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RESEARCH ARTICLE

Optimizing Product Variety for Balancing Market Share and Complexity Cost in Product Family Design

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ABSTRACT Product variety has a complex impact on both market share and complexity cost, so determining an optimal variety is a difficult task for a manufacturing company. This paper proposes a variety optimization model that reflects the relationships among market, design, and production units considering the increasing tendencies of market share (concavity) and complexity cost (convexity). Optimization model for finding an optimal variety consists of two main parts: a demand model and a complexity cost model. A demand model is constructed with the nested logit model showing the concavely increasing tendency of variety impact on market share, and a complexity cost model is developed by adopting the zero-based costing approach in which complexity cost is measured by incremental cost depending on the addition of variants. In the case study, we applied a front chassis module family of an automobile to the optimization model by analyzing data from the Korean and European markets. The results show that the greater the similarity level, the perceived similarity of a company's products, the better it is to provide less variety. Also, the more flexible a company's production facilities are, the more diverse the products it can produce.

INDEX TERMS Product family design, product variety, combinatorial optimization, nested logit model, complexity cost.

I. INTRODUCTION

Global manufacturing companies produce a variety of products in order to cover broad market segments and diverse customer needs. Product family design is an effective strategy providing a wide range of products while achieving cost saving from commonality effect [2]. A product family creates product variants by combining modules under modular product architecture [3]. Fig. 1 shows two examples of representative product families: automobiles and smartphones. Automobiles are structured into body, chassis, engine, and transmission modules, which can be combined as needed. Similarly, smartphones consist of modules such as display, camera, processor, battery, etc. In 2018, Hyundai-Kia Automotive Group launched a total of 48 models from six automobile platforms, offering over 150 model variants only in the US market. Similarly, Samsung Electronics Company provides a wide range of smartphone series with sub-models, such as Galaxy S, A, and Z series, in order to cover diverse customers and global regions. In this stream, designing a right range of variants has become an important task for manufacturing companies that produce product families including automobiles, smartphones, computers, home appliances, etc., all of which are based on the modular product architectures.

Finding an optimal variety is one of the most important challenges for managers who plan product families, because it is not only related to design domain, but also market and production domains [4]. Developing too much variety generates unsold products in the market and manufacturing complexity in the production. Fig. 2 conceptually describes a relationship of product variety with market revenue and production cost. Wan et al. [5] showed that a marginal impact of

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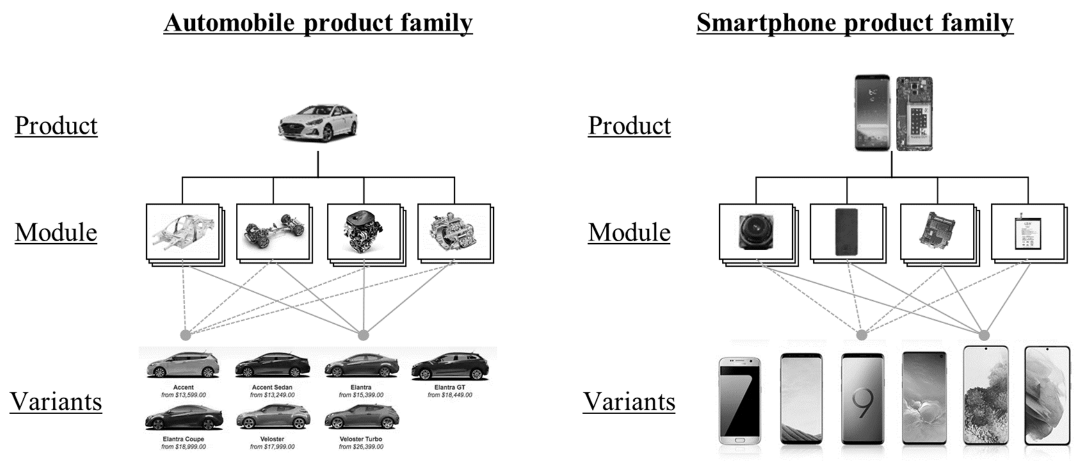


FIGURE 1. Product family design examples.

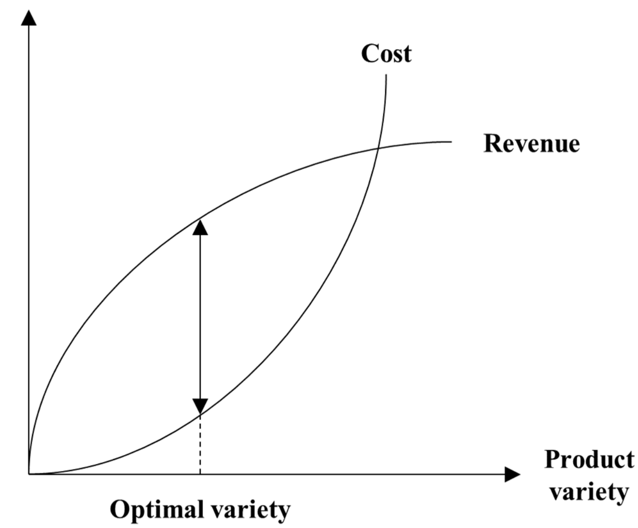


FIGURE 2. Revenue and cost from variety.

product variety on revenue decreases as the number of variety increases. In production domain, on the other hand, many researchers, such as MacDuffie et al. [6] and Mather [7], figured out that production cost generated from manufacturing complexity increases exponentially. Thus, as described in the graph in Fig. 2, we arrive at a conclusion that there is an optimal variety at the point where the gap between revenue and cost is greatest.

This paper aims to develop an optimization model that reflects the increasing tendencies of market share (concavity) and complexity cost (convexity) for finding an optimal level of variety. The model will assist manufacturing companies and managers in product family design by supporting balanced decisions that simultaneously reflect the impacts of variety on sales and complexity cost. A demand model is constructed based on the *nested logit model* that shows the concavely increasing tendency of market share due to variety. The nested logit model takes into account the similarity of product variants in the same family, reflecting the concavely increasing tendency of the impact of variety on market share. A complexity cost model is developed using the *zero-based costing approach*. The zero-based costing approach has been generally used to measure complexity cost with the concept of the incremental cost generated by the addition of a variant, containing the convexly increasing tendency of complexity cost.

Variety design of a product family takes place in the early stages of product development, specifically during the system-level design phase. This phase establishes a fundamental framework for creating various derivative products based on a product family architecture. In this phase, companies and managers should carefully decide both product variety and architecture design. The variety design process is divided into three phases depending on the level of decision-making: architecture design, configuration design, and instantiation design [8]. In the architecture design phase, diverse design methodologies, such as design for manufacturing and assembly, modularization, or quality function deployment (QFD), can be applied to encourage coordination across multiple domains. In our previous works [9], [10], we introduced an architecture design methodology, named *variation architecture*, for planning product variety. Building upon the previously defined architecture, this paper focuses on the latter two phases of configuration and instantiation design under the assumption that the product family architecture is already constructed.

The process of product family design in this paper is composed of two phases: *configuration planning* and *variety optimization*. The first phase generates a possible set of product candidates based on the cross-domain relationships among market, design, and production units. In the second phase, product family members are selected from the optimization model among a given set of possible product configurations. Since a manufacturing company generally makes a decision on product variety after a basic outline of product configurations is planned, this paper describes the sequential decision process, beginning with the generation of product candidates followed by the selection of product family members.

The paper is organized into six sections. Section II reviews the previous research related to product family design and variety optimization. Section III describes the generation process of product configurations based on a given product family architecture. Section IV begins with developing a demand model and a complexity cost model. Then, the optimization model is formulated. In section V, a case study is conducted with an automobile front chassis family. This section covers finding optimal solutions, conducting sensitivity analysis, and discussing the limitations of the model. Lastly, section VI concludes the paper.

II. LITERATURE REVIEW

Product family design is a holistic decision-making process from market to design and production domains [2]. Especially in determining product variety, a cross-domain viewpoint is necessary since decisions on variety are closely related to customer satisfaction in market domain and manufacturing complexity in production domain [11]. This section reviews previous studies that focused on the variety optimization problem across each of the domains in product family design.

Configurational product family design is a major stream of research in the design field. Configurational product family design aims to develop a modular platform from which product family members are derived by combining modules [12]. Research in the design field has focused on obtaining product configurations defined by design parameters. In many studies, the number of product variety was predetermined by the assumption that a single product was positioned to each market segment. Fujita et al. [13] developed an optimization model that focuses on determining the number of modules shared across a product family given a fixed number of products. Agard and Bassetto [14] proposed a method for optimizing module combinations of product variants considering product quality and cost, but the number of product variety was still fixed. Van den Broeke et al. [15] have attempted to consider a variety decision in planning a product portfolio, but their study offered a limited consideration of the impact of variety on other domain concerns.

In marketing research, on the other hand, the number of product variety has been more relaxed as a decision variable. Ramdas and Sawhney [16] developed an optimization model that reflects both cost and revenue interactions within a product family. Jiao and Zhang [17] addressed customer-engineering interactions to include variety impacts on cost and cycle time in the portfolio planning problem, but a product configuration was only represented as market attributes, rather than design and production units. Kumar et al. [18] allowed the release of multiple products to various market segments and subsequently estimated market share of a product family using the nested logit model. Kwong et al. [19] formulated a multi-objective optimization problem for market share, cost, and development time to select an appropriate number of product profiles combined by different attribute levels. Michalek et al. [20] covered both marketing and engineering decisions on product configurations by developing the analytical target cascading (ATC) model that implements a dynamic decision process in the product family development. Then, Goswami et al. [21] proposed a methodology to find an optimal product variety with product configurations in a single market by utilizing function-based cost estimation and multi-linear regression.

Previous research in the production field has considered product variety as a critical decision variable and has tried to evaluate the amount of manufacturing complexity. Zhu et al. [22] developed a metric to assess manufacturing complexity in mixed-model assembly lines, specifically addressing the complexity induced by product variety. Wang et al. [23] proposed a multi-objective optimization approach to balance product variety and manufacturing complexity. Their model has derived various possible solutions, each characterized by different market shares and complexity levels according to the number of variety and product configurations. In the field of supply chain management, Fujita et al. [24] simultaneously considered the processes of product family design and supply chain construction. In their research, optimization models were formulated by reflecting how a number of product variants and their configurations interact with a supply chain structure. Moussa and ElMaraghy [25] proposed a holistic non-linear optimization model for designing multi-period product platforms considering inventory cost of components having different features.

As reviewed in the previous paragraphs, product family design has continuously been studied to reflect primary considerations in market, design, and production domains. Many works have tried to consider variety interactions with market share and manufacturing complexity, however, there were few works to identify an optimal variety in reflecting increasing tendencies of market share and complexity cost simultaneously. In order to fill in this gap, this study focuses on finding an optimal variety by reflecting both tendencies of market share and complexity cost affected by variety.

III. PLANNING OF PRODUCT CONFIGURATIONS

Variety optimization at first needs to plan product configurations based on a product family architecture. This paper adopts the concept of variation architecture proposed in our previous work [9], [10]. This section begins with introducing the product family architecture as defined in the previous work and then describes the process of obtaining product configuration candidates prior to optimizing variety.

A. PRODUCT FAMILY ARCHITECTURE

Product family design is a multi-domain problem that covers market, design, and production domains. A product

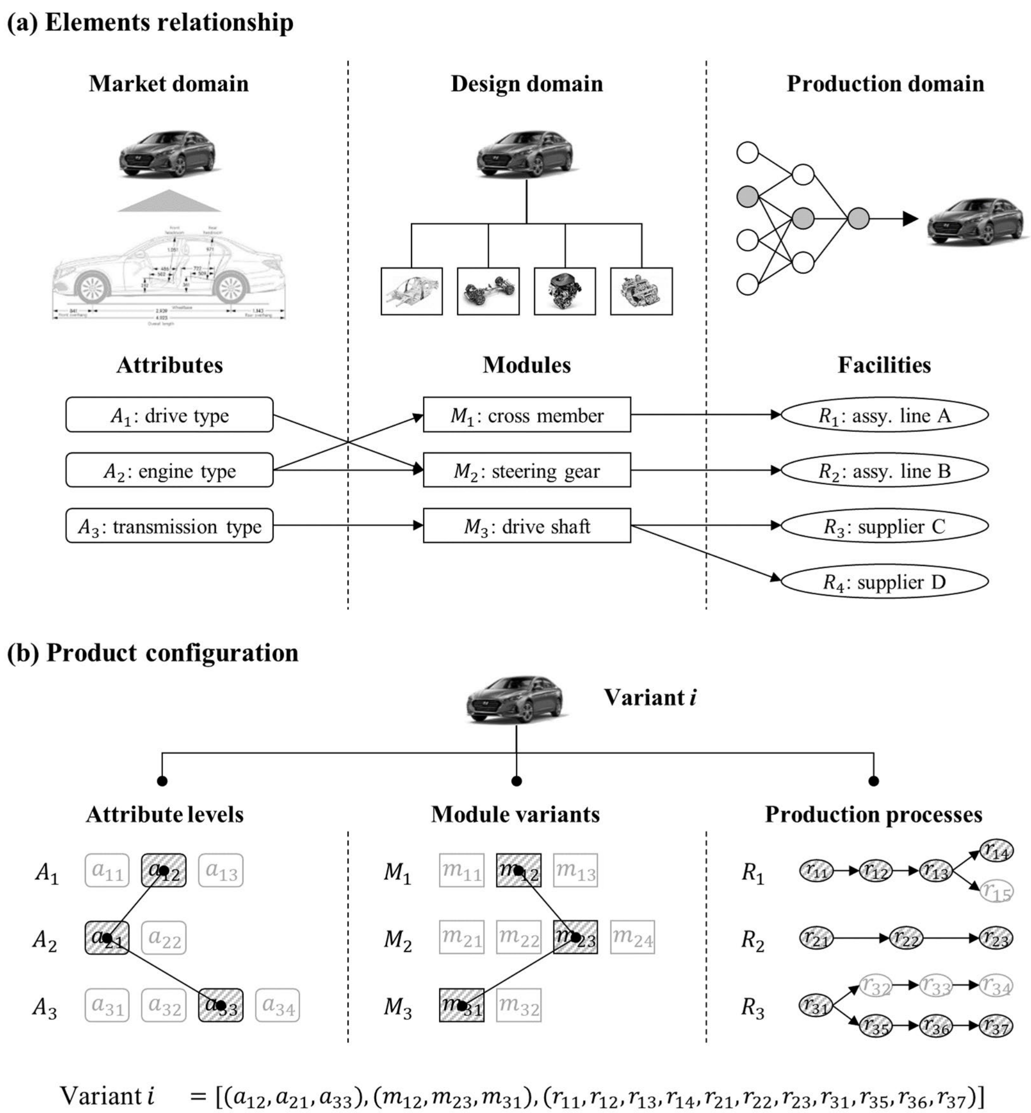


FIGURE 3. Product family architecture (a) Generic relationship and (b) Product configuration.

family architecture is composed of domain elements and their cross-domain relationships. Fig. 3 describes an example of a product family architecture in which domain elements are connected to each other and a product configuration is defined as variants of domain elements.

In market domain, a product family architecture represents a product as a set of attributes. An *attribute* is a customer desired property of a product, e.g., engine type, transmission type, and wheel size of an automobile. Attributes also include market-dependent characteristics such as drive type and weather type. In design domain, a product family architecture views a product as a combination of modules. A *module* is a physical chunk that materializes market attributes into compositions of a product. For example, an automobile consists of a body, chassis, engine, and transmission module, and product variants are created by combining those modules. Lower-level parts, such as cross member, steering gear, and drive shaft, can also be considered as modules. In production domain, a product is produced by a series of production processes conducted in a set of facilities. A *facility* is a system where production processes are taken place. Facilities of an automobile include assembly lines and suppliers. In a facility, some processes are shared by module variants, and others are not.

A product family architecture contains cross-domain relationships between domain elements, and product variety is restricted by their relationship types. In Fig. 3(a), drive type and engine type attributes are related to both a cross member and a steering gear, having complex relationships. The number of module variants increases rapidly as these attributes are more differentiated, generating various attribute levels. On the other hand, the transmission type attribute has a

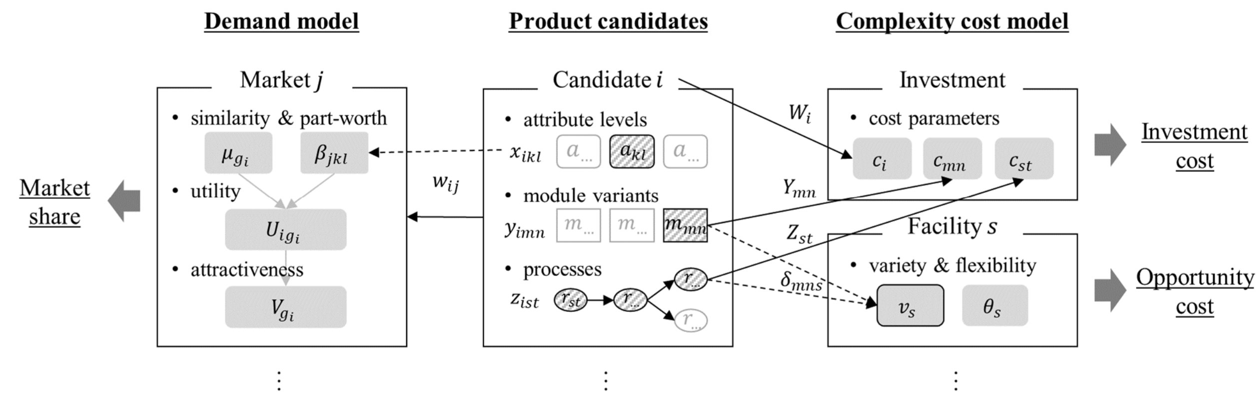


FIGURE 4. Structure of model variables and parameters.

one-to-one relationship with a drive shaft module. In this case, the number of module variants increases linearly as the number of attribute levels increases. This one-to-one type is more efficient in differentiating attributes than the n-to-m type is. In practice, however, most of the cases are the n-to-m relationship type.

There are also several relationship types between modules and facilities. In Fig. 3(a), a cross member module is assigned to assembly line A, having one-to-one type. This relationship type is advantageous for producing various module variants, given that a facility has high capability to produce multiple module variants without loss of productivity. In practice, a manufacturing company contracts with a mega supplier to have those one-to-one or n-to-one relationship types. On the other hand, if a facility has low capability to produce multiple module variants, a company needs to contract with multiple suppliers for a single module, e.g., a drive shaft in the figure. In this n-to-m (or one-to-m) relationship type, a company should work with several small suppliers to improve compatibility and assemblability between module variants produced by different suppliers. Thus, product variety is restricted with these complex relationship types.

B. PRODUCT CONFIGURATION

After establishing a product family architecture, candidates of product configurations are created under the architecture. The variety optimization problem uses a product family architecture to prepare candidates for product family members. A product variant is defined as a configuration of attributes, modules, and facilities. A configuration of a product variant is described as follows:

$$P = [As, Ms, Rs] \tag{1}$$

where As, Ms, and Rs are a set of attributes, modules, and production processes, respectively. This definition includes all views of the three domains for a product variant. Fig. 3(b) is an example of a product configuration. A product configuration is realized by selecting variants of domain elements, i.e., attribute levels, module variants, and production processes. At the bottom of the figure, the realized product configuration i is represented as variants of elements.

When a company creates product configurations, there are an infeasible combination space due to marketing and technical constraints. Combination rules between variants can be applied to reduce a combination space of product configurations. A combination rule is a constraint on the combinability between variants within and across the domains. An example of the rule is that if an automobile includes a 2,400 cm3 engine, then it only comes with 17-inch wheels. The same logic is applied to other domain elements. After setting combination rules within and across the domains, candidates of product configurations can be obtained. All potential candidates can be listed by equation (1). The details of the list will be described in the case study.

IV. VARIETY OPTIMIZATION MODEL

A. OPTIMIZATION MODEL

This subsection formulates a multi-objective combinatorial optimization model for selecting product variants to be released while balancing market share and complexity cost. Before formulating, candidates of product variants are derived from the configuration planning phase. Based on the relationships between domain elements and combination rules between variants, the following information about the configuration of candidate i is given for the optimization model:

$$\begin{aligned} x_{ikl}, y_{imn}, z_{ist} &\in \{0, 1\}\ \forall i, k, l, m, s, t \\ \delta_{mns} &\in \{0, 1\}\ \forall m, n, s \end{aligned} \tag{2}$$

x_{ikl}, y_{imn}, and z_{ist} are binary variables indicating whether candidate i is configured by attribute level a_{kl}, module variant m_{mn}, and production process r_{st} respectively, and δ_{mns} represents the assignment relationship between module variant m_{mn} and facility s. This variable is used in the optimization model for counting the number of module variants produced in facility s.

Fig. 4 shows the structure of variables and parameters that consist of the optimization model. The figure describes how

Given

x_{ikl}, y_{imn}, z_{ist}	Configuration of candidate i
δ_{mns}	Assignment relationship of m_{mn} to facility s
D_j	Number of customers in market j
P_{ij}	Price of candidate i in market j
Λ_j	Aggregated value of all competitor products in market j
β_{jkl}, μ_j	Estimated parameters in demand model
c_{st}, c_{mn}, c_i, ϕ_s, θ_s	Estimated parameters in complexity cost model

Decision variables

$w_{ij} \in \{0,1\}$	Whether candidate i is released to market j
$W_i \in \{0,1\}$	Whether candidate i is released to more than one market
$Y_{mn}, Z_{st} \in \{0,1\}$	Whether module m_{mn}, and process r_{st} are used
$v_s \in \mathbb{Z}$	The number of variety produced in facility s

Objective functions

$$\max_{w_{ij}} MS = (\sum_{j=1}^{J} D_j \times MS_j)/(\sum_{j=1}^{J} D_j)$$

$$\min_{w_{ij}} C = \sum_{s=1}^{S}\sum_{t=1}^{T_s} c_{st}Z_{st} + \sum_{m=1}^{M}\sum_{n=1}^{N_m} c_{mn}Y_{mn} + \sum_{i=1}^{I} c_i W_i + \sum_{s=1}^{S} \phi_s (v_s - 1)^{\theta_s}$$

Constraints

$$\left.\begin{aligned} & MS_j = \exp(V_j)/(\exp(V_j) + \Lambda_j) \\ & V_j = (1-\mu_j)\ln \textstyle\sum_{i=1}^{I} \exp(V_{ij}/(1-\mu_j)) \\ & V_{ij} = w_{ij} \textstyle\sum_{k=1}^{K}\sum_{l=1}^{L_k} \beta_{jkl} x_{ikl} \end{aligned}\right\}$$ Equations for market share described in subsection 5.1

$\sum_{j=1}^{J} w_{ij} \le J W_i$	W_i is a binary variable whether product i is released to any market or not
$\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} y_{imn} \le IJ Y_{mn}$	Y_{mn} is a binary variable whether m_{mn} is produced or not
$\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} z_{ist} \le IJ Z_{st}$	Z_{st} is a binary variable whether r_{st} is needed or not
$v_s = \sum_{m=1}^{M}\sum_{n=1}^{N_m} Y_{mn}\delta_{mns}$	v_s is the number of module variants produced in facility s

FIGURE 5. Optimization model.

market share and complexity cost are calculated depending on whether product candidates are selected and which markets and facilities they are assigned to. The optimization model is formulated in Fig. 5. The model involves information about product configurations of candidates and estimated values of parameters. Objective functions are to maximize market share and to minimize complexity cost simultaneously. Decision variable w_{ij} is a binary variable determining whether candidate i is released to market j or not. Other decision variables for calculating market share and complexity cost are also included. A set of constraints includes the equations in the demand model and the complexity cost model.

The goal of the optimization model is to find an optimal variety for practical suggestions to a product family planning

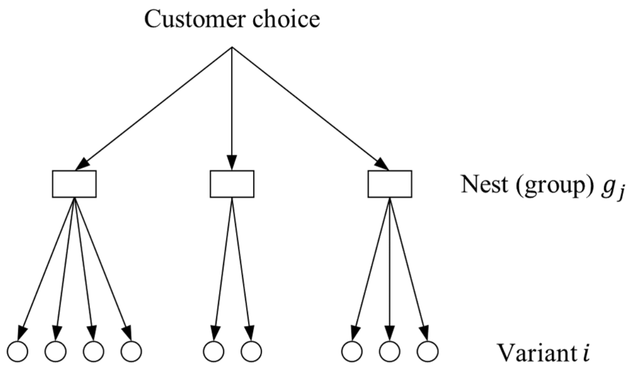


FIGURE 6. Structure of the nested logit model.

manager. Since product family design is a combinatorial optimization problem, many studies use evolutionary algorithms to solve the problem, such as MOGA, NSGA II, and SPEA-2. Among them, this study adopts NSGA II (non-dominated sorting genetic algorithm) that has been verified to outperform other algorithms [26]. It has been used by D'Souza and Simpson [27] and Kwong et al. [19] to solve multi-objective optimization problems in product family design. This study implements the algorithm by using the Python module *Platypus*, which derives Pareto optimal solutions for a multi-objective optimization problem.

B. DEMAND MODEL

This subsection constructs a demand model to estimate market share of product family members using the *nested logit model* introduced by Ben-Akiva [28]. The nested logit model, reflects the similarity of product variants in the same group (nest), considering the practical decision process for the customer choice problem. The nested logit model involves a structure of the hierarchical decision process described in Fig. 6. The structure shows that a customer first chooses a nest, which is a group of similar product variants, and then selects a variant in the nest. According to McFadden's research [29], when a commuter faces a choice problem among a car, a red bus, and a blue bus, it is more reasonable that a commuter considers between a car and buses in advance and selects a color of a bus afterward. The nest structure is easily found in the marketplace. Østli et al. [30] demonstrated that a nest structure is suitable for the car market because general customers tend to consider a car brand first and then choose a trim model.

Under the nest structure, market share (equal to the choice probability) of product variant i included in nest g_j in market segment j is formulated by the conditional probability as below:

$$MS_{ij} = P(i, g_j) = P(g_j) \times P(i|g_j) \tag{3}$$

where $P(g_j)$ is the probability of choosing nest g_j and $P(i|g_j)$ is the probability of choosing variant i given the first selected nest g_j.

The choice probability is obtained by the *utility* which is defined as the attractiveness of a product variant represented by a set of attribute levels [31]. Jiao and Zhang [17] adopted a utility function constructed by part-worth utilities of attribute levels in product family design. Part-worth utilities can be estimated by conjoint analysis [32] based on customers' choice data. In conjoint analysis, a part-worth utility of each attribute level is estimated by decomposing the preference of a product profile into the preferences of attribute levels. Following the utility function of Jiao and Zhang [17], the utility function of variant i in nest g_j is defined as:

$$U_{ig_j} = V_{ig_j} + (1 - \mu_{g_j})\varepsilon_{ig_j} = \sum_{k=1}^{K}\sum_{l=1}^{L_k} \beta_{jkl}x_{ikl} + (1 - \mu_{g_j})\varepsilon_{ig_j} \tag{4}$$

where V_{igj} is the expected attractiveness of variant i in nest g_j, β_{jkl} is the part-worth utility of level l of attribute k in segment j, x_{ikl} is a binary variable indicating whether level l of attribute k is included in variant i, ε_{igj} is the choice error of customers and it is assumed that independently and identically double exponentially distributed, and μ_{gj} is the scaling parameter of the error term.

In a discrete choice model, a customer chooses a variant having the maximum utility value. In the nested logit model, the aggregate attractiveness of a nest is measured by the expectation of the maximum utility among variants in a nest as below:

$$V_{g_j} = E[\max_{i \in g_j} U_{ig_j}] \tag{5}$$

For the double exponentially distributed error term, the attractiveness of nest g_j is transformed into the following equation [33]:

$$V_{g_j} = (1 - \mu_{g_j}) \ln \sum_{i \in g_j} \exp(V_{ig_j}/(1-\mu_{g_j})) \tag{6}$$

Based on (3) and (5), the attractiveness of a variant and a nest, the choice probabilities in (2) are stated by the logit model as below:

$$P(g_j) = \frac{\exp(V_{g_j})}{\sum_{g'_j \in G_j} \exp(V_{g'_j})} \tag{7}$$

$$P(i|g_j) = \frac{\exp(V_{ig_j}/(1 - \mu_{g_j}))}{\sum_{i' \in g_j} \exp(V_{i'g_j}/(1 - \mu_{g_j}))} \tag{8}$$

where G_j is a set of all nests in market j, and the scaling parameter $\mu_{gj} \in [0,1)$ represents the degree of similarity of variants in nest g_j. The case $\mu_{gj} = 0$ means that all variants are equally distinguished as if each variant is in an individual nest. In this case, the formula reduces to the multinomial logit model. The other extreme case $\mu_{gj} \to 1$ means that all variants in a nest become perfect substitutes each other, where the number of variants in a nest does not affect market share.

This paper uses aggregate sales data to estimate part-worth utilities of attribute levels and similarity parameters.

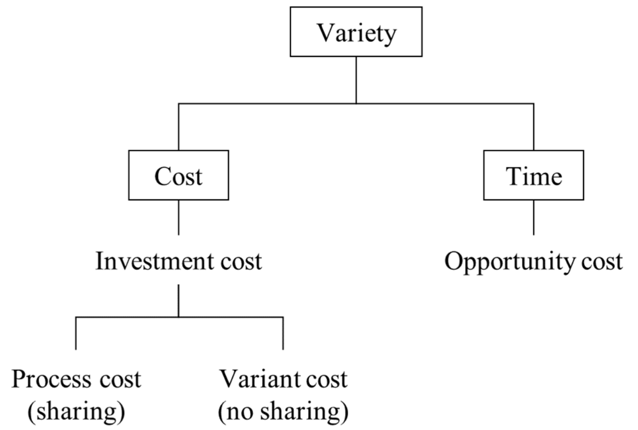


FIGURE 7. **Structure of complexity cost.**

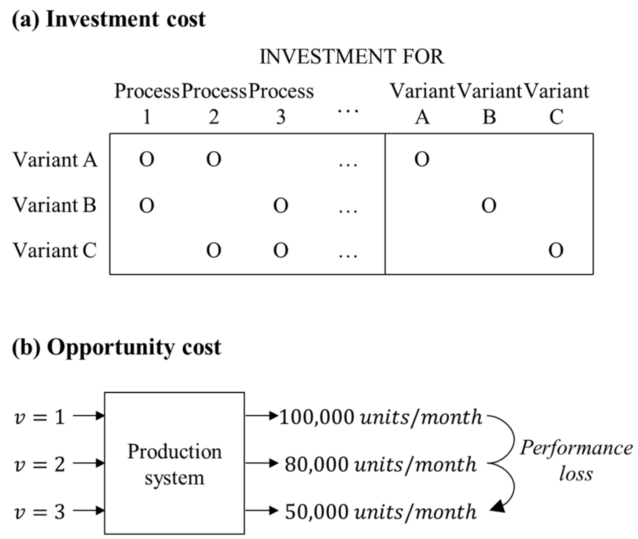


FIGURE 8. **Complexity cost of a facility (a) Investment cost and (b) Opportunity cost.**

Berry [34] proposed a technique in which the choice probabilities constructed by the nested logit model are transformed into a linear form. The technique obtains the estimate of a part-worth utility of each attribute level and the similarity parameter of each nest through a linear regression analysis. The estimates are used for the variety optimization to calculate market share for product variants configured by attribute levels. The demand model constructed in this subsection reflects the tendency of concavely increasing revenue. The increasing tendency of market share will be analyzed in the case study.

C. COMPLEXITY COST MODEL

This subsection formulates a cost model that estimates complexity cost generated in production domain. Since complexity cost is difficult to trace where it comes from, previous studies [13], [35], [36] have attempted to estimate the cost as the incremental cost associated with the increasing variety. Lechner et al. [36] introduced the *zero-based costing approach* in which an incremental cost and time are allocated to each additional variant compared to the case when the variant is not produced. Along with the previous studies, the complexity cost model is represented by a degree of change in a production system affected by an additional variant. Fig. 7 shows the structure of variety impacts on cost and time. Variety basically influences production cost and process time. In the model, production cost is defined as the additional investment cost in a production system, and process time is converted into the opportunity cost derived from loss of productivity.

One of the major parts of the complexity cost is the investment cost incurred when a variant is added. Whereas the investment cost is traditionally regarded as a fixed cost, it should be calculated as a variable cost because it increases with the increasing variety [35]. Fujita et al. [13] estimated an additional investment cost as a variable cost based on the design similarity between variants to be produced. In this study, the investment cost for the shared processes is defined as the *process cost*, and the cost for the non-shared facilities is termed the *variant cost*. Fig. 8(a) describes the process cost shared by variants and the variant cost incurred by each variant. If a variant is produced in the facility, the relevant processes marked with an 'O' should be invested. On the other hand, the variant cost is imposed only on a particular variant, such as inventory cost. The variant cost generated in a module production facility is allocated to each module variant, and the cost incurred in a final assembly line is assigned to each product variant. The investment cost (IC) is represented as follows:

$$IC = \sum_{s}\sum_{t} c_{st}Z_{st} + \sum_{m}\sum_{n} c_{mn}Y_{mn} + \sum_{i} c_i W_i \tag{9}$$

where Z_{st}, Y_{mn}, and W_i are binary variables indicating the existence of production process r_{st}, module variant m_{mn}, and product candidate i, respectively. Parameters c_{st}, c_{mn}, and ci represent the process cost, module variant cost, and product variant cost.

Complexity cost also arises from the loss of productivity due to the incremental process time. The reasons are that variety reduces the learning effect in a facility and demands frequent setups to processes. The cost generated by lower productivity is considered as an opportunity cost because it is not counted up in a traditional costing system. As shown in Fig. 8(b), the opportunity cost is estimated by a change in production volume compared to the possible production volume when a single variant is produced. The opportunity cost from the production volume change can be estimated by historical data or a predicted value. The opportunity cost can be represented as a function of the number of variety. This study introduces a general function that reflects an increasing tendency of the opportunity cost as the increasing variety. The opportunity cost (OC) function of facility s is as below:

$$OC_s = f_s(v_s) = \phi_s(v_s - 1)^{\theta_s} \tag{10}$$

where ϕ_s is the cost difference between when $v_s = 1$ and $v_s = 2$, and θ_s describes an increasing tendency of the cost where $v_s \geq 3$. If θ_s equals to one, the cost linearly increases with the amount of loss of production volume, and if θ_s is larger than one, the function reflects that the cost increases convexly. This study calls θ_s as the flexibility parameter. For the case $\theta_s = 1$, a facility experiences no complexity, indicating that the opportunity cost increases linearly with the increased variety. On the other hand, the case $\theta_s > 1$ means that production loss increases with the increased variety (e.g., longer production time and higher inefficiency of production), indicating that the facility becomes less flexible. The higher the parameter value, the greater the impact of the variety. Most facilities have parameter values greater than 1, unless a facility operates as an ideally modular assembly line.

The parameter estimation requires historical data. Thonemann and Brandeau [35] applied an estimation approach in which cost is allocated to activities and converted to variants. The approach's key idea is to conduct sensitivity analysis investigating how complexity cost changes as a variant is added. Another useful approach is to establish an activity-based costing (ABC) system. Park and Simpson [37] developed a framework for activity-based costing that activity costs are allocated to a variant in a product family through cost modularization. Using these estimating and costing approaches introduced in this paragraph will be helpful to estimate the process cost and the variant cost. After conducting sensitivity analysis, regression analysis will help to identify fitted parameter values to reflect the tendency of the incremental opportunity cost.

V. CASE STUDY

A. CASE DESCRIPTION

In this case study, the optimization model is applied to a front chassis family. A front chassis is a part of an automobile and forms a family by creating front chassis variants. Fig. 9 shows a front chassis composed of nine modules. The nine modules are related to twelve attributes having differentiated levels. The attributes are arranged in rows of the matrix in Fig. 10, and this matrix represents the relationships between attributes and modules. The relationships have the n-to-m type, thus many module variants can be required to cover diverse combinations of attribute levels. In production domain, each module is produced by each supplier and assembled to a complete product in a single assembly line. The relationships between modules and facilities are close to the one-to-one type.

The case study is conducted on two mid-sized sedan models, Hyundai Sonata and Kia Optima. The two models share the front chassis family but are considered in different brands. Target markets of both models are diverse, but the two best-selling regions, the Korean and European markets, are analyzed in the case study. Table 1 shows the description of market segments. The European market is divided into three

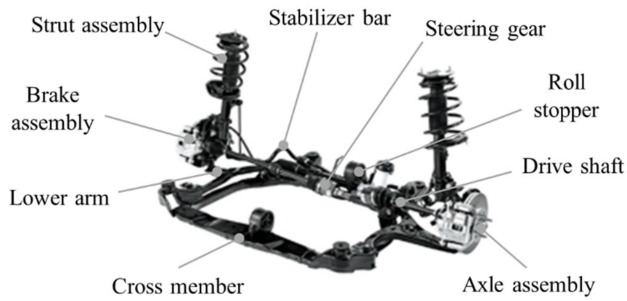


FIGURE 9. Automobile front chassis.

		m_1 Brake assembly	m_2 Axle assembly	m_3 Lower arm	m_4 Drive shaft	m_5 Cross member	m_6 Roll stopper	m_7 Steering gear	m_8 Stabilizer bar	m_9 Strut assembly
a_1	Drive type					X		X		
a_2	Weather type					X				
a_3	Regional char.									X
a_4	Model									
a_5	Body type								X	X
a_6	Engine type				X	X	X	X	X	X
a_7	Transmission type				X					
a_8	Steering gear type					X		X		
a_9	Suspension type			X	X					X
a_{10}	S/A performance									X
a_{11}	Disc size	X	X							

FIGURE 10. Attribute-module relationship matrix.

segments depending on the market-dependent characteristics, which are drive type (DT), weather type (WT), and regional characteristic (RC), having different market sizes. Hyundai and Kia have launched a total of 17 model variants to the Korean market, and only Kia has targeted the European market with 5, 10, and 2 model variants for each segment. A front chassis variant is matched to a model variant. To configure all front chassis variants, a total of 88 module variants have been developed.

B. DATA SOURCE

Market sales data were collected from *auto.danawa.com* (for sales in the Korean market) and *carsalesbase.com* (for sales in the European market), covering two years from January 2017 to February 2019. The data include market sales, specifications, and price of each model variant (trim model). Information about competitive models was also obtained, such as SM5, SM6, and Malibu in the Korean market, and Passat, Superb, Peugeot 508, Mondeo, and Insignia in the European market.

TABLE 1. Market segment description.

Market *j*		DT		WT		RC		Size	No.
		L	R	T1	T2	T1	T2	(year)	variants
1	Korea	1			1	1		150,000	17
2	Europe 1	1		1		1		125,000	5
3	Europe 2	1			1	1		300,000	10
4	Europe 3		1		1	1		75,000	2

DT: drive type (L: left; R: right), WT: weather type (T1-2: type 1-2),
RC: regional characteristic (T1-2: type 1-2)

Other information, such as structures, configurations, BOM (bill-of-materials) of the car models, is sourced from Hyundai-Kia Automotive Group's R&D Center. It was hard to access process data for security reasons, so production processes were recreated from BOM data of all module variants. A BOM has a generic form by which all parts in module variants are listed, and each part is assigned to the used module variant. Using these data, production processes by each module variant were predicted. For example, if a part is shared across several module variants in a BOM, the shared process was created. The process cost and the variant cost were numerically generated. Historical data in costing systems would be a good solution to update the costs.

C. OPTIMIZATION SETTING

Firstly, the configuration planning phase was conducted to generate candidates of product configurations. Parameters in the demand model and complexity cost model were also estimated. Candidates were created based on the relationships between attributes and modules as shown in Fig. 10. To reduce the number of possible candidates, combination rules were also set based on the current specifications of trim models already launched in the markets. Table 2 is a sample of all candidates of product configurations. Each row represents a combination of attribute levels of a candidate. A total of 96 candidates were created. Then, a candidate was represented by a configuration of module variants and production processes. All configurations were added as binary variables in the optimization model.

Parameter estimation was conducted to set the optimization model. The transformation technique suggested by Berry [34] was used to estimate part-worth utilities and similarity parameters. A logit function was transformed into a linear function and a linear regression was performed to estimate the parameters using aggregate market sales data. Table 3 is the result of estimating similarity parameters of all brands in the markets. Part-worth utilities of attribute levels were also estimated by a linear regression, and some nonsignificant results were excluded from the study. For similarity parameters, most brands in the markets have values more than 0.8, which indicates that customers consider product variants in the same brand highly similar. The flexibility parameter θ_s in the cost model was set to 2.0 to reflect the convexly increasing tendency.

D. RESULT

Fig. 11(a) shows the result of solving the optimization problem with the evolutionary algorithm. Pareto optimal solutions are represented as black dots, and dominated solutions are marked as grey dots. Market share grows fast between 11.5% and 14.0% without too much increase of complexity cost, and then complexity cost is steeply increased after 14.0% of market share. For the Pareto optimal solutions, market share and complexity cost were separately analyzed to identify the relationship with variety. In Fig. 11(b), the circles on the upper curve are the selected solutions which have the highest market share for each number of variety, and the squares close to the lower curve are the solutions which are the lowest value of complexity cost for each number of variety. The result shows the increasing tendencies of market share and complexity cost as addressed in the introduction section. We noticed that an optimal variety exists at the point where the gap between revenue and complexity cost is greatest.

Combining all results of market share and complexity cost, Fig. 12 shows the optimal variety of the case. To find the optimal variety, price of each product variant was multiplied by its estimated demand. The price was obtained from regression analysis with the market sales data of the released product variants. The two curves in Fig. 11(b) are combined into the single curve in Fig. 12, where the optimal variety can be found at the top of the curve. In this case, profit is maximized when the number of products is 12, but we have found that nearby values have almost equal values of profit. While the optimal number of products may fluctuate with slight variations in parameters, a prevailing trend shows that launching fewer products is advantageous compared to launching a larger number. The first reason is that car brands tend to have high levels of similarity, which is observed in this case study where the similarity levels exceed 0.7. For this reason, launching a large number of products may cannibalize their individual market shares. The second reason for the lower optimal variety is that the flexibility parameter θ_s was set to 2.0, which means lower flexibility of production facilities.

From the result, it is worth considering whether the company is launching too many product variants. The number of front chassis currently in the markets is 88, but the case study suggests 12. This indicates that the complexity cost may increase significantly. It would be more cost-effective to release fewer product variants by commonizing parts, integrating unnecessary variants, etc. While it may be necessary to offer a large number of product variants to satisfy a broader market, it may not be necessary if the complexity cost outweighs the gain in market share. In this context, it is an important task for manufacturing companies to find the right level of product variety, and this paper emphasizes the need for a balanced view of variety. In the next subsection, sensitivity analysis is conducted to analyze the impacts of variety in different situations.

TABLE 2. Candidates of front chassis configurations.

Product candidates	DT		WT		RC		M		BT	ET						TT				MDPS		ST	SP		DS			
	L	R	T1	T2	T1	T2	S	K	S	T1	T2	G1	G2	D1	D2	A6	A8	S7	M6	C	R	T1	L1	L2	L1	L2	L3	L4
1	1			1	1		1		1	1								1		1		1	1		1			
2	1			1	1		1		1	1								1			1	1		1		1		
3	1			1	1		1		1	1								1			1	1		1			1	
4	1			1	1		1		1		1							1			1	1	1			1		
5	1			1	1		1		1		1							1			1	1		1			1	
6	1			1	1		1		1		1							1			1	1		1				1
…															…													
96		1		1	1			1	1						1				1	1		1		1			1	

DT: drive type (L: left; R: right), WT: weather type (T1-2: type 1-2), RC: regional characteristic (T1-2: type 1-2), M: model (S: Sonata; K: K5), BT: body type (S: sedan), ET: engine type (T1-2: turbo 1-2; G1-2: gasoline 1-2; D1-2: diesel 1-2), TT: transmission type (A6-8: automatic 6-8; S7: semi-automatic 7; M: manual), MDPS: motor-driven power steering (C: column-mounted; R: rack-mounted), ST: suspension type (T1: type 1), SP: shock absorber performance (L1-2: level 1-2), DS: disk size (L1-4: level 1-4)

TABLE 3. Estimates of similarity parameters.

Market	Brand	Similarity value
Korea	Hyundai	0.860
	Kia	0.829
	Renaultsamsung	0.892
	Chevrolet	0.883
	BMW	0.827
	Benz	0.839
Europe	Kia	0.860
	Ford	0.873
	Mazda	0.853
	Opel	0.747
	Peugeot	0.864
	Renault	0.829
	Skoda	0.858
	Toyota	0.881
	Volkswagen	0.881

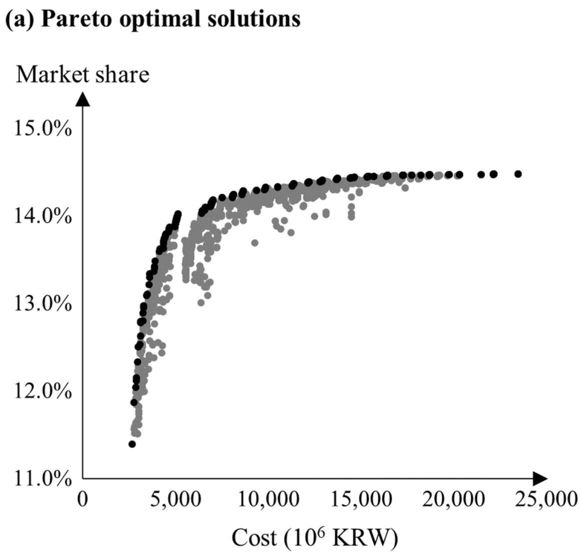
E. EXPERIMENTS

When a company implements a variety strategy, it should consider the similarity level of product variants and the flexibility level of facilities. Firstly, sensitivity analysis was conducted to discuss the impact of the company's similarity level compared to the competitors' levels. The purpose of the experiment is to find the appropriate range of product variety to launch, taking into account customers' perceived similarity to a company's existing products. With the competitors' similarity parameters fixed at 0.7, the company's similarity parameter was adjusted from 0.5 to 0.9 with an interval of 0.1 to investigate the change in an optimal variety. In this analysis, the flexibility parameter θ_s was fixed at 1.0.

Fig. 13(a) shows three comparable results with values of 0.6, 0.7, and 0.8 for the similarity parameter. By changing the similarity parameter from 0.6 to 0.7 to 0.8, the optimal variety was reduced from 66 to 50 to 16, and the profit also decreased from 8,997 to 7,059 to 5,930 million KRW, respectively. The findings indicate the importance of determining the number of product variants based on the perceived similarity level of a brand's offerings. When customers perceive a high level of similarity among a brand's products, a strategy of launching fewer product variants is advisable. On the other hand, if a company would like to launch a diverse range of products, it becomes crucial to prioritize concerted efforts toward product differentiation, reducing the level of similarity.

Another analysis was conducted to identify the impact of the increasing tendency of complexity cost by changing the flexibility parameter θ_s. The flexibility parameter was adjusted from 1.0 to 2.0 with an interval of 0.2, with the similarity parameter fixed at 0.5. Fig. 13(b) represents the result of the three comparable values: 1.0, 1.4, and 1.8. As the parameter value was changed from 1.0 to 1.4 to 1.8, the optimal variety decreased from 78 to 50 to 40. The profit was also reduced from 11,559 to 10,264 to 9,265 million KRW, respectively. The result has demonstrated that the flexibility—the ability of a facility to maintain productivity even if a large number of variants are produced—needs to be improved to reduce negative effects of variety. Thus, when an automobile manufacturer wants to produce a wide range of product variants through multiple module variants, a module production line should have the flexibility to produce multiple variants without losing productivity as in a final mixed-model assembly line.

The above two experiments were then combined to identify an optimal variety by a combination of the two parameters. The result is summarized by a two-dimensional table in Fig. 14. Darker cells indicate higher variety values. The result shows that the smaller the similarity and flexibility parameters are, the higher the optimal variety is. One noticeable point is that several cells have the same variety. This indicates that the optimal variety is derived in the form of a step function rather than a linear function. This is because each product



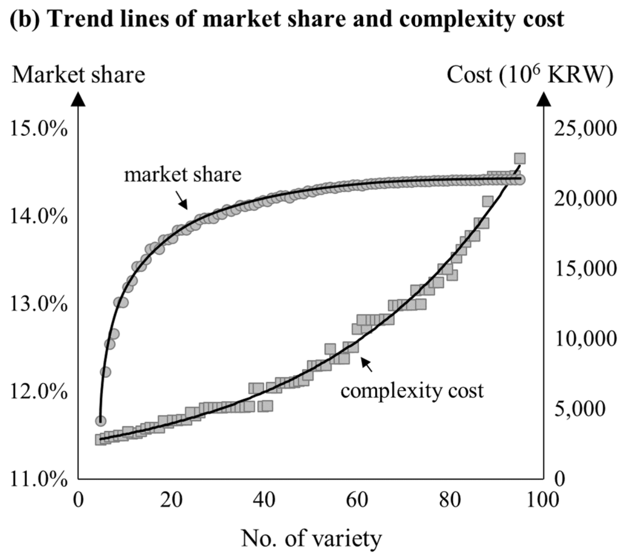


FIGURE 11. Optimization result (a) Pareto optimal solutions and (b) Trend lines of market share and complexity cost.

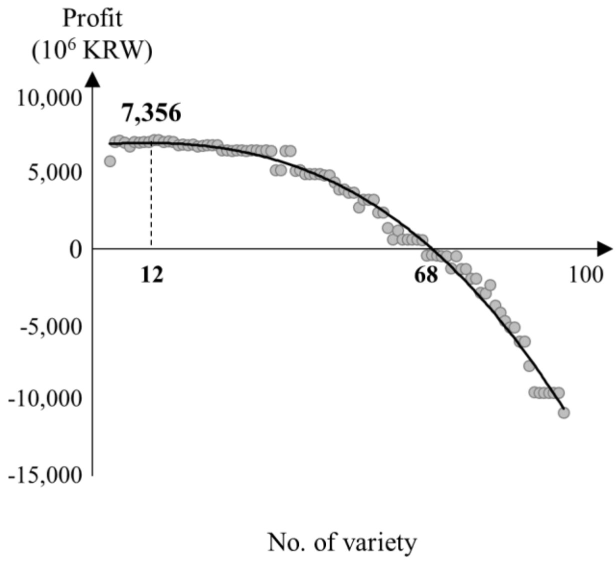


FIGURE 12. Optimal variety.

variant has a different impact on market share and complexity cost. Some product variants are created with more additional module variants and production processes, whereas the rest of the variants can be configured by existing module variants and production processes without additional elements. Consequently, it can be said that variety management is not just a problem of finding an optimal variety, but a problem of configuring product variants. A manufacturing company should focus on product configurations composed of attribute levels, module variants, and production processes rather than just the number of variety.

F. DISCUSSION

In this subsection, we discuss two main components of the optimization model: customer preferences and complexity cost factors.

Customer preferences are important factors in analyzing the characteristic of market segments. There are various ways to obtain customer preference values, but this study focused on the historical choices made by existing customers in each market. We used the method of calculating the part-worth utility of each attribute of products based on the demand data. Thus, the choice history of existing customers indicates the responsiveness of future customers in the same market segment to each product attribute level, which is an important factor in determining the specifications of product variants and the number of products released.

This study adopted part-worth utility for the preference model. Part-worth utility represents the value of each attribute level of a product and is calculated from customers' choice data within the same segmented market. Customers in the same market are assumed to have identical utility values for each attribute level, except for the error term, implying 'homogeneity' among customers in the market. Thus, in order to effectively analyze customer preferences, it is crucial to consolidate as many homogeneous customers as possible into a single market segment; otherwise, customer preferences may be misinterpreted.

The case study applied conventional segmentation criteria commonly used in the automotive industry, such as sales region, driver position, weather, and vehicle class. These criteria are general, but high-level, so it is difficult to ensure that customers have identical preferences. In the case study, we restricted the market to the mid-sized sedan to allow for as homogeneous a market as possible. However, in order to make the proposed demand model more effective, it is necessary to conduct an analysis of market segmentation at a deeper level and to incorporate other critical factors, including regional demographics, regulatory environments, cultural preferences, market dynamics, customers' economic

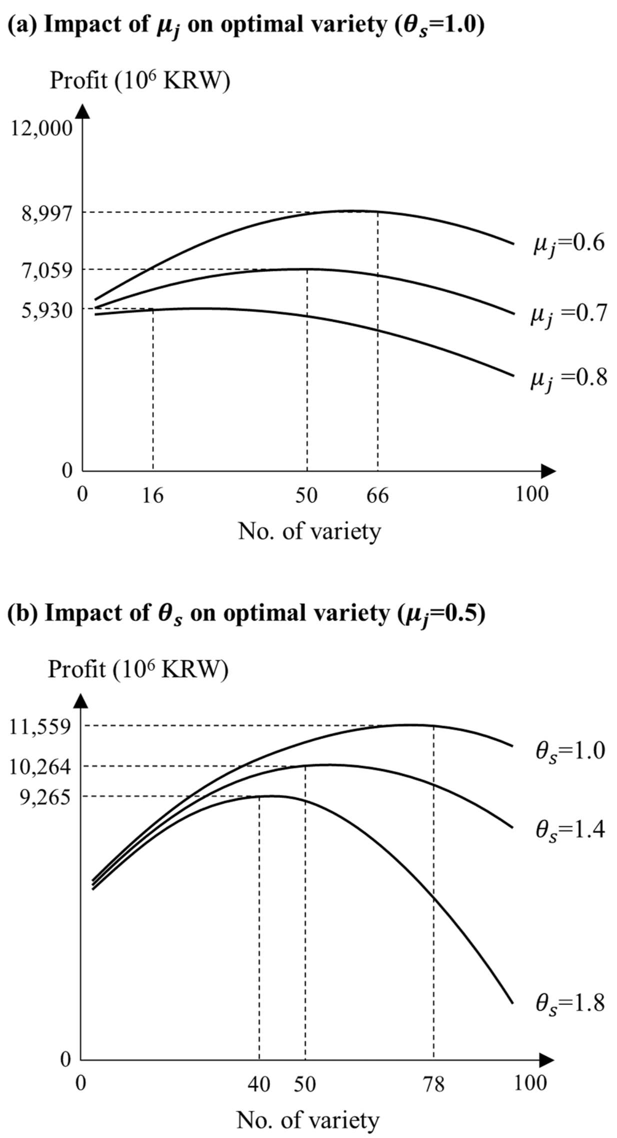


FIGURE 13. Sensitivity analysis (a) Impact of μ_j on optimal variety (θ_s =1.0) and (b) Impact of θ_s on optimal variety (μ_j =0.5).

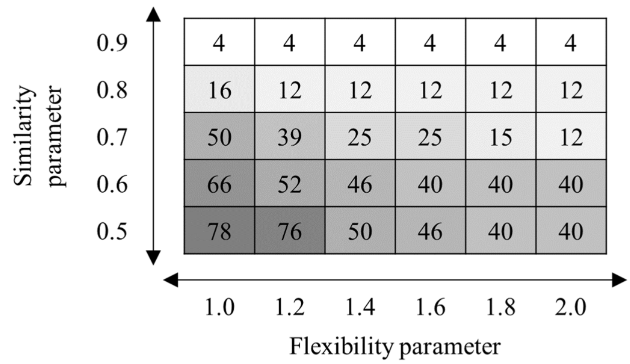


FIGURE 14. Optimal variety in different scenarios.

and living conditions, etc. Considering these factors, which were not explored in detail at this time, customer preferences should be complemented by in-depth analysis and is a key area for future research.

Next, we discuss complexity cost factors induced from variety. Although this study primarily focuses on production cost and process time, variety-induced complexity in practice occurs across various domains such as design, logistics, supply chain, operations, and maintenance. Furthermore, the concept of complexity encompasses more than just cost and time, making it challenging to quantify complexity as cost. Capturing all the complexity factors is extremely hard, however, to overcome this challenge, there have been efforts to evaluate them in the previous research. One of the most useful methodologies is activity-based costing (ABC), which is a methodology that tracks costs based on activities occurring across multiple domains. Time-based ABC [38] and variant-based ABC [36] have been subsequently proposed to address the intertwined relationships among variants. These methodologies use time or variant as base units for costing.

The complexity cost model proposed in this paper is based on the concept of variant-based ABC. The model has focused on representing convexly increasing tendency of complexity cost resulting from the complex relationships among variants, rather than reflecting all complexity factors. In this process, a simplified version of the model has been defined, assuming various complexity factors as a single parameter, variant cost. In order to apply the model to practical cases, however, the cost model should be improved to calculate actual complexity cost, considering various factors across different domains. The model may require additional variables and parameters. To reflect as many factors as possible, practical experiences or historical data would be necessary to fit the appropriate level of the cost model. In further research, the cost model should evolve from the simplified version to a more detailed one, taking into account various complexity factors across multiple domains such as design, logistics, supply chain, etc.

VI. CONCLUSION

This paper proposed a variety optimization model to find an optimal product variety, a balanced solution between market share and complexity cost in product family design. The two-step approach was adopted by decomposing the optimization process into the configuration planning and the variety optimization phases. The key contribution of this study is to reflect the increasing tendencies of market share (concavity) and complexity cost (convexity) in the optimization model. A demand model was developed based on the nested logit model to consider the tendency of market share. A complexity cost model was constructed through the zero-based costing approach by which the incremental concept of complexity cost was reflected. Finally, a multi-objective combinatorial optimization model was formulated to identify Pareto optimal solutions. In the case study, the optimization model was applied to the front chassis family. The case study analyzed how an optimal variety is changed by the similarity level of product variants and the flexibility level of facilities. The analysis demonstrated that the model is useful for coordinating a number of requirements from multiple domains, finding an appropriate level of product variety and configurations in various situations.

There are some future works in improving the optimization model. While this study focused on an automobile family design, it can be applied to other industries where companies launch a series of products, such as smartphones, computers, home appliances, etc. The proposed model is suitable for modular product families where products have module-level specifications and are produced with module-based assembly processes. In addition, as discussed, there is a need for in-depth study of customer preference and complexity cost. Since high-level market segmentation does not guarantee homogeneity of customers, a lower-level market segmentation technique should be analyzed in detail. The analysis can reflect regional demographics, regulatory environments, cultural preferences, and customer characteristics at a more granular level. Next, how to define complexity cost still remains a challenge to overcome. This paper regarded complexity cost as the investment cost for production processes and the opportunity cost due to loss of productivity. Future works require an in-depth study of complexity sources throughout the entire lifecycle of a product family.

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