Reliability-based design for market systems (RBDMS): Case study on electric vehicle design

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Abstract

The reliability-based design optimization (RBDO) approach allows decision-makers to achieve target reliability in product performance under engineering uncertainty. However, existing RBDO studies use target reliability as a given parameter and do not determine optimum reliability. Designing a product with high reliability can satisfy many customers and increase market demand, but it can generate a large cost that reduces the profit of the company. Therefore, reliability should be a decision variable, and it is necessary to find the optimum reliability that maximizes the profit of the company. This paper proposes a reliability-based design for market systems (RBDMS) framework by integrating RBDO and design for market systems (DMS) approaches to find the optimum reliability. The framework is applied to electric vehicle (EV) design problems, and the effect of reliability on profit and engineering performance is derived. Reliability in a framework is used as follows: (1) as a decision variable, (2) as an attribute that directly influences customer preference, (3) as a standard for determining advertised performance, and (4) as target reliability in an engineering model. Several observations about optimum reliability are presented from the optimization results of various scenarios and parametric studies.

Keywords: Reliability-based design optimization, design for market systems, electric vehicles, reliability, uncertainty

Nomenclature

SoC: state of charge of battery
DoD: depth of discharge of battery
D: DoD battery
F: additional fraction of nominal capacity
P: penalty factor for deeper DoD
A: capacity loss factor
σ: standard deviation of (1 - A)
$\mathbf{\Pi}$: profits
$\mathbf{D}$: market demands
MC: manufacturing cost
$\mathbf{C}$: compensation costs
$\mathbf{X}$: deterministic decision variable vector
$\mathbf{X}_{power}$: powertrain design variable vector
R: reliability
W: warrantied battery lifetime
$Price$: price
$P_F^{\mathbf{Target}}$: target probability of failure for reliability constraints
$\mathbf{g}$: inequality constraints
$\mathbf{G}$: probabilistic constraints
$\mathbf{B}$: battery design variables
FR: final gear ratio
$\mathbf{RP}_e$: random parameter vector of engineering model
$\mathbf{P}_{\mathrm{EV}}$: matrix of probabilistic performance vectors
$\mathbf{P}_{\mathrm{EV}_{\mathrm{MPGe}}}$: vector of probabilistic MPGe
$\mathbf{P}_{\mathrm{EV}_{\mathrm{range}}}$: vector of probabilistic driving range
$\mathbf{P}_{\mathrm{EV}_{\mathrm{speed}}}$: vector of probabilistic top speed
$\mathbf{P}_{\mathrm{EV}_{\mathrm{accel}}}$: vector of probabilistic acceleration
$\mathbf{P}_{\mathrm{EV}_{\mathrm{Batt}}}$: vector of probabilistic battery lifetime
$\mathbf{A}$: advertised attribute vector
$\mathbf{A}_{\mathrm{eng}}$: vector of advertised attributes determined from engineering model
$f_{\mathrm{engineering}}$: engineering model
$f_{\mathrm{attribute}}$: attribute model
$f_{\mathrm{marketing}}$: marketing model
$f_{\mathbf{X}}(\mathbf{x})$: joint probability density function
Ω_F: failure set

1. Introduction

Engineering design generally aims to maximize the functionality of a system while satisfying constraints. To enhance the functionality of an objective system, deterministic optimization has been successfully used in engineering fields as it often provides optimal solutions at the boundaries of design constraints [1]. However, small variations in design variables and other parameters are derived from many uncertainties such as geometrical tolerance, physical properties of materials, and operating conditions, often leading to design failure. Currently, the stochastic nature of engineering systems is naturally considered when solving optimization problems [2], and the reliability of a system is significantly considered. Therefore, reliability-based design optimization (RBDO) maximizes the functionality or utility of a system while satisfying the target reliability regardless of inherent uncertainties in the design variables and parameters. In RBDO, the reliability analysis focuses on the evaluation of probabilistic constraints to guarantee that the target reliability is satisfied, whereas optimization focuses on searching for optimal solutions. RBDO has been widely used in various engineering fields such as aerospace [3–6], civil [7, 8], and mechanical engineering [9–18], and in various applications such as composite structures [19].

However, existing RBDO studies do not suggest how to determine the target reliability, and thus designers use predetermined target reliability for design optimization. This study proposes the integration of design for market systems (DMS) and RBDO to find the optimum reliability from the perspective of the market. DMS emerged from the objective of maximizing specific values such as profit or social welfare from the perspective of manufacturers or producers [20–23]. This research area focuses more on selling products or services rather than optimizing functional performances. To determine the optimal product designs for a market system, an optimization problem that maximizes the specific profit or social welfare while satisfying engineering or other constraints is formulated into a mathematical problem. Quantitative market demand models are commonly utilized in the marketing field for estimating customer preferences (market demand) as a function of design attributes and the prices of products. Therefore, expressing design attributes as functions of decision variables or parameters must be performed first to plug the market demand models into the product design problem. DMS has been utilized for electric vehicle (EV) and hybrid EV design problems [24–28].

When designing a product performance with high reliability based on the same performance, sales volume can be increased owing to increasing customer satisfaction, but the company's profit can be reduced owing to increasing cost. On the other hand, a low reliability design can lower cost and increase the margin, but it can reduce customer satisfaction and reduce sales volume, and ultimately reduce a company's profit. Therefore, from the perspective of an entrepreneur, the target reliability should be a decision variable rather than a fixed parameter, and optimum target reliability should be sought to maximize the profit that can be gained by selling the product.

There are some issues to consider in linking RBDO and DMS through reliability. In a marketing model, reliability is one of the attributes that are evaluated by customers and is related to market demand. On the other hand, in an engineering model, a probabilistic constraint that defines a feasible solution is limited to reliability as in the existing RBDO approach, and reliability determines the performance of products that are related to market demand. Therefore, the engineering model and marketing model are coupled through reliability so that how reliability as a decision variable affects each model should be identified.

In addition, in order for reliability to be linked from engineering to marketing, it is necessary to define probabilistic attributes on the engineering side and advertised attributes on the marketing side. A probabilistic attribute represents the performance distribution obtained when uncertainties exist, and has a constraint boundary to satisfy the target reliability, as shown in Fig. 1. An advertised attribute represents the product performance advertised to the customer as the value of the product performance that can satisfy the reliability, and the advertised attribute is the same as the engineering constraint boundary. As the target reliability increases, the constraint boundary of the performance that satisfies the reliability must be moved to the left, which means that the advertised attribute value becomes smaller.

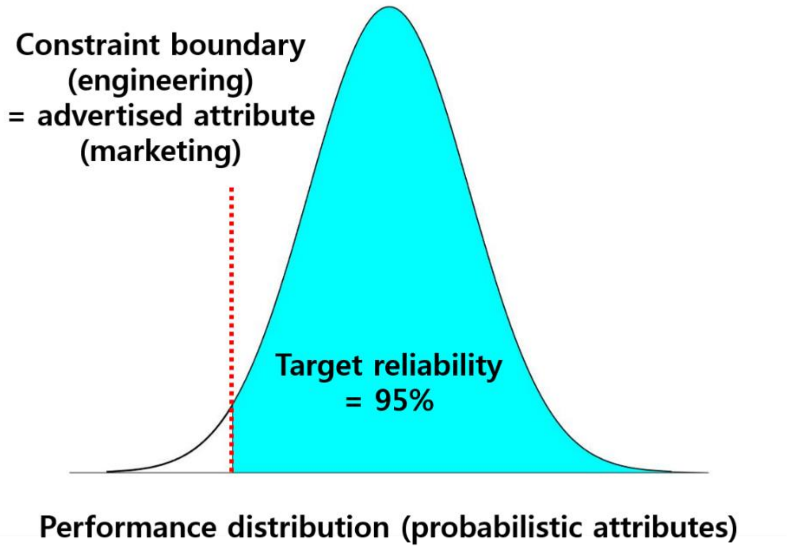

Fig. 1 Advertised attribute determination

Reliability not only determines the advertised attribute value, but the reliability itself can also be an attribute of the product and affect the customer's purchase of the product. However, reliability is not given to the customer in reality, and the customer evaluates the reliability of the product or brand through word-of-mouth effects, product ratings, or product comparisons in market reports. In this study, an EV design problem is used as a case study, and the reliability rating of a vehicle provided by J.D. Power is assumed to represent the reliability. The assumption is that if a company designs a product with high reliability, it can get a high J.D.

Power rating for reliability, and the customer chooses a product considering both the advertised performance and J.D. Power reliability rating. In order to accurately map the reliability and the J.D. Power rating, performance data for the vehicle are required, but this study replaces this with a parametric study.

By addressing the issues above, this study suggests a reliability-based design for a market systems (RBDMS) framework. Reliability, which affects both engineering and marketing models, is used as follows: (1) as a decision variable, (2) as an attribute that directly influences customer preference, (3) as a standard to determine advertised performance, and (4) as the target reliability in the engineering model. Therefore, reliability is a decision variable, an attribute, and a determining factor for a feasible solution at the same time in RBDMS.

This study implements RBDMS through a case study of EV design and introduces a design for EV powertrain systems, a Li-ion battery, and a market system that maximizes the profit of an EV manufacturing company while ensuring the reliability of the advertised performance and warrantied battery lifetime.

We compare optimal designs obtained under three design methods (shown in Fig. 2):

- Method 1 (RBDO): maximizing *engineering performance* with *fixed* reliability
- Method 2 (RBDO + DMS): maximizing *profit* with *fixed* reliability
- Method 3 (RBDMS, proposed): maximizing *profit* by using reliability as a *decision variable*

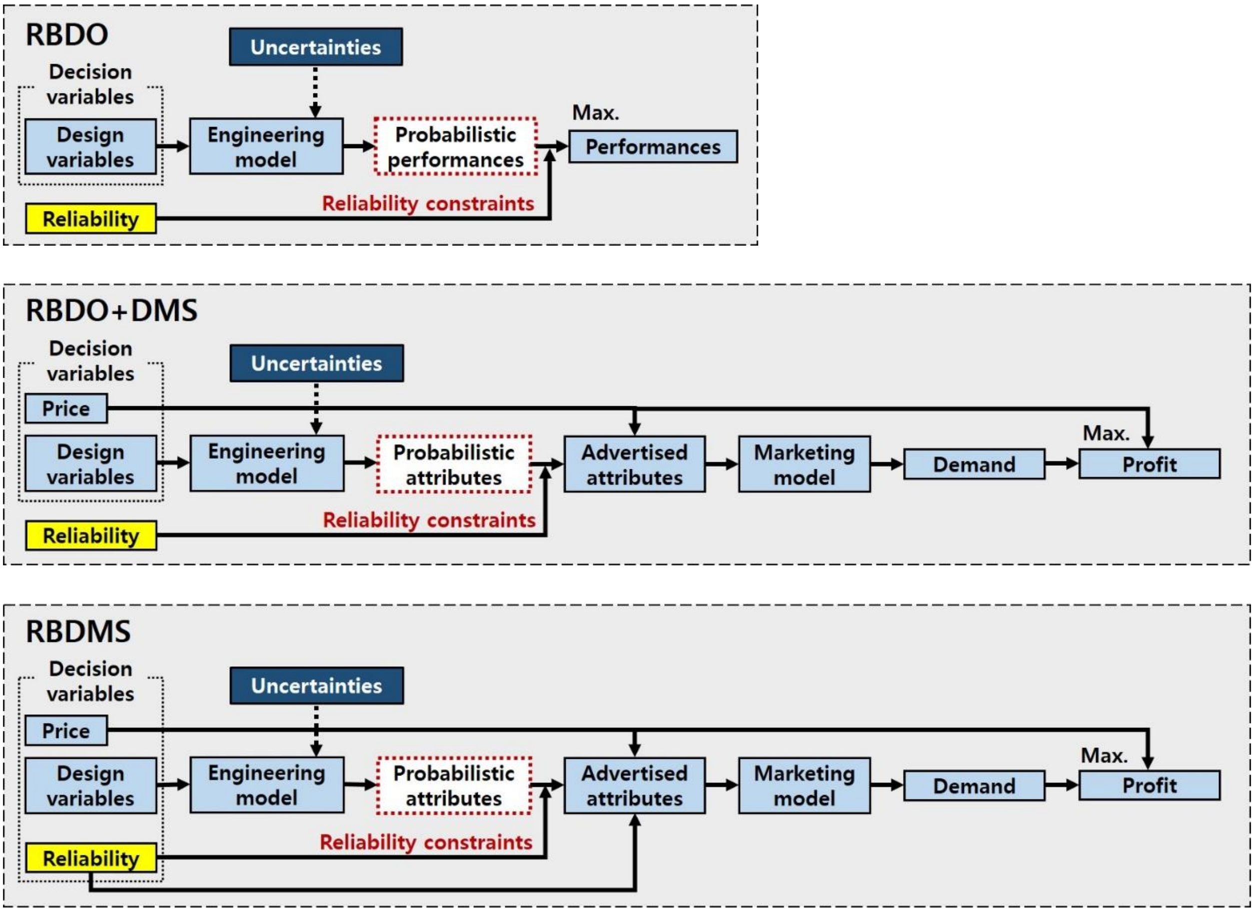

Fig. 2 Comparison between RBDO and RBDMS

The remainder of this paper is organized as follows. Section 2 introduces the engineering model and uncertain factors in Li-ion battery characteristics, daily driving distance, and driving cycles of users. Section 3 presents the marketing model for estimating customers' preferences. Section 4 provides the RBDMS formulation and modeling assumptions. In Section 5, the proposed RBDMS framework is utilized in an EV design case, and the optimal results of three design methods are compared. Finally, Section 6 concludes the paper and describes future research directions.

2. Engineering Model

2.1 EV Simulation Model

To understand how uncertainties at the engineering level affect performances and battery lifetime, two engineering models are presented: an EV performance model that simulates vehicle performance while considering uncertainties in battery and driving characteristics for different mechanical designs, and a battery degradation model that presents the life cycle of a Li-ion battery with respect to initial battery capacity, miles per gallon gasoline equivalent (MPGe), and daily driving distance.

2.1.1. Performance model

EV performance such as MPGe, driving range, top speed, and acceleration are determined by the design of the powertrain, which contains a battery pack and motor that are connected to wheels through a final drive. To simulate such a model, we utilize the specifications of the Nissan Leaf. These specifications are listed in Table 1 [29, 30]. The powertrain system of the Nissan Leaf is also used in the EV performance model. AMESIM software and a battery degradation model are combined to modify our analytical EV performance model [31].

In the battery pack, the cells connected in series form a branch, and several branches are connected in parallel. The number of cells in series and parallel connections are used as decision variables. The battery capacity is determined by the number of cells, which is directly related to the driving range of the EV. Furthermore, the array of cells in the battery pack influences the battery voltage and current limits, which affect the output power of the motor. The weight of the battery pack, which is proportional to the number of cells, also influences the total weight of the EV and in turn affects the EV acceleration and MPGe.

High speed and low torque output from the motor are transformed to low speed and high torque output through the final drive. The final drive ratio, which is one of the decision variables, is the ratio of the input and output speeds. A large torque is achieved from a high ratio, which in turn leads to high acceleration performance but low maximum speed, whereas a small torque is achieved from a low ratio, which in turn leads to low acceleration performance with high maximum speed. Fuel economy, MPGe, is also related to the final drive ratio in terms of different energy consumptions.

Table 1 Specifications of EV model

Vehicle curb weight	1,631 kg
Frontal area	2.27 m^2
Rim diameter	406.4 mm
Tire width	205 mm
Coefficient of drag	0.29
Motor(s) type	Permanent Magnet AC Synchronous
Max. motor(s) power	80 kW
Max. motor(s) torque	280 Nm
Max. motor(s) speed	10,390 rpm
Rated cell capacity	33.1 Ah
Nominal cell voltage	3.8 V

2.1.2. Battery degradation model

The lifetime of a battery depends highly on the daily driving distance. The battery degradation model used in this study plays a crucial role in reflecting different daily driving distances of users. Li-ion battery capacity decreases owing to increased cell impedance caused by solid-electrolyte interface growth, loss of accessible lithium ions, and degradation of electrical parts because of cycling [32,33]. The state of charge (*SoC*) is the amount of useful remaining charge compared to its initial fully charged state:

$$SoC(\mathrm{t}) = \frac{\int_{t_0}^{t} I(\tau)\,d\tau}{Q_0} \times 100 \tag{1}$$

where I is the charging current, Q_0 is the total charge of the battery, and $\int_{t_0}^{t} I(\tau)\,d\tau$ refers to the delivered charge. The discharged battery capacity, which is the complement of *SoC*, that is, the depth of discharge (*DoD*), is defined as

$$DoD = SoC_{\text{initial}} - SoC_{\text{final}}. \tag{2}$$

The capacity fade is related to the number of cycles and *DoD* of the batteries [34]. In general, an EV battery should be replaced when its capacity decreases to 80% of its initial capacity [28].

The life cycle, which results from capacity fades with regard to the *DoD* of batteries, was theoretically and experimentally presented by Thaller [35] as

$$Life\ Cycle = \frac{1 + F - D}{(A + 2\sigma)(1 + PD)D} \tag{3}$$

where *D* corresponds to the *DoD* of the battery, *F* is the additional fraction of the nominal capacity, *P* stands for the penalty factor for the deeper *DoD*, *A* is the capacity loss factor, and σ represents the standard deviation of (1 - *A*). The distribution of the capacity loss factor originates from the connections between cells. In this study, battery life is considered as the life cycle on the assumption that all drivers drive every day and that the battery is recharged once a day. This statement is reasonable in terms of rigorous battery lifetime estimation. Although the battery degradation model depends highly on specific battery chemistry, temperature, and storage conditions, these factors are ignored in this paper.

In this battery degradation model, *DoD* is calculated using the initial battery capacity and driving distance. By utilizing MPGe, which is predetermined using the EV performance model, the given driving distance of the designed EV can be converted into energy consumption; and using the initial capacity of the battery, *DoD* is determined by Eqs. (1) and (2).

2.2 Engineering Uncertainty

2.2.1. Battery capacity, voltage, and weight

The Li-ion battery is one of the best candidates for EVs owing to its high-energy density, long life span, and relative safety [36–38]. Given the hypersensitivity of Li-ion batteries to uncertainties, uniformity at the component level is highly required [39]. However, some deviations of material and physical properties exist between cells and occur during manufacturing [38]. Dubarry et al. [40] conducted an experiment with statistical and electrochemical analyses on 100 $LiCoO_2$ Li-ion battery cells using an equivalent circuit model, and displayed distributions of the capacity, open circuit voltage, and weight of cells. Uncertain cell properties such as solid particle size and porosity may lead to variations in cell characteristics [41]. Distributions of these uncertainties are adapted in our engineering model. The mean and standard deviation of the cell capacity, cell voltage, and cell weight are 33.1 Ah and 0.5 Ah, 3.8 V and 0.02 V, and 0.7864 kg and 0.0149 kg, respectively [40].

2.2.2. Driving distance

Although it features the same battery capacity, the *DoD* of the battery used is directly related to the daily driving distance because it differs with energy consumption [29]. For example, an EV with a battery capacity of 80 mi will experience 100% *DoD* for driving 80 mi, whereas the same EV will experience only 50% *DoD* for driving 40 mi.

To deal with the uncertainty of daily driving distances of users, we use the daily vehicle miles of travel (VMT) data of the 2009 National Household Travel Survey (NHTS) [42]. The NHTS dataset contains daily trip level data for 150,147 households. After postprocessing, only the data of cars that traveled more than 10 mi are included in the dataset, and the average daily VMT is found to be 29.3 mi. The distribution of the daily VMT results in a wide range of battery lifetimes. To determine the actual lifetime of batteries, Eq. (3) is integrated with the distribution of *DoD* for 5 years.

2.2.3. Driving cycle

Various driving patterns affect EV performance. These patterns include the driving range and thus the MPGe [43]. Standard driving cycles, which represent driving patterns as vehicle speed over time, have been used to report the fuel consumption of vehicles by the US Environment Protection Agency (EPA). Similarly, to reflect actual driving patterns in the engineering model, representative standard driving cycles provided by EPA are applied when calculating the driving range: the urban dynamometer driving schedule (UDDS) represents driving conditions in the city for light-duty vehicles at low speed, the New York City cycle (NYCC) represents frequent stop-and-go traffic conditions at low speed, LA92 represents high-speed aggressive driving in city conditions, the highway fuel economy test (HWFET) represents driving conditions on a highway under 60 mph, and US06 represents an aggressive driving pattern that involves high acceleration and extreme engine loads. Table 2 summarizes the characteristics of standard driving cycles [44]. Given that combinations of different driving cycles are frequent and natural in actual driving conditions, an average driving range that is calculated from five random standard driving cycles with given input variables is used as the driving range of the designed vehicle in this paper. Various combinations of driving cycles result in various driving ranges, and reliability determines the advertised driving range among these actual driving ranges.

Table 2 Characteristics of standard driving cycles

	UDDS	NYCC	LA92	HWFET	US06
Characteristics	City/ low speed	City/ frequent stops with low speed	City/ aggressive driving	Highway/ under 60 mph	Aggressive driving
Top. speed	56.70 mph	27.7 mph	67.20 mph	59.90 mph	80.30 mph
Avg. speed	19.58 mph	7.09 mph	25.92 mph	48.20 mph	47.97 mph
Max. acceleration	1.48 m/s^2	2.68 m/s^2	3.08 m/s^2	1.43 m/s^2	3.76 m/s^2
Avg. acceleration	0.50 m/s^2	0.62 m/s^2	0.64 m/s^2	0.19 m/s^2	0.67 m/s^2
Distance	7.45 mi	1.18 mi	6.99 mi	10.26 mi	8 mi
Time	22.8 min	10 min	16.2 min	12.8 min	10 min

2.3 Reliability in Engineering Model

Actual performances and battery lifetime fluctuate and vary because of the engineering uncertainties mentioned above. Therefore, EV performances and warrantied battery lifetime that are advertised to customers are determined by engineering reliability, which is regarded as a criterion for determining a feasible solution. For example, regardless of any condition, 90% engineering reliability implies that among all produced vehicles, fewer than 10% show lower performance and actual battery lifetime than the advertised values. Thus, as engineering reliability increases, advertised attributes and warrantied battery lifetime are lowered to achieve more confidence in them.

As product reliability is related to customer-perceived value, a product with high reliability continuously attracts customers through word-of-mouth [45–47]. Therefore, as engineering reliability itself influences the EV selection of customers, the reliability of EVs should be available to customers for reference when making a purchase. A method to measure the reliability delivered to customers will be described in Section 3.3.

3. Marketing Model

A marketing model estimates market demand by estimating customer preferences toward the attributes and price of a designed product. This section discusses the prediction of market demand from customer preference and heterogeneity, which influences the final optimal design and company profit.

3.1 Utility Model and Product Attributes

In market systems, a product design problem can be formulated as a mathematical optimization problem that maximizes profit while satisfying various constraints. Such a mathematical optimization problem includes an economic model that is based on market demand and product cost.

To express customer demand as a function of attributes, a research study on product characteristics assessed by the customer, representing the design attributes with respect to decision variables, must be initially performed. As the designer or company chooses the decision variables, product attributes are determined or calculated through simulation. Therefore, based on the customer preference of the designed product and competitors, choice probability (market share) can be predicted using the logic model. Then, market demand is calculated as the product of market share and market potential (market size).

Individual-level utility v_{ij}, which is the sum of part-worths of the designed product, can be defined as follows:

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \boldsymbol{\beta}_{ikl} \mathbf{z}_{jkl} \tag{4}$$

where $\boldsymbol{\beta}_{ikl}$ represents the part-worth of the l-th level of the k-th attribute for the i-th individual, and z_{jkl} corresponds to a binary dummy number, which is equal to 1 if level l of the k-th attribute is selected for alternative j, and 0 otherwise. For given utilities of competing products, the market share is calculated according to the following equation:

$$P_{ij} = \frac{e^{v_{ij}}}{\sum_{j' \in J} e^{v_{ij'}}} \quad (5)$$

which is similar to the probability of the i-th individual selecting option j from a set of alternatives J. By using part-worth data of individual i, the predicted market demand for the designed product, which represents the preference of individual i, can be expressed as the product of market share P_{ij} and potential market size s. Accordingly, the predicted profit is defined as the product of market demand and margin, which is the price minus unit production and warranty costs. In this paper, the fixed cost for an EV body and its battery cost, which are determined by the number of battery cells in series and parallel, are included in the unit production cost.

The data needed for the market share estimation above can be obtained from customer responses or questionnaires answered by customers. The method of using questionnaires is more general and suitable for studying customer preferences toward new product concepts such as EVs. Several multiple-choice questions are included in the questionnaire, and a set of designs with combinations of various levels of attributes (listed in Table 3) is presented to respondents. Specifications of general EVs in the real market are used to choose attribute levels. The respondents are asked to answer 16 choice questions, and then select the most preferred design in each question. When no satisfactory designs exist, the respondents may pick none of the options. The importance presented in Table 3 is the percentage of the difference between the maximum and minimum values of the part-worths of the attribute level. The larger the difference between levels, the more important the attribute.

Table 3 Attribute levels and their part-worths

Reliability	Level	5 rating	4 rating	3 rating	2 rating	Importance
	Mean	2.412	1.515	-0.450	-3.476	38.9%
	(Std)	(1.844)	(1.147)	(0.845)	(2.379)	
Warrantied battery lifetime	Level	3 years	7 years	11 years	15 years	Importance
	Mean	-1.089	-0.114	0.563	0.640	11.5%
	(Std)	(1.061)	(0.432)	(0.481)	(0.541)	
Range	Level	80 mi	130 mi	180 mi	230 mi	Importance
	Mean	-1.331	0.038	0.489	0.803	14.1%
	(Std)	(1.782)	(0.554)	(0.896)	(1.106)	
MPGe	Level	90	100	110	120	Importance
	Mean	-0.044	-0.037	-0.008	0.088	0.9%
	(Std)	(0.156)	(0.144)	(0.091)	(0.381)	
Top speed	Level	70 mph	90 mph	110 mph	130 mph	Importance
	Mean	-0.434	0.098	0.154	0.182	4.1%
	(Std)	(0.617)	(0.231)	(0.216)	(0.236)	
0–60 mph	Level	6 s	8 s	10 s	12 s	Importance
	Mean	0.119	0.030	-0.060	-0.090	1.4%
	(Std)	(0.266)	(0.192)	(0.189)	(0.243)	
Price	Level	$15,000	$25,000	$35,000	$45,000	Importance
	Mean	1.930	0.894	-0.356	-2.468	29.1%
	(Std)	(2.093)	(0.871)	(0.836)	(2.294)	

3.2 Hierarchical Bayesian

To obtain the individual-level part-worth distribution, actual respondent results collected from a choice-based conjoint (CBC) study are needed. Given the existence of various customer preferences toward product attributes, the part-worths for similar attributes differ. This study uses a hierarchical Bayesian (HB) approach [48–50] to build a heterogeneous market. Based on the results of a survey conducted using Mturk [51], which was targeted for the US, individual-level part-worth distribution is derived. Responses are drawn from 252 subjects living in the US: 49% were male and 51% were female; 9% were 15–24 years of age, 44% were 25–34 years of age, 28% were 35–44 years of age, 12% were 45–54 years of age, and 7% were 55–64 years of age. The average ages of the survey respondents and EV buyers are 39.2 and 43, respectively [52], so survey respondents are likely to be potential EV buyers.

First, a CBC analysis is performed, followed by the HB approach, to estimate individual part-worths. Responses from the survey are utilized in the HB analysis to estimate individual part-worths using Markov-chain Monte Carlo. In the HB conjoint, an individual's part-worths $\boldsymbol{\beta}_i$ are assumed to be derived from a multivariate normal distribution $\boldsymbol{\beta}_i \sim (\boldsymbol{\theta}, \boldsymbol{\Lambda})$, where $\boldsymbol{\theta}$ is a vector of means of distributions of individuals, and $\boldsymbol{\Lambda}$ is the distribution's covariance matrix.

Part-worths can explain a heterogeneous market because an individual-level market demand sP_{ij} is used for calculating profit in system-level optimization. The average profit of all individual market scenarios can then be used as the objective function. Although part-worth coefficients are discrete, the interpolation of intermediate attribute values using a nature cubic spline enables individual-level utility models to cope with continuous attributes. As presented in Table 3, the wide variance of part-worths demonstrates that heterogeneous preferences should be considered in market system design.

In order to validate the respondents of the survey, the predicted EV market share of six popular EVs in the market is compared to the actual EV market share, and the results are provided in Table 4 [53]. As a result of goodness of fit, the P-value is 0.0806, and it can be said that the survey subjects represent potential customers in the EV market in the US.

Table 4 Comparison between actual market share and predicted market share

	Chevrolet Bolt	Nissan Leaf	Fiat 500e	Volkswagen e-Golf	Ford Focus	Kia Soul
Actual market share	16%	15%	8%	4%	2%	2%
Predicted market share	14.2%	20.4%	7.8%	6.3%	3.7%	6.3%

3.3 Reliability in Marketing Model

The reliability used for the questionnaire listed in Table 3 is based on J.D. Power. The predicted reliability provided by J.D. Power, which is a statistically derived formula that uses power circle ratings from the initial quality study (IQS) and vehicle dependability study (VDS), provides consumers with information on a vehicle's reliability over time [54]. IQS measures the initial vehicle quality during the first 90 days of ownership, whereas VDS measures long-term vehicle quality after three years of ownership. To estimate how customers perceive EV reliability, this paper uses the power circle ratings introduced by J.D. Power: 5 = "among the best," 4 = "better than most," 3 = "about average," and 2 = "the rest." Then, each rating perceived by customers is matched to a certain reliability depending on the reliability distribution of EVs in the market.

4. RBDMS

The engineering model (Section 2) and the marketing model (Section 3) described above are combined through a reliability-based design optimization (RBDO) framework. From the decision variables provided, the advertised performances and warrantied battery lifetime can be determined. Thus, product utility can be calculated by part-worths drawn from survey results. The final product then competes against other conventional EVs, and market share can be estimated from the result of choice probability. Once the predicted market demand is derived from the market share and market size, the profit of the manufacturing company will be the product of the market demand and margin, which subtracts the manufacturing cost and warranty cost from the price. To estimate the feasible range of decision variables, an extensive simulation with a set of constraint functions and specifications of EVs in the real world is included. The boundary constraints of the decision variables are listed in Table 5.

Table 5 Decision variables and boundary constraints

Decision variable	Lower bound	Upper bound
Reliability	10%	100%
Price	\$15,000	\$45,000
Warrantied battery Lifetime	3 years	15 years
Number of battery cells in series	80	250
Number of battery cells in parallel	1	4
Gear ratio	2	12

4.1 RBDMS Formulation

Based on a general expression of the RBDO problem [55], RBDMS, which integrates RBDO with DMS, can be formulated as follows:

$$
\begin{aligned}
\max_{\mathbf{X}} \quad & \mu(\boldsymbol{\Pi}) = \mu\left(\mathbf{D}\times\left(Price-MC\right)-\mathbf{C}\right) \\
\text{with respect to} \quad & \mathbf{X} = \left[\mathbf{X}^{\mathrm{T}}_{power}, R, W, Price\right] \\
\text{subject to} \quad & \mathbf{lb} \le \mathbf{X} \le \mathbf{ub} \\
& \mathbf{g}(\mathbf{A}_{\mathrm{eng}}) \le 0 \\
& P\left[\mathbf{G}\left(\mathbf{X}, \mathbf{RP}_e\right) > 0\right] \le P_F^{\mathrm{Target}} \\
\text{where} \quad & \mathbf{X}_{power} = \left[\mathbf{B}^{\mathrm{T}}_{\mathrm{EV}}, FR_{\mathrm{EV}}\right] \\
& \mathrm{P}_{\mathrm{F}}^{\mathrm{Target}} = 100 - \mathrm{R} \\
& \mathbf{P}_{\mathrm{EV}} = \left[\mathbf{P}_{\mathrm{EV}_{\mathrm{MPGe}}}, \mathbf{P}_{\mathrm{EV}_{\mathrm{range}}}, \mathbf{P}_{\mathrm{EV}_{\mathrm{speed}}}, \mathbf{P}_{\mathrm{EV}_{\mathrm{accel}}}, \mathbf{P}_{\mathrm{EV}_{\mathrm{Batt}}}\right] \\
& \mathbf{A} = \left[\mathbf{A}^{\mathrm{T}}_{\mathrm{eng}}, \mathrm{R}, \mathrm{W}, \mathrm{Price}\right] \\
& \mathbf{A}_{\mathrm{eng}} = \left[\mathrm{A}_{\mathrm{MPGe}}, \mathrm{A}_{\mathrm{range}}, \mathrm{A}_{\mathrm{speed}}, \mathrm{A}_{\mathrm{accel}}\right]^{\mathrm{T}} \\
& \left[\mathrm{MC}, \mathbf{P}_{\mathrm{EV}}\right] = \mathrm{f}_{\mathrm{engineering}}(\mathbf{X}_{\mathrm{power}}, \mathbf{RP}_{\mathrm{e}}) \\
& \left[\mathbf{C}, \mathbf{A}_{\mathrm{eng}}, \mathrm{W}\right] = \mathrm{f}_{\mathrm{attribute}}(\mathbf{P}_{\mathrm{EV}}, \mathrm{R}) \\
& \mathbf{D} = \mathrm{f}_{\mathrm{marketing}}(\mathbf{A})
\end{aligned}
\tag{6}
$$

The objective is to maximize the mean of profits $\boldsymbol{\Pi}$. $\mu(\cdot)$ represents the mean value; **D**, MC, and $\mathbf{C}$ correspond to the vector of market demand, manufacturing cost, and vector of compensation cost, respectively; $\mathbf{X}$ is the deterministic decision variable vector; $\mathbf{X}_{power}$ stands for the powertrain design variable vector; R, W, and *Price* indicate the decision variable of reliability, warrantied battery lifetime, and price, respectively; $P[\cdot]$ depicts the probability measure; P_F^{Target} is the target probability of failure for the reliability constraints; **lb**, **ub**, **g**, and **G** indicate the lower boundary, upper boundary, inequality constraints on advertised performances, and probabilistic constraints, respectively; **B** and *FR* represent the battery design variable vector and decision variable of the final gear ratio, respectively; $\mathbf{RP}_e$ denotes random parameter vectors of the engineering model; $\mathbf{P}_{\mathrm{EV}}$ represents the matrix of probabilistic performance vectors; **A** is the advertised attribute vector; $\mathbf{A}_{\mathrm{eng}}$ denotes the vector of advertised attributes that are determined from the engineering model; $f_{\mathrm{engineering}}$, $f_{\mathrm{attribute}}$, and $f_{\mathrm{marketing}}$ indicate the engineering model, attribute model, and marketing model, respectively; and $f_{\mathrm{attribute}}$ determines the compensation cost, engineering advertised attributes, and warrantied battery lifetime by applying reliability constraints to probabilistic performances.

In this probabilistic design problem, a reliability analysis of the system with uncertainties involves the calculation of the probability of failure, which is defined as follows:

$$P_F = P\left[G(\mathbf{X}) > 0\right] = \int_{\Omega_F} f_{\mathbf{X}}(\mathbf{x})\mathrm{d}\mathbf{x} \tag{7}$$

where $f_{\mathbf{X}}(\mathbf{x})$ represents the joint probability density function, and Ω_F is the failure set defined as $\{\mathbf{x}: G(\mathbf{X}) > 0\}$. In this study, a Monte Carlo simulation is used to perform a reliability analysis. Fig. 3 illustrates the information flow of RBDMS for EV design from the viewpoint of the manufacturer.

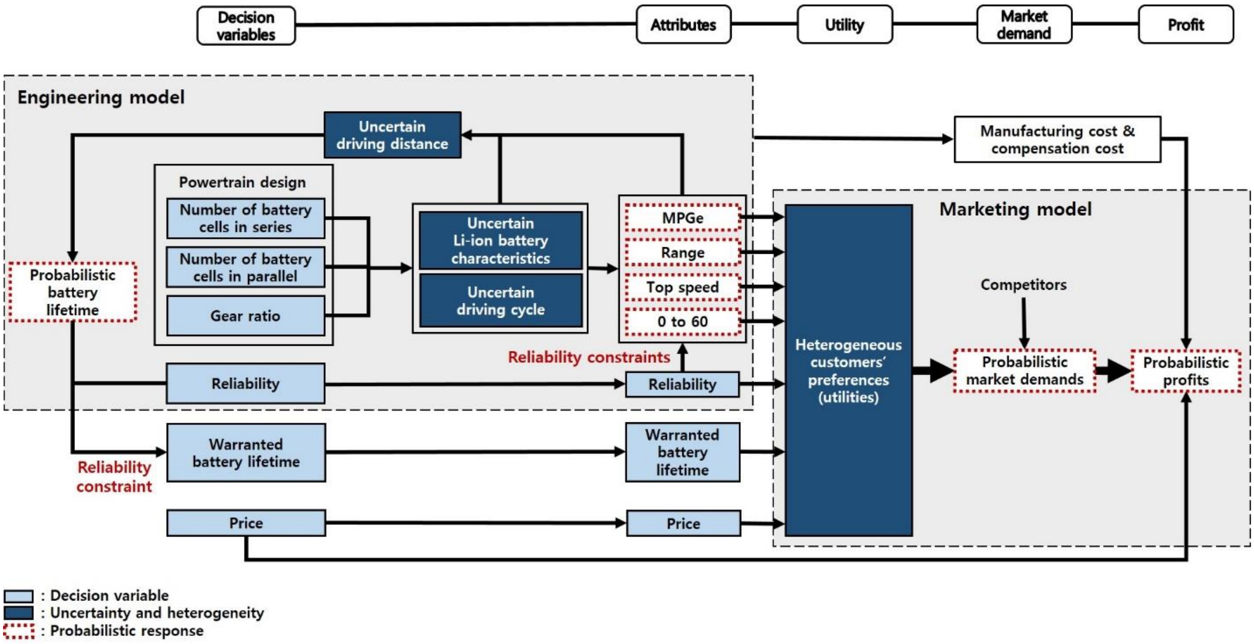

Fig. 3 Information flow of RBDMS for EV design

4.2 Modeling Assumption

Several assumptions are provided when modeling the entire framework. Some assumptions are associated with the models themselves, whereas others are related to parameter values that do not affect the models themselves. For the latter, different results may be achieved when executing models with different parameter values. Supplementary detailed assumptions are provided in the relevant model explanations.

- In computing the market share in the market system model, two competitors are used: the 2017 Nissan Leaf and the 2017 Chevrolet Bolt. These products are competitive in terms of reasonable price, and their good performance may indicate high market shares. Part-worths of their MPGe, range, 0-mph-to-60-mph acceleration, top speed, warrantied battery lifetime, and price determine competitor utilities. The two competitors' market sizes in the U.S. are used to determine the market demand. Although the optimization results cannot be generalized by only two vehicles in the actual marketplace, it is possible to implement RBDMS and show its application possibility for various cases.

- To satisfy the minimum performances of an EV to drive in the real world, constraints are applied to the performances of the EV in all scenarios: the driving range should be more than 80 mi, the 0-mph-to-60-mph acceleration should be shorter than 12 s, and the top speed should be faster than 70 mph.

- The compensation cost is assumed to compensate for 10% of the battery capacity only for failures within the warrantied battery lifetime period.
- It is necessary to map the reliability used in the engineering model and the reliability (J.D. Power rating) used in the customer survey of the marketing model. In this study, customers score the reliability power circle with ratings of 5, 4, 3, and 2, which correspond to 100%, 75%, 50%, and 25% reliability, respectively. According to J.D. Power, the Nissan Leaf scores 4 for predicted reliability, and the engineering model based on the Leaf shows 78% of produced vehicles satisfying the advertised performance and warrantied battery lifetime, which nearly matches the assumption [56]. A further parametric study about the power circle rating and engineering reliability is provided in the discussion section.
-

4.3 Three Design Methods

To investigate the importance of RBDMS in EV market systems, three different methods are examined, as shown in Figure 2. Method 1 utilizes RBDO that maximizes performance with fixed reliability without a marketing model. Only design variables become decision variables, where reliability is given as a parameter that is used for reliability constraints. Since the product has multiple performances (objectives), we use the weighted sum of the engineering performances as the objective function, where the weights are determined by the importance of each performance (see Table 3).

Method 2 simply connects the objective function of RBDO with DMS and adds price as a decision variable. Reliability, a fixed parameter, is applied to reliability constraints. Attribute values that satisfy constraints are determined as advertised attributes, and they are used in the marketing model. The objective function is to maximize profit. Method 2 is an intermediate scenario to clearly explain the benefits and differences of proposed RBDMS.

Method 3 (RBDMS) is a method proposed in this study. Compared to Method 2, Method 3 optimizes reliability to maximize profit by using reliability as a decision variable rather than a fixed parameter, and reliability is used as an advertised attribute itself. Reliability directly influences customer preference while it is used as a standard to determine the advertised performance and target reliability of the probabilistic attributes. A target reliability value (99.87%) commonly used in the field of RBDO for vehicles is used for the fixed reliability of Methods 1 and 2 [9]. The optimization results by the three methods are shown in the next section.

5. Results and Discussion

This section compares results by the three methods explained in Section 4.3. In all three methods, we vary the number of battery cells in parallel with respect to discrete variables, treat the number of battery cells in series as continuous variables, and solve the optimization problem in Eq. (6) using sequential quadratic programming with multiple initial points. Optimal values of the number of battery cells in series are then rounded up to discrete values. Computation requires 25 h on average using a standard desktop (Intel i7 6900 CPU @ 3.20 GHz with 64.0 GB of RAM).

Table 6 summarizes the optimal designs and outcomes of the three methods. The table shows the mean and standard deviation of profit and market share for Methods 2 and 3, and the mean and standard deviation of the actual battery lifetime and actual performance for the probabilistic engineering model in all methods. The advertised attribute is the value presented to customers when purchasing EVs, and actual performance is the result affected by engineering uncertainty.

Table 6 Optimal designs and outcomes of three design methods

		Method 1 (RBDO)	Method 2 (RBDO + DMS)	Method 3 (RBDMS)
Decision variable	Reliability	**99.87%***	**99.87%**	92.69%
	Warrantied battery lifetime	12.1 year	3.28 year	5.63 year
	Price	**$34,658**	$30,654	$33,154
	Number of battery cells in series	220	112	142
	Number of battery cells in parallel	3	2	2
	Gear ratio	8.58	8.66	9.5
Outcomes	Profit	-$850M ($259M)**	$71.9M ($46.1M)	$77.3M ($47.3M)
	Market share	59.3% (18.1%)	19.7% (16.7%)	24.4% (14.9%)
Cost	Manufacturing cost	$47,507	$20,087	$23,861
	Warranty compensation cost	$0.11M	$14,194	$1.1M
Advertised attributes	Battery lifetime	12.1 year	3.28 year	5.63 year
	MPGe	93.1	101.5	109.1
	Range	229.9 mi	86.2 mi	115.4 mi
	0–60 mph	7.02 s	7.83 s	6.8 s
	Top speed	89.5 mph	83.4 mph	83.7 mph
Probabilistic attributes (Actual performance)	Battery lifetime	16.06 year (1.48 year)	4.92 year (0.57 year)	6.69 year (0.72 year)
	MPGe	105.89 (5.35)	119.21 (6.44)	118.18 (6.37)
	Range	262.07 mi (14.09 mi)	100.04 mi (5.51 mi)	125.76 mi (6.74 mi)
	0–60 mph	6.93 s (0.037 s)	7.74 s (0.031 s)	6.77 s (0.023 s)
	Top speed	89.69 mph (0.087 mph)	83.69 mph (0.099 mph)	83.75 mph (0.062 mph)

* Fixed values, which are not decision variables, are in bold.
** Standard deviations are enclosed in parentheses.

Since Method 1 maximizes performance without considering profit, the total number of battery cells can be extremely high because price and cost are irrelevant to the objective function. In addition, the performances, especially range and battery lifetime, which have a large importance of attributes (see Table 3), are designed to exhibit high performance. Based on the cost, the profit becomes positive when the price is higher than the manufacturing cost (\$47,507). Assuming that the price is the average price of two competitors, the profit is negative. Therefore, from the market's point of view, this can be an infeasible design when considering RBDO only when not considering DMS.

Method 2, which simply combines the objective function of RBDO with DMS, results in feasible design and marketable outcomes. When compared to Method 1 (RBDO), higher profit can be achieved since the objective function is to maximize profit, and the overall advertised attributes are lowered because of cost.

The result of Method 3 (RBDMS) goes beyond a simple combination of RBDO and DMS, and shows a difference in optimization using reliability as a decision variable. By comparing Methods 2 and 3, the following can be found.

First, although the reliability is designed to be relatively low, profit can be further increased (from \$71.9M to \$77.3M). This is because the increasing advertised attributes owing to the lower reliability have a higher effect than the lower reliability itself, and therefore the market share can be increased (from 19.7% to 24.4%). In addition, owing to the high advertised attributes, the price can be relatively high (from \$30,654 to \$33,154). When we look at the tradeoff of utility, the reduced utility owing to decreasing reliability and increasing price are 0.1496 and 0.3344, respectively. The increased utility owing to increasing advertised performance and warrantied battery lifetime are 0.9282 and 0.5867, respectively.

Second, the battery capacity is increased (the number of battery cells in series increased from 112 to 142). Based on the same design, the cost can be expected to decrease by lowering the battery capacity when the reliability is lowered, but this shows that the optimization problem is not simple because the battery design itself is related to the decision variables. Instead of lowering the reliability, a strategy is required to improve the advertised attributes than Method 2 by increasing the battery capacity, and to increase price.

Third, the warrantied battery lifetime is increased. Even for the same battery capacity, the warrantied battery lifetime advertised to customers is increased as reliability decreases. In addition, as described above, the battery capacity is increased as the reliability decreases, and thus the battery will experience a smaller *DoD* for the same driving distance. Then, from Eq. (3), the battery lifetime can be increased owing to the decreased *DoD*.

Since Method 2 takes profit into account, it significantly reduces the warrantied battery lifetime compared to Method 1. Thus, the warranty compensation cost is reduced (from \$0.11M to \$14,194). However, Method 3 increased the warrantied battery lifetime than Method 2, while taking a large increase in warranty compensation cost. It can be said that the optimum reliability finds the optimum value of the warrantied battery lifetime and warranty compensation cost.

Fourth, the gear ratio is designed to be high. When comparing the results of Methods 1, 2, and 3, the optimum gear ratio is significantly affected by the reliability rather than the number of battery cells. For the same design, the advertised attributes are increased when the reliability decreases. The increment of the advertised attribute that occurs when the reliability decreases tends to increase as the gear ratio increases. Therefore, as the reliability is lowered, the gear ratio is determined to be higher than the optimum gear ratio that was determined when the reliability was high.

Fifth, the variation in performance tends to decrease when performance increases. This can be confirmed by comparing the coefficient of variation (CV) obtained with the mean and standard deviation of the actual performance in Methods 2 and 3. Owing to the large capacity of the battery, there is a tendency to be less sensitive to engineering uncertainties such as driving distance and driving cycle, so that the effect of an engineering uncertainty on the variation in performance is weakened. Therefore, even if the performance is increased, decision-makers do not need to be greatly concerned about engineering uncertainties.

Sixth, it is confirmed that the optimization problem can be solved even if reliability is used as a decision variable and a constraint. When optimization is performed with 100 initial variables considering tradeoffs between attributes, the case of 87% converges to the same value as that listed in Table 6, which is considered to be a global optimum.

From the results of various parametric studies, several observations about optimum reliability are as follows:

(a) The reliability and reliability variation of other competitors affect the design of optimum reliability. As previously mentioned, in order to map the J.D. Power rating to the actual reliability, experimental data is required, but the analyses are based on a parametric study instead of the experiment in this study. We compare three scenarios: high reliability market (HRM), medium reliability market (MRM), and low reliability market (LRM). The matches between customers' perceived reliability and actual reliability are listed in Table 7. The optimization results of Method 3 in Table 6 are based on a case of MRM in which market competitors have medium reliability. A high-reliability market is a case in which the reliability range is narrowed as compared with a medium reliability market, and a relatively high reliability is required in order to obtain a high rating. For example, in order to receive a rating of 4 or higher, the reliability must exceed 80%, which means that the competitors in the market have high reliability. A low-reliability market is a case in which the reliability range is increased compared with a medium reliability market, and a relatively high reliability can be obtained. For example, to obtain a rating that is higher than 4, the reliability must exceed 70%, which means that the competitors in the market have relatively low reliability. With regard to optimizing the three cases of HRM, MRM, and, LRM, Fig. 4 presents results of a parametric study on the power circle rating and engineering reliability for Method 3. When the reliability of the market competitors is high, such as in HRM, it can be seen that the optimum reliability should be increased. In addition, profit tends to decline because reliability should be increased.

Table 7 Matches between perceived and actual reliability

Perceived reliability	Actual reliability		
Power circle rating	HRM	MRM	LRM
5 rating (among the best)	100%	100%	100%
4 rating (better than most)	80%	75%	70%
3 rating (about average)	60%	50%	40%
2 rating (the rest)	40%	25%	10%

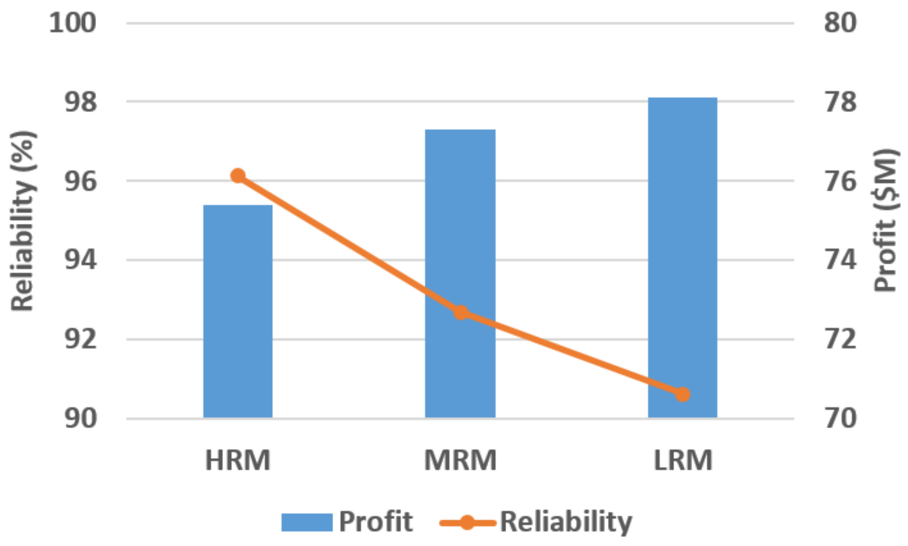

Fig. 4 Parametric study on reliability matching

(b) Further parametric studies of profit according to reliability are presented in Fig. 5. In Method 3, optimization can be conducted by using reliability as a decision variable, but in this parametric study, optimization is performed by changing the reliability as a fixed parameter to see how reliability affects profit. The optimum reliability in each scenario is marked with a red dot, and it can be said that the optimization is done well since the red dot indicates the highest profit. In addition, profit decreases when the reliability is far from the optimum reliability. In particular, when market competitors have low reliability, such as in LRM, an excessive increase in reliability has a very negative impact on profit (profit drops sharply when the reliability increases from 98% to 100%). This shows that it is not advantageous for a company to increase the reliability more than necessary when market competitors have low reliability.

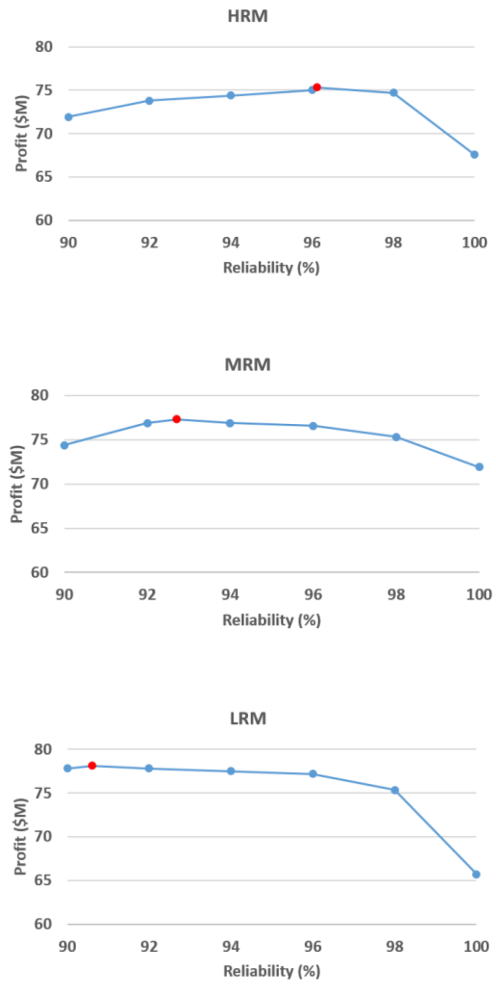

Fig. 5 Parametric study on profit according to reliability in Method 3

6. Conclusion

Existing RBDO research sought to find an optimized vehicle design that can satisfy a given reliability, but this research failed to provide a design with optimum reliability from a market perspective. The presented work suggests an RBDMS framework that integrates RBDO with DMS, and implements it in EV design. RBDMS finds the optimal target reliability by considering design variables, price, market demand, and cost at the same time. RBDMS helps companies to model and optimize the complex tradeoffs that occur when determining reliability.

The advantages of RBDMS using reliability as a decision variable are presented by comparing the optimization results of three methods (RBDO, RBDO + DMS, and RBDMS). Although a simple integration of RBDO and DMS can maximize profit with fixed reliability results with a feasible design and marketable outcomes, RBDMS can find the optimum reliability as a decision variable and obtain more profit while satisfying engineering constraints. This research can be considered a stepping stone for optimizing reliability, and can be applied to various RBDO problems in choosing the correct reliability.

In this study, reliability is used to connect engineering and marketing as follows: (1) as a decision variable, (2) as an attribute that directly influences customer preference, (3) as a standard for determining advertised performance, and (4) as the target reliability in an engineering model. In addition, the relationship between the probabilistic attributes considering uncertainty from the engineering aspect, and the concept of the advertised attribute on the marketing side used by the customer in selecting the product, is established. The optimization results show that reliability can be optimized as a decision variable, as well as constraints, and a global optimum can be found.

The proposed approach can be applied to other design problems. For example, with regard to smartphones and notebooks, the battery lifetime varies greatly depending on the usage environment, and there is a large gap between the real battery lifetime and the advertised battery lifetime. Based on this study, companies can find the optimum balance between reliable product design and profitable product design.

There are several limitations in this work. We used the power circle rating in J.D. Power to reflect the reliability from the perspective of customers, and assumed the reliability of other competitors. However, in future work, additional research should center on reflecting the reliability from the perspective of customers. Future work also should revise several assumptions and reflect more fidelity in the engineering model and its uncertainties. The uncertainty of the market, and not its heterogeneity, can be considered in future research [27], and the customer preference for a targeted market, which considers geographic effects, local regulations, etc., can be considered.

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