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

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Abstract

When designing a product, both engineering uncertainty and market heterogeneity should be considered to reduce the risk of failure in the market. Reliability-based design optimization (RBDO) approach allows decision makers to achieve target confidence in product performance under engineering uncertainty. Meanwhile, the design for market systems (DMS) approach helps decision makers to develop profit-maximized product design under market heterogeneity. This paper proposes a reliability-based design for market systems (RBDMS) framework by integrating RBDO and DMS approaches and applying this framework to electric vehicle (EV) design. In RBDO, product quality is controlled based on target reliability determined by a designer. However, from company perspective, appropriate target reliability should be set because better reliability increases manufacturing cost and consumer satisfaction. Therefore, in modeling how target reliability affects customer choice, optimum target reliability, which maximizes profit, should be derived. "Reliability" in the framework is used as follows: (1) a decision variable; (2) an attribute that directly influences customer preference; (3) a standard for determining advertised performance; and (4) as target reliability in an engineering model. We optimize and compare four scenarios depending on whether engineering systems are deterministic or probabilistic and whether a market is homogeneous or heterogeneous. Results show that designing an entry EV model with low reliability is recommended under engineering uncertainty and market heterogeneity, whereas designing a premium EV model with high reliability is recommended to ensure robustness of profit.

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
D: market demands
MC: manufacturing cost
C: compensation costs
X: deterministic decision variable vector
$\mathbf{X}_{power}$: powertrain design variable vector
R: reliability
W: warranted battery lifetime
Price: price
$P_F^{\mathbf{Target}}$: target probability of failure for reliability constraints
g: inequality constraints
G: probabilistic constraints
B: battery design variables
FR: final gear ratio
RP: matrix of random parameter vectors
$\mathbf{RP}_e$: random parameter vector of engineering model
$\mathbf{RP}_m$: random parameter vector of marketing 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
$\mathbf{P}_{\mathrm{EV}_W}$: vector of probabilistic warranted battery lifetime
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 functionality or utility of a system while satisfying constraints. To enhance functionality or utility 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 derived from many uncertainties, such as geometrical tolerance, physical properties of materials, and operating conditions, often lead to design failure. Currently, the stochastic nature of engineering systems, which is referred to as reliability, is naturally considered when solving optimization problems [2]. Therefore, reliability-based design optimization (RBDO) maximizes functionality or utility of systems while satisfying target reliability level regardless of inherent uncertainties in design variables and parameters. In RBDO, reliability analysis focuses on evaluation of probabilistic constraints to guarantee that target reliability levels are 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].

Design for market systems (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, which maximizes the specific profit or social welfare while satisfying engineering or other constraints, is formulated into a mathematical problem. To formulate the mathematical optimization problem, engineering models that contain design decisions and engineering functionalities must be combined with economic models. Engineering functionality is obtained from engineering analyses and simulations through physical models, and economic models connect design decisions with profit or social welfare according to market demand and product cost. Quantitative market demand models are commonly utilized in the marketing field for estimating customer preferences (market demand) as a function of design attributes and price 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].

However, existing RBDO problems have not considered heterogeneous customer preferences. Thus, the effect of various customer preferences on decision on engineering performances cannot be identified. Furthermore, conventional DMS has not considered uncertainties at the engineering level. Consequently, using only DMS results in difficulty in predicting the effect of probabilistic engineering performances on company profit. Therefore, this study suggests a reliability-based design for market systems (RBDMS) framework and validates it through a case study of EV design.

Reliability, which affects both engineering and marketing models, is used as follows: (1) a decision variable; (2) an attribute that directly influences customer preference; (3) a standard to determine advertised performance; and (4) target reliability in the engineering model.

As presented in Fig. 1, RBDMS differs from DMS in that uncertainties in engineering model generate distributions of performances, whereas advertised attributes are determined by reliability constraints. For example, with 95% target reliability, the advertised attribute that a customer refers to when purchasing a product is assumed to be the product performance that satisfies 95%

reliability, and the advertised attribute can be determined at the constraint boundary, as shown in Fig. 2. Therefore, reliability is used as criterion in determining advertised attributes from probabilistic performances, and engineering uncertainties can be reflected into the utility function through reliability. Reliability itself is also used as an attribute to be evaluated by customers in RBDMS.

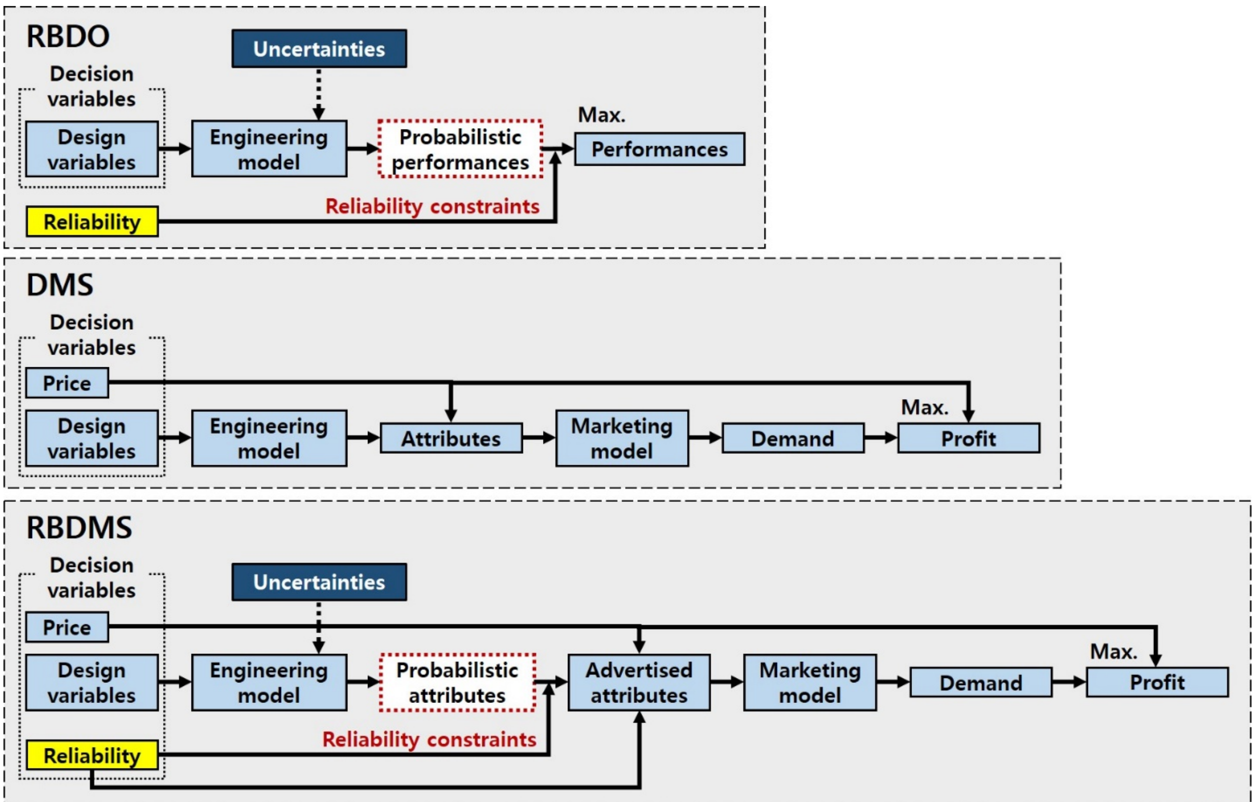

Fig. 1 Comparison between DMS and RBDMS

This paper introduces a design for EV powertrain systems, a Li-ion battery, and a market system that maximizes profit of an EV manufacturing company while assuring reliability of advertised performances and warranted battery lifetime. We also compare optimal designs obtained using the proposed RBDMS framework under four scenarios: (1) deterministic engineering model with homogeneous market; (2) deterministic engineering model with heterogeneous market; (3) probabilistic engineering model with homogeneous market; and (4) probabilistic engineering model with heterogeneous market. Through comparative study, decision makers, such as company owners, can gain insights and make an educated judgement when maximizing profit.

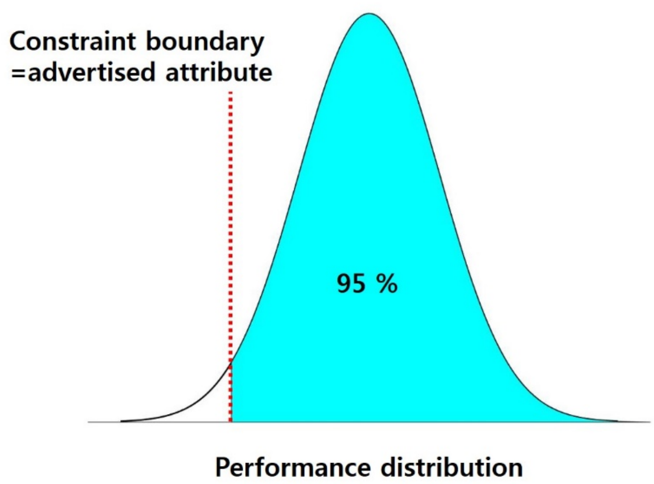

Fig. 2 Advertised attribute determination

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 and its heterogeneity in customer product preferences are. Section 4 provides modeling assumptions and RBDMS formulation. In Section 5, the proposed RBDMS framework is utilized in various case studies of EV design under four scenarios. Finally, Section 6 concludes the paper and describes future research direction.

2. Engineering Model and Uncertainty

2.1 Engineering 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 performances while considering uncertainties in battery and driving characteristics for different mechanical designs; 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. EV performance model

EV performances, such as MPGe, driving range, top speed, and acceleration, are determined by the design of the powertrain, which contains a battery pack and motors that are connected to wheels through a final drive. To simulate such a model, we utilize specifications of the Nissan Leaf, which is listed in Table 1 [29, 30]. Powertrain systems of Nissan Leaf are also used in the EV performance model. AMESIM software and 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. Battery capacity is determined by the number of cells, which is directly related to the driving range of EV. Furthermore, the array of cells in the battery pack influences battery voltage and current limits, which affect output power of motors. Weight of the battery pack, which is proportional to the number of cells, also influences the total weight of EV and in turn affects EV acceleration and MPGe.

High speed and low torque output from the motor is 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 between input and output speeds. A large torque is achieved from high ratio, which in turn leads to high acceleration performance but low maximum speed, whereas a small torque is achieved from 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

Lifetime of batteries highly depends on daily driving distance. The battery degradation model used in this study plays a crucial role in reflecting differing daily driving distances of users. Li-ion battery capacity decreases due 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]. 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 total charge of the battery, and $\int_{t_0}^{t} I(\tau)\,d\tau$ refers to the delivered charge. Discharged battery capacity, which is the complement of *SoC*, that is, depth of discharge (*DoD*) is defined as follows:

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

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

Life cycle, which results from capacity fades with regard to *DoD* of batteries, has been theoretically and experimentally presented by Thaller [35] as follows:

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

where D corresponds to *DoD* of the battery, F is additional fraction of nominal capacity, P stands for penalty factor for the deeper *DoD*, A is capacity loss factor, and σ represents the standard deviation of $(1-A)$. Distribution of capacity loss factor originates from the connection among cells. In this study, battery life is considered as the life cycle on the assumptions that all drivers drive every day, and battery is recharged once a day. This statement is reasonable in terms of rigorous battery lifetime estimation. Though 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

Li-ion battery is one of the best candidates for EVs due 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 analysis on 100 $LiCoO_2$ Li-ion battery cells using an equivalent circuit model and displayed distributions of 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. Means and standard deviations of variables are respectively as follows: cell capacity: 33.1 Ah and 0.5 Ah; cell voltage: 3.8 V and 0.02 V; cell weight: 0.7864 kg and 0.0149 kg.

2.2.2. Driving distance

Although it features the same battery capacity, *DoD* of battery used is directly related to 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 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 post processing, only data of cars, station wagons, SUVs, and trucks that traveled more than 10 mi are included in the dataset, and average daily VMT is found to be 34.4 mi. 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 performances, such as driving range, and thus MPGe [43]. Standard driving cycles, which represent driving patterns as vehicle speed over time, have been used to report fuel consumption of vehicles in the US Environment Protection Agency (EPA). Similarly, to reflect actual driving patterns into the engineering model, representative standard driving cycles provided by EPA are applied when calculating the driving range: urban dynamometer driving schedule (UDDS) represents driving conditions in the city for light duty vehicles with low speed; New York City cycle (NYCC) represents frequent stop-and-go traffic conditions with low speed; LA92 represents high-speed aggressive driving in city conditions; highway fuel economy test (HWFET) represents driving conditions on a highway under 60 mph; and US06 represents an aggressive driving pattern which involves high acceleration and extreme engine loads. Table 2 summarizes 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, which 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.

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 mph60 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 Engineering Reliability

Actual performances and actual battery lifetime fluctuate and vary because of the engineering uncertainties mentioned above. Therefore, EV performances and warranted battery lifetime that are advertised to customers are determined by engineering reliability, which is regarded as a decision variable. For example, regardless of any condition, 90% engineering reliability implies that among all produced vehicles, less than 10% show lower performances and actual battery lifetimes than advertised values. Thus, as engineering reliability increases, advertised performances and warranted battery lifetime are lowered to achieve more confidence on 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 EV selection of customers, reliability of EVs should be available to customers for reference when purchasing.

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 [48]. IQS measures 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 reliability distribution of EVs in the market.

3. Marketing Model and Heterogeneity

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

3.1 Marketing Model

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

To express customer demand as a function of attributes, a research 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 decides on decision variables, product attributes are determined or calculated through simulation. Therefore, customer-perceived values of the designed product are also determined, resulting in choice probability (market share). 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:

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

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

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

which is similar to the probability of *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, 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 battery cost, which are decided by the number of battery cells in series and parallel, are included in the unit production cost.

The data needed for market share estimation above can be obtained from sales data of existing markets, which include 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 (shown in Table 3) is presented to respondents. The respondents then select the most preferred design. When no satisfactory designs exist, the respondents may pick none of the options.

Table 3 Attribute levels and their part-worths

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

To obtain individual-level posterior part-worth distribution, actual respondent results collected from the choice-based conjoint (CBC) study and prior characteristics of the type of consumer are used. Estimation of individual part-worths can be performed by hierarchical Bayes estimation [49–51], and details are provided in the following section.

3.2 Market Heterogeneity

Given the existence of various customer preferences toward product attributes, part-worths for similar attributes differ. This paper uses hierarchical Bayesian (HB) approach to build a heterogeneous market. Based on results of the survey conducted using Mturk [52], 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.

First, CBC analysis is performed, followed by the HB approach, to estimate individual part-worths. Responses from the survey are utilized in 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. Average profit of all individual market scenarios can then be used as the objective function. Though part-worth coefficients are discrete, 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 for market system design.

4. RBDMS

From the decision variables provided, EV performances and warranted 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, profit of the manufacturing company will be the product of market demand and margin, which subtracts manufacturing cost and warranty cost from the price. To estimate the feasible range of decision variables, extensive simulation with a set of constraint functions and specifications of EV in the real world are included. Ranges of decision variables are listed in Table 4.

Table 4 Decision variables

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

4.1 Modeling Assumption

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

- The integrated model, which embraces both engineering and marketing model, assumes that the size of battery pack is changeable. Furthermore, EV manufacturer determines the designs of decision variables, including powertrain and battery, warranted battery lifetime, and price.

- In computing the market share in the market system model, two competitors are used: 2017 Nissan Leaf and 2017 Chevrolet Bolt. These products are competitive in terms of reasonable price and whose good performance may indicate high market shares. Part-worths of their MPGe, range, 0 mph to 60 mph acceleration, top speed, warranted battery lifetime, and price determine competitor utilities, which affect market share, whereas EV market size of the US is used to determine market demand.

- In deterministic engineering model, mean values of cell capacity, cell voltage, cell weight, daily driving distance, and driving cycles are used to solve the optimization problem. Furthermore, means of part-worths are utilized in the homogeneous marketing model.

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

- Compensation cost is assumed to compensate for 10% of the battery capacity only for failures within the warranted battery lifetime period.

4.2 Four Market Scenarios

To investigate the influence of uncertain and heterogeneous factors in EV market systems, four different scenarios are examined (shown in Fig. 3): scenario 1 is deterministic optimization with no uncertain and heterogeneous factors; instead of uncertain factors at the engineering level, scenario 2 considers a heterogeneous market; in scenario 3, the market is homogeneous, but uncertainties at the engineering level are considered; scenario 4 considers all uncertainties at the engineering level and heterogeneity at the market system level.

In the comparison of four market scenarios, customers score 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, Nissan Leaf scores 4 in predicted reliability, and the engineering model based on Leaf shows 78% of produced vehicles satisfying the advertised performances and warranted battery lifetime, which nearly matches the assumption [53]. Further parametric study about power circle rating and engineering reliability is provided in the discussion section. The following section explains RBDMS formulation for scenario 4.

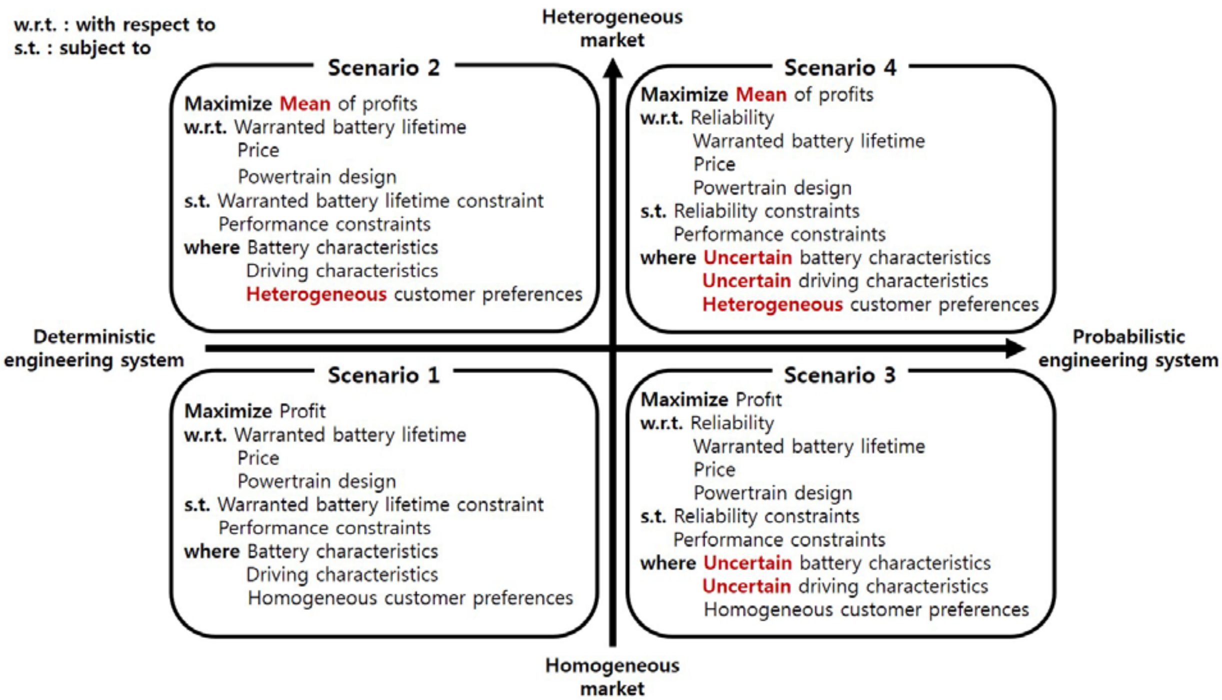

Fig. 3 Four scenarios for decision making

4.3 RBDMS Formulation

A general expression of the RBDO problem [54] is applied to scenario 4, which considers all engineering uncertainties and market heterogeneity. In this scenario, RBDMS, which integrates RBDO and DMS, can be formulated as follows:

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

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

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

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

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, Monte Carlo simulation is used to perform reliability analysis. Fig. 4 illustrates information flow of RBDMS for EV design with all uncertain and heterogeneous factors from the viewpoint of the manufacturer.

As previously stated, RBDO focuses on achieving confidence of product reliability, whereas robust design optimization (RDO) enhances product quality by minimizing output performance variation [55]. Given that the required reliability and quality of a product cannot be guaranteed when utilizing RBDO and RDO individually, researchers aspire to integrate both methods to develop a reliability-based robust design optimization (RBRDO) [56]. This paper also suggests a RBRDO framework for a market system to guarantee robust profit of EV companies when engineering uncertainty and market heterogeneity exist. Therefore, formulation of RBRDO for a market system in scenario 4 is the same as that of RBDMS except for the objective function, which is defined as follows:

$$\text{Maximize} \quad w_1 \frac{\mu(\mathbf{\Pi})}{\mu(\mathbf{\Pi})_0} - w_2 \left(\frac{\sigma(\mathbf{\Pi})}{\sigma(\mathbf{\Pi})_0} \right)^2 \tag{8}$$

where $\sigma(\cdot)$ is the standard deviation, and w_1, w_2 correspond to weights of the mean and variance, respectively.

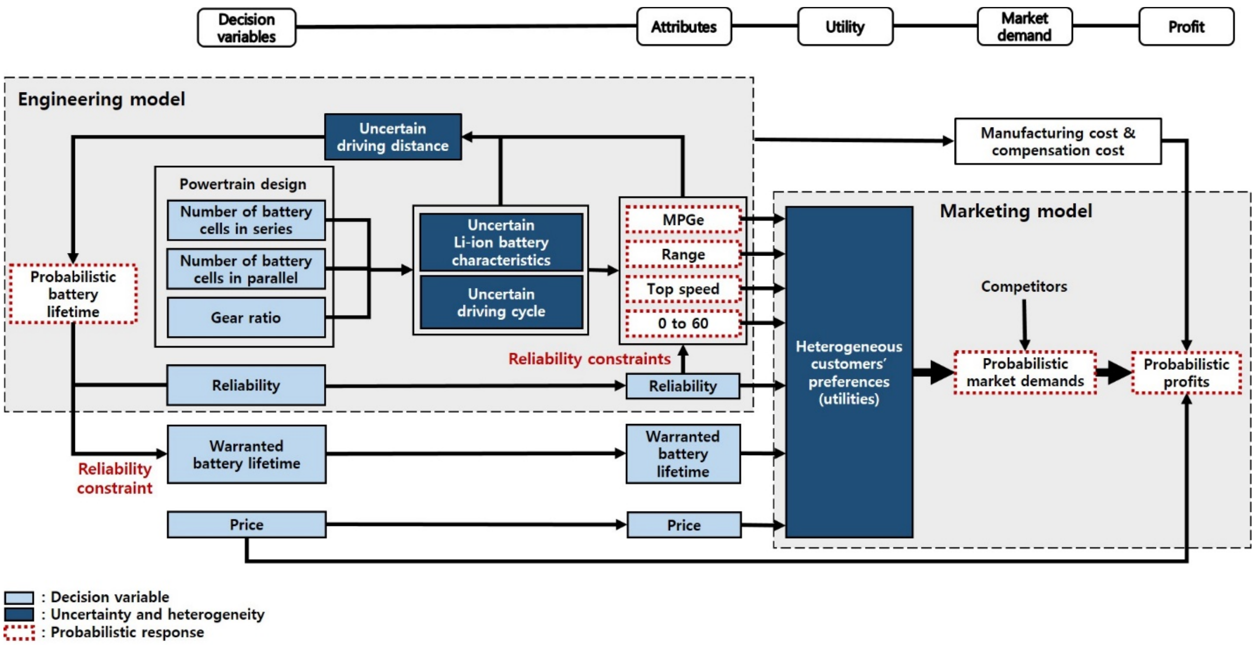

Fig. 4 Information flow of RBDMS for EV market systems

5. Results and Discussion

This section compares results of the four scenarios explained in Section 4.2. In all four scenarios, 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 and 64.0 GB RAM).

Table 5 Optimal designs and outcomes of four scenarios

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Reliability	–	–	95.5%	92.3%
Warranted battery lifetime	7.7 year	6.9 year	6.9 year	5.6 year
Price	$35,762	$34,851	$35,415	$32,954
Number of battery cells in series	161	147	170	140
Number of battery cells in parallel	2	2	2	2
Gear ratio	9.6	9.8	9.8	9.6
Profit	$381M	$354M ($146M)*	$251M	$249M ($156M)
Market share	35.9%	30.5% (12.5%)	28.3%	24.4% (15.3%)
Battery lifetime	7.7 year	6.9 year	6.9 year	5.6 year
MPGe	117.2	118.0	106.1	109.8
Range	141.5 mi	130.0 mi	135.6 mi	114.5 mi
0–60 mph	6.5 s	6.6 s	6.4 s	6.8 s
Top speed	86.5 mph	85.2 mph	86.2 mph	83.1 mph
Battery lifetime	7.7 year	6.9 year	8.26 year (0.83 year)	6.59 year (0.69 year)
MPGe	117.2	118.0	116.64 (5.91)	118.56 (6.25)
Range	141.5 mi	130.0 mi	148.66 mi (7.76 mi)	124.38 mi (6.75 mi)
0–60 mph	6.5 s	6.6 s	6.39 s (0.022 s)	6.78 s (0.023 s)
Top speed	86.5 mph	85.2 mph	86.31 mph (0.057 mph)	83.29 mph (0.149 mph)

* Standard deviations are enclosed in parentheses.

Table 5 summarizes optimal designs and outcomes of four scenarios. For scenarios 2 and 4, market share shows distribution because various customer preferences exist in the heterogeneous marketing model. The table also shows mean and standard deviation of profit and market share for scenarios 2 and 4; and mean and standard deviation of actual battery lifetime and actual performance for the probabilistic engineering model in scenarios 3 and 4. Advertised performance is the value presented to customers when purchasing EVs, and actual performance is the result affected by engineering uncertainty.

From the optimization results, several observations are listed as follows:

Observation 1: Designing a low-price and entry EV model with low performance is advantageous for the profit of an EV company when the market is heterogeneous. Comparisons of scenarios 1 and 2 with scenarios 3 and 4 show lower performances, warranted battery lifetimes, and prices in scenarios 2 and 4 than those in scenarios 1 and 3, but the decreased amounts are larger when engineering uncertainty is considered. As more variables should be considered when customers are heterogeneous, and various customers are difficult to satisfy at the same time, profit and market share decrease in heterogeneous markets. Designing a high-performance and low-price EV to satisfy various customers will increase cost and reduce the margin excessively. On the contrary, lowering the performance and raising the price to increase margin will decrease market share excessively. Therefore, the trade-off between margin and market share is required.

Given that EV performance is proportional to the number of battery cells, market share increases with the number of battery cells. Fig. 5 shows sensitivity analysis of the market share in relation to performance. When the market is heterogeneous, market share growth, which results from performance increase, is lower than that of homogeneous markets. As a result, performance is designed to be lower when considering heterogeneous markets because when customers are heterogeneous, designing a high-performance EV will not immediately lead to increase in market share.

As performance is lowly designed, market share and cost decrease. Hence, price is lowered to raise market share and obtain the appropriate margin, and the optimum design is a low-price and low-performance EV when the market is heterogeneous.

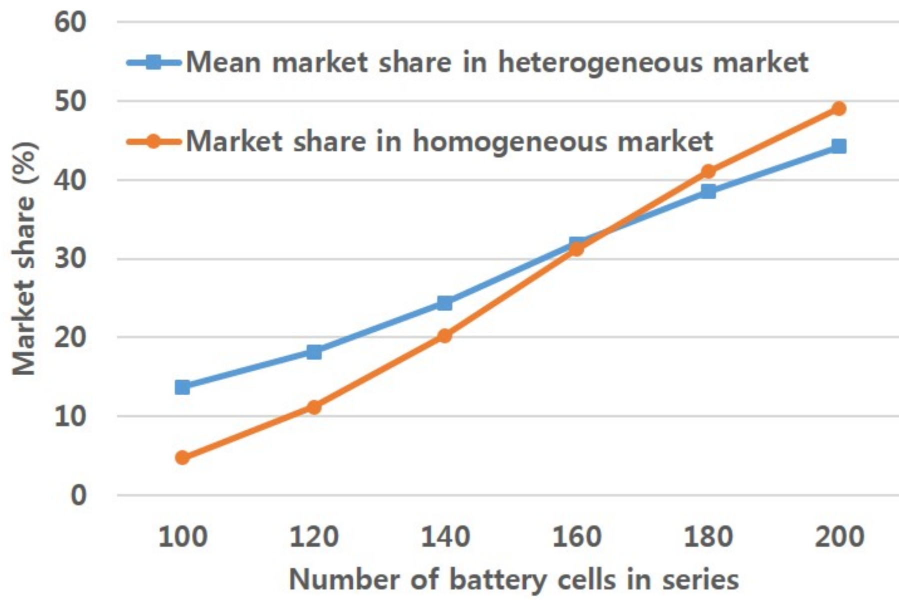

Fig. 5 Sensitivity analysis of market share

Observation 2: Optimum engineering reliability is designed to be relatively low when the market is heterogeneous. As reliability increases, part-worth of reliability increases because customers perceive high reliability itself as positive, whereas part-worth of performance decreases due to decreased advertised performance to ensure high reliability.

Fig. 6 compares decrements of performance part-worths according to reliability in different performance levels. As performance increases, customers become less concerned about performance, and thus, growth rate of performance part-worth decreases. Furthermore, given the large battery capacity, a high-performance case is less sensitive to engineering uncertainties, such as driving distance and driving cycle, such that effects of engineering uncertainty to variance of EV performances and warranted battery lifetime decrease. Therefore, as performance level increases, growth rate of performance part-worth decrement decreases as reliability increases, indicating that part-worth decrement is less sensitive to increasing reliability. Consequently, as part-worth decrement increase more with increasing reliability in low performance level, optimum reliability is designed to be relatively low when performance is low, and lower reliability in scenario 4 than in scenario 3 can be explained by the lower performance.

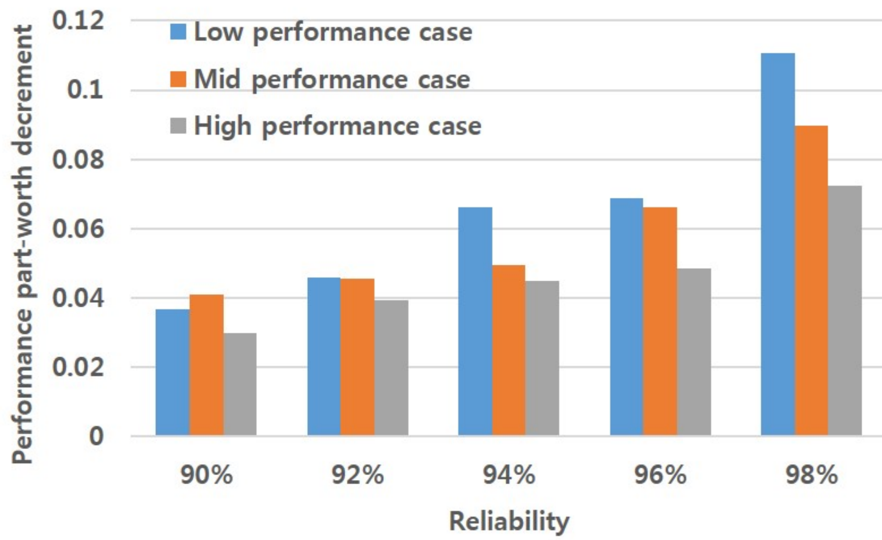

Fig. 6 Comparison of performance part-worth decrement for reliability

Observation 3: Lowering the price is more advantageous in market share than increasing performance when engineering uncertainty exists. Prices in scenarios 3 and 4 are lower than those in scenarios 1 and 2. With engineering uncertainty, although EV is designed to exhibit high performance, the performance advertised to customers is low to ensure reliability. Thus, the impact of performance on market share is smaller than that of price, which is not influenced by engineering uncertainty. Therefore, low price is designed to ensure fine market share in probabilistic engineering model. Cost also reduces, which results in low performance. Market share and profit decrease compared with those in the deterministic engineering model because reliability and warranty cost are secured.

Observation 4: Considering that engineering uncertainty and market heterogeneity can maximize profit, to compare influences of engineering uncertainty and market heterogeneity on profit, the optimum design of each scenario is applied in scenarios 1, 2, 3, and 4, and results are presented in Fig. 7. The comparison shows that loss of profit that comes from not considering engineering uncertainty or market heterogeneity can be identified. To maximize company profit in the actual market, scenario 4, engineering uncertainty, and market heterogeneity should be considered.

This study discovers that engineering uncertainty is more important than market heterogeneity. However, further research, which should focus on identifying the relative importance of engineering uncertainty and market heterogeneity from given input data, should be provided as such importance may change depending on properties of engineering uncertainty and market heterogeneity. When a condition must be considered selectively under unavoidable circumstances, this approach can suggest which condition to select in terms of company profit.

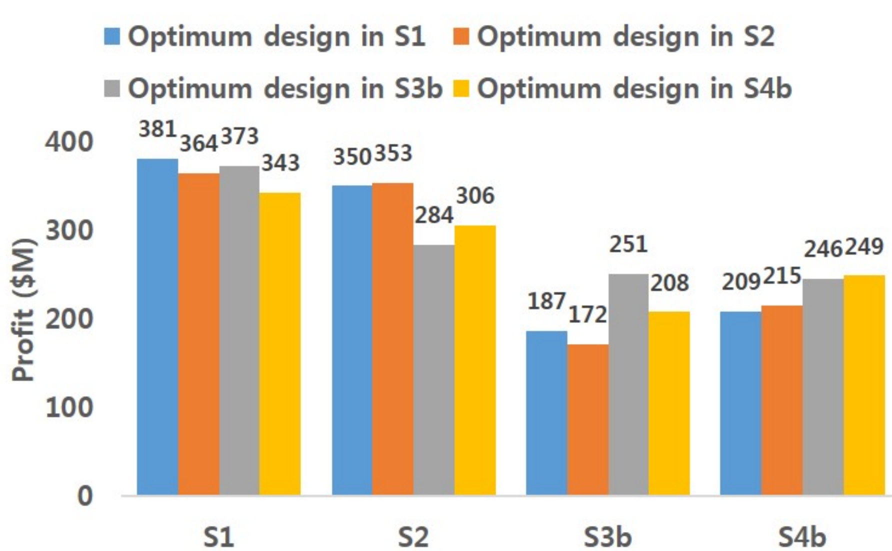

Fig. 7 Parametric study for optimum design in each scenario

Observation 5: Reliability and reliability variation of other competitors affect the design of optimum reliability. Fig. 8 presents results of the parametric study on power circle rating and engineering reliability for scenarios 3 and 4. In the matching between customer-perceived reliability and actual reliability shown in Table 6, S3c indicates scenario 3, which assumes that customers perceive 100%, 70%, 40%, and 10% reliability as "among the best," "better than most," "about average," and "the rest," respectively. Thus, other competitors feature relatively low reliability in S3c, and variation of reliability is relatively high compared with S3a and S3b.

Results show that reliability of the optimum design is lowered when that of other competitors is lowered, and reliability variation is large because the designed product can be evaluated relatively well by customers even when reliability is low. In addition, the manufacturer is more likely to earn higher profit because of low competitor quality. Lower reliability and profit in scenario 4 than those in scenario 3 can be explained by market heterogeneity.

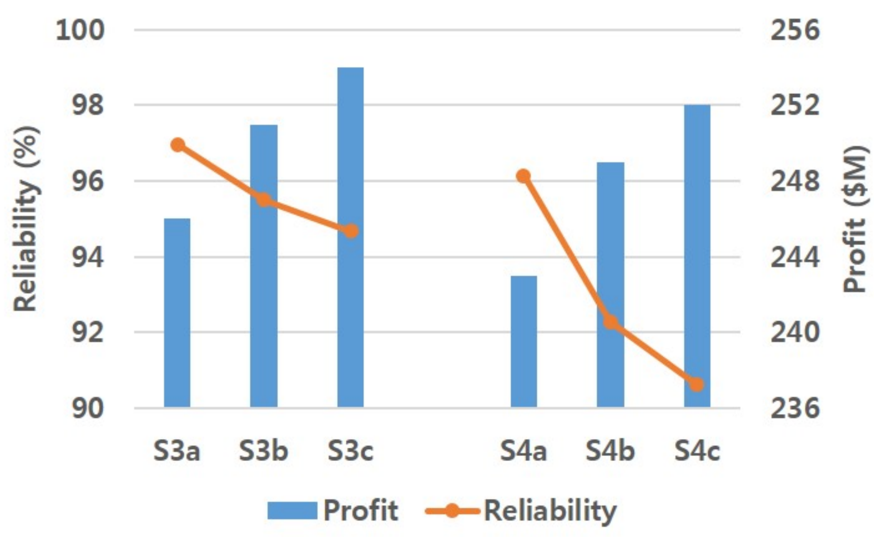

Fig. 8 Parametric study on reliability matching

Table 6 Matching between perceived reliability and actual reliability

Perceived reliability	Actual reliability		
Power circle rating	a	b	c
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%

Observation 6: To achieve high market share with high probability in heterogeneous market, designing a low-priced and high-performance EV with high reliability is recommended even when company profit decreases. Various market share constraints are applied to scenario 4: A, B, and C satisfy market shares of 10%, 20%, and 30% with a probability higher than 70%, respectively; D, E, and F satisfy market shares of 10%, 20%, and 30% with a probability higher than 80%, respectively; and G, H, and I satisfy market shares of 10%, 20%, and 30% with a probability higher than 90%, respectively. As shown in Fig. 9, optimum reliability increases as market share constraints become stricter because performance is enhanced to obtain a high market share. Profit is reduced due to decreased price, which is also an effort to increase market share. The sudden decrease in profit, which may drop to negative value, means that market heterogeneity is extremely high that the EV design, which can obtain a high market share with high probability, is nearly impossible.

Observation 7: To ensure robustness and to maximize profit, designing a luxury EV with high performance and high reliability is recommended even when the price is high. By using RBRDO formulation given in Eqs. (6) and (8), optimal design and results, such as profit and its variance, are obtained and presented in Table 7.

Given the difficult of reducing variance of market share, margin is decreased to reduce profit variance, whereas market share is increased to raise profit. Increasing the number of battery cells enhances overall performance and in turn raises the market share, which increases profit. At the same time, increased cost decreases the margin and therefore reduces variance of the profit. In case the weight of profit variance becomes larger than that of profit mean, which is not recommended in the company's perspective, price is reduced to decrease the margin.

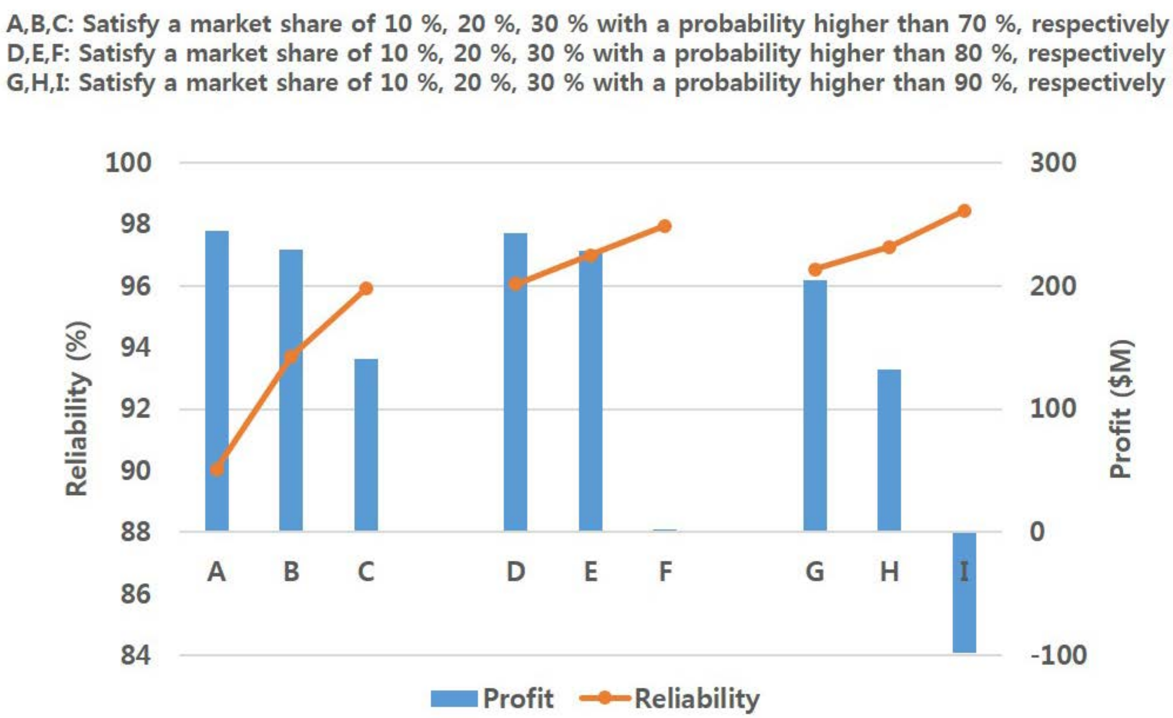

Fig. 9 Parametric study for market share constraints

Table 7 Optimal design and results of profit and profit variance

w_1	w_2	$\mu_{Profits}$	$\sigma_{Profits}$	$\mu_{Market\ shares}$	$\sigma_{Market\ shares}$	Price	Number of battery cells	Reliability	Margin
1	0	$249M	$156M	24.4%	15.3%	$32,954	280	92.3%	$21,345
0.9	0.1	$247M	$135M	28.1%	15.4%	$33,907	316	92.7%	$20,034
0.7	0.3	$234M	$119M	30.7%	15.7%	$34,348	340	93.1%	$18,965
0.5	0.5	$199M	$91M	33.7%	15.9%	$35,083	376	93.9%	$17,437
0.3	0.7	$86M	$40M	34.6%	16.1%	$33,200	396	97.2%	$14,295
0.1	0.9	$19M	$9M	40.0%	20.3%	$31,527	399	99.2%	$12,434

6. Conclusion

Different from the existing DMS, the work presented considers uncertainties at the engineering level. Reliability, which directly affects both engineering and marketing models, determines advertised performances and warranted battery lifetime from probabilistic performances and battery lifetime under uncertainties, and significantly affects utility as an attribute. Lowering reliability to increase advertised performances results in the loss of product credibility in the market over time. In the case of automobiles, product reliability is delivered to customers through evaluation results, such as word of mouth or J. D. Power. In this study, reliability rating of J. D. power is used as product reliability that customers can consider when purchasing. After illustrating how reliability influences performance and customer choice, optimum reliability, which maximizes profit, can be derived.

The presented work suggests a RBDO problem considering engineering uncertainty and market heterogeneity. Combining RBDO and DMS can provide an insightful analysis on how engineering uncertainty and market heterogeneity interact. In addition, the effect engineering uncertainty on decision making can be identified. This research can be considered a stepping stone for RBDO problems in various fields.

When designing an EV in real world, considering engineering uncertainty and market heterogeneity is recommended. Designing a low-priced EV with low performance and low reliability is also recommended. Furthermore, the design of optimum reliability is influenced by reliability and reliability variation of other competitors. Although company profit is decreased, EV should be designed at low cost with high performance and high reliability, which benefit customers, to obtain high market share at high probability in a heterogeneous market. A luxurious and expensive EV with high performance and high reliability is recommended to ensure robustness and to maximize profit.

This study enables manufacturers to achieve maximum profit while securing certain reliability on engineering performances despite uncertainty factors at the engineering level. The same research concept can be applied to other problems. For example, the existing emission test raises the problem of varying emissions, which can exceed legal emission limits in real-world driving conditions [57], and the fine may lower profits of vehicle manufacturing companies. Based on this study, companies can find the optimal balance between reliable product design and profitable product design.

This study also suggests a design methodology that can satisfy manufacturers and customers with its optimization results. By setting engineering reliability as a decision variable, manufacturers can achieve maximum profit and fair market share, whereas customers can obtain products with reasonable performance reliability. Therefore, customers do not suffer from using faulty or defective products regardless of usage conditions. Without the suggested methodology, companies will fail to effectively design a product that maximizes profit in the presence of uncertainty, and customers will lose confidence in these companies, which will lead to profit loss.

The research also suggests an EV design that can maximize profit while achieving robustness by combining RBRDO and DMS. This design will help companies reduce the probability of achieving a critically low profit.

Future work should revise several assumptions and reflect more fidelity on the engineering model and its uncertainties. Additional research should center on reflecting reliability from the perspective of customers. In this study, power circle rating in J. D. Power is used to reflect reliability from the perspective of customers, and reliability of other competitors is assumed. Uncertainty of market, not its heterogeneity, can be considered in future research [27].

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