Design for Enhancing the Mechanical Performance of NB Using a Hybrid ANN-PSO Approach

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Abstract

In the trend of ultra-thin and lightweight design for notebook computer (NB), to enhance the structural strength of NB products, a cross-scale systematic finite element simulation model has been established for whole-machine mechanical testing (static pressure testing and ball drop testing). Validated through testing, this model is capable of accurately assessing risks such as light leakage and fragmentation during the tests. Furthermore, based on the Design of Experiments (DOE) data from finite element simulations , this paper particularly focuses on the development of a Hybrid Artificial Neural Network - Particle Swarm Optimization (ANN-PSO) Approach AI model for predicting NB mechanical testing risks. This AI model can accurately and rapidly analyze design schemes, guiding NB product design to improve product strength and ensure product reliability.

Author Keywords

NB Mechanical Testing; Cross-Scale; Finite Element Simulation; AI Simulation; Hybrid ANN-PSO Approach.

1. Introduction

In recent years, the trend towards ultra-thin and lightweight design in Notebook (NB) products has become increasingly pronounced. The protection offered by the cover or other structural components to the liquid crystal display (LCD) screens is becoming increasingly limited, leading to a higher probability of light leakage and fragmentation during use [1]. Various manufacturers have established different testing standards to evaluate the mechanical strength of the display panel (Panel), the liquid crystal module (LCM), or the NB machine [2]. Whole-machine testing of NB can reflect the strength status during actual product use, but it involves more influencing factors, a more complex analysis process, and higher testing costs. Simulation can provide optimized designs that save costs [3]. However, in the current industry, there are few cases where simulation analysis for product strength comprehensively considers multiple dimensions, such as cover design, module design, and even panel design.

This paper focuses on the static pressure and ball drop testing of the NB machine [4], comprehensively considering the impact of design factors from the cover to the display module and the internal structure of the Panel. A cross-scale finite element simulation model capable of analyzing the overall mechanical strength has been established. To verify the accuracy of the finite element simulation model, this paper conducted experimental validation that matched the simulation scheme. The distribution of compressive stress (Fps) on the panel surface derived from the static pressure simulation matches the experimentally measured distribution in terms of trend and magnitude. Similarly, the trend of force distribution on the glass in the ball drop simulation aligns with the distribution trend of crack initiation points observed in experimental measurements.

To enhance the efficiency of evaluating design schemes, an AI model for predicting mechanical testing risks was established based on the Hybrid ANN-PSO Approach [5], utilizing a vast amount of DOE simulation data from various design factor combinations. The AI prediction results can achieve an accuracy rate of up to 97% compared to the simulation model results. Through this model, key factors such as the A-cover foam have been identified, and optimization design suggestions for these critical factors have been provided.

2. Mechanical Testing Experiment

The NB machine system primarily consists of the external cover (A/B/C/D cover), computer hardware, and the LCM, with the LCM including the backlight and panel. The structural schematic is shown in Figure 1.

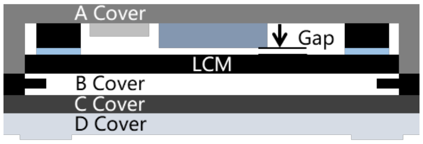


Figure 1. NB machine System.

The mechanical testing of the NB machine system encompasses a variety of tests, among which static pressure and ball drop test have higher failure rates, leading to light leakage and fragmentation. Therefore, this paper investigates the above two types of tests, with the test specifications shown in Table 1.

Table 1. Mechanical Test Specifications

items	Static Pressure	Ball drop
Load type	25KG 30mm head	2.5KG steel ball, ball drop height: 25cm
Load position	Center of the A-cover upper surface	Hinge side of the A-cover upper surface
Judgement	No light leakage	No fragmentation

3. Finite Element Simulation

3.1 Cross-scale simulation model establishment

The cover system model is simplified and extracted, assembled together with the LCM as shown in Figure 2, where the LCM includes the backlight and panel.

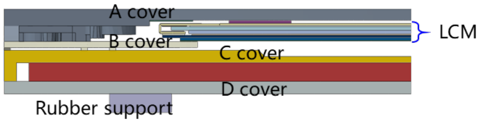


Figure 2. Simulation model section.

Due to the static pressure test, light leakage are primarily caused by damage to the liquid crystal (LC) alignment layer (PI). There is a significant difference in the dimensions of the overall machine structure and the microstructure inside the panel. To reflect the cross-scale impact of the squeeze between the thin-film transistor (TFT) and the color filter (CF) on the microscale photo spacers (PS) and PI , a detailed simulation model of an individual pixel period PS and key film layers inside the panel was established. Through this model, the compressive characteristics of the periodic PS can be obtained, as shown in Figure 3.

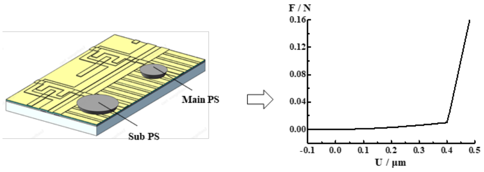


Figure 3. Detailed simulation model inside the panel.

The compressive characteristics are applied to the simplified connector elements of a individual pixel period in the whole-machine simulation model. As shown in Figure 4, a periodic number of composite Connector units are set between the CF and the TFT substrates. Each composite unit consists of a compression unit (translator) and a sliding unit (planer), with the compression properties obtained from inside the panel detailed model. By applying the composite units, it is possible to analyze the inside the panel PS compressive stress (Fps) and the shift between CF and TFT in the whole-machine simulation model. Through the cross-scale simulation model, the damage extent of the inside the panel film layers and the risk of light leakage during whole-machine testing can be analyzed.

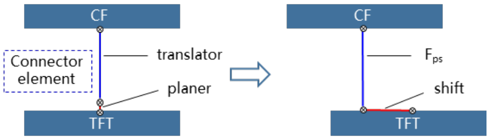
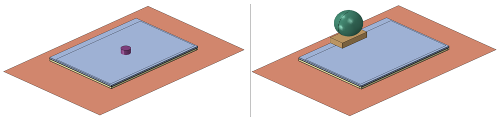


Figure 4. Cross-scale connector units.

For the Static Pressure test and Ball drop test conditions, boundary conditions and loads corresponding to the test conditions are constructed as shown in Figure 5.

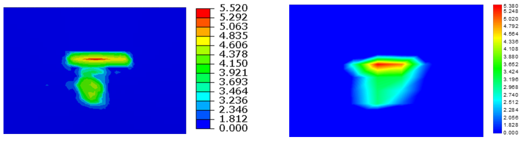


(a) Static Pressure (b) Ball drop

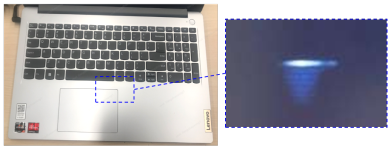
Figure 5. Simulation conditions.

3.2 Model Calibration and Verification

In the static pressure test simulation, the distribution of Fps between the panel and the C-cover was extracted (Figure 6.a), and it was compared with the Fps distribution measured by thin-film sensors (Figure 6.b), which was then compared to the measured distribution (Figure 6.c). The distribution trends are consistent. The corresponding Fps of the panel when the light leakage is just noticed is approximately 3.62N.



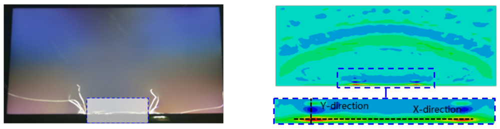
(a) Simulated Fps distribution (b) Measured Fps distribution



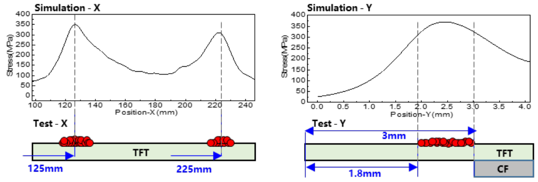
(c) Measured light leakage

Figure 6. Comparison of Fps distribution.

In the ball drop simulation, the stress distribution contour map of the TFT and the stress distribution curve of the stress concentration areas were extracted, and these were compared with the distribution trend of the crack initiation points from the test, as shown in Figure 7. The distribution of stress magnitudes can be well matched with the actual crack initiation distribution data. The crack initiation point corresponds to a minimum fragmenting stress of 303.2MPa.



(a) Test Fragmentation (b) Stress contour map



(c) X-direction comparison (d) Y-direction comparison

Figure 7. Ball drop crack initiation point calibration.

The above validation confirms the accuracy of the simulation model, which can be used to predict failure risks in mechanical testing and assess the quality of design schemes.

4. DOE Simulation and AI Model

4.1 DOE Simulation

A DOE simulation plan was formulated for design factors of the entire machine cover (material, size, foam layout, etc.) and the display module (backplane material, size, Glass thickness, etc.), with the DOE data presented in Table 2 (Due to confidentiality requirements, variable factors are represented by X1 to X10). Simulations for static pressure testing and ball drop testing were conducted for these DOE plans. The corresponding Fps and maximum TFT stress (Smax) were extracted as the risk.

Table 2. DOE Simulation Plan

Design Factors	Value Count	Total DOE Combinations
X1	5	300+
X2	5	
X3	5	
X4	2	
X5	3	
X6	5	
X7	3	
X8	3	
X9	3	
X10	3	

4.2 Methodology for training AI model

A hybrid approach integrating Artificial Neural Networks (ANN) and Particle Swarm Optimization (PSO) is utilized to predict the results in NB mechanical tests. Figure 8 presents the flowchart detailing the training process of the PSO-ANN model. In this framework, the ANN acts as the core predictive model, with neurons in the input and output layers representing the mechanical test parameters and the target values, respectively. The Mean Squared Error (MSE) serves as the loss function for backpropagation in the ANN, guiding the optimization process. The model undergoes iterative refinement through an adaptive trial-and-error approach to minimize the loss function effectively.

The PSO algorithm is utilized to optimize the hyperparameters of the ANN model, such as the number of hidden layers, the number of neurons per hidden layer, and the learning rate. This approach reduces reliance on trial-and-error or grid search methods for hyperparameter tuning. The search space for these hyperparameters is defined as follows: the number of hidden layers ranges from 1 to 4, the number of neurons per hidden layer ranges from 5 to 20, and the learning rate ranges from 0.001 to 0.01.

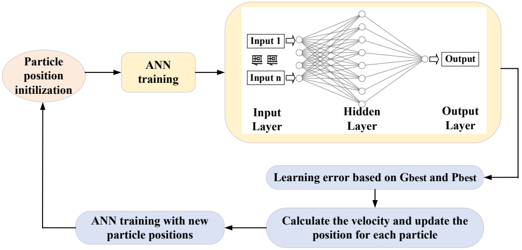
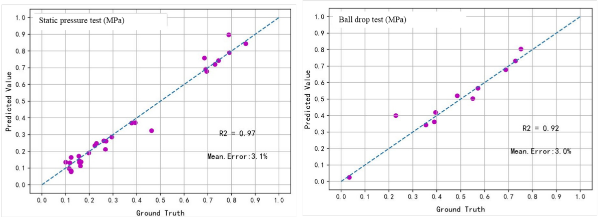


Figure 8. The flowchart for training PSO-ANN model.

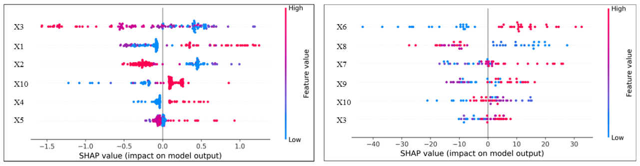
Figure 9 illustrates the performance of the optimal PSO-ANN models in predicting values for the static pressure test and ball drop test. Note that all stress values have been normalized to maintain confidentiality. For both tests, the predicted stress values closely align with the simulation results. The R^2 metrics for the static pressure and ball drop tests are 0.97 and 0.92, respectively. Additionally, the Mean Absolute Percentage Error (MAPE) metrics are 3.1% for the static pressure test and 3.0% for the ball drop test, demonstrating the model's high accuracy and reliability.



(a) static pressure test (b) ball drop test

Figure 9. The performance of the optimal PSO-ANN models in predicting stress values for (a) static pressure test and (b) ball drop test.

As shown in Figure 10, the SHAP diagrams for the static pressure and ball drop tests illustrate the primary influencing factors. The SHAP plots demonstrate that the A-cover foam has a significant effect on both tests. Increasing the foam appropriately can reduce Fps and Smax, thereby reducing the risk associated with the tests.



(a) static pressure test (b) ball drop test

Figure 10. The feature importance explained using SHAP analysis: (a) static pressure test (b) ball drop test.

4.3 16-inch NB Product Testing

Considering the significant impact of the A-cover foam on the overall test results, during the actual project development process, an AI model was utilized to perform extensive simulations on the size, thickness, and position of the A-cover foam. Six schemes were selected, and based on the critical values of Fps & Smax (3.62N & 303.2MPa), it was predicted that schemes 1 to 3 would not pass (NG), while schemes 4 to 6 would be acceptable (OK). Actual tests were conducted on the aforementioned schemes, as shown in Figure 11 and Table 3, and the test results were consistent with the predictions made by the AI model. Considering cost factors, Scheme 4 was selected for the actual product. The results indicate that the AI model can effectively provide rapid analysis and guidance for actual project development.

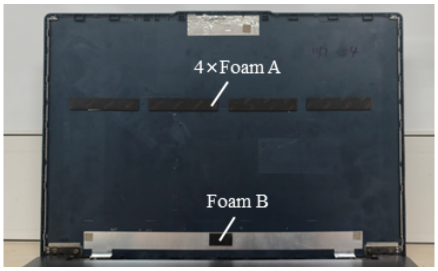


Figure 11. A-cover foam layout.

Table 3. Application Verification Results

No.	A-cover foam*		AI Simulation Values		Test	
	Foam A	**Foam B**	**Fps**	**Smax**	**static pressure**	**ball drop**
1	50×5	20×5	5.52	340.5	NG	NG
2	65×10	20×10	4.15	318.2	NG	OK
3	65×15	40×10	3.95	309.1	NG	NG
4	70×15	60×10	3.44	289.5	OK	OK
5	60×20	80×10	3.42	287.7	OK	OK
6	65×20	100×10	3.13	271.3	OK	OK

*Foam thickness 0.5mm.

5. Conclusions

This paper has established a cross-scale simulation model for NB mechanical testing, conducting a comprehensive analysis and assessment of the mechanical strength of the NB machine system for static pressure testing and ball drop testing. The model takes into account the impact of design factors across various dimensions, from the external cover to the display module and the panel. The accuracy of the finite element simulation model was verified through benchmarking with test data. Based on DOE simulation data, a mechanical testing risk prediction AI model was trained and established, which can rapidly predict test outcomes for new design schemes. An AI simulation design was conducted for the A-cover foam, and the results indicate that this AI model can effectively provide quick analysis and guidance for actual project development.

6. References

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