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CONCEPTUAL DESIGN OF TIRES USING MULTI-OBJECTIVE DESIGN EXPLORATION

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Abstract. The importance of the rule of simulation at a conceptual design stage is pointed out recently. The methodology using multi-objective design optimization and data mining, which is called MODE (Multi-Objective Design Exploration), is helpful to find out design knowledge. In this study, we show that the design knowledge found by MODE is fruitful for decision making at a conceptual design stage of real world example i.e. contour design of a fuel efficient tire. Our procedure of MODE consists of nonlinear FEA (Finite Element Analysis) to predict tire performance, evolutional computation to get desirable solutions including Pareto solution, and data mining to find out design knowledge. SOM (Self-Organizing Map) and decision tree are used to obtain appropriate design variables and their threshold. In this study, SOM with MLS (Moving Least Square) filter is proposed to obtain the structured smooth data of design variables in an objective function space. We can overlook the whole causation with the objective functions and the design variables using this map. On the other hand, the decision tree gives a rule to get the aimed performance balance. In order to demonstrate the validity of the knowledge, we produced prototype tires. The experimental results of them guaranteed the validity and the effectiveness of the knowledge and MODE. Furthermore, the latest fuel efficient tire, which was designed based on the obtained knowledge, was released in July 2013.

1 INTRODUCTION

For the reduction of the time and cost of product development the importance of simulation at a conceptual design stage is pointed out recently. And the role of simulation for product development gradually changed from a pure virtual testing tool of products to a supporting tool to get a new idea for product innovation. The methodology using multi-objective design optimization and data mining [1,3] which is called MODE (Multi-Objective Design

Exploration) [2,4] is helpful to find out design knowledge as a tool to think. In this study, we show that the design knowledge found by MODE is fruitful for decision making at a conceptual design stage of real world example i.e. contour design of a fuel efficient.

2 MULTI-OBJECTIVE DESIGN EXPLORATION (MODE)

The decision making in the real world depends on multiple criteria. Multiple criteria decision making is indispensable even in the design process of tires. Tires are required many characteristics including low rolling resistance for fuel efficiency of an automobile. The design of tires is so-called multi-objective design optimization. The multi-objective design optimization is to find design variables which minimize or maximize each objective function i.e. performance of a tire. Since some of objective functions have trade-off relation, a set of optimal solutions called Pareto solution is found out in the multi-objective optimization. We can obtain structured design information, which can be called 'design knowledge', by clarifying the relationship between objective functions and design variables in design space including Pareto solutions. The design knowledge can be used for the multi-criteria decision making at a conceptual design stage.

MODE is a methodology to get structured information between objective functions and design parameters using multi-objective optimization and data mining. From the structured information we can find new design knowledge. Figure 1 shows procedure to get new design knowledge in the framework of MODE. Our procedure of MODE consists of FEA to simulate tire performance, evolutional computation e.g. multi-objective genetic algorithm in Isight to get desirable solutions including Pareto solution and data mining e.g. SOM (Self-Organizing Map) and decision tree to find out design knowledge.

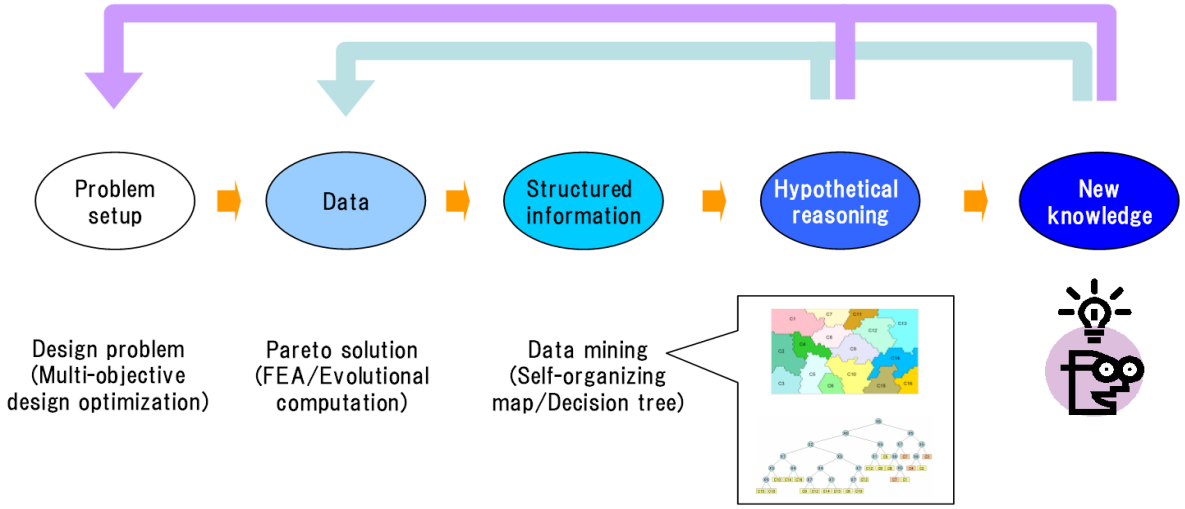

Figure 1: Procedure to get new design knowledge using the framework of MODE

3 APPLICATION OF MODE TO TIRE DESIGN

Fuel saving is one of the most important issue from the viewpoint of CO_2 reduction and natural resource saving. The development of environment conscious technology is high priority not only for car manufactures but also for tire manufactures. Although the reduction of rolling resistance is the key issue for tire manufactures, stiffness of a tire is also important

characteristic. In this study, we apply MODE to tire contour design to obtain design knowledge between tire characteristics and tire contour.
MODE of tire contours is carried out as followings;

1. Problem setup, definition of baseline design of tire contour, design variables and objective functions,
2. Multi-objective optimization by GA (Genetic Algorithm) with meta-models,
3. Data mining using SOM and decision tree,
4. Validation of design knowledge and application of it at a conceptual design stage.

3.1 Problem Setup

The tire FE model of baseline design is shown in figure 2. The tire size is 195/65R15. In MODE procedure, definition of design variables is the most important issue. Since our objective is to obtain the design knowledge which can be used at a conceptual design process, we would like to define design variables and their domain of definition in order to set a large design space. So we use basis vector method for the definition of a tire contour. The geometry of a tire FE model is defined as linear combination with base vector and its coefficient, so we can write

$$Y = Y_0 + \sum_i X_i (\chi_i - Y_0) \tag{1}$$

where Y_0 is nodal coordinate of baseline FE model, χ_i is nodal coordinate of FE model of i-th basis vector and X_i is i-th coefficient.

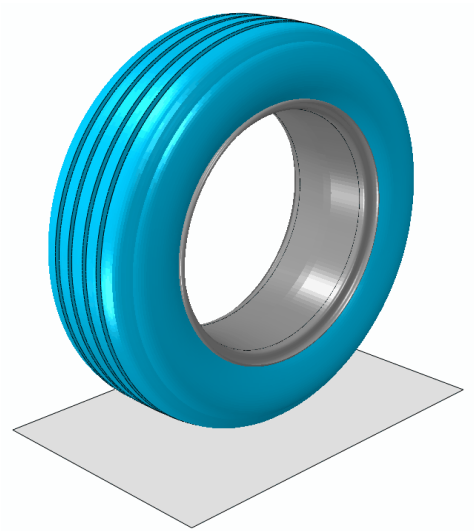

Figure 2: Tire FE model of baseline design

The coefficients are the design variables of tire contour. We define the seven basis vectors based on eigen modes extracted by natural frequency analysis of axisymmetric FE model of a baseline tire. Seven design variables, $X_i\ (i = 1, 7)$ and their domain of definition are considered to extract Pareto solutions. Some of basis vectors contribute to some changes of the tire cross-section. And the others change overall shape of the tire cross-section. Rolling resistance

(RollRes), lateral stiffness (LatStiff), vertical stiffness (VertStiff) and longitudinal stiffness (LongStiff) are chosen as objective functions. These objective functions are calculated by Abaqus/Standard.

Therefore, we consider the following problem:

Minimize $\mathrm{RollRes}(X_i)$ and $\mathrm{VertStiff}(X_i)$

Maximize $\mathrm{LatStiff}(X_i)$ and $\mathrm{LongStiff}(X_i)$

subject to

$$X_{i\_\min} \le X_i \le X_{i\_\max}, \quad i = 1,7$$

by multi-objective GA with meta-models.

3.2 Multi-objective optimization by GA with a meta-model

GA simulates biological evolutionary theories on computer to solve optimization problem. According to the evolutionary theories, only the most fitting elements in a population are likely to survive and transmit their biological heredity to the next generation. This leads to the evolution of species through operators such as competition among individuals, natural selection and mutation of the DNA. GA is likely to obtain a global optimum instead of local one. In this study, NCGA implemented in Isight [9] is used to find the Pareto solution. NCGA is one of GA which is improved to be able to obtain Pareto solution directly and effectively.
In the case of multi-objective optimization using GA e.g. NCGA, we must calculate objective functions a great deal of times. A meta-model which is also called response surface method or surrogate method is powerful for the reduction of calculation time of nonlinear FEA in multi-objective optimization. A meta-model reduces computational time required for objective function evaluation in optimization process. A polynomial function and Kriging are used widely as a meta-model.

The design of experiment (DOE) is helpful to obtain a set of proper sampling points for making a meta-model. Latin-hypercube, orthogonal array and so on are used for the purpose. FEA is carried out at each sample point of DOE to evaluate the objective function corresponding to the design variables at the same sample point. Therefore, the choice of DOE and meta-model is essential to find certain Pareto solution effectively. In this study, polynomial-based meta-models are prepared based on FEA at the sample points of a Latin-hypercube. Several hundred times of jobs using Abaqus/Standard [8] were performed by parallel computation on in-house HPC (High Performance Computer). However, Pareto solutions were extracted in a few minutes on a desktop PC.

3.3 Data mining using SOM and decision tree

In two-objective optimization problems, Pareto solutions form curves. In three-objective problems, those form surfaces in 3-dimensional solution space. In more than 3-dimensional objective function space, Pareto solutions cannot be visualized by usual way. To visualize higher dimensions, self-organizing map (SOM) is employed in this study. It provides a mapping with preserving topology from the high dimensional space to map units. Map units, or neurons, usually form a 2-dimensional lattice of hexagonal cell. SOM is a mapping from

high dimensions onto 2-dimensions. The mapping with preserving topology means that nearby points in the input space are mapped onto the nearby units in SOM. Roughly speaking, a relation between high-dimensional data and SOM is similar to the relation between the earth and world map. Nearby countries on the earth are mapped to nearby positions on world map. SOM can be used as a cluster analysis tool for high-dimensional data. SOM is useful not only for visualize high-dimensional Pareto solutions but also for the cluster analysis.

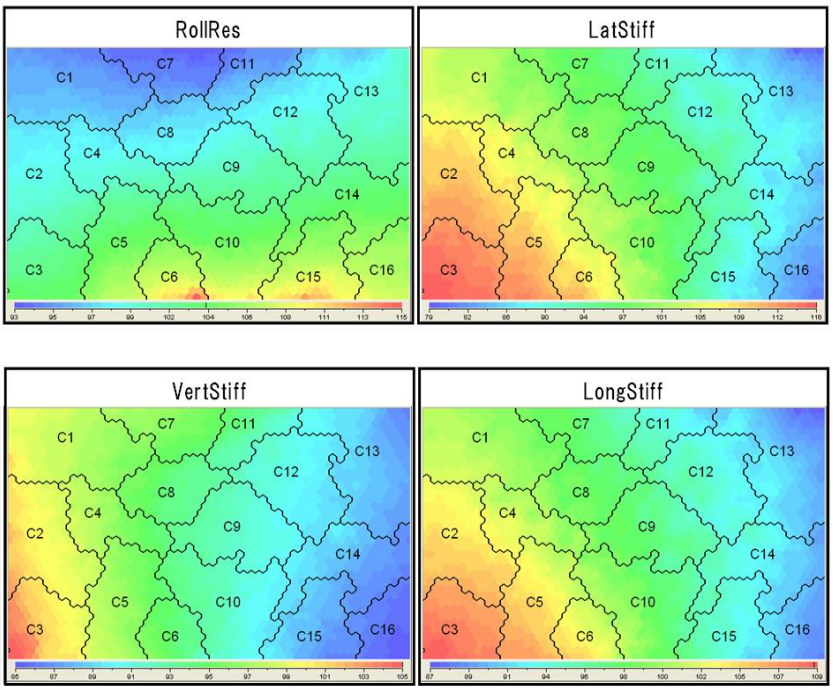

Figure 3: SOM of objective functions

Figure 3 shows SOM constructed by the objective functions of the obtained Pareto solution. Each unit of the SOM has eleven attributes. Four attributes consist of objective functions and seven attributes consist of design variables. Here, SOMine [6] is used to make SOM. Each map shown in figure 3 is divided into sixteen clusters, C1-C16. Four maps in figure 3 are same, but each map is colored by the numerical value of each objective function. On the maps blue color shows low value and red color shows high value. The relation between each objective function can be understood visually by comparing four maps. The figure shows that LatStiff (to be maximized) has a tradeoff with RollRes (to be minimized) and VertStiff (to be minimized). Furthermore, the figure shows strong correlation between LatStiff and LongStiff (to be maximized). Cluster C7 is the best design domain on minimization of RollRes. The desirable cluster to maximize LatStiff is C3. The compromised design domain on both of RollRes and LatStiff is cluster C1, C2 and C4. C4 where two characteristics, RollRes and LatStiff are well balanced is one of the design domains that we should aim at. We would like to pay attention to the relation between RollRes, LatStiff and the design variables, X1-X7. Design variables can be mapped onto the same map constructed by the objective functions shown in figure 3. Figure 4 shows the map of RollRes and LatStiff and all design variables. Since the SOM is constructed in objective function space, color maps of the design variables

have more noises than that of objective functions.

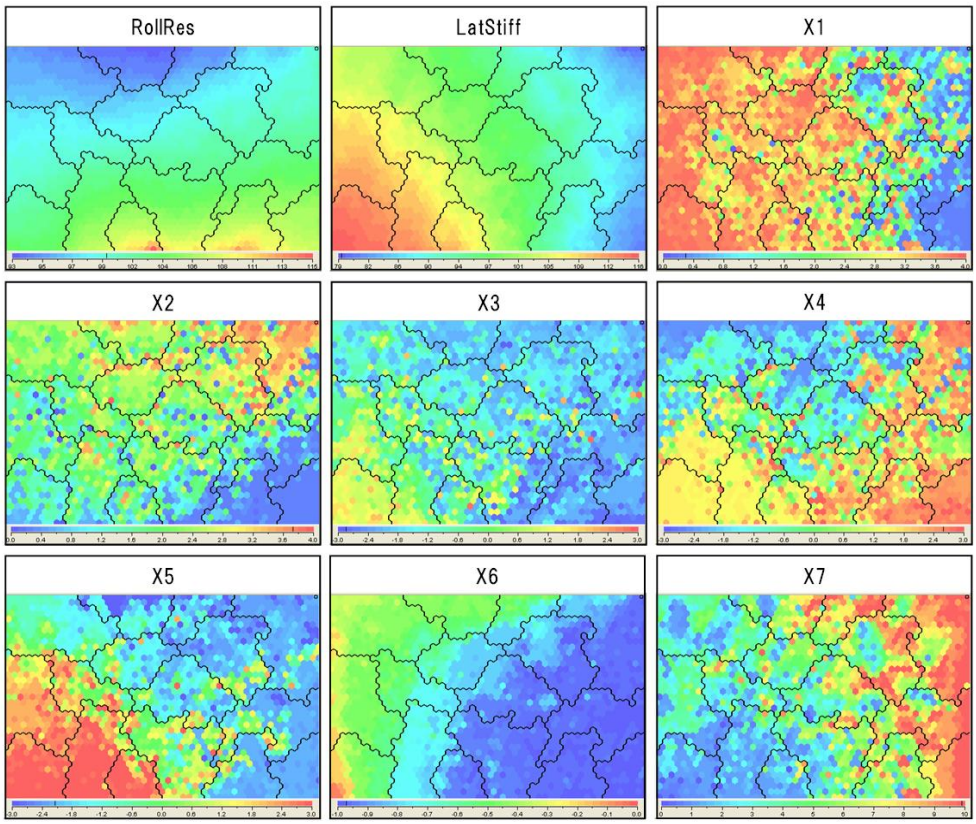

Figure 4: Self-organizing map. The map shows relation between the objective functions (RollRes and LatStiff) and the design variables (X1-X7)

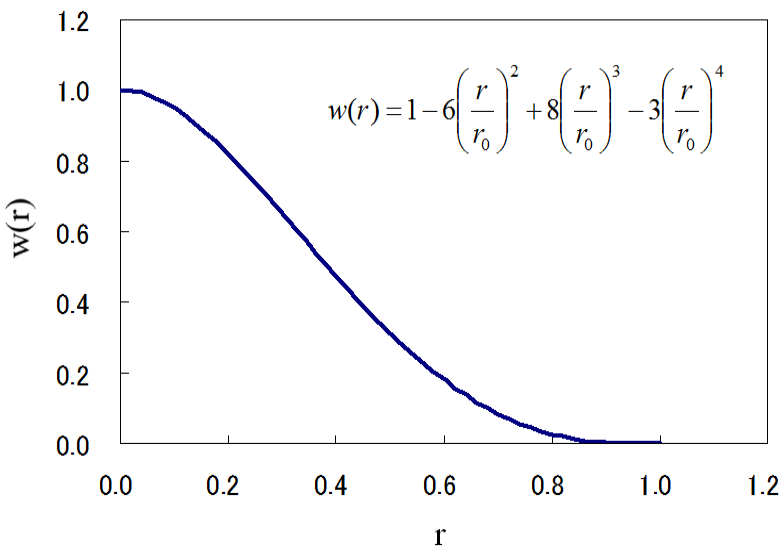

Figure 5: Typical weight function for MLS filter

Here, we propose MLS (Moving Least Square) filter to get a map of design variables with a few noises in objective function space. Figure 5 shows typical weight function for MLS filter, and figure 6 shows the SOM using MLS filter. The color maps of design variables shown in figure 6 have few noises than that of figure 4. The MLS filter helps visual understanding of global relation between objective functions and design variables. According to visual data mining using figure 6, we obtained following hypothesis;

- X6 might be the most important design parameter to get good performance of RollRes and LatStiff,
- X5, X4 and X7 will play to change the weight between RollRes and LatStiff,
- X6 seems to be orthogonal to X5.

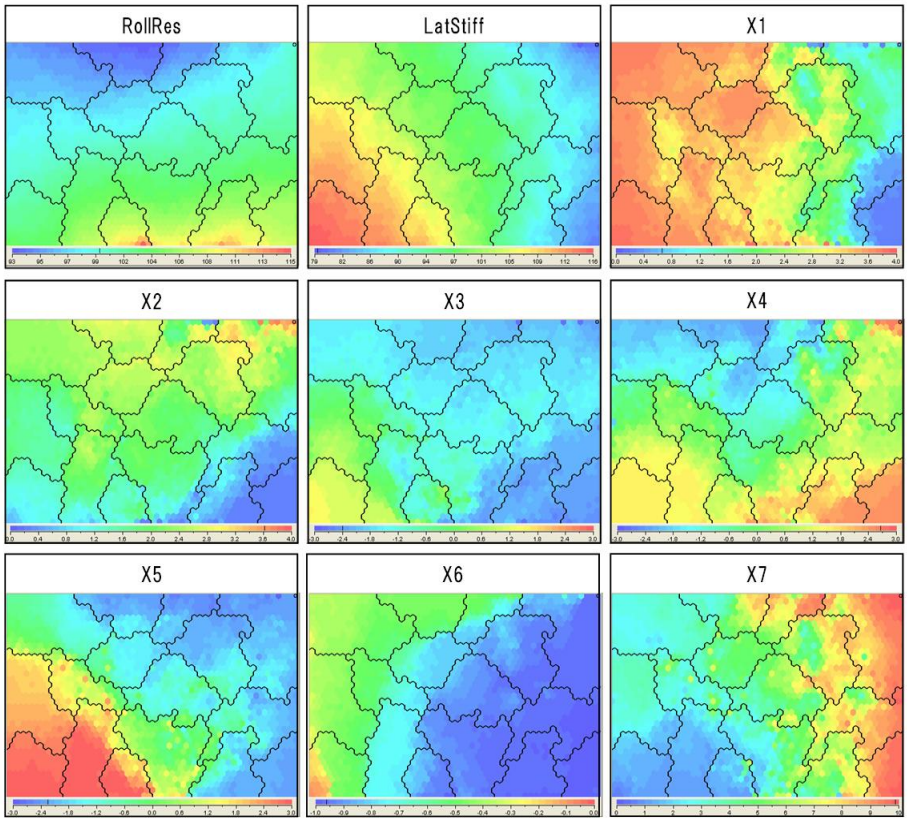

Figure 6: SOM using MLS filter

As above, SOM is helpful to find out the relation between performance of a product and specification of it visually. Using SOM, we can obtain the information which is the mapping from balance of performances to design specifications. The provided information is useful at a design process. In other words, it is design knowledge which can be use for decision making at a conceptual design stage.

Moreover we apply decision tree to find out design knowledge more in detail. Decision tree is one of machine learning method used for classification and regression. Applying decision tree to our study, we can find appropriate design variables to use for decision making. Figure 7 shows the obtained tree structure using Weka [7]. Each cluster (C1-C16) shown in

figure 7 is the specific performance balance of a tire and is obtained by SOM shown in figure 3. Here, C3, C4 and C7 are the clusters which have aimed performance balance. As we mentioned above, C4 is the compromised design domain of RollRes and LatStiff. C7 and C3 are the best design for improvement of RollRes and LatStiff, respectively. Figure 7 shows that X6 is the most appropriate design variable to improve the performance of RollRes and LatStiff. And we also found the appropriate design variables, X5, X6 and X7 and their threshold as design knowledge. The design knowledge can be use for decision making at a conceptual design stage. The results of decision tree support the efficiency of visual data mining using SOM. However, using decision tree we can find out objective roles quantitatively.

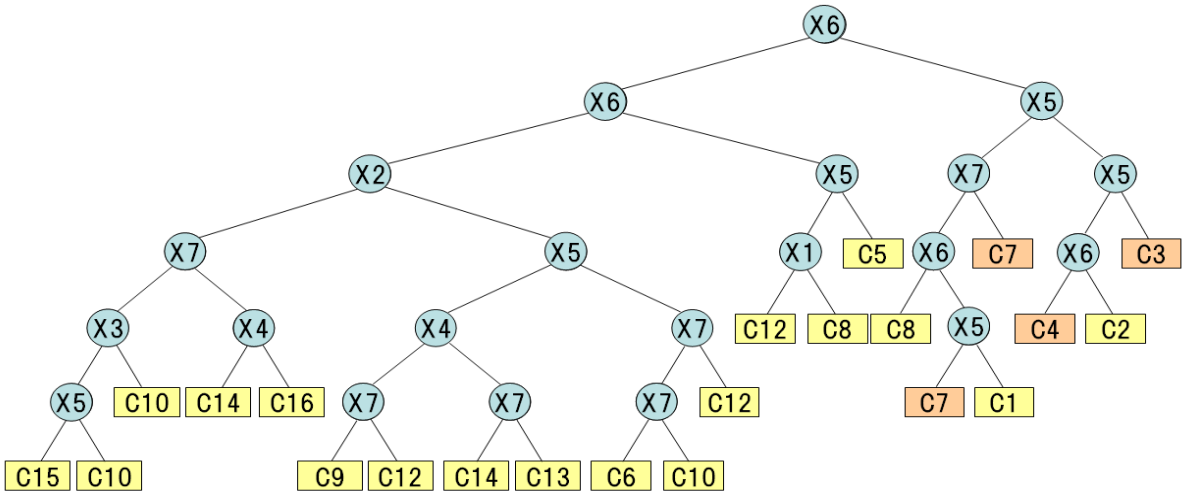

Figure 7: Decision tree for clusters (C1-C16) and design variables (X1-X7)

3.4 Validation of design knowledge and application of it at a conceptual design stage

For the validation of the obtained design knowledge, we produced two kinds of prototype tire. One (TIRE-B) was designed based on the appropriate design variables and their threshold to specialize in lateral stiffness, and the other (TIRE-A) is designed based on the design knowledge consist of C3 which is specialized in rolling resistance.

Table 1: Comparison of the performance of prototype tires (FEA vs. experimant)

		RollRes	LatStiff
TIRE-A (C7)	FEA	92	100
	Experiment	94	105
TIRE-B (C3)	FEA	100	109
	Experiment	100	112

Table 1 shows the performance of prototype tires, TIRE-A and TIRE-B. The numerical value of objective function is displayed by the index which assumes a baseline design 100. As for RollRes, small numerical value shows good performance. On the other hand, large

numerical value of LatStiff shows good performance. The experimental results guaranteed the validity and the effectiveness of the obtained design knowledge.

After that, we designed a contour based on the design knowledge obtained by MODE at a conceptual design stage of a new fuel efficient tire. At a design stage, we also considered the design knowledge on aerodynamic force reduction of a vehicle [4,5] and some constraints. A new fuel efficient tire shown in figure 8 was released in July 2013.

Figure 8: A new fuel efficient tire designed by MODE

4 CONCLUSIONS

- The design knowledge of fuel efficient tire contour was obtained by multi-objective design exploration (MODE).
- The obtained design knowledge was validated by the experimental results of prototype tires.
- A new fuel efficient tire, “BluEarth-1 EF20” was designed based on the knowledge and was launched in July 2013.
- Our procedure of MODE consists of Abaqus/Standard to simulate tire performance, evolutional computation, NCGA in Isight to get Pareto solution and data mining, self-organizing map (SOM) and decision tree to find out design knowledge.
- MLS (Moving Least Square) filter is proposed to obtain the structured smooth data of design variables in an objective function space.

- SOM with MLS filter helps visual data mining of global relation between objective functions and design variables.
- Decision tree is a powerful tool to get appropriate design variables and their threshold as design knowledge. Those can be used for decision making at a conceptual design stage.
- It is possible to find a new idea to lead to product innovation by using MODE.

REFERENCES

[1] Obayashi, S. and Sasaki, D., Self-Organizing Map of Pareto Solutions Obtained from Multi-Objective Supersonic Wing Design, (2002) AIAA Paper 2002-0991.

[2] Obayashi, S., Jeong, S. and Chiba, K., Multi-Objective Design Exploration for Aerodynamic Configurations, (2007) AIAA Paper 2005-4666.

[3] Koishi, M. and Shida, Z., Multi-Objective Design Problem of Tire Wear and Visualization of Its Pareto Solutions, Tire Science and Technology, (2006) **34**:170-194.

[4] Koishi, M. Application of the Simulation to Elevate the Product Value, Journal of the Japan Society of Mechanical Engineers, (2013) **116**:101-103.

[5] Kimura, Y., Suzuki, M., Yamamoto, M., Kodama, Y. and Koishi, M., "Numerical study on the effect of Dimple in the Flow Field around Wheel", Proceeding of 25th CFD Symposium, (2011) A05-3.

[6] Viscovery SOMine Users Manual, Version 4.0, Eudaptics Software GmbH, Vienna, Austria.

[7] Witten, I. H., and Frank, E., *DATA MINIG, Practical Machine Learning Tools and Techniques*, 2nd Edition, Morgan Kaufmann Publishers, (2005).

[8] Abaqus Users Manual, Version 6.13-1, Dassault Systémes Simulia Corp., Providence, RI.

[9] Isight Users Manual, Version 5.7, Dassault Systémes Simulia Corp., Providence, RI.