A Practical Framework for Managing Uncertainties in Power Device Model Evaluation

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Abstract- **All models are only abstractions of the real systems and their performances are greatly dependent on the assumptions. As different models with different assumptions were introduced, the circuit designers face evaluation problems. In this paper we adopted uncertainty reasoning and the framework of decision-making under incomplete knowledge to solve the problems. The framework produces a range of the model-fit index according to the circuit designers' subjective or *a priori* specification on the importance of the performance criteria. Case studies were performed for practical applications of the framework. In the case study, it could be observed that the outcome of the model-fit index is more influenced by the order of the criteria than the way they are ranked.**

I. INTRODUCTION

Presently, power electronic circuit design practice relies heavily on extensive testing of components, subsystems and devices. With rapidly increasing computational capability, the modeling and simulation-based design is taking on increased responsibility for the success of new engineering systems. However, all models are only abstractions of the real systems and their performances are greatly dependent on the assumptions. As different models with different assumptions were introduced, the circuit designers face evaluation problems. The complex behavior of electronic devices prohibits circuit designers from evaluating the proper inclusion of model physics and from determining the best-fit model to fulfill their circuit simulations. Therefore, for circuit designers, there are practical needs: the fitness and uncertainties of models must be assessed before simulation process. This paper addresses a practical issue relating to the quantitative evaluation of the uncertainty.

Among the issues in power device models, the performance criteria are the most important ones regarding the problems of model evaluation and adoption. Recently, a comprehensive work was performed to review the criteria and the concerns on modeling problems in power semiconductor device [1, 2]. The study raised issues about the uncertainty in models for circuit simulation, which stems from the need to simultaneously fulfill contradicting requirements like high accuracy, low demand of computing power, and easily accessible model parameters. Also, the study concluded that a favorable trade-off between these contradicting requirements is necessary. In this paper we adopted uncertainty reasoning and the framework of decision-making under incomplete knowledge to manage the uncertainties. The framework produces a range of the model-fit index according to the circuit designers' subjective or *a priori* specification on the importance of the performance criteria.

II. DECISION MAKING UNDER INCOMPLETE KNOWLEDGE

The classical decision theory provides a framework such that a decision-maker can select one of a number of strategies open to it. In the problem of selecting and evaluating power semiconductor device models, circuit designer usually has some information about the performance criteria, but the information is not comprehensive enough to enable exact specification of the favorite level of the criteria. This situation is called decision making under incomplete knowledge [3].

In decision making under incomplete knowledge, it is assumed that the performance criteria are ranked in terms of their importance such as $C_1 \geq C_2 \geq ... \geq C_n$, where each C_i indicates one of the criteria. It is also assumed that, using subjective specification of the models, the "favorite levels" of each model under each individual criterion are assigned[4]. Under these assumptions, the framework for decision making under incomplete knowledge can be expressed in a matrix (favorite matrix) using the components of A_{ij}, *a priori* favorite level of model M_i under criterion C_j. In the application of the decision framework, there are two practical methods in deriving the range of expected performance, "model-fit index": weak and strict ranking of the importance of the criteria.

A. Model-fit index given weak ranking of the importance of the criteria

This situation assumes that the circuit designer is able to roughly rank the importance of the criteria for a circuit simulation purpose. In this situation, the expected model-fit index of a model i under a criterion j, F_{ij}, can be found by computing partial averages as shown below [3].

$$F_{ij} = \frac{1}{j}\sum_{k=1}^{j} A_{ik}\ , \quad j = 1, ..., n, \text{ and } i = 1, ..., m. \qquad (1)$$

where m indicates the number of candidate models and n, the number of criteria.

B. Model-fit index given strict ranking of the importance of the criteria

This situation has more information about ranking of importance on the criteria, i.e., $C_j - C_{j+1} \geq K_j$, j=1, ..., n. where, $C_{n+1} = 0$ and K_j are positive constants. The expected model-fit index for this situation can be calculated by the following equation suggested in [3].

$$F_{ij} = \frac{1}{j}\sum_{l=1}^{j} A_{il}\,(1-\sum_{l=1}^{j} K_l) + \sum_{l=1}^{j} K_l A_{il} \qquad (2)$$

III. APPLICATION OF THE FRAME WORK

To apply the decision making under incomplete knowledge, it is necessary to provide necessary information on the models and *a priori* or subjective specifications. From the various references [5-7], in addition to [1] and [2], the most common criteria mentioned and applied are, in an arbitrary order, the following five: accuracy, computation time, number of parameter, parameter extraction, and simulator types supported. For *a priori* specification, we referred [1] and [2] that attempted to find "objective" expected performance, which inevitably included authors' subjective favorites. Using the findings in [1] and [2], we are able to find the favorite levels of models under the following five criteria: accuracy, computation time, and parameter extraction, number of parameter, and simulator type. The numerical values of the favorite level are classified into five groups: 5 for excellence, 4 for very good, 3 for good, 2 for fair, and 1 for poor. Table I and II show *a priori* specification table for the criteria.

TABLE I. THE *a priori* SPECIFICATION TABLE FOR THE THREE CRITERIA

Model Type	Accuracy	Computation Time	Parameter Extraction
Functional	5	2	1
Approximation Solution	2	3	3
Transformation	2	3	3
Lumped Model	4	1	2
Numerical Solution	1	5	5

TABLE II. *A priori* SPECIFICATION TABLE FOR THE OTHER TWO CRITERIA

number of parameter		simulator type	
< 10	5	All	5
11 - 20	4	SPICE & SABER	4
21 - 30	3	SPICE only	3
31 - 40	2	SABER only	2
>40	1	Other	1

We applied the framework to determine the model-fix indices, under two different scenarios, for the four models of power diode selected from [1]. Information of the models is tabulated in Table III. The five criteria and *a priori* specification tables I and II are used in the case study.

TABLE III. SELECTED MODELS

Model #	Model Type	Simulator	Number of Parameter	Remark
1	Analytical	PSPICE, SABER	6	model # 8 in [1]
2	Analytical	SABER	59	model # 9 in [1]
3	Numerical	SABER	26	model # 13 in [1]
4	Numerical	Other	6	model # 14 in [1]

A. Case Study 1

In case 1, we assumed the criteria are ranked in the order of accuracy (C_1), computation times (C_2), parameter extraction (C_3), number of parameter (C_4), and simulator type (C_5). Using the model information and the *a priori* specifications, we formed the favorite matrix as shown in Table IV.

1) *Weakly Ranked Criteria:* When the criteria are weakly ranked, we apply equation (1) to calculate the expected model-fit index for each model. Model-fit indices for the models are derived and the ranges of the model-fit indices of the models are: F_1=(5.0, 2.7), F_2=(5.0, 2.2), F_3=(3.7, 1.0), and F_4=(4.0, 1.0). By observing the model-fit index ranges, one may choose either model #1 or #2 over the other two.

2) *Strictly Ranked Criteria:* Let's consider when the criteria are ranked in numbers such that C_1 =5, C_2 =4, C_3=3, C_4=1.5, and C_5=1. Then, we first calculate the constants K_j= C_j-C_{j+1} and derive them as K_1= 1, K_2= 1, K_3= 1.5, K_4= 0.5, and K_5= 1. (C_6 is assumed to be 0.) We then use equation (2) for model-fit index calculation. The ranges of the model-fit indices are derived, and they are: F_1=(5.0, 1.3), F_2=(5.0, 1.8), F_3=(4.5, 1.0), and F_4=(4.3, 1.0)

By observing the ranges, it is apparent that the choice is either model #1 or #2.

TABLE IV. FAVORITE MATRIX FOR CASE 1

$$\begin{array}{c c} & \begin{array}{ccccc} C_1 & C_2 & C_3 & C_4 & C_5 \end{array} \\ \begin{array}{c} M_1 \\ M_2 \\ M_3 \\ M_4 \end{array} & \begin{pmatrix} 5 & 2 & 1 & 5 & 4 \\ 5 & 2 & 1 & 1 & 2 \\ 1 & 5 & 5 & 3 & 2 \\ 1 & 5 & 5 & 5 & 1 \end{pmatrix} \end{array}$$

B. Case Study 2

In case 2, the criteria are ranked differently: the order now is computation time (C_1), parameter extraction (C_2), simulator types (C_3), accuracy (C_4), and number of parameter (C_5). Using the same information on the selected models and the *a priori* specification tables, we construct another favorite matrix as shown in Table V.

TABLE V. FAVORITE MATRIX FOR CASE 2

$$\begin{array}{c} \\ M_1 \\ M_2 \\ M_3 \\ M_4 \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & C_4 & C_5 \end{array} \\ \begin{pmatrix} 2 & 1 & 4 & 5 & 5 \\ 2 & 1 & 2 & 5 & 1 \\ 5 & 5 & 2 & 1 & 3 \\ 5 & 5 & 1 & 1 & 5 \end{pmatrix} \end{array}$$

1) *Weakly Ranked Criteria:* When criteria are weakly ranked, we use equation (1) to calculate the ranges of the model-fit indices of the models, and they are: F_1=(3.4, 1.5), F_2=(2.5, 1.7), F_3=(5.0, 3.2), and F_4=(5.0, 3.0). Therefore, in this scenario, one surely chooses either model #3 or #4 over #1 and #2.

2) *Strictly Ranked Criteria:* For the strictly ranked criteria such as C1 =5, C_2=4, C3=3, C_4=1.5, and C5=1, the constants are derived as K_1=1, K_2=1, K_3=1, K_4=1.5, and K_5=0.5. By using equation (2), the ranges of the model-fit indices are calculated and they are: F_1=(4.0, 1.5), F_2=(4.2, 1.5), F_3=(5.0, 2.1), and F3=(5.0, 2.0). Similarly, the apparent choice is either model #3 or #4.

C. Observations

As illustrated in the case study, the model-fit index of a model changes when the rank of the criteria is changed. Also, we can observe that the outcome of the model-fit index is more influenced by the order of the criteria than the way they are ranked, either weakly or strictly.

IV. CONCLUSIONS

The uncertainty in modeling and simulation in power device comes from many different sources. This uncertainty brings a question of how to choose the best-fit model for a specific purpose and environment of a circuit designer. In this paper we adopted the framework of decision making under incomplete knowledge to accommodate the uncertainties around the power device model evaluation and selection. The framework produces a range of the model-fit index for the candidate models according to the circuit designer's subjective rank of the performance criteria. Case studies are performed for practical applications of the framework. It is hoped that circuit designers can select the best-fit model of their objectives by the framework of decision making under incomplete knowledge.

V. REFERENCES

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