ON VEHICLE EVALUATION AND DESIGN USING DATA ENVELOPMENT ANALYSIS WITH HIERARCHICAL CONCEPTS

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ABSTRACT

In recent years, product complexity in terms of function and structure has been driven by technological development in complementary components. Designing unbiased product evaluation metrics being to grasp the complex relationships of product features, and able to capitalize on market needs has become a challenge in industrial practice.

In this paper, we propose a hybrid framework in which evaluation models are generated by integrating Interpretive Structural Modeling (ISM), Hierarchical Clustering and Data Envelopment Analysis (DEA). Whereas ISM constructs hierarchical digraphs (skeletons), Hierarchical Clustering reduces dimensionality of pairwise comparisons (correlations) of design variables, and suggests possible evaluation configurations, and DEA computes weights to provide optimal evaluation metrics. Our computational experiments using more than twenty thousand vehicles from 1982 to 2013 confirmed the feasibility and usefulness of DEA with hierarchical concepts to generate the optimal vehicle evaluation metric, and to suggest configurations for vehicle design layouts.

Keywords: Design informatics, New product development, Conceptual design

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1 INTRODUCTION

Along with the development of complementary technology, the complexity of the structure and the functionality of mechanical products have continuously expanded in recent years, e.g. vehicles as complex multi-functional systems. And along with differentiation and consumer satisfaction needs, machines have become more complex and diverse. To accurately grasp changes in diversified markets, companies have been analyzing large amounts of data to design effective R&D policies to capitalize on the gap between consumer needs and product development. In line with the above, since the early 20's, the use of *data-driven product evaluation* has attracted the attention of business stakeholders, in which weighted indexes often combine qualitative and quantitative metrics, and algorithmic techniques aid in the multi-objective optimization of the product evaluation metrics.

However, multi-objective optimization requires the definition of weights, which in the context of product design, biases towards local optima metrics (Tavana *et al.* (2016)). To avoid biased weights on evaluation metrics, Data Envelopment Analysis (DEA) (Charnes *et al.* (1978)) is a well-known non-parametric approach which computes weights based on the fact that each evaluation item gets the highest evaluation in relative terms; thus, it is possible to construct a one-dimensional indicator avoiding biases to local optima judgements (Barat *et al.* (2018); Forsund (2018)), which has positive implications for marketing and product development.

There exists several studies focusing on DEA, for instance, the work by (Doyle (2014)) and (Seiford and Zhu (2003)) on printers, and the work by (Papagapiou *et al.* (1997)) on vehicles. Also, (Papagapiou *et al.* (1997)) studied automobiles released in 1996, and divided the evaluation items into groups which define economic evaluation items and technical evaluation items, demonstrating the usefulness of DEA to compare and decide a particular product based on the rich information provided by DEA. Also, Gonzalez *et al.* (2015) studied the efficiency of 2092 cars, and found that dealers' discounts is inversely related to car efficiency. Voltes-Dorta *et al.* (2013) tested the ability of car manufacturers in Spain to meet CO_2 emission targets with the existing technological trends.

In addition, (Fernandez-Castro *et al.* (2002)) have shown the consistency of DEA with consumer choice in Economics literature, and provided an example on the manageable reduction of number of diesel cars which need user assessment. Also, (Papahristodoulou (1997)) evaluated the efficiency of 121 personal cars in 1997, provided comparisons in a normative manner with economic and technical parameters. Also, (Cantner *et al.* (2012)) used product variables of German vehicles over the period 2001 to 2006, constructed a fitness evaluation ratio based on DEA, and found its direct relationship to market share and consistency with evolutionary theory of "growth of the fit".

The use of historical information and the use of DEA-inspired evaluation models for vehicle design offer the possibility to explore and expand towards multi-functional mobility models. In the past research, for instance, (Papagapiou *et al.* (1997)) has evaluated 121 car models, and (Fernandez-Castro *et al.* (2002)) evaluated 44 cars. Thus, DEA has been a useful method to evaluate vehicle performance using historical data, enabling the recommendation of new product layouts and product choices. However, DEA requires the definition of input and output variables in product configurations, which diminishes the effectiveness if not properly identified. Thus, in complex product configurations, it is likely to generate a large biased number of DEA evaluation models based on arbitrary user views of input-output variables.

Interpretive Structural Model (ISM) (Warfield (1973a,b, 1974a,b, 1973c, 1974c)) is a promising tool to aid in model choice and visualization of relationship among design variables, being useful to tackle the above-mentioned problem. Generally speaking, ISM constructs network structures portraying the hierarchical nature of relationships among components in a product. For instance, (Raut *et al.* (2017)) identified the critical success factors for adopting cloud computing in the Indian companies; and (Hsiao *et al.* (2013)) established the hierarchical architecture of a bicycle by using the Interpretive Structural Model (ISM), and obtained the optimal performance of the hierarchical modules after market segmentation. (Han *et al.* (2015)) analyzed the energy efficiency of Chinese ethylene industry by integrating the main factors for energy consumption identified by ISM, whose arbitrariness in selection is avoided, and whose efficiency is solved by slack variables in DEA. Also, a recent extension of DEA is applied to energy and environment studies (Sueyoshi *et al.* (2017)).

Although the integration of DEA and ISM is a potential tool to generate effective evaluation metrics in vehicle studies (Papagapiou *et al.* (1997); Gonzalez *et al.* (2015); Voltes-Dorta *et al.* (2013); Fernandez-Castro *et al.* (2002); Papahristodoulou (1997); Cantner *et al.* (2012)), there still exists gaps in model

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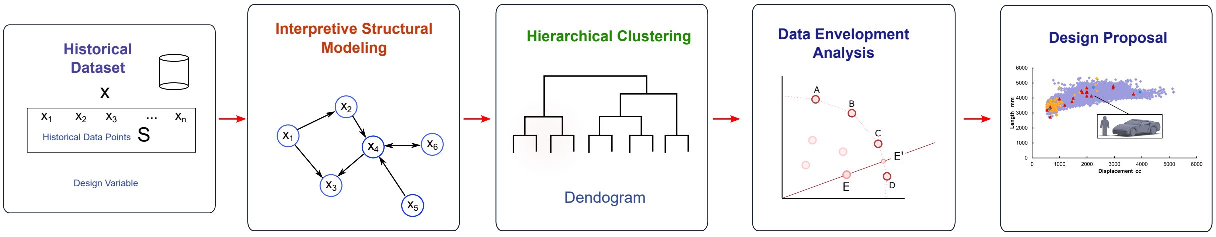

Figure 1. Basic idea of proposed approach.

selection: the large number of vehicle variables makes difficult to evaluate the entire space of configurable models. Thus, previous studies on vehicle design based on DEA metrics have focused only on a limited amount of historical information (Papagapiou *et al.* (1997); Gonzalez *et al.* (2015); Voltes-Dorta *et al.* (2013); Fernandez-Castro *et al.* (2002); Papahristodoulou (1997); Cantner *et al.* (2012)).

In this research, in order to fill the above-mentioned gap, we propose a new method to generate comprehensive evaluations based on the integration of Interpretive Structural Modeling, Hierarchical Clustering and Data Envelopment Analysis as shown by Figure 1. Basically, ISM constructs the hierarchical digraph (skeleton) based on relationships of vehicle variables, and Hierarchical Clustering reduces the dimensionality of pairwise comparisons (correlations) of design variables, and suggests the useful configurations of evaluation models. Finally, Data Envelopment Analysis computes the optimal weights and provides a metric to evaluate vehicle performance by considering the relationship of vehicle design variables. In particular, our contributions are as follows:

1. A hybrid framework to generate evaluation metrics based on Interpretive Structural Modeling (ISM), Hierarchical Clustering (HC) and Data Envelopment Analysis DEA.
2. Computational experiments show the feasibility of our proposed approach over 27, 858 vehicle models from 1982 to 2013, containing 12 design variables, including vehicle sizing, torque, engine performance, fuel consumption, price and weight.
3. A comprehensive evaluation metric for vehicle design consisting of a hierarchical and modular digraph, as well as proposals for new vehicle design layouts with maximal performance metric.

We believe our proposed method offers the useful tools which aids in the generation of unbiased vehicle evaluation metrics and models and achieving the maximal performance frontiers. In the next sections we describe our proposed approach, as well as the computational experiments to evaluate its feasibility.

2 PROPOSED METHOD

2.1 Basic idea

The basic idea of our method is portrayed by Figure 1, which is based on the following tenets:

1. A historical dataset of design variables is known a-priori, where in x_1 ... x_n denote the set of n variables within a time frame.
2. The hierarchical digraph is computed by using the Interpretive Structural Modeling, whose role is to provide a compact graph structure whose definition depicts the relationship among the design variables x_1 ... x_n.
3. Hierarchical Clustering computes modules of design variables in order to reduce dimensionality of pairwise comparison of design variables.
4. Data Envelopment Analysis computes the efficiency ratio on pairwise comparisons rendered by the Hierarchical clustering.
5. New Design Proposals are suggested based on the evaluation ratio of DEA on the historical dataset.

2.2 Interpretive structural modeling

The Interpretive Structural Modeling (ISM) is a method proposed by Warfield aiming to represent organized knowledge in binary matrices and multilevel digraphs (Warfield (1973a,b, 1974a,b, 1973c, 1974c)), which aids to the visual expression of relationships among elements of a system through hierarchical structure and transitivity of relationships. Let $X = x_i$ be the set of design variables; then a boolean

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matrix B is first created with 1 (0) denoting the presence (absence) of relationship between elements in the system X. Then, the reachability matrix M, or transitive closure of B, is computed as follows:

$$(B+I)^{k-1} \neq (B+I)^{k} = (B+I)^{k+1} = M, \tag{1}$$

where k is a positive integer which is less the number of elements in the set X. In the above, there is a unique reachability matrix M for any square boolean matrix B.
On the basis of the reachability matrix M, if we connect and render all the elements of the matrix M, the network becomes complex and difficult to understand. Therefore, a skeleton matrix is created by deleting paths within a module, by which a hierarchical diagram is created (Warfield (1973b, 1974a,b)).

2.3 Hierarchical clustering

Hierarchical Clustering classifies computes dendrogram to group the similarity of design variables. Here, the correlation between two design variables is considered as distance between points, and the Ward's approach is considered for distance between groups.
Although it is possible to use the k-means and spectral approaches, Hierarchical Clustering is advantageous to reduce the dimensionality of pairwise comparisons and is useful to render a hierarchy of clusters in terms of correlation factors; thus its becomes possible to compute compact and highly related set of design variables.

2.4 Data envelopment analysis

Data Envelopment Analysis (DEA) was developed by A. Charnes and W. W. Cooper in the late 70's with the aim of comparing the efficiency of Decision Making Units (DMUs) with multiple inputs and multiple outputCharnes *et al.* (1978). In this method, the measure of efficiency of a DMU is computed as the maximum ratio of weighted outputs to weighted inputs subject to the condition that the upper bound of similar ratios is one. Formally,

$$\begin{aligned}
&\text{Maximize} \\
&\qquad \theta_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \\
&\text{subject to} \\
&\qquad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1,\ j = 1,\ldots,m. \\
&u_r, v_i \geq 0; r = 1,...,s; i = 1,...,m.
\end{aligned} \tag{2}$$

where y_{rj} are known outputs and x_{ij} are known inputs of the j-th DMU; and $u_r, v_i \geq 0$ are the weights to be computed from the solution of the above problem. The efficiency θ_o is set relative to other DMUs, which implies that the maximization enables computing favorable weights within the allowable constraints (efficient frontier). Thus, the weight coefficients u_r, v_i are set such that the evaluation value θ_o becomes the maximum on the condition that the evaluation value θ for $j = 1,\ldots,m$ does not exceed 1. On the other hand, proposals for improvement of inefficient targets can be introduced based on relationships to the *excellent group* (efficient frontier). Furthermore, solutions to Eq. 2 is computable by conversion to linear programs.

3 GENERATING EVALUATION METRICS USING VEHICLE DATA

In order to evaluate the feasibility of our proposed method, we performed computational experiments within the context of vehicle layout design. This section describes our experimental settings, and discusses our obtained results.

3.1 Dataset and variables

In this study, we collected twelve design variables of 27,858 vehicle models between 1982 to 2013, whose key description is shown by Table 1.

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	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
01 Torque↑		×							●		●		●								●		●	
02 Torque↓	×									●		●		●								●		●
03 Maximum Output↑				×					●		●		●								●		●	
04 Maximum Output↓			×							●		●		●								●		●
05 Displacement↑	●		●			×														●				
06 Displacement↓		●		●	×														●					
07 Length↑								×													●		●	
08 Length↓							×							●								●		●
09 Width↑										×										●	●		●	
10 Width↓									×							●			●			●		●
11 Height↑												×								●	●		●	
12 Height↓											×							●	●			●		●
13 Indoor Length↑							●							×							●			
14 Indoor Length↓													×									●		
15 Indoor Width↑									●							×					●			
16 IndoorWidth↓															×							●		
17 Indoor Height↑											●							×			●			
18 Indoor Height↓																	×					●		
19 Fuel Consumption↑																				×				
20 Fuel Consumption↓																			×					
21 Price↑																						×		
22 Price↓																					×			
23 Weight↑	●		●																	●	●			×
24 Weight↓																			●			●	×	

Figure 2. Design structure matrix of vehicle layout with 24 evaluation items.

Table 1. Vehicle variables.

Variable	Description	Units
x_1	Total Length	mm
x_2	Total Width	mm
x_3	Total Height	mm
x_4	Indoor Length	mm
x_5	Indoor Width	mm
x_6	Indoor Height	mm
x_7	Torque	kg.m
x_8	Maximum Output	ps
x_9	Displacement	cc
x_{10}	Fuel Consumption	km/l
x_{11}	Price	JPY
x_{12}	Weight	kg

Furthermore, in order to define the relationships between variables, we divided the variables in two subtypes: one which denotes increment (↑), and one which denotes decrement (↓). Therefore, our study analyzed the relationship among variables with 24 evaluation items[1].

3.2 Interpretive structural modeling

Pairwise comparisons are shown in Figure 2, and the hierarchical digraph (skeleton) obtained by the Interpretive Structural Modeling is shown by Figure 3-(a). By observing Figure 3-(a), we can readily note that the hierarchical digraph is roughly divided into two independent groups. Also, the observed patterns for increment and decrement between the two groups are non-repeatable, in which (01) Torque ↑, (03) Maximum Output ↑, (05) Full Length ↑, (07) Full Width ↑, (09) Total Height ↑, and (23) Weight ↑ create a different structure. Furthermore, variations in the 24 evaluation items induces in variations of

[1] 24 = 12 variables × 2 instances, ↑ and ↓, per variable.

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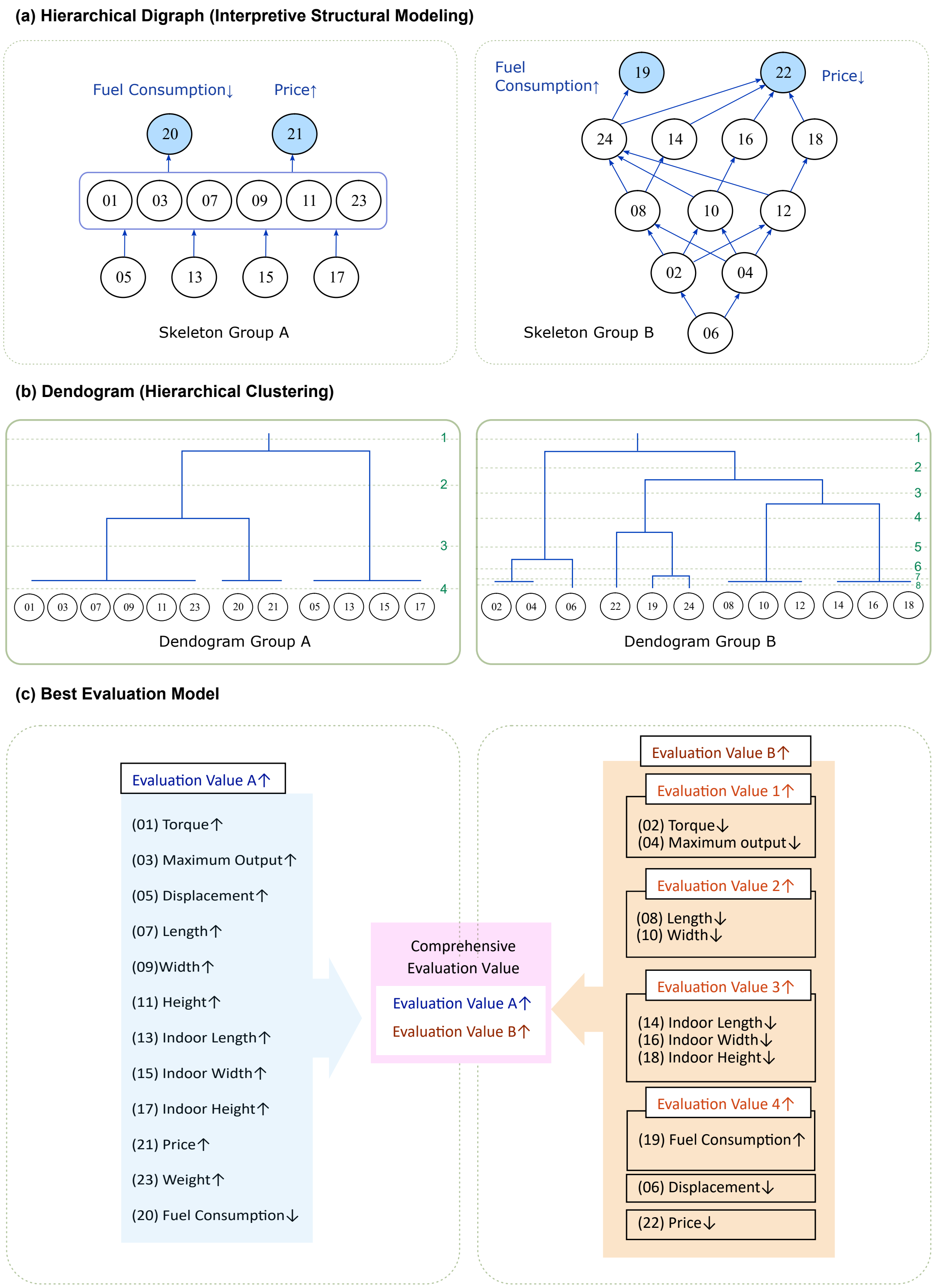

Figure 3. (a) Hierarchical digraph computed by interpretive structural modeling, (b) Dendrograms computed by hierarchical clustering, (c) Evaluation model constructed from dendrogram.

(19) Fuel Consumption ↑, (20) Fuel Consumption ↓, (21) Price ↑ and (22) Price ↓, due to being located in the upper stratum of the hierarchical digraph. For convenience, we denote the skeleton located at the left of Figure 3-(a) as Group A, and denote the skeleton located at the right of Figure 3-(a) as Group B.

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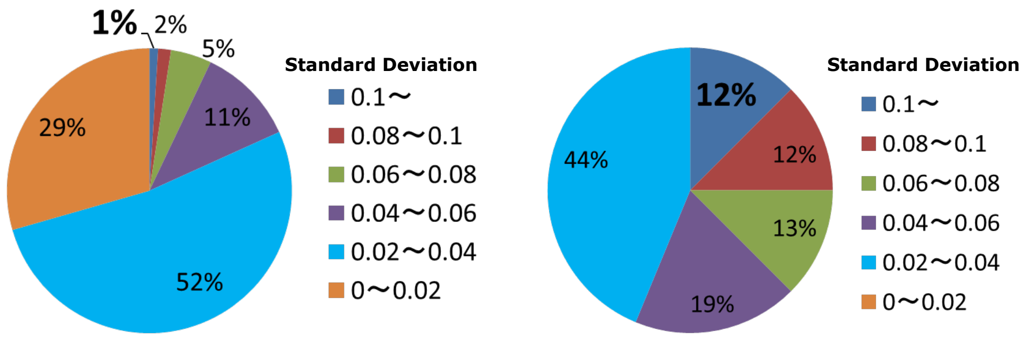

(a) DEA (b) Proposed Method

Figure 4. Frequency of standard deviation in (a) DEA and (b) Propose method.

3.3 Hierarchical clustering

Then, by using the skeletons from Figure 3-(a), dendrograms are constructed by agglomerative clustering, whose results are shown by Figure 3-(b). The shape of the dendrogram of Group A is more simple compared to that of Group B. We believe this occurs due to the fact that Group A has a hierarchical digraph with a modular component, which implies rendering a shallow dendrogram; on the other hand, the dendrogram of Group B is deeper due to the presence of a diverse set of uncorrelated of variables.
In order to compute a comprehensive evaluation, all models combining all hierarchies of Group A and Group B were evaluated, and the model with the maximum standard deviation is selected (large dispersion in evaluations implies better coverage). The hierarchies in each group are computed by applying threshold cuts in the vertical axis of each dendrogram; for instance, there exists 4 types of hierarchies in Dendrogram A by applying 4 thresholds cuts (numbered-dotted-green lines) in Figure 3-(b). As a result of we evaluating 32[2] models, model with maximum standard deviation of 0.110 is depicted by Figure 3-(c).
As we can readily note, Figure 3-(c) shows the following facts: (1) the evaluation in Group A consists of a single cluster with large number of increments, and the evaluation of Group B consists of a large number of clusters and decrements. (2) as for Group B, it is possible to induce in variations in the evaluation result by classifying according to characteristics such as engine performance (Torque and Maximum Output), external size (Length and Width), inner size (Indoor Length, Width and Height), Fuel Consumption, Displacement and Price.

3.4 Comparison with DEA

In order to evaluate the effectiveness of introducing the hierarchical concepts into the construction of models, we compared our proposed approach with that of conventional Data Envelopment Analysis (DEA), as follows: (1) The vehicle variables were classified as either input or output, and all 4096 configurations[3] corresponding to all combinations of input-output were evaluated by DEA. (2) The frequency of standard deviation comprising all models is shown by Figure 4. We can observe the following facts:

1. DEA has less frequency of higher standard deviation compared to our proposed approach: DEA has 1% of its models having standard deviation equivalent to 0.1 or more, while 12% of our models in our proposed approach has standard deviation of 0.1 or more.
2. DEA comprises more models with less standard deviation: about 81% of its models has standard deviation of 0.04 or less, while 56% of our models has standard deviation of 0.04 or less.

The above insights have implications on the feasibility of our approach to explore the search space of robust evaluation metrics more effectively. Whereas shallow-DEA limits its search space to the configuration of design variables, the DEA with hierarchy concepts is able to expand the search space due to the combinatorial nature of modules rendered by and Hierarchical Clustering.

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[2] 4 hierarchies in Group A × 8 hierarchies in Group B
[3] $2^{12} = 4096$ configurations

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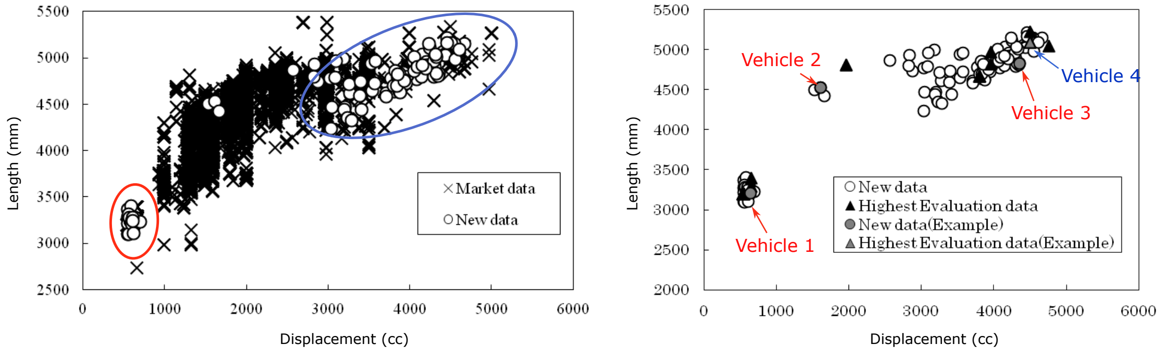
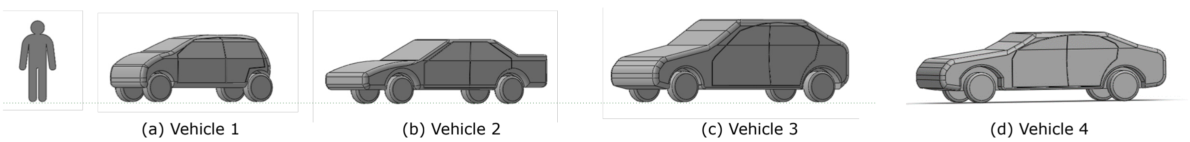


Figure 5. Relationship of displacement and length (new vehicle data and highest evaluation data).



(a) Vehicle 1 (b) Vehicle 2 (c) Vehicle 3 (d) Vehicle 4

Figure 6. Optimized vehicles.

Table 2. Comparison of existing vehicle and the proposed layout by our evaluation method.

Variable	Existing Vehicle	Proposed Layout
Displacement	4494 cc	4357 cc
Total Length	5090 mm	4830 mm
Total Width	1825 mm	1945 mm
Total Height	1425 mm	1700 mm

3.5 Optimization result

In order to show the feasibility to propose new design models and the usefulness to aid in decision making, we compared the performance of our proposed method with that of the existing vehicles in the dataset as follows:

1. There are 31 vehicles with the overall DEA evaluation value of 1 in the best model of Figure 3-(c). Since DEA ratios based on Figure 3-(c) provide recommendations on the evaluation of vehicle models, we evaluated 1,200 vehicles within the upper and lower bound of vehicle variables and found 108 vehicles with DEA ratio of 1, which is the maximum achievable ratio.
2. Figure 5 shows the relationship between Displacement and Total Length of vehicles of 108 vehicles with DEA ratio 1 (labed as New Data) and our dataset (labeled as Market Data).

By observing Figure 5, we can readily observe that our model is able to localize vehicle layouts being at the extreme frontiers of the plot (marked with ellipsoids with red and blue color in Figure 5). On the other hand, there exists few vehicles with a total Length between 3500 to 4000 mm. This fact confirms the ability of our proposed method to localize vehicle models in the performance frontiers, which implies the usefulness to aid in the selection of vehicle layouts (consumer choice) or guiding the efforts of new vehicle development.

In order to exemplify the kind of existing vehicles and the kind of vehicles which our evaluation model is able to propose, Figure 6 shows the outline of the vehicles highlighted in Figure 5 - right column with numbers 1 to 4, along with a male dummy model (171 cm). Also, Table 2 shows the comparison in variable dimensions of existing vehicles with maximum evaluation ratio. As we can observe from Figure 6 and Table 2, our proposed model eases the evaluation of the performance frontiers not only of the existing vehicle layouts, but also offer insights on the new vehicle layouts. We believe our proposed approach is useful to aid in the evaluation and proposal of product layouts.

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4 FINAL NOTES

In this paper, we proposed Data Envelopment Analysis with hierarchy concepts, to generate evaluation models by integrating with Interpretive Structural Modeling (ISM) and Hierarchical Clustering (HC). Here,

1. ISM constructs hierarchical digraphs (skeletons),
2. HC reduces the dimensionality of pairwise comparisons (correlations) of design variables, and suggests possible evaluation configurations, and
3. DEA computes weights suggesting optimal evaluation metrics.

Computational experiments using more than twenty thousand vehicles from 1982 to 2013 confirmed the usefulness to (1) generate the diverse vehicle evaluation metrics, and (2) to suggest optimal configurations for vehicle design layouts.

Future work aims at integrating with studies in differentiation and integration in complex mechanical products (Ishii (2017)), using nonconvex learning algorithms to sample the design search space with exploration and exploitation concepts (Parque *et al.* (2013); Parque and Miyashita (2015, 2017, 2018a,b)), using succinct and canonical representation of the combinatorial search space of correlation variables to render a compact set of vehicle design variables (Parque and Miyashita (2018c,d)), and using Topology Optimization to aid towards the definition of optimal vehicle structures. Also, the feasibility of incorporating soft data as consumer satisfaction in the vehicle variables is in our agenda.

We believe the introduction of hierarchy into DEA-based studies enables the construction of deeper evaluation models, which is advantageous to explore robust metrics, and thus, to tackle the challenge to evaluate complex mechanical products effectively.

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