

# AI Model for LCD Module Strength and Warpage Simulation

Wencheng Luo\*, Zhi Li\*, Min Quan\*, Bowen Xiong\*, Yansheng Sun\*, Dayu Zhang\*, Jinhong Zhang\*

\*Chongqing BOE Optoelectronics Technology Co., Ltd., Chongqing 400714, China

## Abstract

Aiming at the LCD display warpage and L0 light leakage NG at system match stage with ultra-thin and narrow design, a module warpage and strength prediction model by AI is proposed to improve LCDs strength immunity and provide design guide. The comparison between the experiment measurement and the predicted results shows that the model can accurately predict the module strength and warpage under different design conditions and provide effective technical support and guidance.

## Author Keywords

Module Strength and Warpage; AI Model; L0 Light Leakage; Artificial Intelligence

## 1. Introduction

Liquid-crystal display panels (LCDs) are widely used in various display devices. The module strength would decrease and the warpage would increase with ultra-thin and ultra-light design. Therefore, we establishment model to evaluation module strength and warpage with DOE validate data, But the model is manual assignment, and the degree of accuracy is low that there are still issues occurred at system match stage. The module strength and warpage are influenced by parts of designs, the relationship of key factors are perplexing and can't be calculate accuracy by manual. As the artificial intelligence is rapid growth, we suppose that AI may be used on module strength and warpage to calculate, so we proposed the AI model to simulation strength and warpage.

## 2. Establishment of module strength and warpage experiment platform

System match failure mainly caused by weaker strength and bigger warpage that caused L0 image uneven with system assembly and daily use.

**2.1 Strength Measurement Platform:** The strength measurement platform was built to simulate display module force situation and reflect strength performance of different positions. The machine consists of testing platform and weight. The upper surface of the machine is used to place the module. The weight is placed on different position, we would gradually increasing and inspect the L0 image until there is obviously light leakage, then record the weight.

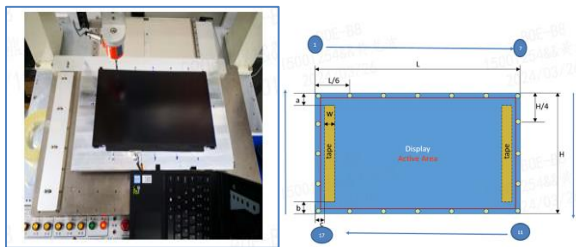


Figure 1. Module strength pressure testing equipment and test points

**2.2 Warpage Measurement Platform:** The platform is conclude marble platform and plug gauge, Put the module on the

marble platform with display surface adown, Insert plug gauge at 7 points as Figure2 with the thinnest thickness and gradually increase until it can't be inserted and record the thickness.

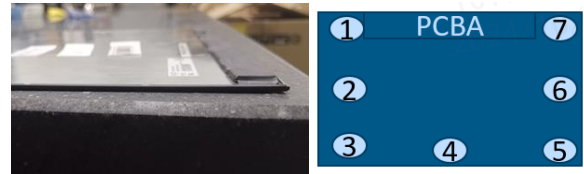


Figure 2. Module warpage testing equipment and test points

## 3. Simulation Research on Module Strength and Warpage

As we know, the display module consists of backlight and display substrate. Specifically, the backlight mainly consists of back cover, frame, light bar, light guide, brightening film, and reflection film. Furthermore, the display substrate mainly includes liquid crystal, TFT and CF glass, and polarizer. The L0 light Leakage mainly influenced by external pressure, system assemble, daily use, and the module is not flatness enough. As we analysis, the light's polarization states exists in all direction from BLU, After passing through TFT Polarizer, it becomes horizontally linearly polarized light, when it reaches CF polarizer and would be absorbs, then there is no light leakage(Figure 3), but if we exert force on the module or the module is not flatness enough, the angle of liquid crystal between TFT and CF would be changed and the glass would deformation that caused light birefringence, so the horizontally linearly polarized light would be changed to elliptically polarized light after TFT glass, liquid crystal and CF glass and the light leakage occurred (Figure 4). The phase difference  $\Delta \varphi$  generated by birefringence of a glass substrate is related to the optical elastic coefficient (SOC) of the glass material, the thickness of the glass substrate, and the deformation force acting on the glass substrate, following the formula as Figure 5. As we analysis, if we need reduce the L0 light leakage, the module should be flatness enough, but the display substrate and polarizer substrate like sandwich structure, they would curved after bonding as the formula (Figure6), when polarizer attach on the glass, polarizer will shrink and produce the stress  $F_t$ , which contains the stress for the each layer of the polarizer, and is proportional to the D and H Value of the Polarizer. So if we decrease the thickness of the polarizer, the stress will decrease to improve the warpage. If the thickness of CF and TFT polarizer is similar, the stress of CF and TFT polarizer will be balanced, and the warpage will be smaller, also if we use thicker glass and higher Y's modulus material, the smaller warpage. After assembled with BLU, the warpage would be smaller, so the stronger blu also could decrease warpage. Based on module force and warpage analysis, the strength and warpage model composed of upper and lower polarizers, CF and TFT glass, back cover, etc. was conducted to present stress and warpage situation under different designs. The following assumptions are made to facilitate calculation convergence: (1) Elastomer assumption: glass is a brittle material, which shows ideal elastic-

plastic characteristics when the limit load is not exceeded; (2) Rigid body assumption: the pressure head is a rigid body; (3) Gravity assumption: the downforce is far greater than the weight of the glass, ignoring the influence of its own weight; (4) The glass and module manufacturing processes are stable.

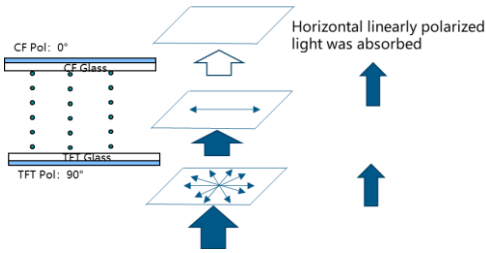


Figure 3. Without Force

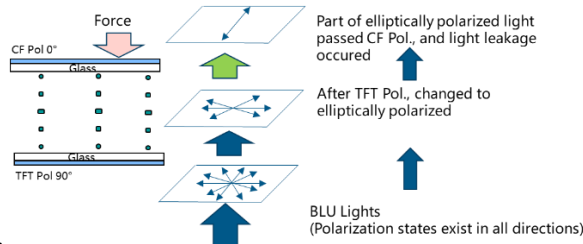


Figure 4. With Force

$$\Delta\varphi = SOC * T * \Sigma$$

Figure 5. Phase Difference Formula

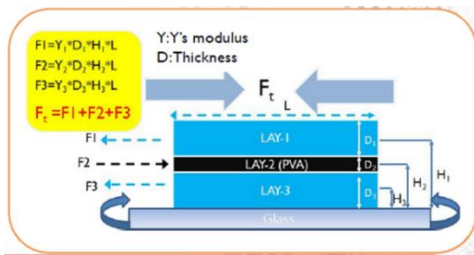


Figure 6. Ft Stress Formula

#### 4. Experimental Study on Module Strength and Warpage

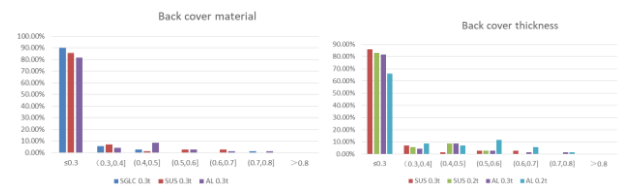
To quantify the coefficient of influence of different factors on module strength and warpage, 16.0 WUXGA product was selected as the experimental platform. The single factor crossover method was used to study the influence of different backlight and panel designs on module strength and warpage. The scheme is shown in Table 1 and Table 2.

**4.1 Warpage:** For warpage, the backlight variables are the material, thickness of the back cover, the panel design mainly focuses on glass and polarizer thickness and material, also the panel size would add on the research, randomly select 50 modules under different conditions for warpage testing and record the test data. As shown in Figure 7, under a certain thickness of the back cover (0.3 mm), the module warpage is positively correlated with the strength of the back cover material, the higher yield strength material, the smaller the warpage; and under a certain material of the back cover (GM55), the module warpage is positively correlated with the thickness of the back cover; the result of glass test data follows back cover, and the thinner the polarizer and smaller thickness difference of CF/TFT polarizer, the smaller the warpage, all test datas match

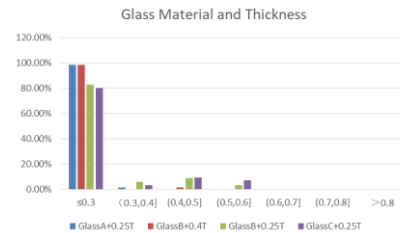
the theory, as the Figure 7 shown, we separated the data with less than 0.3mm, between 0.3mm and 0.4mm, between 0.4mm and 0.5mm and beyond 0.5mm, the data less than 0.3mm shows quite a lot of part by total data, so we use the ratio of less than 0.3mm to compare each key factors influence. The relationship of the key factors are complex, so we should use artificial intelligence model to calculate.

Table 1. Single factor test table for module warpage

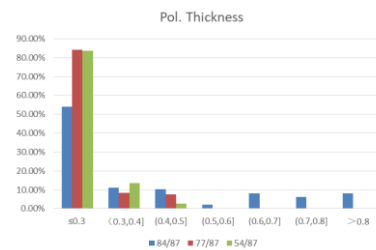
Item	Design variable	Details
Backlight	Material	AL/SUS/SGLC/...
	Thickness	0.2 mm /0.3 mm/...
Panel	Material	Glass A/ Glass B / Glass C/...
	Thickness	0.4 mm/0.2 mm/...
Polarizer	Thickness	84&87um/77&87um/54&87um/...



(a)Module warpage under different back cover material and thickness



(b)Module warpage under different glass material and thickness



(c)Module warpage under different polarizer thickness

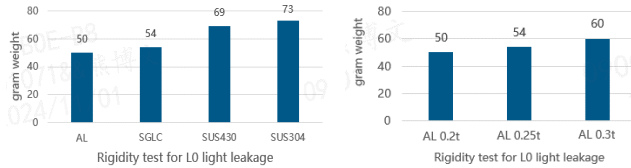
Figure7

**4.2 Strength:** For strength, the backlight variables are the material, thickness of the back cover, the panel design mainly focuses on glass type and thickness, randomly select 50 modules under different conditions for strength testing and record the test data. As shown in Figure 8, under a certain thickness of the back cover (0.3 mm), the gram weight of L0 leakage light is positively correlated with the strength of the back cover material, the higher yield strength material, the higher gram weight; and under a certain material of the back cover (AL), the gram weight of L0 leakage light is positively correlated with the thickness of the back cover;

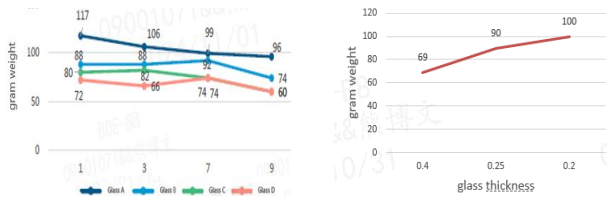
For glass strength, the higher Young's modulus of the glass, the higher gram weight; For glass thickness, the smaller the glass thickness, the smaller the glass phase difference  $\Delta\varphi$ , the less L0 light leakage and the higher the gram weight.

**Table 2.** Single factor test table for module strength

Item	Design variable	Details
Backlight	Material	AL/SUS/SGLC/...
	Thickness	0.2 mm /0.3 mm/...
Panel	Material	Glass A/ Glass B / Glass C/...
	Thickness	0.4 mm/0.25 mm/...



(a)Module strength under different back cover material and thickness



(b)Module strength under different glass material and thickness

**Figure8**

**5. Artificial Intelligence Model of NB module strength and warpage**

As we know the artificial intelligence have a lot advantage as below:

**Efficiency:** Artificial intelligence can process large amounts of data, learn and predict through algorithms and models, and can complete a large amount of work in a short period of time, and improving production efficiency.

**Accuracy:** Compared to humans, artificial intelligence can work and predict more accurately, discover patterns and correlations in data, and make accurate judgments in future predictions.

**Self-learning:** Artificial intelligence can continuously learn and optimize itself through data and models, gradually improving the accuracy and efficiency of its predictions and decisions.

**Fatigue free:** Artificial intelligence does not feel tired or emotionally unstable like humans, and can continue to work and learn, thereby improving its efficiency and performance.

**High stability:** Once the model and algorithm are determined, artificial intelligence can maintain high stability and reduce errors in large amounts of data and complex situations;

**5.1 Parameter Arrangement:** Artificial intelligence model are similar to a black box that constructs a mapping relationship and obtain corresponding output data based on the input data vector. Based on our research, we have already know that polarizer, glass, back cover are the key factors, but the three parts for AI model are too little as input, so we depart the polarizer substrate, glass thickness and material, back cover thickness and material, size and etc., that we could get 19 rows parameter(a/b/c...) as input as

Table3 shows, and if we select the research data as output, the quantity of data can't support to establishment AI model, so we collect mass product's data about 2578 rows as output, and we managed the data with average value and maximum value as Table 4 shows.

**Table 3.** Input Parameter

Item	a	b	c	d	e	f	...
14	-	-	-	-	-	-	...
13.3	-	-	-	-	-	-	...
...	...	...	...	...	...	...	...

**Table 4.** Output Parameter

Item	ID	Warpage								
		1	2	3	4	5	6	7	Avg.	Max.
13.3	1	0.05	0.05	0.15	0.05	0.10	0.10	0.05	0.08	0.15
	2	0.05	0.10	0.10	0.15	0.10	0.05	0.15	0.10	0.15
	3	0.05	0.10	0.05	0.10	0.05	0.10	0.10	0.08	0.10
	4	0.05	0.15	0.10	0.10	0.05	0.15	0.10	0.10	0.15
	5	0.05	0.05	0.15	0.15	0.05	0.10	0.10	0.09	0.15

Item	gram weight												Avg.	Max.
	1	2	3	4	5	6	7	8	9	10	11	12		
13.3	113	110	114	109	105	122	114	101	128	105	125	106	112	128
14.0	101	104	123	124	120	117	102	123	108	129	105	128	115	129

**5.2 AI mode Training and Testing:** There are many AI model for data training like A, B, C , D and etc., The input data consists of 2578 rows and 19 rows parameters, of which 9 parameters are categorical variables. To ensure that the parameter features are not lost, One Hot Encoding is used to convert them into a 0/1 sparse matrix with 151 columns. First we choose average value as output for model training, Secondly, we choose maximum value as output for training and the result as bellow:

Do not oversample-Average:

Compare four algorithms: A,B,C,D, Use 80% of the dataset as the training set and 20% as the testing set, and perform five-fold cross validation on the training set, model training results (cross validation) are not ideal, and the best accuracy R<sup>2</sup> of the four models is 0.7830 as Figure 9.

Target	Model	Evaluating Indicator				
		R <sup>2</sup>	MAE	MSE	RMSE	Calculation Time
Average	A	0.6173	0.0307	0.00203	0.05017	0.66s
	B	0.7347	0.02516	0.00168	0.041031	6.16s
	C	0.7830	0.0204	0.00117	0.03424	3.29s
	D	0.7822	0.0202	0.00118	0.03437	4.13s

**Figure 9.** Model Training Results by Average Value without Oversample

Do oversample-Average: The SMOTE (Synthetic Minority Over sampling Technique) algorithm was used to oversample the samples, and the final sample size was expanded from 2578 to 4503.

Compare four algorithms: A, B, C, and D, Use 80% of the dataset as the training set and 20% as the testing set, and perform five-fold cross validation on the training set, the model training results accuracy R<sup>2</sup>could update to 0.8998 as Figure 10. , which is a quite perfect value.

Target	Model	Evaluating Indicator				
		R <sup>2</sup>	MAE	MSE	RMSE	Calculation Time
Average	A	0.7255	0.0315	0.00203	0.05017	0.66s
	B	0.7858	0.02416	0.001483	0.03852	6.09s
	C	0.8998	0.02799	0.00222	0.04717	6.46s
	D	0.8991	0.02848	0.00226	0.04756	4.02s

Figure 10. Model Training Results by Average Value with Oversample

Based on the training result, we use another 20% of the dataset as the testing set, the average value testing result could match the training result as Figure 11.

Target	Model	Evaluating Indicator	
		R <sup>2</sup>	MSE
Average	A	0.7026	0.00203
	B	0.7958	0.00142
	C	0.8883	0.00254
	D	0.8755	0.00284

(a)With Oversample

Target	Model	Evaluating Indicator	
		R <sup>2</sup>	MSE
Average	A	0.6042	0.00258
	B	0.7308	0.00204
	C	0.7408	0.00155
	D	0.7160	0.00156

(b)Without Oversample

Figure 11. Model Testing Results by Average Value without and with Oversample

Do not oversample-Maximum: The best accuracy R<sup>2</sup> of the four models is 0.75696 as Figure 12.

Target	Model	Evaluating Indicator					
		R <sup>2</sup>	MAE	MSE	RMSE	MAPE	Calculation time
Maximum	B	0.68101	0.06233	0.00812	0.09012	0.34374	3.16s
	C	0.75696	0.00131	0.02260	0.03624	0.21351	1.32s
	D	0.66228	0.06274	0.00785	0.08865	0.34554	4.13s

Figure 12. Model Training Results by Maximum Value without Oversample

Do oversample-Maximum: The best accuracy R<sup>2</sup> of the four models is 0.84339 as Figure 13.

Target	Model	Evaluating Indicator					
		R <sup>2</sup>	MAE	MSE	RMSE	MAPE	Calculation time
Maximum	B	0.83330	0.06696	0.00967	0.09834	0.25395	2.36s
	C	0.84339	0.06311	0.00908	0.09532	0.23780	1.32s
	D	0.83540	0.06667	0.00954	0.09772	0.24152	3.26s

Figure 13. Model Training Results by Maximum Value with Oversample

Based on the training result, we use another 20% of the dataset as the testing set, the maximum value testing result could match the training result as Figure 14.

Target	Model	Evaluating Indicator					
		R <sup>2</sup>	MAE	MSE	RMSE	MAPE	Calculation time
Maximum	B	0.62948	0.06756	0.01032	0.10158	0.34374	6.16s
	C	0.72018	0.05894	0.00735	0.08573	0.32078	1.28s
	D	0.61988	0.06860	0.01056	0.10276	0.35067	4.13s

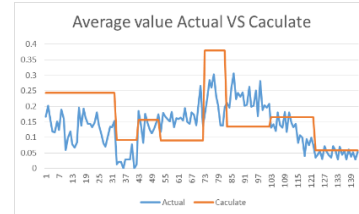
(a)Without Oversample

Target	Model	Evaluating Indicator					
		R <sup>2</sup>	MAE	MSE	RMSE	MAPE	Calculation time
Maximum	B	0.83544	0.06772	0.00974	0.09869	0.25394	2.21s
	C	0.85041	0.06253	0.00885	0.09410	0.23350	1.28s
	D	0.84018	0.06736	0.00945	0.09726	0.23299	3.13s

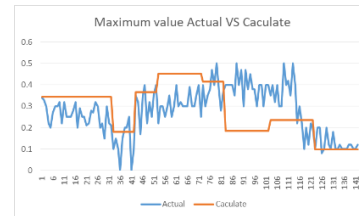
(b)With Oversample

Figure 14. Model Testing Results by Maximum Value

As we have already model trained, we choose 8 products to validated, and the actual data could match the calculate data as the Figure 15 shows.



(a)Average value validate result



(b)Maximum value validate result

Figure 15. Model Validate Results

## 6. Conclusion

Based on AI model training and testing, the C model shows better performance than other models, and the testing results could meet training results. First the AI model can simulation our warpage accurately. Secondly the AI model could also used on strength simulation. Finally the AI model analysis the influence of different key factors and predict the average and maximum value of module's warpage and strength, provide design guide for our module design. This can save a lot of validate cost, cycle and decrease the ratio of issues.

## 7. Reference

- [1] YANG Y F , KIMAN K , QIN G K , et al. Simulation and experimental study on light leakage in ADS mode LCDs [J].SID Symposium Digest of Technical Papers , 2014, 45(1): 1251-1254 .
- [2]FENG W , et al. Research and improvement of influencing factors on ADS TFT-LCD light leakage sensitivity [J]. Chinese Journal of Liquid Crystals and Displays, 2019, 34(03): 241-244. (in Chinese )
- [3] YOU J , JIA Q , YANG Y F , et al. Improvement of dark state light leakage in ADS mode LCDs [J].SID Symposium Digest of Technical Papers , 2015, 46(1): 1544-1547