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RESEARCH PAPER

Selection of optimal target reliability in RBDO through reliability-based design for market systems (RBDMS) and application to electric vehicle design

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Abstract

Reliability-based design optimization (RBDO) allows decision-makers to achieve target reliability in product performance under engineering uncertainties. However, existing RBDO studies assume the target reliability as a given parameter and do not explain how to determine the optimal target reliability. From the perspective of the market, designing a product with high target reliability can satisfy many customers and increase market demand, but it can generate a large cost leading to profit reduction of the company. Therefore, the target reliability should be a decision variable which needs to be found to maximize the company profit. This paper proposes a reliability-based design for market systems (RBDMS) framework by integrating RBDO and design for market system (DMS) approaches to find the optimal target reliability. The proposed RBDMS framework is applied to electric vehicle (EV) design problems to validate effect of the target reliability on company profit—or market share—and engineering performances of EV. Several observations about the optimal target reliability are presented from the case study with various scenarios. From the EV design case study, it is verified that the proposed RBDMS framework is an effective way of finding the optimal target reliability that maximizes the company profit, and the optimal target reliability varies depending on the situation of market and competitors.

Keywords Reliability-based design optimization (RBDO) · Design for market systems (DMS) · Electric vehicles · Target reliability · Uncertainty

Abbreviation

SoC	State of charge of battery
DoD	Depth of discharge of battery
D	DoD
F	Additional fraction of nominal capacity
P	Penalty factor for deeper DoD
A	Capacity loss factor
σ	$1-A$
$\mathbf{\Pi}$	Profits
$\mathbf{D}$	Market demands
MC	Manufacturing cost
$\mathbf{C}$	Compensation costs
$\mathbf{X}$	Deterministic decision variable vector
$\mathbf{X}_{\text{power}}$	Powertrain design variable vector
R	Target reliability
W	Warranted battery lifetime
$Price$	Price
P_F^{Target}	Target probability of failure for probabilistic constraints
$\mathbf{g}$	Inequality constraint functions
$\mathbf{G}$	Probabilistic constraint functions
N_{S}	Number of battery cells in series
N_{P}	Number of battery cells in parallel
FR	Final gear ratio
$\mathbf{RP}_e$	Random parameter vector of engineering model

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$\mathbf{P}$	Matrix of probabilistic performances
$\mathbf{P}_{\mathrm{MPGe}}$	Vector of probabilistic MPGe
$\mathbf{P}_{\mathrm{range}}$	Vector of probabilistic driving range
$\mathbf{P}_{\mathrm{speed}}$	Vector of probabilistic top speed
$\mathbf{P}_{\mathrm{accel}}$	Vector of probabilistic acceleration
$\mathbf{P}_{\mathrm{Batt}}$	Vector of probabilistic battery lifetime
$\mathbf{PR}$	Vector of engineering performances that satisfy the target reliability
$\mathbf{A}$	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 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 (Lee and Jung 2008). 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 (Frangopol and Maute 2003), and the target 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 and prediction of target probability of failure, whereas optimization focuses on searching for optimal solutions. RBDO has been widely used in various engineering fields such as aerospace (Allen and Maute 2002; Pettit 2004; Lee et al. 2009; Missoum et al. 2010), civil (Ellingwood and Galambos 1982; Nowak 1995), and mechanical engineering (Youn et al. 2004, 2005; Dong et al. 2007; Noh et al. 2009; Lee et al. 2010, 2013; Yoo and Lee 2014; Shin and Lee 2014, 2015; Lim et al. 2015), and in various applications such as composite structures (Qu et al. 2003).

On the other hand, 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 (Lewis et al. 2006; Frischknecht et al. 2010; Kang et al. 2013; Kang 2014). This research area focuses more on selling products or services rather than optimizing products based on their performances. To determine the optimal product design for a market system, an optimization problem that maximizes 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 product prices. 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 successfully utilized for electric vehicle (EV) and hybrid EV design problems (Kang et al. 2015, 2016, 2017, 2018; Helveston et al. 2015).

However, existing RBDO studies do not suggest how to determine the target reliability, which affects the product reliability that customers consider when purchasing a product, and thus, designers use predetermined target reliability for design optimization. On the other hand, existing DMS studies focus on maximizing profit, but do not consider the impact of the product reliability on profit. Therefore, a new design framework is needed to overcome the aforementioned disadvantages of each method. It should also determine optimal target reliability that maximizes a manufacturer's profit by considering how the target reliability affects the engineering model and customer's product purchase. For this purpose, a reliability-based design for market systems (RBDMS) framework, which integrates RBDO and DMS to find the optimum target reliability from the perspective of the market, is proposed in this paper.

The target reliability plays a key role in integrating RBDO and DMS in the RBDMS framework. In an engineering model, the target reliability is used in the probabilistic constraints of RBDO and determines product performances advertised to customers. On the other hand, in a marketing model, customers recognize the target reliability determined by the designer as the product reliability through word-of-mouth, internet reviews of those who have used the product in advance, and institutional evaluation. This product reliability, along with product performances, is one of the attributes that customers evaluate when purchasing a product, and thus, it affects market demand. As the product reliability improves, market demand for the product grows, assuming the price does not increase. Therefore, the engineering model and marketing model are strongly coupled through the target reliability in RBDMS, and thus, how the target reliability affects each model should be identified. This is why the target reliability is a decision variable in RBDMS to maximize profit. Figure 1 displays the interaction of three types of decision variables—target reliability, design variables, and price—for profit maximization in the RBDMS framework. Target reliability and

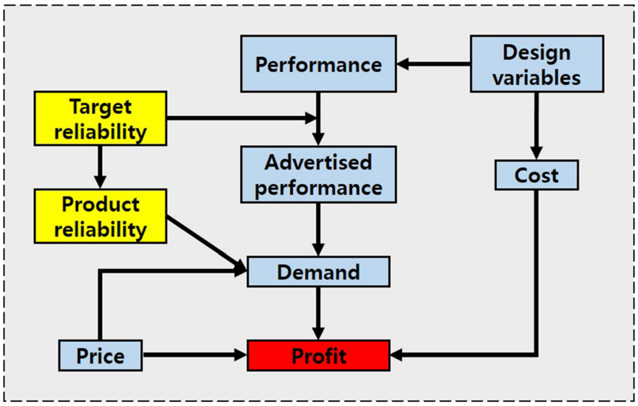

Fig. 1 Interaction of target reliability, design variables, and price for profit maximization

Table 1 Specifications of EV model

Vehicle curb weight	1631 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

design variables determine advertised performance, and then, this advertised performance determines market demand along with product reliability and price. The proposed RBDMS framework is verified in this paper through a case study of EV design which shows a new EV design that maximizes profit of an EV manufacturer while ensuring reliability of advertised product performances.

The remainder of this paper is organized as follows. Section 2 introduces the engineering model and uncertain factors. Section 3 presents the marketing model for estimating customers' preferences. Section 4 provides the RBDMS formulation and modeling assumptions. In Sect. 5, the proposed RBDMS framework is applied to an EV design case, and the optimal results of three design methods are compared. Finally, Sect. 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 EV performances, two engineering models are presented: (1) an EV performance model that simulates vehicle performances while considering uncertainties in battery and driving characteristics for different mechanical designs, and (2) a battery degradation model that presents the cycle life of a Li-ion battery.

2.1.1 EV performance model

EV performances such as MPGe, driving range, top speed, and acceleration are determined by the design of powertrain, which contains a battery pack and motor that are connected to wheels through a final drive. To simulate such an EV performance model, we adapt the powertrain system of the Nissan Leaf and its specifications listed in Table 1 (Energy Efficiency and Renewable Energy 2011a, 2011b). AMESim software and a battery degradation model explained in Sect. 2.1.2 are combined to modify our analytical EV performance model (AMESim 2016). The EV model comprises of each submodel for driver, control unit, motor torque control, battery, three-phase inverter, permanent magnet synchronous motor, and gear, respectively. Vehicle performances are then determined based on driving cycle. The parameters related to the EV performance model are similar to Nissan Leaf. In the battery pack, the cells connected in series form a branch and several branches are connected in parallel. Battery characteristics are given by

$$\begin{aligned} r_{\mathrm{Batt}} &= r_{\mathrm{cell}} \times \frac{N_{\mathrm{S}}}{N_{\mathrm{P}}} \\ \mathrm{OCV}_{\mathrm{Batt}} &= \mathrm{OCV}_{\mathrm{Cell}} \times N_{\mathrm{S}} \end{aligned} \tag{1}$$

where r_{Batt} and r_{cell} are the internal resistances of battery and cell, respectively; N_{S} and N_{P} are the number of battery cells in series and parallel, respectively; and $\mathrm{OCV}_{\mathrm{Batt}}$ and $\mathrm{OCV}_{\mathrm{Cell}}$ are the open-circuit voltages of battery and cell, respectively. 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.

The motor output torque can be calculated using stator inductances, stator currents, permanent magnet flux linkage, and the number of pole pairs as follows:

$$\begin{aligned} &T = N_{\mathrm{Pole}}\left(\varphi_d I_q - \varphi_q I_d\right) \\ \text{where} \quad &\varphi_d = L_d I_d + \sqrt{\frac{3}{2}}\varphi_{\mathrm{PM}} \\ &\varphi_q = L_q I_q \end{aligned} \tag{2}$$

where φ_d and φ_q are the stator flux linkages of the d and q axis, respectively; φ_{PM} is the permanent magnet flux linkage; L_d

and L_q are the stator inductances of the d and q axis, respectively; I_d and I_q are the stator currents of the d and q axis, respectively; T is the motor torque; and N_{Pole} is the number of pole pairs.

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 and is obtained using

$$\begin{aligned} T_{\text{shaft}} &= FR \times T_{\text{motor}} \\ w_{\text{motor}} &= FR \times w_{\text{shaft}} \end{aligned} \tag{3}$$

where T_{shaft} and T_{motor} are the torques of shaft and motor, respectively; w_{shaft} and w_{motor} are the velocities of shaft and motor, respectively; and FR is the gear ratio. Fuel economy, MPGe, is also related to the final drive ratio in terms of different energy consumptions.

2.1.2 Battery degradation model

The lifetime of a battery depends highly on the daily driving distance. 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 (Ning et al. 2003; Lawder et al. 2014). The state of charge (SoC) is the amount of useful remaining charge compared to its initial fully charged state given by

$$SoC(t) = \frac{\int_{t_0}^{t} I(\tau)d\tau}{Q_0} \times 100 \tag{4}$$

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

$$DoD = SoC_{\text{initial}} - SoC_{\text{final}}. \tag{5}$$

The capacity fade is related to the number of cycles and DoD of the batteries (Peterson et al. 2010). In general, an EV battery should be replaced when its capacity decreases to 80% of its initial capacity (Helveston et al. 2015).

The cycle life, which results from capacity fades with regard to the DoD of batteries, was theoretically and experimentally presented by Thaller (1983) as

$$Cycle\ Life = \frac{1 + F - D}{(A + 2\sigma)(1 + PD)D} \tag{6}$$

where D corresponds to the DoD of the battery; F is the additional fraction of the nominal capacity used to represent excess capacity; P stands for the penalty factor that leads to a higher rate of capacity loss for the deeper DoD due to higher shedding rates, mechanical stresses, and severe mass transport environments; A is the capacity loss factor associated with capacity loss in each cycle; and σ represents the standard deviation of $(1-A)$. The multiplication of parameters A and D represents the amount of capacity loss in a cycle, and the multiplication of parameters P and D indicates the additional capacity loss in deeper DoD. All parameters, which are used equally as in Thaller (1983), are chosen to yield the expected cycle life when operating the actual EV and to be able to calculate the cycle life conservatively. In this study, battery life is considered as the cycle life 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. (4) and (5).

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 (Gomadam et al. 2002; Millner 2010; Tong et al. 2015). Given the hypersensitivity of Li-ion batteries to uncertainties, uniformity at the component level is highly required (Santhanagopalan and White 2012). However, some deviations of material and physical properties that occur during manufacturing exist between cells and parameter uncertainties should be quantified to estimate battery performance more accurately (Jing et al. 2014; Tong et al. 2015). Dubarry et al. (2010) 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 (Hadigol et al. 2015). Properties of these uncertainties are adapted in the engineering model explained in Sect. 2.1. Table 2 lists statistical properties of all the random parameters including daily driving distance and driving cycle used in the engineering model.

2.2.2 Driving distance

Even with the same battery capacity, the DoD of the battery differs with energy consumption depending on the

Table 2 Properties of random parameters

	Distribution	Mean	Standard deviation
Cell capacity	Normal	33.1 Ah	0.5 Ah
Cell voltage	Normal	3.8 V	0.02 V
Cell weight	Normal	0.7864 kg	0.0149 kg
Daily driving distance	Log-normal	3.11 mi	0.62 mi
Driving cycles	Combination of the standard driving cycles drawn randomly with the same probability		

driving distance (Lawder et al. 2014). To deal with the uncertainty of daily driving distances of users, we use the daily vehicle miles of travel (VMT) data of 2009 National Household Travel Survey (U.S. Federal Highways Administration 2009). Log-normal distribution is used to describe daily driving distance of drivers as shown in Table 2 (Plötz et al. 2017). The distribution of the daily VMT results in a wide range of battery lifetimes. To determine the actual lifetime of batteries, Eq. (6) is integrated with the distribution of *DoD*.

2.2.3 Driving cycle

Various driving patterns affect EV performances such as driving range and thus MPGe (Berry 2010). Standard driving cycles, which represent driving patterns as vehicle speed over time, have been used to report fuel consumption of vehicles by the US Environment Protection Agency (Environmental Protection Agency 2017). Similarly, to reflect actual driving patterns in the engineering model, representative standard driving cycles provided by EPA are applied when calculating the driving range. Table 3 summarizes the characteristics of the EPA standard driving cycles (EPA website). Given that combinations of different driving cycles are frequent and natural in actual driving conditions, an average driving range calculated from the combination of the standard driving cycles drawn randomly with the same probability is used as the driving range of the designed vehicle in this paper (Kamble et al. 2009).

2.3 Target reliability in engineering model

Actual performances fluctuate and vary because of the engineering uncertainties mentioned above, and form performance distributions which can be defined as probabilistic attributes. Therefore, EV performances that are advertised to customers can be described using the target reliability. For example, 95% target reliability implies that vehicles less than 5% among all produced ones will show lower EV performances than the advertised values as shown in Fig. 2. Thus, as the target reliability increases, advertised product attributes will be lowered for the product to satisfy the target reliability. When certain target reliability is used in RBDO, then we assume that the product reliability evaluated by customers and used in a marketing model is identical with the target reliability which will be explained in more detail in Sect. 3.3.

3 Marketing model

A marketing model estimates market demand by estimating customer preferences toward price of a designed product and its attributes. This section discusses how to predict the market demand from customer preferences and heterogeneity which influence the optimal product 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

Table 3 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

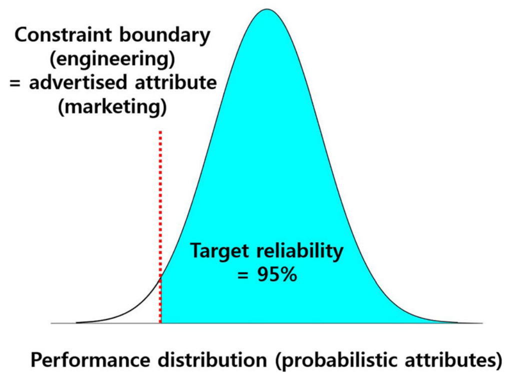

Fig. 2 Advertised attribute determination

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 design attributes that are the product properties evaluated by the customers, research on product characteristics assessed by customers, 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, after estimating part-worths (customer preferences), a set of weights which indicate the importance of each design attribute perceived by customers, choice probability can be predicted using the logit model. Then, market demand is calculated as the product of the market share and market potential or market size.

Individual-level utility v_{ij}, which is the sum of part-worths of the designed product, can be defined as (Green and Krieger 1996)

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \boldsymbol{\beta}_{ikl} z_{jkl} \tag{7}$$

where $\boldsymbol{\beta}_{ikl}$ represents the part-worth of the lth level of the kth attribute for the ith individual, and z_{jkl} corresponds to a binary dummy number, which is equal to 1 if the level l of the kth attribute is selected for the jth alternative, and 0 otherwise. For given utilities of competing products, the choice probability is calculated using

$$P_{ij} = \frac{e^{v_{ij}}}{\sum_{j' \in J} e^{v_{ij'}}} \tag{8}$$

which is similar to the probability of the ith 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 the market share P_{ij} and potential market size s. Accordingly, the predicted profit is defined as the product of the 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 is 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 explained above can be obtained from customer survey. A method using questionnaires for the survey 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 as listed in Table 4 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 design exists, respondents may pick none of the options. Importance in Table 4 means the difference percentage between the maximum and minimum values of the part-worths of the attribute level. The larger the difference between levels is, the more important the attribute is.

3.2 Hierarchical Bayesian approach

To obtain the individual-level part-worth distribution, actual respondent results collected from a choice-based conjoint (CBC) survey are needed. Given existence of various customer preferences toward product attributes, the part-worths for similar attributes differ. This study uses a hierarchical Bayesian (HB) approach (Train 2001; Rossi et al. 2005; Orme 2009) to build a heterogeneous market. Based on the results of a survey conducted using Mturk (Amazon 2017), which was targeted for the customers in the USA, individual-level part-worth distribution is derived. Responses are drawn from 252 subjects living in the USA: 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.

CBC analysis is first performed to estimate individual part-worths, and then HB analysis follows. Responses from the survey are utilized in the HB analysis to estimate individual part-worths using the 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 and $\boldsymbol{\Lambda}$ is a 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

Table 4 Attribute levels and their part-worths

Attribute		Part-worth				Importance
Product reliability	Level	5 rating	4 rating	3 rating	2 rating	38.9%
	Mean	2.412	1.515	− 0.450	− 3.476	
	(Std)	(1.844)	(1.147)	(0.845)	(2.379)	
Warranted battery lifetime	Level	3 years	7 years	11 years	15 years	11.5%
	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	14.1%
	Mean	− 1.331	0.038	0.489	0.803	
	(Std)	(1.782)	(0.554)	(0.896)	(1.106)	
MPGe	Level	90	100	110	120	0.9%
	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	4.1%
	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	1.4%
	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	29.1%
	Mean	1.930	0.894	− 0.356	− 2.468	
	(Std)	(2.093)	(0.871)	(0.836)	(2.294)	

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 describe continuous attributes. As presented in Table 4, the large variance of part-worths demonstrates that heterogeneous preferences should be considered in the market system design.

3.3 Product reliability in marketing model

As product reliability is related to customer-perceived value, a product with high reliability continuously attracts customers through word-of-mouth (Levin and Kalal 2003; Huang et al. 2007; Park et al. 2007). Therefore, as the product reliability influences EV selection of customers, the reliability of EVs should be available to customers for reference when making a purchase. The product reliability used for the questionnaire listed in Table 4 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 (J.D. Power 2017). IQS measures initial vehicle quality during the first 90 days of ownership, whereas VDS measures long-term vehicle quality. 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.

This product reliability in the marketing model is equal to the target reliability in the engineering model, and it determines product performances (advertised attributes) as explained in Sect. 2.2. It will be explained in Sect. 4 how to integrate the engineering model and the marketing model using the target reliability to propose a RBDMS framework.

4 RBDMS

The engineering model explained in Sect. 2 and the marketing model explained in Sect. 3 are integrated into a RBDMS framework to find the optimal product design which maximizes a manufacturer's profit and product performances at the same time. Figure 3 illustrates the information flow of RBDMS for EV design from the viewpoint of the manufacturer. The target reliability, which is one of decision variables, is equally used in reliability constraints of the engineering model. It determines product performances that

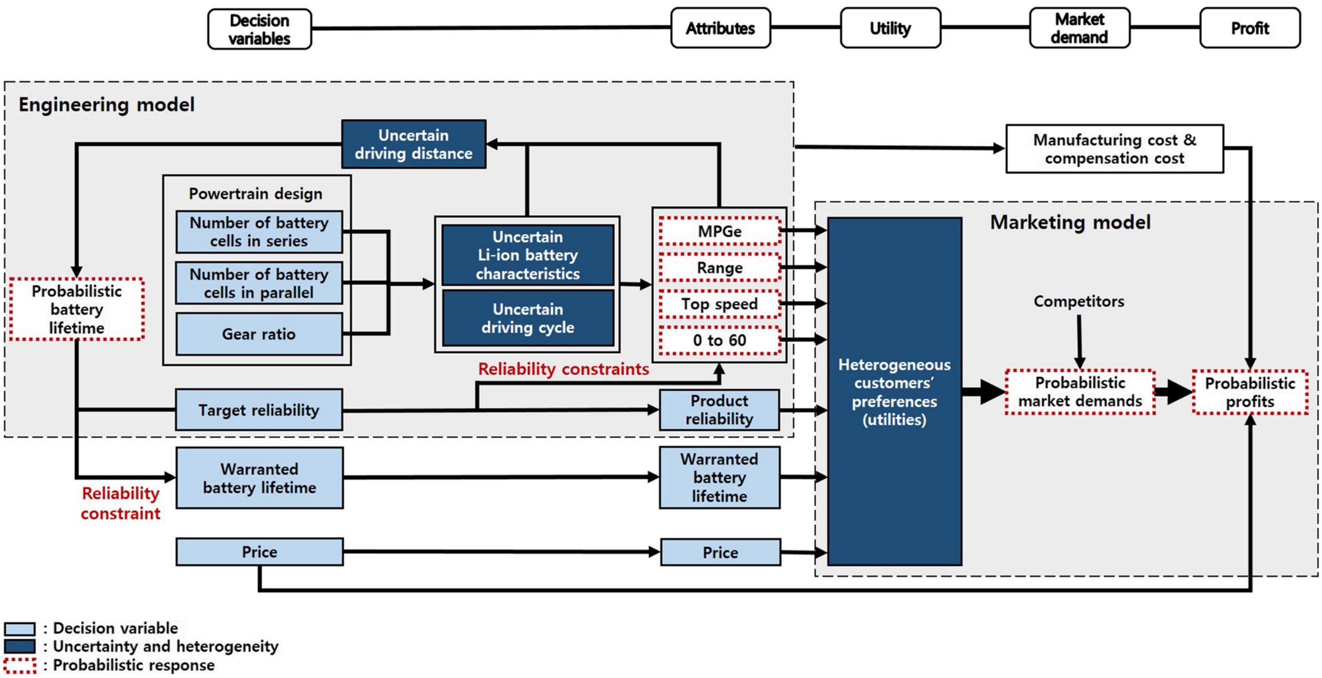

Fig. 3 Information flow of RBDMS for EV design

satisfy the target reliability and are advertised to customers such as MPGe, range, top speed, 0 to 60 mph, and warranted battery lifetime. Then, customers perceive the target reliability as the product reliability, which is one of product attributes and considering factors when purchasing an EV through J.D. Power circle ratings. The product attributes determined from the engineering model along with EV price are passed on to the marketing model and thus the product utility can be calculated by the 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 manufacturer will be the product of the market demand and margin. 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 performed. The decision variables used in the EV case study and their bounds are listed in Table 5.

Table 5 Decision variables and their bounds for EV design

Decision variables	Lower bound	Upper bound
1. Target reliability (R)	10%	100%
2. Price ($Price$)	\$15,000	\$45,000
3. Warranted battery lifetime (W)	3 years	15 years
4. Number of battery cells in series (N_S)	80	250
5. Number of battery cells in parallel (N_P)	1	4
6. Gear ratio (FR)	2	12

4.1 RBDMS formulation

Based on a general formulation of RBDO (Lee et al. 2011), RBDMS is formulated as

$$
\begin{aligned}
&\text{find} && \mathbf{X} = \left[\mathbf{X}_{power}^{\mathrm{T}}, R, W, Price\right] \\
&\max_{\mathbf{X}} && \mu(\mathbf{\Pi}) = \mu(\mathbf{D} \times (Price - MC) - \mathbf{C}) \\
&\text{subject to} && \mathbf{lb} \le \mathbf{X} \le \mathbf{ub} \\
& && \mathbf{g}(\mathbf{A}_{\mathrm{eng}}) \le 0 \\
& && P[\mathbf{G}(\mathbf{X}, \mathbf{RP}_e) > 0] \le P_F^{\mathrm{Target}} \\
&\text{where} && \mathbf{X}_{power} = [N_{\mathrm{S}}, N_{\mathrm{P}}, FR] \\
& && P_F^{\mathrm{Target}} = 1 - R \\
& && \mathbf{P} = \left[\mathbf{P}_{\mathrm{MPGe}}, \mathbf{P}_{\mathrm{range}}, \mathbf{P}_{\mathrm{speed}}, \mathbf{P}_{\mathrm{accel}}, \mathbf{P}_{\mathrm{Batt}}\right] \\
& && \mathbf{A} = \left[\mathbf{A}_{\mathrm{eng}}^{\mathrm{T}}, R, W, Price\right] \\
& && \mathbf{A}_{\mathrm{eng}} = \left[A_{\mathrm{MPGe}}, A_{\mathrm{range}}, A_{\mathrm{speed}}, A_{\mathrm{accel}}\right]^{\mathrm{T}} \\
& && [MC, \mathbf{P}] = f_{\mathrm{engineering}}\left(\mathbf{X}_{power}, \mathbf{RP}_e\right) \\
& && \left[\mathbf{C}, \mathbf{A}_{\mathrm{eng}}, W\right] = f_{\mathrm{attribute}}(\mathbf{P}, R) \\
& && \mathbf{D} = f_{\mathrm{marketing}}(\mathbf{A})
\end{aligned}
\tag{9}
$$

where the objective is to maximize the mean of profits $\mathbf{\Pi}$; $\mu(\cdot)$ represents the mean value; $\mathbf{D}$, MC, and $\mathbf{C}$ correspond to the vector of market demand, manufacturing cost, and 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 the target reliability, warranted battery lifetime, and price, respectively; $P[\cdot]$ is the probability measure; P_F^{Target} is the target probability of failure; **lb**, **ub**, **g**, and **G** indicate the lower bounds, upper bounds, inequality constraints on advertised performances, and probabilistic constraints, respectively; FR represents the decision variable of the final gear ratio; $\mathbf{RP}_e$ denotes random parameter vectors of the engineering model; **P** represents the probabilistic performance matrix; **A** is the advertised attribute vector; $\mathbf{A}_{\text{eng}}$ denotes the vector of advertised attributes determined from the engineering model; $f_{\text{engineering}}$, $f_{\text{attribute}}$, and $f_{\text{marketing}}$ indicate the engineering model, attribute model, and marketing model, respectively.

In Eq. (9), the probabilistic constraint is evaluated through a reliability analysis which calculates the probability of failure defined as

$$P_F = P[G(\mathbf{X}) > 0] = \int_{\Omega_F} f_{\mathbf{X}}(\mathbf{x})\mathrm{d}\mathbf{x} \tag{10}$$

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 utilized to perform the reliability analysis since both the engineering and marketing models are computationally efficient.

4.2 Modeling assumption

Four assumptions are made when modeling the entire framework for EV design. First, in computing the market share of the designed EV, we assumed that there are two competitors in the market: 2017 Nissan Leaf and 2017 Chevrolet Bolt. Two competitors' market sizes in the USA are used to determine the market demand. Second, to satisfy the minimum performances of an EV to drive in the real world, following constraints are applied to EV performances in all scenarios tested: the driving range should be more than 80 mi, 0to 60 mph acceleration should be shorter than 12 s, and the top speed should be faster than 70 mph. Third, the compensation cost is assumed to compensate for 10% of the battery capacity only for failures within the warranted battery lifetime period. Fourth, it is necessary to map the product reliability and the reliability used in the customer survey—that is, J.D. Power rating. 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.

4.3 Three design methods

To investigate the importance of RBDMS for EV design, three different design methods shown in Fig. 4 are examined:

- Method 1 (RBDO): maximizing *engineering performances* with *fixed* target reliability
- Method 2 (RBDO + DMS): maximizing *profit* with *fixed* target reliability
- Method 3 (RBDMS, proposed): maximizing *profit* with *optimal* target reliability

Comparison of Method 1 with other methods is necessary to show that an unprofitable product can be designed when designing a product using conventional RBDO without considering the market system. In addition, the reason for comparing Method 2 with Method 3 is to prove that profit can be reduced if the target reliability is set excessively without using and searching for the optimal target reliability, even when the market system is considered.

Method 1 utilizes RBDO that maximizes performances with fixed target reliability and does not involve a marketing model for EV design. In Method 1, design variables become decision variables and the target reliability is predetermined before performing RBDO. For the probabilistic performances resulting from engineering uncertainties, the performances that satisfy the given target reliability are determined. Since EV has multiple performances (objectives), the weighted sum of the engineering performances is used as the objective function where the weights are determined by the importance of each performance as listed in Table 4. Then, Method 1 is formulated as

$$\begin{aligned}
&\text{find} && \mathbf{X} = \mathbf{X}_{power}^{\mathrm{T}} \\
&\max_{\mathbf{X}} && \sum_{i=1}^{np} w_i \mathrm{PR}_i \\
&\text{subject to} && \mathbf{lb} \le \mathbf{X} \le \mathbf{ub} \\
& && \mathbf{g}(\mathbf{A}_{\text{eng}}) \le 0 \\
& && P[\mathbf{G}(\mathbf{X}, \mathbf{RP}_e) > 0] \le P_F^{\text{Target}} \\
&\text{where} && \mathbf{X}_{power} = [N_S, N_P, FR] \\
& && P_F^{\text{Target}} = 1 - R \\
& && \mathbf{P} = [\mathbf{P}_{\text{MPGe}}, \mathbf{P}_{\text{range}}, \mathbf{P}_{\text{speed}}, \mathbf{P}_{\text{accel}}, \mathbf{P}_{\text{Batt}}] \\
& && \mathbf{PR} = [\mathrm{PR}_{\text{MPGe}}, \mathrm{PR}_{\text{range}}, \mathrm{PR}_{\text{speed}}, \mathrm{PR}_{\text{accel}}, \mathrm{PR}_{\text{Batt}}] \\
& && \mathbf{P} = f_{\text{engineering}}(\mathbf{X}_{power}, \mathbf{RP}_e) \\
& && \mathbf{PR} = f_{\text{reliability}}(\mathbf{P}, R)
\end{aligned} \tag{11}$$

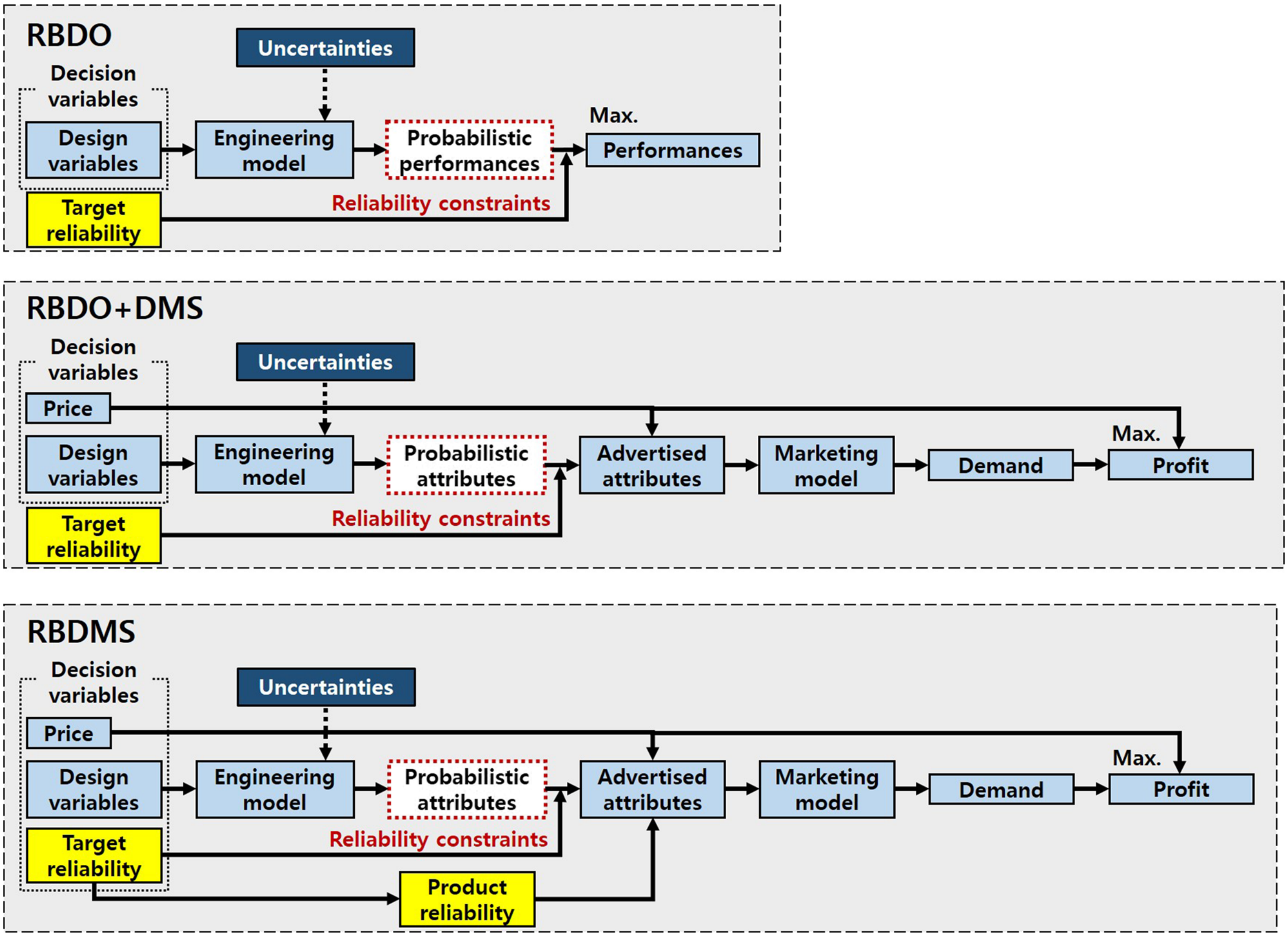

Fig. 4 Comparison among RBDO, RBDO+DMS, and RBDMS

where the objective is to maximize the weighted sum of the engineering performances that satisfy the target reliability; w is the weight determined by the importance of each performance; np is the number of engineering performances; **PR** represents the vector of engineering performances that satisfy the target reliability; and $f_{\text{reliability}}$ indicates the reliability model that determines the engineering performances that satisfy the target reliability.

Method 2 simply connects the objective function of RBDO with DMS and the EV price is included in decision variables. In Method 2, the target reliability is still fixed and predetermined as in Method 1 before performing RBDO and optimization is performed without considering the impact of the target reliability on engineering and marketing models. Attribute values obtained from RBDO are used as advertised attributes in the marketing model. Method 2 uses profit as the objective function and is an intermediate scenario to clearly explain benefits of the proposed RBDMS. The mathematical formulation of Method 2 can be expressed as

$$
\begin{aligned}
\text{find} \quad & \mathbf{X} = \left[\mathbf{X}_{power}^{\mathrm{T}}, W, Price\right] \\
\max_{\mathbf{X}} \quad & \mu(\boldsymbol{\Pi}) = \mu(\mathbf{D} \times (Price - MC) - \mathbf{C}) \\
\text{subject to} \quad & \mathbf{lb} \le \mathbf{X} \le \mathbf{ub} \\
& \mathbf{g}(\mathbf{A}_{\text{eng}}) \le 0 \\
& P[\mathbf{G}(\mathbf{X}, \mathbf{RP}_e > 0)] \le P_F^{\text{Target}} \\
\text{where} \quad & \mathbf{X}_{power} = [N_{\mathrm{S}}, N_{\mathrm{P}}, FR] \\
& P_F^{Target} = 1 - R \\
& \mathbf{P} = \left[\mathbf{P}_{\text{MPGe}}, \mathbf{P}_{\text{range}}, \mathbf{P}_{\text{speed}}, \mathbf{P}_{\text{accel}}, \mathbf{P}_{\text{Batt}}\right] \\
& \mathbf{A} = \left[\mathbf{A}_{\text{eng}}^{\mathrm{T}}, W, Price\right] \\
& \mathbf{A}_{\text{eng}} = \left[A_{\text{MPGe}}, A_{\text{range}}, A_{\text{speed}}, A_{\text{accel}}\right]^{\mathrm{T}} \\
& [MC, \mathbf{P}] = f_{\text{engineering}}\left(\mathbf{X}_{power}, \mathbf{RP}_e\right) \\
& \left[\mathbf{C}, \mathbf{A}_{\text{eng}}, W\right] = f_{\text{attribute}}(\mathbf{P}, R) \\
& \mathbf{D} = f_{\text{marketing}}(\mathbf{A})
\end{aligned}
\tag{12}
$$

where the objective is to maximize the mean of profits affected by the price, which is a decision variable, and the market share determined by the design variables and the given target reliability. The difference between Methods 2 and 3 is that the target reliability is excluded from decision variables and advertised attributes.

Method 3, presented in Eq. (9), is the proposed RBDMS where the target reliability is optimized as a decision variable to maximize profit as explained in Sects. 4.1 and 4.2. Here, the product reliability that customers consider when purchasing a product is used as an advertised attribute. In Method 3, RBDO and DMS are combined through the target reliability, and optimization is performed simultaneously considering the effect of the target reliability on advertised performances, the effect of design variables on performance and cost, and the effect of the target reliability, advertised performances, and price on market demand.

A target reliability value of 99.87% commonly used in the field of RBDO for vehicles is used for the fixed target reliability in Methods 1 and 2 (Youn et al. 2004). The EV design optimization results obtained using Methods 1, 2, and 3 are shown and compared in the next section.

5 Results and discussion

This section compares optimization results obtained by three methods explained in Sect. 4.3. In all three methods, we deal with the number of battery cells in parallel and in series as discrete and continuous variables, respectively, and solve the optimization problem in Eq. (9) using sequential quadratic programming with multiple initial points. Optimal values of the number of battery cells in series are then rounded up to natural numbers. Computation time for one optimization is 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 obtained using 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 attributes are the values presented to customers who want to purchase an EV, and actual performances are the performance results obtained from RBDO with the fixed target reliability in Methods 1 and 2 and the optimal target reliability in Method 3.

Since Method 1 maximizes performances 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, performances such as range and battery lifetime which have a large importance of attributes in Table 4 are extremely high as well. 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, $31,820 for Leaf and $37,495 for Bolt, the profit becomes negative. Therefore, from the market's point of view, RBDO without considering DMS yields an infeasible design. Method 2 results in a feasible design and marketable outcomes. When compared to Method 1, higher profit is achieved since the objective is to maximize profit, and lower overall advertised attributes are obtained because of cost. Method 3 shows an optimum design with the maximum profit since the target reliability is optimized—in this case study, it was lowered from 99.87 to 92.69%—and good product performances simultaneously.

By comparing design optimization results of Methods 2 and 3, following observations can be made:

1. The optimal target reliability in Method 3 is lower than the target reliability in Method 2 to maximize profit which increases from $71.9 M in Method 2 to $77.3 M in Method 3. This is because the improved advertised attributes owing to the lower target reliability have higher effect than the lower product reliability, and thus, the market share has increased from 19.7 to 24.4%. In addition, due to the improved advertised attributes, the price can be relatively high (from $30,654 to $33,154). When the tradeoff of utility is considered, reduced part-worths due to the lower target reliability and increased price are 0.1496 and 0.3344, respectively. Increased part-worths due to the improved advertised performance and warranted battery lifetime are 0.9282 and 0.5867, respectively. This shows that the increased utility due to improved advertised performance and warranted battery lifetime ($0.9282 + 0.5867 = 1.5149$) is much larger than the decreased utility due to lower target reliability and increased price ($0.1496 + 0.3344 = 0.4840$).
2. The number of battery cells in series in Method 3 increases from 112 in Method 2 to 142. As the target reliability varies, the optimal design is also affected since the advertised attributes change. In Method 3, optimization is performed considering changes in advertised attributes, cost, and market share caused by changes in the target reliability, design variables, and price, as shown in Fig. 1. In the optimal design of Method 3, if the number of battery cells in series decreases from 142 to 112, the utility of advertised performance and warranted battery lifetime is decreased by 1.1 and the cost is decreased by $3,774. As a result, market share decreases from 24.4 to 15.8%. Since this effect is worse than the reduction of cost, Method 3 therefore derives a design to increase the number of battery cells in series. That is, as the target reliability decreases, the number of battery cells in series increases even though the cost rises in order to maximize the utility of advertised performance and warranted battery lifetime. Method 3 finds a strategy to improve

Table 6 Optimal designs and outcomes obtained using three design methods

		Method 1 (RBDO)	Method 2 (RBDO + DMS)	Method 3 (RBDMS)
Decision variables	Target reliability	*99.87%*	*99.87%*	92.69%
	Warranted battery lifetime	12.1 years	3.28 years	5.63 years
	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	– $850 M ($259 M)*	$71.9 M ($46.1 M)	$77.3 M ($47.3 M)
	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	$0.11 M	$14,194	$1.1 M
Advertised attributes	Battery lifetime	12.1 years	3.28 years	5.63 years
	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 years (1.48 year)	4.92 years (0.57 year)	6.69 years (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 italics

*Standard deviations are enclosed in parentheses

advertised attributes with more battery capacity, and thus to increase the final price to maximize profit.

3. The warranted battery lifetime in Method 3 increases from 3.28 years in Method 2 to 5.63 years. With the improved battery capacity as mentioned in Observation 2, the battery in the EV design obtained using Method 3 will experience a smaller *DoD* for the same driving distance which leads to longer battery time from Eq. (6). From the increased warranted battery lifetime and as a result significantly increased warranty compensation cost, it can be said that Method 3 finds the optimum value of the warranted battery lifetime and warranty compensation cost by optimizing the target reliability.
4. It is confirmed that the optimization problem can be solved with the target reliability as a decision variable. When performed with 100 initial designs considering tradeoffs between attributes, the optimizations with 87 different initial designs converge to the same optimum design listed in Table 6 which is considered to be the global optimum.

In addition to the comparative study among Methods 1, 2, and 3, parametric studies are performed using Method 3 to see the effect of the target reliability on profit based on different types of the market. For the parametric study, three different reliability markets are considered: high reliability market (HRM), medium reliability market (MRM), and low reliability market (LRM). For example, HRM is a market in which reliability range is narrow compared with MRM and LRM, and a relatively high reliability is required in order to obtain a high reliability rating. The optimization results using Method 3 in Table 6 are based on the MRM case in which market competitors have medium reliability. Matches between customers' perceived and actual reliability are listed in Table 7. Figure 5 shows parametric study results on reliability matching in three cases of HRM, MRM, and LRM. For HRM, it can be seen that the optimum target reliability should be increased, and

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. 5 Optimal target reliability and profit in three reliability markets

profit tends to decrease due to the increased target reliability. For MRM and LRM, the optimum target reliability decreases to maximize profit since competitors' reliabilities are relatively low.

To further investigate the effect of the target reliability on profit in three reliability markets, parametric study by changing the target reliability is performed. In this parametric study, the target reliability is not considered as a decision variable but a fixed given parameter for optimization. The optimal target reliability in each market is marked with a red dot in Fig. 6 which is corresponding to the optimal target reliability in Fig. 5. In all cases, excessive increase in the target reliability has a very negative impact on profit, that is, the profit drops sharply when the target reliability increases from 98 to 100%. This shows that it is not advantageous for a company to increase the target reliability more than necessary.

From the EV design case study, it is observed that the proposed RBDMS is an effective way of finding the optimal target reliability that maximizes the company profit by integrating DMS into RBDO. Furthermore, it is also observed that the optimal target reliability varies depending on the situation of market and competitors.

6 Replication of results

The code for this paper is available at the website: (https://drive.google.com/open?id=1_O_Y0VZUe26ASa5X_qLXAwJyOLturp75).

7 Conclusion

In this study, an RBDMS framework that integrates RBDO with DMS to find the optimal target reliability by considering design variables, price, market demand, and cost at the same time is proposed and applied to EV design. The RBDMS framework successfully models how the target reliability is perceived by customers as the product reliability and reflected in the purchase. In the model, target reliability determines the advertised performances from the probabilistic performances of engineering model, and influences market demand by affecting advertised attributes and the product reliability. Therefore, the novelty of this study is to propose a methodology that suggests a way to find optimal target reliability that maximizes profit by considering how the target reliability interacts with engineering and marketing models. The proposed methodology can resolve the problem of existing RBDO yielding unprofitable results and can also solve the problem of not achieving maximum profit when RBDO and DMS are simply combined with fixed target reliability.

The advantages of RBDMS using target 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 with fixed target reliability yields a design with feasibility and marketability, RBDMS can find the optimal target reliability as a decision variable to maximize the profit while satisfying engineering constraints. EV design case study shows that the proposed RBDMS is an effective way of finding the optimal target reliability that maximizes the company profit and the optimal target reliability varies depending on the situation of market and competitors. The proposed approach can be applied to other engineering design problems such as smartphones and notebooks where battery lifetime varies greatly depending on the usage environment, and there is a large gap between real battery lifetime and advertised battery lifetime. There are several limitations in this work. Additional research should focus on measuring the reliability from the perspective of customers, release several assumptions made in this study, and reflect more fidelity in the engineering model and its uncertainties. Market uncertainty and customer preference for a targeted market which considers geographic effects, local regulations, etc. need to be considered in future research as well (Kang et al. 2018).

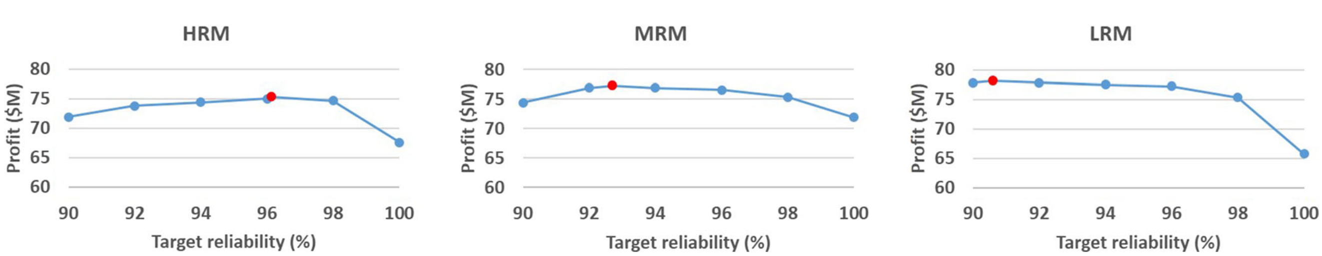

Fig. 6 Effect of target reliability on profit in three markets

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