공학석사학위논문

통계적 모델 검증을 위한 해석모델 개선 방법론

A Model Refinement Framework for Statistical Model Validation

2013 년 2 월

서울대학교 대학원

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이 논문을 공학석사 학위논문으로 제출함

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Abstract

A model refinement framework for statistical model validation

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As the importance of virtual testing has been increased for cost-effective product design and design evaluation, researchers focus on studying validation and verification (V&V) to increase the computational model predictability. Model validation process can make the computational model accurately through the model calibration and validity check process; however, in some cases, unacknowledged uncertainties such as lack of knowledge and human mistakes still exist and decrease the predictability of the model. To overcome this challenge, this thesis presents a model refinement framework for statistical model validation. This framework consists of the three steps; 1) invalidity analysis, 2) invalidity reasoning tree (IRT) and 3) invalidity sensitivity study. Invalidity analysis seeks possible causes for invalidity. Then, the IRT determines a parametric form of refinement candidates from the possible causes and invalidity sensitivity analysis finally checks the effect of the candidates quantitatively. Model calibration and validity check are followed to ensure good model predictability. The proposed method is demonstrated with the TFT-LCD fracture of a smartphone.

Keywords: Model refinement, Verification and validation (V&V), Virtual testing, Model Uncertainty
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Nomenclature

D	critical value
E_g	Young's modulus of glass
E_{p_y}	Young's modulus of polarizer in y direction
f	probability density function (PDF)
f_{u_i}	PDF of u-pooling metric
H_0	null hypothesis
i	number of experimental data
L	likelihood function
n	number of observed (experimental) data
t	thickness of chassis
$\mathbf{X}$	known model variables
$\mathrm{X_m}$	failure displacement of module in Top X
$\mathrm{X_p}$	failure displacement of panel in Top X
Y	yield strength of chassis
$\hat{Y}$	predicted response model
$\mathrm{Y_m}$	failure displacement of module in Top Y
$\mathrm{Y_p}$	failure displacement of panel in Top Y
y	component of a random response
α	significance level

$\boldsymbol{\theta}$ unknown model variables

$\boldsymbol{\Theta}$ calibration parameter vector

Abbreviations

GoF	Goodness of Fit
IRT	Invalidity Reasoning Tree
LCD	Liquid Crystal Display
LGP	Light Guide Panel
PDF	Probability Density Function
PoI	Performances of Interest
V&V	Verification and Validation

Chapter 1. Introduction

As the production cycle has been shorter and product function has been more complicated, the importance of virtual testing has been increased for cost-effective product design and design evaluation. Hopefully, people want that computational model estimates experimental results well to obtain a reliable result. In general, however, it is a grand challenge to build a highly predictable computational model because of our limited knowledge of the model. Model verification and validation (V&V) has to be exercised to overcome this challenge.

The survey articles of AIAA [1], Obercamkf and Trucano [2], Thacker et al. [3], ASME [4], and Obercamkf and Christopher [5] explain the up-to-date techniques and concepts of V&V. In their works, variabilities and uncertainties such as material properties, loading condition, experimental error, boundary condition and manufacturing tolerance bring the discrepancy between the predicted and observed results. Therefore, an understanding of model variability and uncertainties is essential to develop a highly accurate computational model. Jung [6] proposed a hierarchical framework of statistical model validation to improve the reliability of the computational model considering variability and uncertainties through model calibration, validity check and model refinement. Model calibration adjusts the set of unknown model input variables which are selected from model uncertainties to maximize the agreement between the simulation and experiment results. Validity check measures and evaluates the degree of mismatch between the calibrated simulation result and observed result. If model judged invalid through the validity check, the calibrated model should be refined to correct the unacknowledged uncertainties.

Model calibration and validity check have carefully studied in Ref. [6]. However, model refinement was never studied. Model refinement is a process to refine the physical, mathematical, and computational models by eliminating the errors of assumptions and uncertainties that affect model predictability most. This thesis thus presents a model refinement framework that completes statistical model validation.

This paper is organized as follow. Chapter 2 overviews model uncertainties and statistical model validation to help understand model refinement concept. Chapter 3 offers the model refinement procedure. A liquid crystal display (LCD) failure in a smartphone TFT module is used to demonstrate the proposed idea in Chapter 4.

Chapter 2. Literature Review

This chapter presents the state-of-the-art knowledge for the proposed model refinement framework. Section 2.1 explains the basic concept of model uncertainties. Section 2.2 reviews the model validation framework which is composed of model calibration and validity check.

2.1 Model Uncertainties

Engineering systems inherently contain various uncertainties such as manufacturing tolerance, material properties and so on. Moreover, many uncertainties and assumptions are introduced while building computational models. It is of great importance to the successful execution of model validation. Model uncertainties, categorized into aleatory and epistemic [5], have been investigated in many years [5-9]. (see Figure 1)

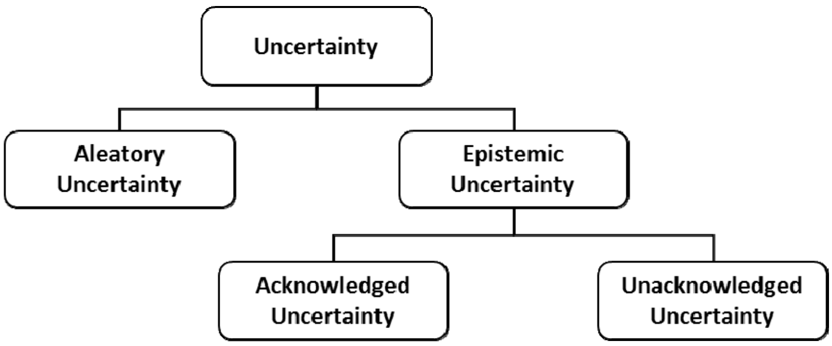

Figure 1. Category of Uncertainties

Aleatory uncertainty is caused by the natural or inherent randomness with sufficient information. This type of uncertainty is also called objective and irreducible uncertainty because the degree of uncertainty cannot be reduced with adding more data. For example, if a coin toss experiment is performed with sufficiently large number of times, we can exactly determine the probabilities of a heads occurring in a flip. Nevertheless, we cannot predict the result of the next flip with better than 50% accuracy because of the inherent aleatory uncertainty. Epistemic uncertainty stems from lack of knowledge such as incomplete information or incomplete knowledge. It is also referred to as subjective and reducible uncertainty. This type of uncertainties is able to reduce the degree of uncertainty by adding more information or obtaining more knowledge. Therefore, technical reference or expert's opinion will be a critical source to reduce the degree of this uncertainty.

Epistemic uncertainty is again divided into acknowledged and unacknowledged uncertainty. Acknowledged uncertainty results from a conscious decision making which is considered to ignore it for practical reason, or to handle it in some specific way. Simplification of the physical process with assumptions in a simulation modeling process can be a common example of an acknowledged uncertainty. This uncertainty can be reduced by considering higher level of physics or applying a multi-precision arithmetic instead of single precision arithmetic. Unacknowledged uncertainty originates from an incognizant of the knowledge incompleteness or the necessity of knowledge to modeling the system of interest. The most common reasons of unacknowledged uncertainty are human errors, or mistakes in judgments. It can be also reducible by adding information or knowledge like as acknowledged uncertainty if we know the reason of this uncertainty. However, this type of uncertainty is usually not recognizable and hard to identify it.

In general, model calibration is performed to optimize the unknown parameters which are cautiously considered from dominant uncertainties. If the calibrated model is judged “invalid,” therefore, it is reasonable to say “the model had unacknowledged uncertainties.” The proposed model refinement framework focuses on detecting this unacknowledged uncertainty and corrects them through series of process.

2.2 Model Validation

Since 1960’s model validation have been actively studied from many organizations and researchers to improve the accuracy of computational model compared to experimental data. As shown in Figure 2, the model validation framework requires three core techniques: (1) statistical model calibration, (2) hypothesis test for validity check, and (3) model refinement [6].

Before the beginning of the statistical model calibration, the problem is identified with model calibration planning (top-down), because the well-defined calibration planning and metric can help to enhance the model predictability efficiently through model calibration [10]. Model calibration planning consists of three activities: (i) Model decomposition planning, (ii) Statistical model calibration planning, and (iii) Experiment planning for model variable characterization. In the first activity, the system is decomposed into subsystem and component level founded on understanding of performances of interest (PoI). In the next activity, the unknown variables which significantly affect the results of the simulation model are determined. Then, statistical characteristic of material properties, physical parameters and test results are defined with goodness-of-fit (GoF) test [11].

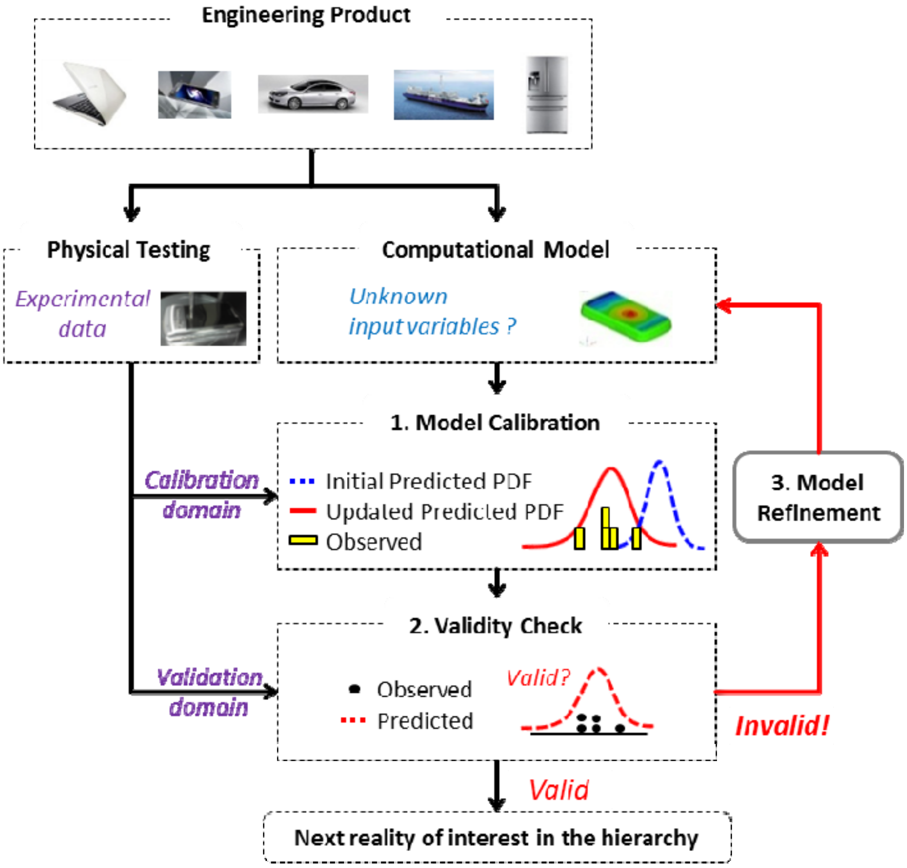

Figure 2. Model Validation Procedure

(Reprinted from [6], Courtesy B. C. Jung)

2.2.1 Statistical Model Calibration

Model calibration technic recently has been developed to increase the accuracy of simulation model. This technic adjusts unknown model variables in order to matching the test result and simulation result. Nonetheless, in a deterministic sense, model calibration can larger the discrepancy between the test and simulation results because of uncertainties such as material property, loading condition, experimental error, boundary condition and manufacturing tolerance. To overcome this drawback, statistical model calibration method is developed to improve the predictive capability of computational models while considering the probability distribution of uncertain sources [12].

In the statistical model calibration, a predicted response model ($\hat{Y}$) is function of known model variables ($\mathbf{X}$) and unknown model variables ($\boldsymbol{\theta}$) which are determined from calibration planning process.

$$\hat{Y} = Y(\mathbf{X}, \boldsymbol{\theta}) \tag{1}$$

The model calibration parameters are determined from unknown variables and statistically characterized and the calibration parameter vector ($\mathbf{\Theta} = \{\boldsymbol{\mu}_{\boldsymbol{\theta}}, \boldsymbol{\sigma}_{\boldsymbol{\theta}}\}$) will be determined by maximizing the agreement between the predicted and observed results as: (see Figure 3)

$$\text{maximize} \quad L(\mathbf{\Theta} \mid y_1, \cdots, y_n) = \sum_{i=1}^{n} log_{10}[f(y_i \mid \mathbf{\Theta})] \tag{2}$$

where y_i is i^{th} experimental response datum; n is number of experimental data; L is likelihood function; and $f(y_i|\mathbf{\Theta})$ is the PDF value of y evaluated at its i^{th} response datum for a given value of $\mathbf{\Theta}$. An unconstrained optimization problem can be solved using a nonlinear optimizer.

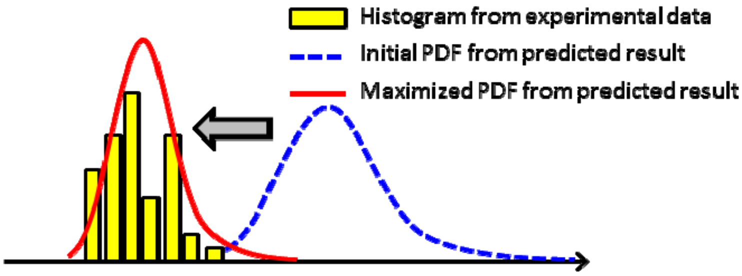

Figure 3. PDF Changes in Statistical Model Calibration Procedure

2.2.2 Validity Check

The hypothesis test for validity check is developed to measures and evaluates the degree of mismatch between the calibrated simulation result and observed result by considering the effect of limited experimental data [6]. In the hypothesis test, the null hypothesis (H_0) is defined as "the calibrated model is valid." Validity check method adopted u-pooling method to overcome the limitation of experimental data. U-pooling method allows experimental data sets which come from different environmental conditions to be integrated into a single metric. U-polling metric (U_m) [13] quantifies a difference between predicted (simulation) and observed (test) results, and it is calculated as:

$$\mathrm{U}_m = area(F_u, F_{\mathrm{uni}}) = \int_0^1 \left| F_u(u) - F_{\mathrm{uni}}(u) \right| du, \quad 0 < u < 1, \quad 0 \le \mathrm{U}_m \le 0.5 \quad (3)$$

F_u is the empirical CDF of cumulative density u_i which is obtained by transforming every experimental datum; and F_{uni} is CDF of the uniform distribution. If the two results has large mismatch, U_m will be closer to 1 otherwise it will be closer to 0.

In validity check process, the null hypothesis (H_0) can be rejected only if a u-pooling metric (U_m) suggests that H_0 is false; otherwise not rejected. The hypothesis test employ $f_{u,i}$ at a given number of experimental data (i) and U_m. Because the $f_{u,i}$ indicates plausible values of U_m in case mother distributions of predicted and observed results are identical, a upper-tailed test can be employed after deciding a rejection region as

$$U_m > D_i(\alpha) \tag{4}$$

where $D_i(\alpha)$ indicates a critical value of u-pooling metric; α is a significance level. If U_m is larger than $D_i(\alpha)$, the calibrated model can be evaluated as invalid (see in Figure 4). If the null hypothesis is rejected, the model should be refined through model refinement activities.

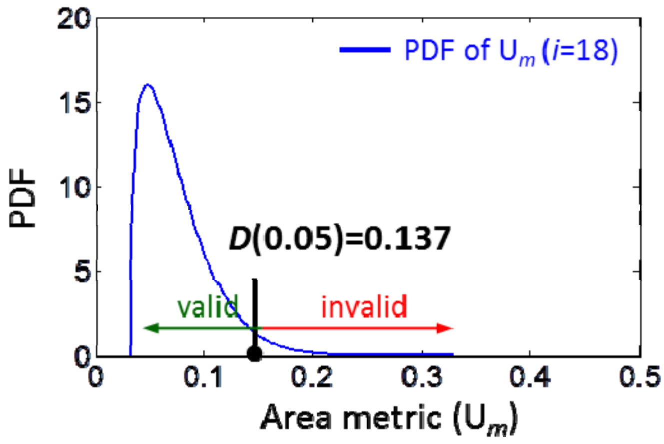

Figure 4. Hypothesis test for validity check

Model refinement process has been explained simply in many researches; however, it is difficult to determine what assumptions or model parameters should be refined. Therefore, following chapter introduce the new model refinement framework to correct the error of simulation model in systematic way.

Chapter 3. Model Refinement Framework

Model invalidity implies that the unacknowledged uncertainties in the calibrated computational model still affect the model predictability significantly. The uncertainties must be eliminated as much as possible so as to minimize the degree of the model invalidity [3, 6, 14]. As mentioned in Chapter. 1, no formal framework to refine the model has been so far developed. This thesis investigates a new model refinement framework that further increases the degree of computational model predictability.

This framework consists of three core steps: (1) invalidity analysis, (2) invalidity reasoning tree (IRT) and (3) invalidity sensitive analysis. The overview of the model refinement framework is depicted in Figure 5.

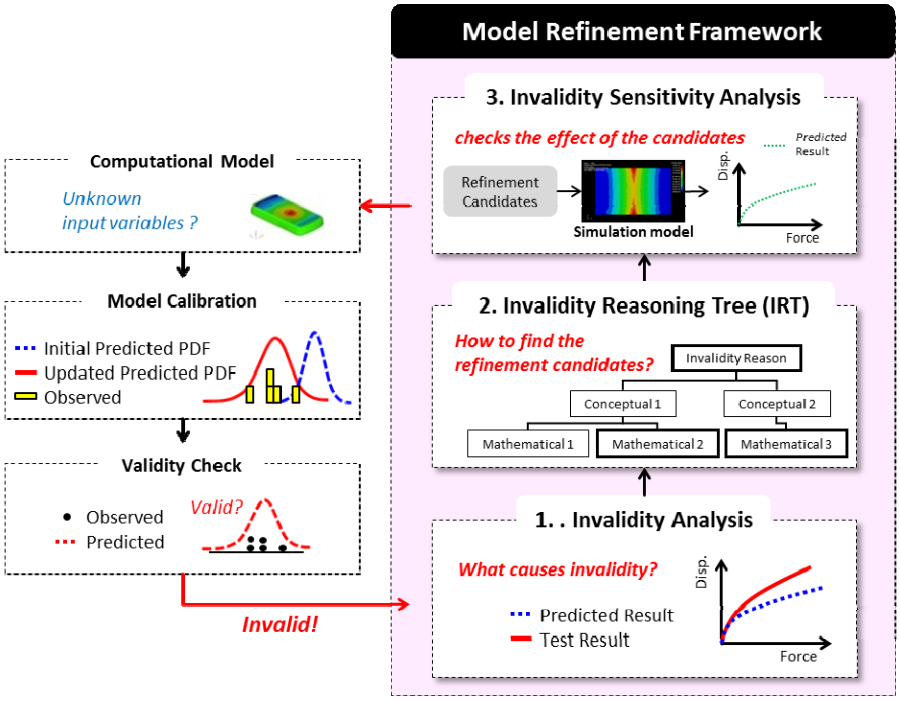

Figure 5. Model Refinement Framework

3.1 Invalidity Analysis

As mentioned in Sec. 2.1, the key idea of the model refinement is to find and remove unacknowledged uncertainties by adding knowledge in Ref. [5]. At this moment, the calibrated computational model was carefully developed through the integration of system experts' knowledge, test data, and calibration results. Thus, as shown in Figure 6, the invalidity analysis process identifies possible causes for model invalidity and supplements the deficient knowledge through two comparative studies; 1) comparative study of simulation and experiment,

2) comparative study of calibration and validation domains.

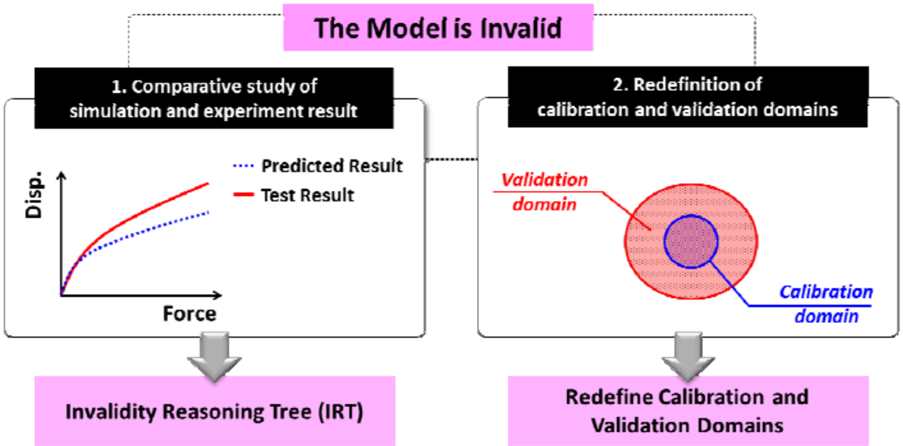

Figure 6. Overview of Invalidity Analysis

First, the simulation and experimental results used in the validity check basically contains much information and shows how the physical phenomena of two results work differently. For example, the displacement and force curve obtained from a computational model (see Figure 5) departs from that from the 3-point bending test after passing through a yield point. This indicates that the materials in the LCD module are not properly models. This kind of observations can offer possible causes for model discrepancy.

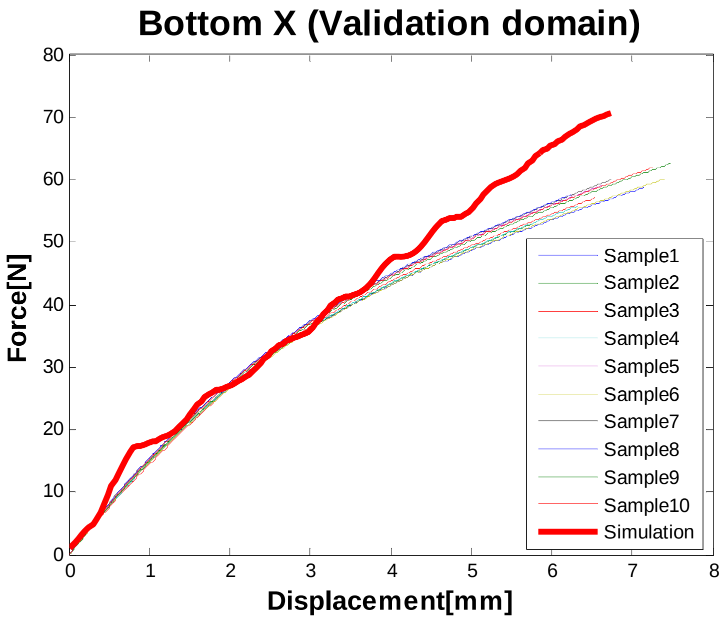

Figure 7. Displacement and Force Curve

Second, model invalidity can be possibly caused by improperly setting calibration and validation domains. The validation domain is normally broader than the calibration domain in terms of operating conditions or design selection [6]. When planning the model calibration, the calibration domain should be carefully chosen not to extrapolate the calibrated results for prediction in the model validation domain. Otherwise, the model discrepancy could remain even after the model calibration. Upon the model invalidity, this issue has to be revisited cautiously. In the end this process can define invalidity causes in the assumptions and uncertainties in the model that affect the model predictability.

3.2 Invalidity Reasoning Tree (IRT)

Traditionally the extraction of parametric refinement candidates depends on empirical knowledge from experts. However, the difference in knowledge and experience among individual experts is not ignorable. A more systematic approach called the invalidity reasoning tree (IRT) is thus proposed to express the invalidity causes (or refinement candidates) in a parametric form. (see Figure 8)

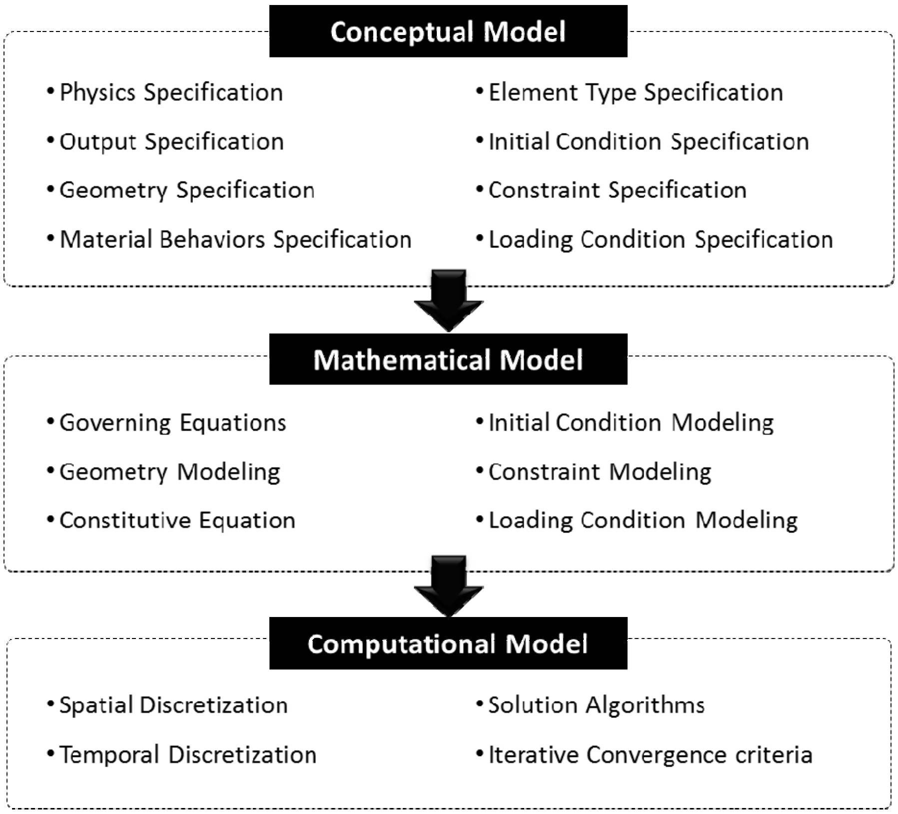

Figure 8. IRT Check List

The IRT helps select the model refinement candidates by sequentially screening the conceptual, mathematical, and computational models.

First, the conceptual model is defined as the assumptions and model descriptions that express the behavior of a physical system [6, 15, 16]. The IRT begins with changing these conceptual models which are related with the 'possible causes of invalidity' selected from the previous step. The check list of the conceptual model is shown in Figure 8. In this level, specification of physics, output, geometry, material behaviors, element type, initial condition, constraint, and loading condition will be studied and refined to strengthen the basic concept of simulation model. In the physics specification category, the invalid model should be carefully checked if the assumptions and concepts of physics sufficiently express the complexity of the model. For example, by expending the modeling assumption from the singled physics such as solid mechanics into multi physics such as structural analysis and heat transfer coupling physics or finite elements with molecular dynamics, the simulation model result can be improved to express more realistic outcomes. In output specification category, the output result form is determined to better present PoI (e.g. maximum tensile stress, displacement, HIC, and system temperature). Also, geometry simplification can be reconsidered (e.g. ignorance of very small holes in a chassis). In material behaviors specification category, linear (e.g. elastic) or nonlinear (e.g. plastic, hyper-elastic, elastic-plastic etc.) behavior of material will be considered. Several theoretical element types such as shell, solid, plate, beam, bar, etc. will be identified in theoretical element type specification category. Consideration of initial velocity or initial displacement will be checked again in the initial condition specification category. In constraint specification category, fixed pinned, contact, and friction conditions are examined for boundary condition check, and bonded, frictionless, and no separation conditions are examined for contact condition. In loading condition specification category, if the applied load is correctly determined such as pressure, point pressure, line pressure, etc. will be checked.

Second, a mathematical model is defined as the mathematical descriptions of the mechanics which are represented in the conceptual model [6, 15, 16]. As shown in Figure 8, governing equations, geometric representation, and constitutive equations must be carefully chosen to model physics of interest. Types of partial differential equations or ordinary differential equations for governing equation will be studied again to detect and remove the possible error in governing equations category. In geometry modeling category, the drawing functions such as simple straight line or type of curve equations such as Hermite Curve, B-spline curve, and NURBS will be changed for the better expression of the simulation model [17]. In the constitutive equation category, the constitutive equations are developed based on refined material behaviors specification and parameters related with each functions are defined. If the initial condition specification is refined in conceptual model, it can be described with very simple equation in the initial condition modeling category. For example, if we consider the one-edge fixed beam, the conceptual equation will be $w=0|_{x=0}$. w is a displacement, and x is a distance from the fixed edge of beam. In constraint modeling category, related simple mathematical equations of boundary condition and contact condition will be developed according to the refinement of constraint specification in the conceptual model. If loading condition specification was refined from previous step, mathematical equation can be changed through the loading condition modeling category.

Lastly, each mathematical model must be implemented with a special care in terms of spatial discretization, temporal discretization, solution algorithms, and iterative convergence criteria as shown in Figure 8.

Based on above categories, invalidity causes will be selected in different models. The IRT will not only help reduce the blunders but also enable time reduction for the model refinement.

3.3 Invalidity Sensitivity Analysis

This step analyzes the degree of importance of the invalidity causes that are identified in Sec. 3.2. The degree of importance of the causes is quantitatively indicated by sensitivity analysis. Once the model refinement step is complete, the model calibration and validity check should continue to improve the prediction capability of the computational model.

Chapter 4. Case Study : LCD Fracture Problem of Smart Phone

Smartphone LCD fracture is one of the smartphone manufacturers' concerns because the LCD becomes larger and thinner. This thesis attempts to build a highly predictive computational model that evaluates the LCD fracture failure of a smartphone TFT module and evaluate the fidelity of the calibrated model.

In Figure 9, the model calibration planning first defined a smart phone LCD fracture mechanism as a PoI of the system, and identified the LDC module as a subsystem and the panel as a component. Then, the Young's modulus of glass (E_g) and polarizer in y direction (E_{p_y}) were selected as unknown variables for panel model, and yield strength (S) and thickness (t) of chassis for module model. For experiment, 3-point bending tests (Top X and Top Y for model calibration; Bottom X for validity check) are used to simulate fracture failures of LCD panel and module under various loading conditions. Top X means load applied from top to bottom direction on the top surface of the LCD panel and module to observe the x-directional failure force, Top Y, from top to bottom direction to observe the y-directional failure force, and Bottom X, load applied from bottom to top direction on the bottom surface to observe the x-directional failure force. The experiment repeated 10 times for each test. The commercial simulation tool, LS-Dyna, was used to build the computational model. The input of computational model is failure displacement of glass, and the output is failure force which is considered to be the response.

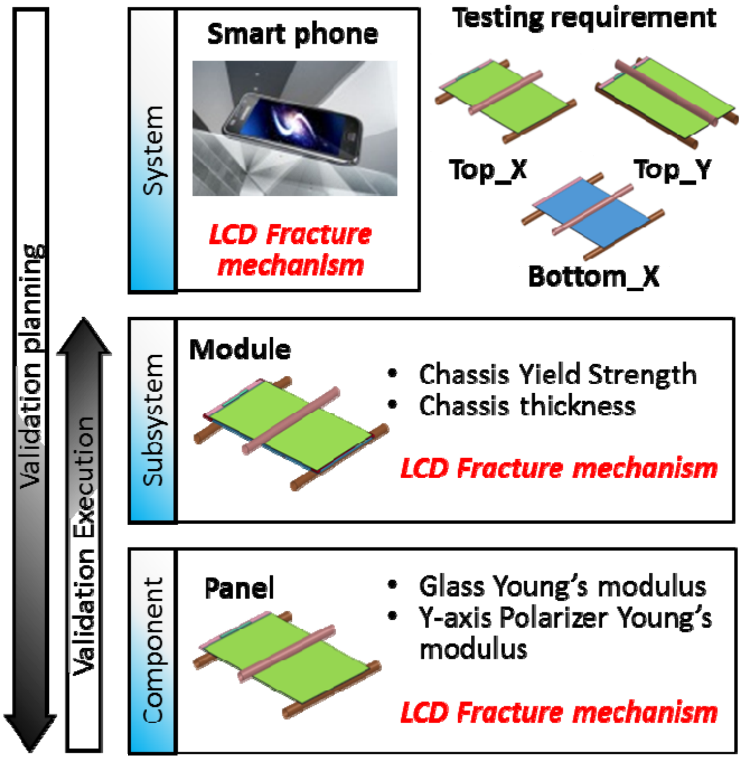

Figure 9. LCD Fracture Problem Overview

4.1 Model Calibration and Validity Check

The model calibration executed from the panel to the module [10]. First, failure force and failure displacement data from 3-point bending test for Top X and Top Y of panel are obtained. Then, failure displacement which follows lognormal distribution is used as loading condition of the computer model, and defined as known random variable (see Figure 10).

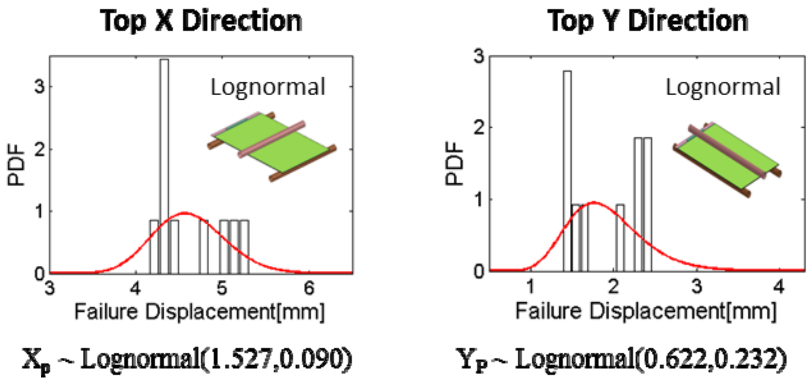

Figure 10. GoF Result of Failure Displacement for Top X and Top Y

Unknown variables, E_g and E_{p_y} are assumed that they follow lognormal distribution. The statistical calibration was performed by comparing the predicted and measured failure force data. Figure 11 and Table 1 illustrate the calibration results of the computational model for Top X and Top Y. The both calibrated simulation results have a good agreement with their experimental result. Figure 12 shows the results of the validity check for the LCD panel. The calibrated model for the LCD panel satisfies the hypothesis test under validation domain. Therefore, the statistical parameter for E_g and E_{p_y} are determined as E_g ~ Lognormal (72.128, 2.858) and E_{p_y} ~ Lognormal (3.397, 1.294) respectively. Now, they can be used as known variables for next level calibration.

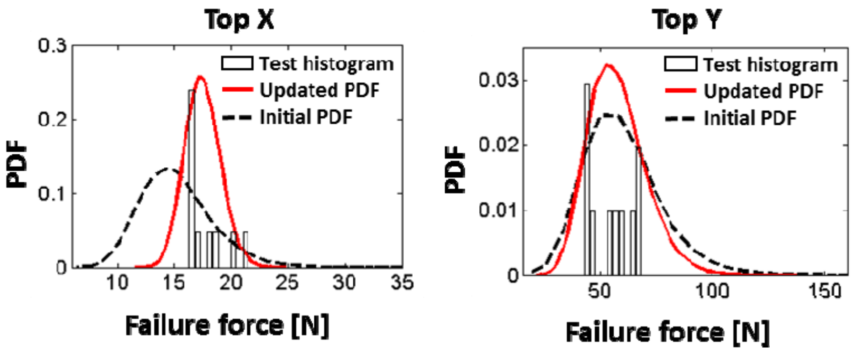

Figure 11. PDF of Calibration Result in Panel Level

Table 1. Model Calibration Result in Panel Level

	μ_{Eg}	σ_{Eg}	μ_{Ep_y}	σ_{Ep_y}	Metric
Initial Value	80	10	3	2.5	26.97
Optimal Value	72.13	2.86	3.40	1.29	24.78

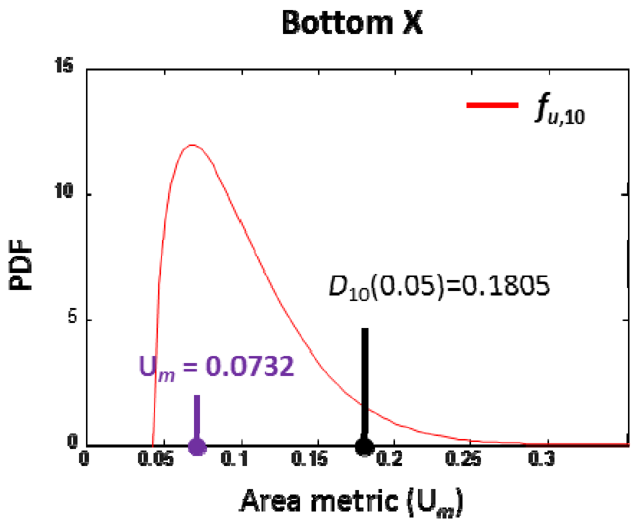

Figure 12. Validity Check Result for Calibrated Panel Model

In module level, E_g, E_{p_y}, X_m ~ Lognormal (1.507, 0.169) and Y_m ~ Lognormal (0.550, 0.324) are determined as known variables. Here, X_m is a failure displacement of module for Top X and Y_m is a failure displacement of module for Top Y. Then, Y (yield strength of chassis) and t (thickness of chassis) are determined as unknown variables. Figure 13 and Table 2 illustrate the calibration results. The calibrated simulation results have a good agreement with their experimental result. However, the module has proved that it is invalid in validation domain (see Figure 14). Therefore, this model necessitates a model refinement process to improve its accuracy by removing its unacknowledged uncertainties.

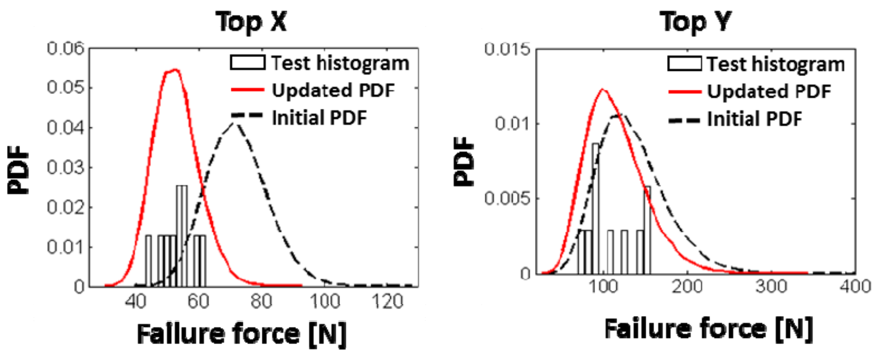

Figure 13. PDF of Calibration Result in Module Level

Table 2. Model Calibration Result in Module Level

	σ_t	μ_Y	σ_Y	Metric
Initial Value	0.0156	750	58	45.39
Optimal Value	2.5e-4	139.95	20.3	34.73

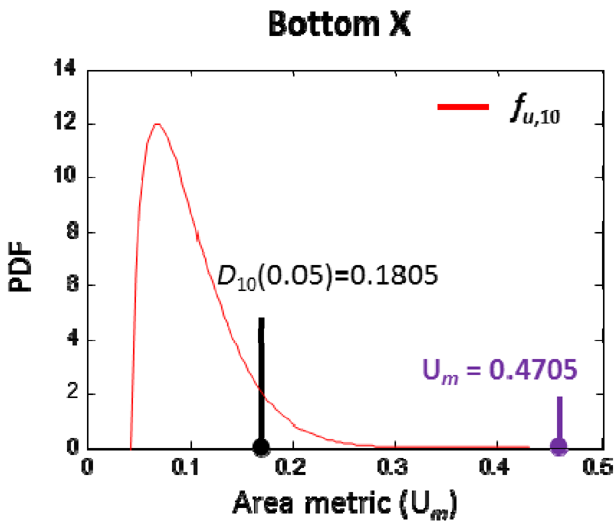

Figure 14. Validity Check Result for Calibrated Module Model

4.2 Model Refinement

In this section, the invalid model revised by performing the proposed model refinement process.

In invalidity analysis, the two invalidity causes was found by comparing 1) simulation and experimental result, and 2) calibration and validation domain. Through the first comparison, one unacknowledged uncertainty is recognizable that the plasticity of model was not exactly included in some parts because the simulation model result mismatches with experimental result in plastic area (see Figure 7). Through the second comparison, the difference between the calibration domain and validation domain was founded. The load is carried directly from the load cell to the glass in calibration domain (Top X and Top Y); on the other hand, the load is delivered from the load cell to the glass through other parts in validation domain (Bottom X) (see Figure 15). Therefore, the different load transfer will be exists because the LCD glass failure affected with load which is transferred through many parts in Bottom X experiment. The first possible cause will be the starting point of IRT and the second possible cause will changes the calibration domain to consider the different load path in z-direction in the calibration domain. Consequently, this result further redefines the Top X and Bottom X as the calibration domain.

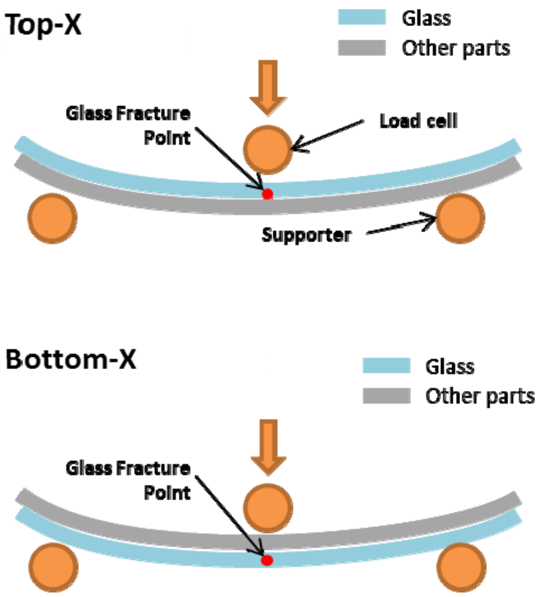

Figure 15. 3-point Bending Test for Top X and Bottom X

As shown in Figure 16, the second process starts from the ‘possible cause of invalidity: need to reconsider the plasticity in TFT-LCD module’ selected from the previous process.

First, the conceptual model is changed from linear to nonlinear behavior. Then, the mathematical model is expended from linear elasticity to plasticity.

Accordingly, the plasticity of mold, reflective, light guide panel (LGP), diffusing, prism A and prism B are selected the refinement candidates. The properties of each material were selected based on Ref. [18-23].

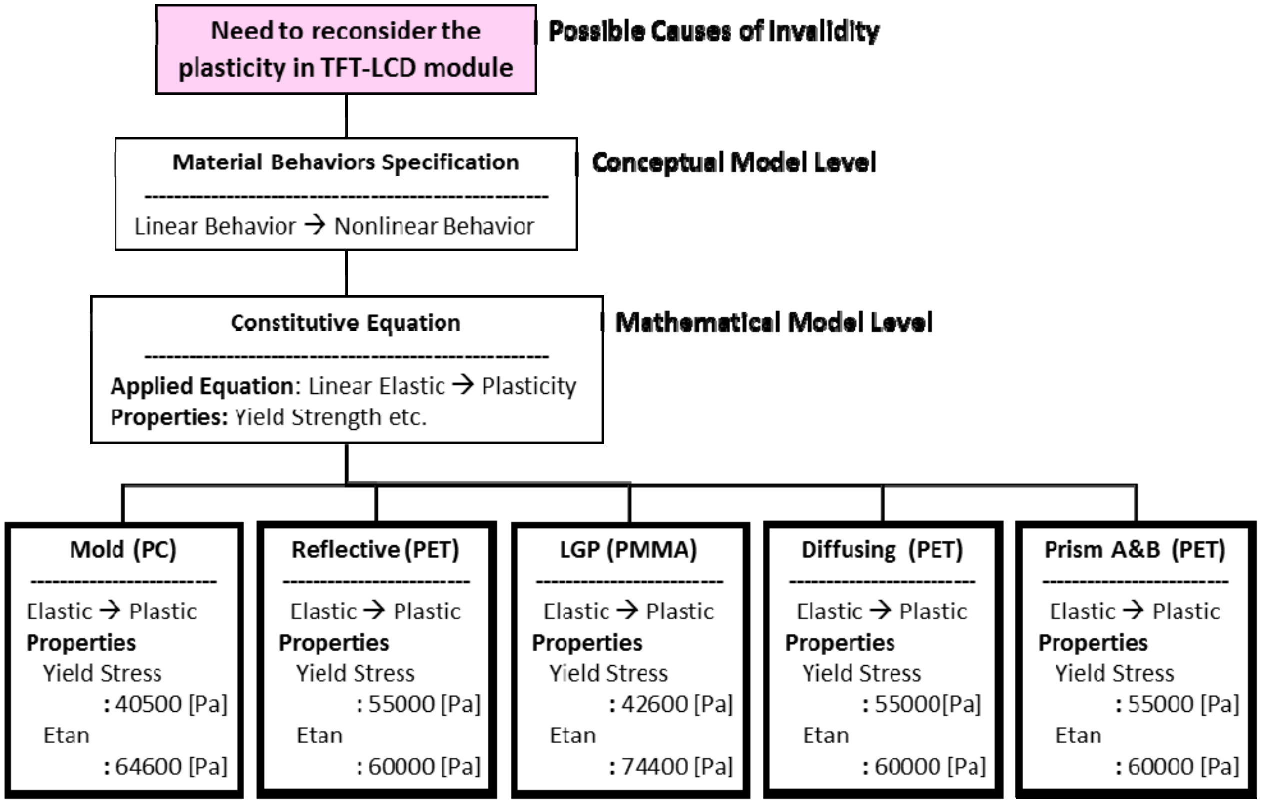

Figure 16. IRT Construction of Module Model

The candidates (see Figure 17) were check quantitatively in the Table 3 to see how they are dominantly effect on the results. Initial force means the force result without change the refinement candidate and the final force means the force result with change the refinement candidate. Finally, the model refinement factors are selected with mold and LGP to be the elastic-plastic material. Then, the model calibration was performed again with the refined model.

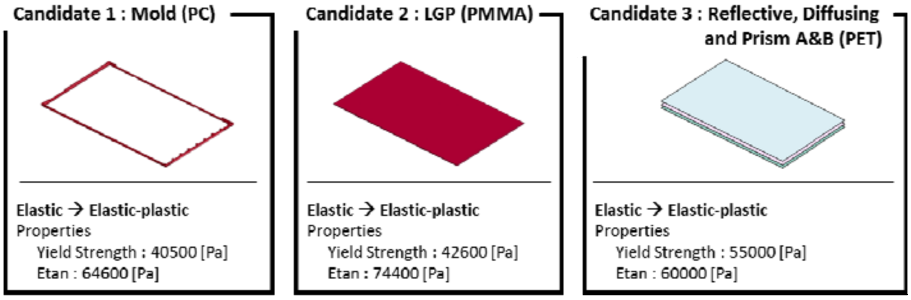

Figure 17. Refinement Candidates in Module

Table 3. Sensitivity Analysis Result

	Initial Force	Final Force	Difference
Mold	72.95	72.27	0.68
LGP	72.95	72.36	0.59
Reflective Diffusing Prism A&B	72.95	72.95	0

Figure 18 and Table 4 show the calibration result and Figure 19 shows the validity check result of refined model. The refined model has good agreement with experimental result in calibration results. Also it satisfies the validity check.

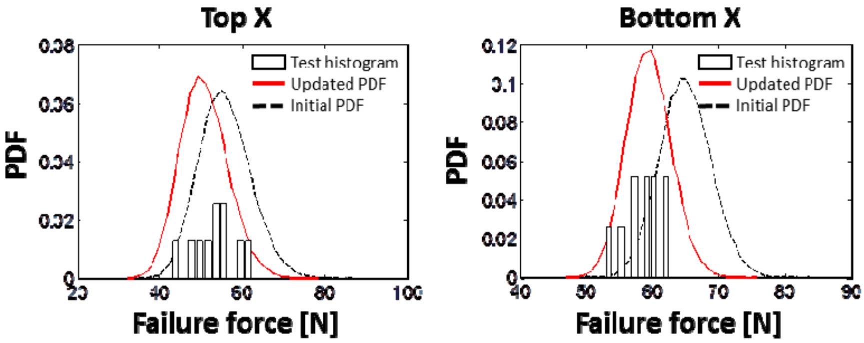

Figure 18. PDF of Calibration Result in Refined Module

Table 4. Model Calibration Result in Refined Module

	σ_t	μ_Y	σ_Y	Metric
Initial Value	6.17e-3	325	32.50	30.96
Optimal Value	2.44e-3	225	12.32	24.82

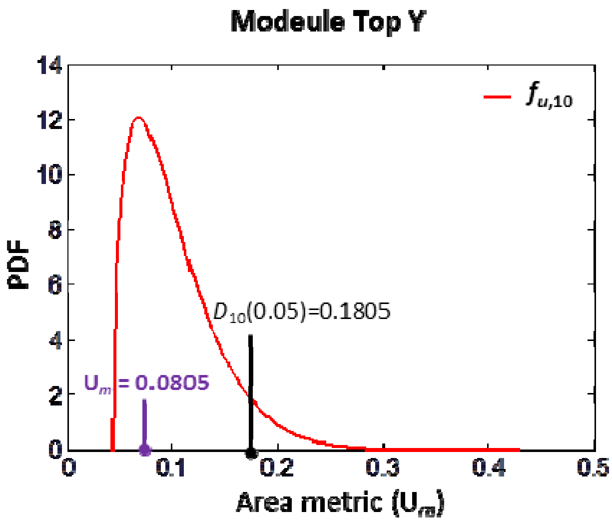

Figure 19. Validity Check Result in Refined Module

Chapter 5. Conclusions

The purpose of this thesis is to develop the model refinement framework for statistical model validation. This framework consists of the three steps: 1) invalidity analysis which seeks possible causes for invalidity, 2) invalidity reasoning tree (IRT) which determines the parametric form of refinement candidates and 3) invalidity sensitivity study which checks the effect of the candidates. The proposed refinement framework is demonstrated with the TFT-LCD fracture of a smartphone. It is shown that the predictability of the TFT-LCD module model is successfully increased by correcting the unacknowledged errors following the model refinement process.

In summary, the proposed model refinement framework helps to increase the predictability of computational model by finding and removing the unacknowledged error. Also, this method improves overall model validation framework by adding the systematic model refinement process.

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국문 초록

제품의 생산 주기가 짧아지고, 구조가 복잡해짐에 따라 새로운 제품을 설계하고 검증하기 위한 가상 시험의 중요성이 증가하고 있다. 그러나 실제 제품에 존재하는 재료 물성, 경계조건, 하중 등의 불확실성으로 인하여 시험과 해석이 일치하는 정확한 해석모델을 개발하는 것은 쉽지 않다. 이를 해결하기 위해, 최근 해석모델의 예측능력 향상을 위한 통계적 모델 검증(statistical model validation)에 대한 연구가 활발히 이루어지고 있다. 모델 보정(model calibration)과 모델 검증 확인을 위한 가설검정(validity check) 과정을 통해 해석모델의 정확도를 향상 할 수 있다. 하지만, 실수 또는 지식, 정보의 부족과 같은 인지되지 않은 불확실성요소(unacknowledged uncertainties)에 의해 모델 보정으로만 해석모델의 정확도를 충분히 향상 할 수 없는 경우가 발생한다. 이를 해결하기 위해, 본 연구에서는 ‘통계적 모델 검증을 위한 해석모델 개선 방법론’을 개발하였다. 모델 개선 방법론은 (1) 무효성 분석(invalidity analysis) (2) 무효성 추론 트리(invalidity reasoning tree, IRT), (3) 민감도 분석(sensitivity study), 세 단계로 구성된다. 첫 번째 단계에서는 해석모델 무효성의 원인을 분석하여 유추하며, 두 번째 단계에서는 이 원인을 개선하기 위해 변경할 모델의 후보를 체계적으로 찾는다.

마지막 단계에서는 각 후보에 대한 민감도 분석을 통하여 최종적으로 모델 개선 사항을 결정한다. 본 논문은 개발된 방법론을 검증하기 위해 스마트폰에 적용한 예를 설명하였다.

주요어: 해석모델 개선, 해석모델 검증 (V&V), 가상 시험, 해석 모델 불확실성
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