion

Electronic packaging technology has become more and more challenging recently. Machine learning technology is experiencing rapid growth, with more researchers leveraging AI models for nonlinear regression and classification tasks. This paper has provided an overview of AI's application within the electronic packaging domain, spanning the design, manufacturing, and testing phases. Furthermore, it has highlighted the innovative AI-assisted Design for Reliability (AI-DfR) approach, concluding with insights into future research directions in AI-DfR.

Distinct needs across various electronic packaging processes drive AI's application. For high-frequency and high-power applications, electronic packaging design challenges often lead to nonlinear circuit responses, with neural networks frequently being the solution of choice. During manufacturing and testing phases, CNN-based methods are utilized to rapidly and accurately analyze instantly captured images.

AI-DfR is particularly valuable for examining time-intensive failure mechanisms, where established numerical methods exist but require significant time investment. This review has covered key areas such as solder joint fatigue, packaging warpage, and multi-physics failures, underscoring the comprehensive nature of AI applications in addressing these challenges.

The paper identifies crucial development trends for AI-DfR, including improving the quality and efficiency of FEM, enhancing database design and optimization, selecting the most appropriate AI models, and ensuring AI models' ongoing maintenance and value extension.

The integration of AI technologies in electronic packaging necessitates a deep fusion of machine learning expertise and practical field application knowledge. Overcoming the technical hurdles to make these innovations widely accepted within the industry requires significant time and effort. Thus, the successful adoption of AI within the semiconductor domain depends greatly on the dedication and persistence of principal investigators and their research organizations, highlighting the collaborative effort needed to advance this field.

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