Filling Rate Analysis for EMC Module of Smartphone's Battery Using Automated Design System

Joon-Seong Lee[1]

[1]A. Dept. of Mechanical System Engineering, Kyonggi University, Suwon, Korea

KEYWORD: Filling Ratio, Automated Design System, Epoxy Molding Compound, Protection Module Package, Mesh Generation

ABSTRACT: Recently, the use of smartphones are growing rapidly and increasing discomfort due to shortages of the battery capacity. Also, consumers are often dissatisfied with the battery life from even the most advanced lithium-ion rechargeable batteries in mobile phone. This paper describes finite element analysis simulation of filling rate for epoxy molding compound module of battery using automated design system. It is considered that if this result is conducted with additional research, it will be possible to plan a better process design.

INTRODUCTION

The Consumers are generally required the use of high energy density batteries. However, most consumers are often dissatisfied with the battery life from even the most advanced lithium-ion rechargeable batteries in mobile phone (Cho,2009). In recent years, plastic products have become thinner and lighter and proper materials, processing technology and product technology have been developed accordingly. Protection Module Package (PMP) has the potential of providing energy densities that are several times more than that Protection Circuit Module (PCM) (Hong, 2014), making them attractive power source for mobile applications, such as next generation cellular phones that require high energy density power sources to enable extended operation times.

The system consists of two main portions. The one is an automated FE analysis system, while the other a design window search system using the multilayer neural network (Rumelhart, 1986). Here the design window means an area of satisfactory solutions in a permissible design parameter space. In practical situations, a design window concept seems more useful than one optimized solution obtained under some restricted conditions. The developed system is applied to evaluate one of epoxy molding compound (EMC) module of smartphone's battery (Jo, 2015).

OUTLINE OF THE SYSTEM

The configuration of the system is illustrated in Figure 1. To efficiently support design processes of practical structures, the automatic FE analysis system (Lee, 1995), which is based on computational geometry techniques, is integrated with a GA. By integrating a GA based optimizer, the system allows automatic search for optimum design solutions. Also, the system allows us to automatically obtain a multi-dimensional design window in which a number of satisfactory design solutions exist using multilayer neural networks (Rumelhart, 1986).

Automated Finite Element Analyzer

One of commercial geometric modeler, Designbase (Chiyokura 1988) is employed for 3D solid structures. Material properties and boundary conditions are directly attached onto the geometry model by clicking the loops or edges that are parts of the geometric model using a mouse, and then by inputting actual values.

In the present system, nodes are first generated, and then an FE mesh is built. In general, it is not so easy to well control element size for a complex geometry. Example of node density function (Lee, 1995) is shown in Figure 2. A node density distribution over a whole geometry model is constructed as follows. The present system stores several local node patterns such as the pattern suitable to well capture stress concentration, the pattern to subdivided a finite domain uniformly, and the pattern to subdivide a whole domain uniformly. An user selects some of those local node patterns, depending on their analysis purposes, and designates their relative importance and where to locate them. Node generation is one of time consuming processes in automatic mesh generation. In the present study, the bucketing method (Asano, 1985) is adopted to generate nodes which satisfy the distribution of node density over a whole analysis domain. Advancing front method (Sloan, 1985) is utilized to generate elements from numerous nodes given in a geometry.

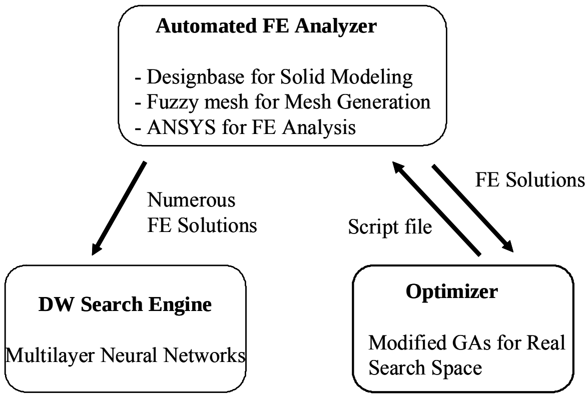

Figure 1. System configuration

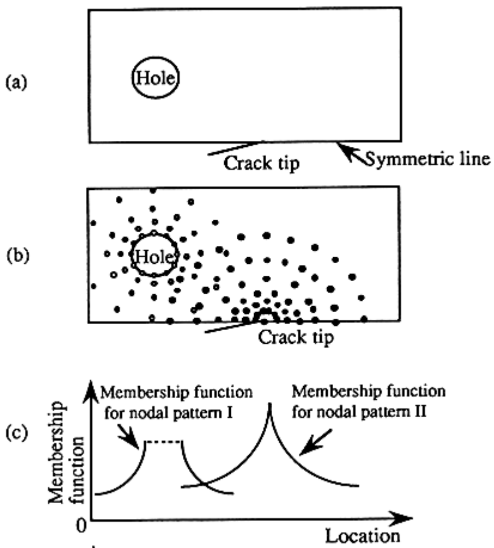

Figure 2. Example of node density & membership function

Then these are automatically attached on nodes, edges, faces and volume of elements. Such automatic conversion can be performed owing to the special data structure of finite elements such that each part of element knows which geometry part it belongs to. Finally, a complete FE model consisting of mesh, material properties and boundary conditions is obtained.

Design window

The design window is a schematic drawing of an area of satisfactory solutions in a permissible multidimensional design parameter space. The design window seems more useful in practical situations than one optimum solution determined under limited consideration. Among several algorithms, the

whole-area search method is employed here. As shown in Figure 3, a lattice is first generated in the design parameter space that is empirically determined by a user. All the lattice points are then examined one by one whether they satisfy design criteria or not. The whole area search method is the most flexible and robust, but the number of lattice points to be examined tends to be extremely huge. Therefore, the present author used a novel method to efficiently search the design window using the multilayer neural network (Rumelhart, 1986).
This method consists of three subprocesses as shown in Figure 4. At first, using the automated FE system, numerous FE analyses are performed to prepare training data sets and test data sets for the neural network, each of which is a coupled data set of assumed design parameters vs. calculated physical values. The neural network is then trained using the training data sets. Here the design parameters assumed are given to the input units of the network, while the physical values calculated are shown to the output units as teacher signal. A training algorithm employed here is the backpropagation (Rumelhart, 1986).

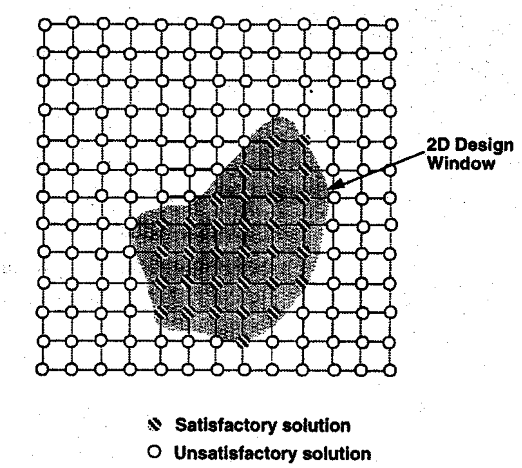

Figure 3. Design window in 2D parameter space

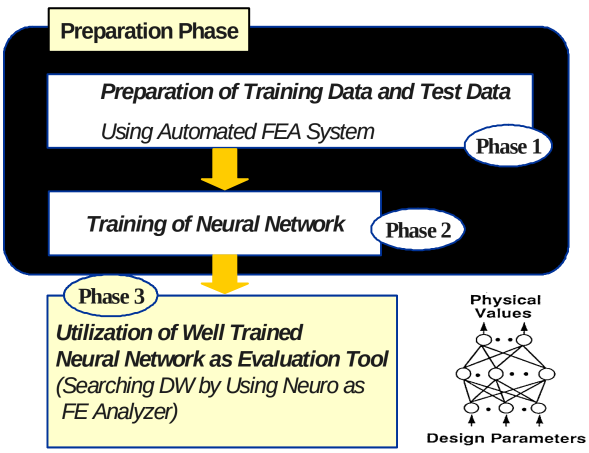

Figure 4. Procedure of design window

After a sufficient number of training iterations, the neural network can imitate a response of the FE system. That means, the well trained network provides some appropriate physical values even for unknown values of design parameters. Finally a multi-dimensional design window is immediately searched using the well trained network together with the whole area search method.

Modified genetic algorithms

In optimum or satisfactory design problems of modern artifacts such as electronic devices, the genetic algorithms have attracted much attention, and have been applied to various inverse problems and optimum designs (Grefenstette, 1984). For continuous search space problems, the conventional genetic algorithms, however, tend to converge slowly, and their accuracy may strongly depend on the bit length of binary code employed. Therefore the present author proposed a new genetic algorithms modified for the real search space, and this formulation was used as an optimization engine.
The fundamental structure of genetic algorithm is shown in Figure 5.

```
k = 0 ;
Initialize P(k) ;
k = k + 1 ;
do
    Recombinate P(k) ;
    Mutate P(k) ;
    Evaluate P(k) ;
    Select P(k);
while terminal condition is not satisfied
```

$$P_s(u_i^k) = \frac{\Phi(u_i^k)}{\sum_{i=1}^{\lambda} \Phi(u_i^k)}$$

Figure 5. Fundamental structure of genetic algorithms

A population of individuals, each represented by a vector, is initially (generation t=0) generated at random, i.e.,

$$P(k) = |\ u_1(k), \ldots\ldots\ldots, u_\lambda \in (k)\ | \in \mathbf{I}^\lambda \tag{1}$$

where $\lambda \in \mathbf{N}$ and $\mathbf{I}$ represent the population size of parental individuals and the space of individual respectively. The population then evolves towards better regions of the search space by means of randomized processes of recombination, mutation and selection though either recombination or mutation operator is not implemented in some algorithms. In the recombination operator $\mathbf{r} : \mathbf{I}^\lambda \rightarrow \mathbf{I}^\gamma$, λ parental individuals breed $\gamma(\in\mathbf{N})$ offspring individuals by combining part of information from the parental individuals. The mutation $\mathbf{m} : \mathbf{I}^\gamma \rightarrow \mathbf{I}^\lambda$, then, forms new individuals by making large alterations with small possibility to the offspring individuals regardless of their inherent information. With the evaluation of fitness for all the individuals, the selection operator $\mathbf{s} : \mathbf{I}^\gamma \cup \mathbf{I}^{\gamma+\lambda} \rightarrow \mathbf{I}^\lambda$ favorably selects individuals of higher fitness to produce more often than those of lower fitness. These reproductive operations form one generation of the evolutionary process, which corresponds to one iteration in the algorithm, and the iteration is repeated until a given terminal criterion is satisfied.
Selection in canonical genetic algorithms emphasizes a probabilistic survival rule mixed with a fitness dependent chance to have different partners for producing more or less spring. By deriving an analogy to the game-theoretic multi-armed bandit problem, Holland identifies a necessity to use proportional selection in order to optimize the trade-off between further exploiting promising regions of the search space while at the same time also exploring other regions (Holland, 1988). For proportional selection $\mathbf{S} : \mathbf{I}^\lambda \rightarrow \mathbf{I}^\lambda$, the reproduction probabilities of individuals $\mathbf{u}_i$ are given by their relative fitness, i.e. $i \in \{1, \ldots, \lambda\}$:

(2)

Sampling λ individuals according to this probability distribution yields the next generation of parents.

ANALYSIS

Boundary condition of mold flow

Figure 6 shows the boundary conditions of EMC of protection module package used in filling rate analysis.

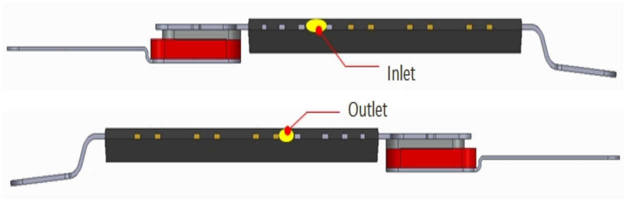

Figure 6. Location of inlet and outlet

EMC Module

Figure 7 shows a configuration modeling for filling rate analysis of EMC module. In this study, a protection module of mobile battery was chosen because it is the flat plate of small thin wall which is expected to have great short shot and flexing. The size of module 3mm × 12mm × 1mm was used in this evaluation. Table 1 shows the property of different epoxy molding.

Table 1. Epoxy molding property

Material	A	B	C	D
Density[g/cc]	1.82	1.88	1.82	1.79
Flexural Mod-ulus[GPa]	12	14	15	17
Poisson' ratio	0.43	0.40	0.36	0.34

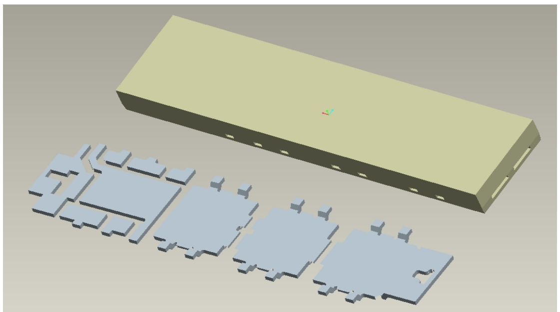

Figure 7. Configuration of model

Figure 8 shows a typical finite element mesh, which consists of 326,214 nodes and 329,849 elements. Among the whole process, interactive operations to be done by user are performed in a reasonably short time of 3～4 minutes.

Figures 9-11 show the result of filling rate analysis of EMC module of smartphone's battery using automate design system

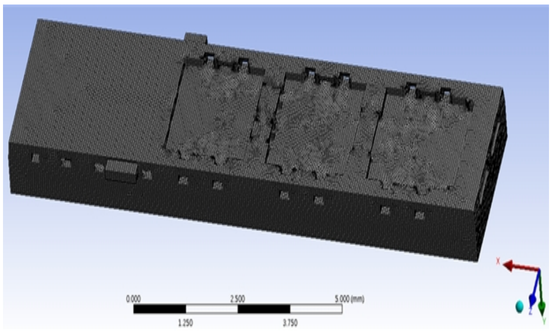

Figure 8. Mesh model for filling rate analysis

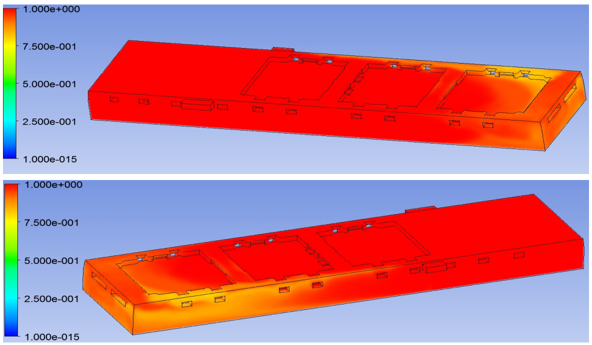

Figure 9. Filling ratio of epoxy material A

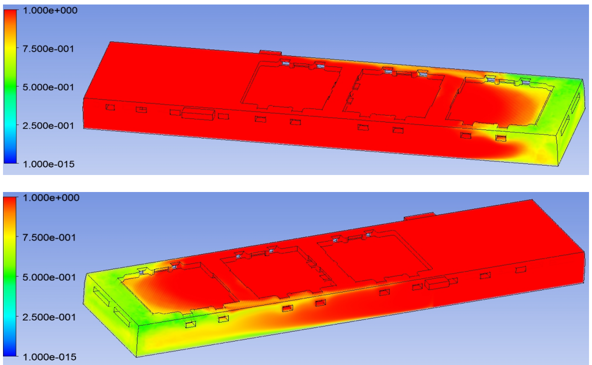

Figure 10. Filling ratio of epoxy material B

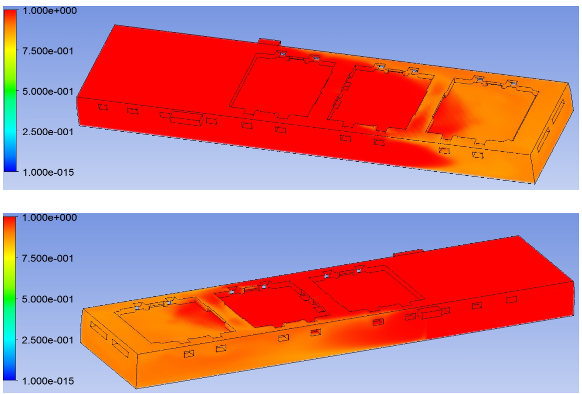

Figure 11. Filling ratio of epoxy material C

The filling rate in order of D → A → C → B depending on epoxy types showed the maximum value when it was type D.

CONCLUSION

A filling rate analysis for EMC module of smartphone's battery is described using automate design system in the present paper. Interactive operations to be done by a user are performed in a reasonably short time.

REFERENCES

[1] Asano, T. 1985. Practical Use of Bucketing Techniques in Computational Geometry, North-Holland.

[2] Chiyokura, H. 1988. Solid Modeling with Designbase: Theory and Implementation, Addition-Wesley.

[3] Cho, J.U., Min, B.S., Han, M.S. 2009. Material of Hand Phone, J. of the Korea Society of Manufacturing Process Engineers, Vol. 8, No. 2, 69.

[4] Grefenstette, J.J. 1984. GENESIS: System for Using Genetic Search Procedures", Proceedings of 1984 Conference Intelligent Systems and Machines, 161-165.

[5] Holland, R. and Jeeves, T.A. 1988. Direct Search Solution of Numerical and Statistical Problems, Vol. 12, 967-973.

[6] Hong, H.R., Lee, J.S., Jo G.H. and Park, D.K. 2014. Analysis on Temperature Change according to Current Injection of EMC Module, Proceedings of KSPE 2014 Spring Conference, KSPE 161.

[7] Jo G.H., Lee, J.S. and Park, D.K. 2015. A Study on the Element Generation Method of PMP Module, Int. J. of Precision Engineering and Manufacturing, in Press.

[8] Lee, J.S. 1995. Automated CAE System for Three-Dimensional Complex Geometry, Doctoral Thesis, The University of Tokyo.

[9] Rumelhart, D.E, Hinton, G.E. and Williams, G.E. 1986. Learning Representation by Back-propagation Errors, Nature 323, 533-536.