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RELIABILITY-BASED DESIGN OPTIMIZATION (RBDO) FOR ELECTRIC VEHICLE MARKET SYSTEMS

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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. Design for market systems (DMS) approach helps decision makers to find profit-maximized product design under market heterogeneity. This paper integrates RBDO and DMS approaches for an Electric vehicle (EV) design. Consumers' preferences on warranted battery lifetime are heterogeneous while battery life itself is affected by various uncertainties such as battery characteristics and driving patterns. We optimized and compared four scenarios depending on whether engineering systems are deterministic or probabilistic, and whether a market is homogeneous or heterogeneous. The results provide some insight on how the optimal EV design should be altered depending on engineering uncertainty and market heterogeneity.

NOMENCLATURE

SoC : state of charge of battery
DoD : depth of discharge of battery
D : DoD of battery
F : additional fraction of nominal capacity
P : penalty factor for deeper DoD
A : capacity loss factor
σ : standard deviation of $(1-A)$
$\mathbf{X}$: vector of decision variables
$\mathbf{P}$: vector of random parameters
$P_{F_j}^{\mathbf{Target}}$: target probability of failure for jth engineering constraint
$P_{F_m}^{\mathbf{Target}}$: target probability of failure for market share constraint
$f_{\mathbf{X}}(\mathbf{x})$: joint probability density function
Ω_F : failure set
q : market demand
c : cost

1. INTRODUCTION

The general goal of engineering design is to maximize the functionality or utility of a system while simultaneously satisfying constraints. To enhance the functionality or utility of an objective system, deterministic optimization has been used in engineering fields, as it often provides optimal solutions at the boundary of design constraints [1]. However, the small variation of design variables and other parameters derived from many uncertainties that exist in manufacturing tolerance, such as physical properties of material and operating conditions, often lead to design failure. Nowadays, it is natural to consider the stochastic nature of engineering systems when solving optimization problems [2]. The reliability is related to the probability of a failure occurring when considering the stochasticity of the system. Therefore, the reliability-based design optimization (RBDO) maximizes functionality or utility of a system while satisfying the required target reliability level in the system, regardless of inherent uncertainties in design variables and other parameters. In general, reliability analysis and optimization are two essential parts of RBDO. Reliability analysis focuses on the probabilistic constraints to guarantee that the target reliability levels are satisfied, while optimization focuses on searching for the optimal solution.

RBDO has been widely used in various engineering fields such as aerospace engineering [3-6], civil application [7,8], composite structure [9], and mechanical engineering [10-19].

The research area of design for market systems (DMS) emerged from the objective of maximizing specific values like profit or social welfare from the perspective of manufacturer or producer [20-23]. This research

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area focuses more on selling products or services rather than optimizing functional performance. To find the optimal design of a product for the market systems, an optimization problem, which maximizes the specific profit or social welfare while satisfying engineering or other constraints, is then casted into the mathematical problem. To formulate the mathematical optimization problem, the relationships between design decisions and engineering functionality must be accompanied with economic models. The engineering functionality is derived from engineering analysis and simulations through physical models, and the economic models connect design decisions with profit or social welfare by market demand and cost of product. Quantitative market demand models are commonly utilized in the marketing field to estimate customer preferences (market demand) as a function of design attributes and price of product. Therefore, expressing the design attributes as functions of the decision variables or parameters must be preceded to plug market demand models into the product design problem. DMS has been used for electric vehicle and hybrid electric vehicle design problems [24-28].

However, existing RBDO problems did not consider market heterogeneity. Thus, the effect of various preference of customers against the decision of engineering performances could not be identified. Further, the conventional DMS research did not consider the uncertainty in engineering level, and therefore, how probabilistic engineering performances affect the company's profit could not be anticipated. Understanding the relationship between uncertainty in engineering performances and heterogeneity in market system is important. Therefore, the RBDO approach that considers uncertain and heterogeneous factors is significantly important. This paper suggests a framework of RBDO for a market system, which is especially applied to the EV market system. This framework is essential to address the uncertainties in Li-ion battery characteristics and driving characteristics of users, such as daily driving distance and driving patterns, which may produce poor actual performances or battery lifetime, which often falls behind declared values. Such failure damages the company's reputation, inconveniences the customers [29], and results in warranty cost. Since there are heterogeneous customer preferences for the designed EV in the real market, the approach suggested above is adequate to use RBDO for the EV market system.

This paper introduces the design for EV powertrain systems, a Li-ion battery, and a market system that maximizes the profit of the EV manufacturing company while assuring reliability of declared performances, warranted battery lifetime, and market share. We also compare the optimal design under four scenarios: (1) deterministic engineering model with homogeneous market; (2) probabilistic engineering model with homogeneous market; (3) deterministic engineering model with heterogeneous market; and (4) probabilistic engineering model with heterogeneous market. Through the comparison of the optimal design of these four scenarios, the decision maker can gain insight and make an educated judgement when choosing the best option.

The remainder of this paper is composed as follows. Section 2 introduces the engineering model and the uncertain factors in Li-ion battery characteristics, daily driving distance, and driving cycles of users. In Section 3, marketing model and its heterogeneity in customer product preferences are presented. Section 4 provides some assumptions of models, the decision framework, and the RBDO formulation. In Section 5, the results and a comparative discussion on the optimal design of the four scenarios is presented. Finally, Section 6 summarizes the conclusions of the study and suggests the directions for future work.

2. ENGINEERING MODEL AND UNCERTAINTY

2.1. Engineering model

To understand how uncertainties at the engineering level affect performances and battery lifetime, two models must be presented. An EV performance model that simulates vehicle performances while considering uncertainties in battery characteristics and driving characteristics for different mechanical designs, and a battery degradation model that presents the cycle life of a Li-ion battery with respect to initial battery capacity, MPGe, and daily driving distance. In this section, various research fields such as mechanical engineering and electrochemical engineering are addressed.

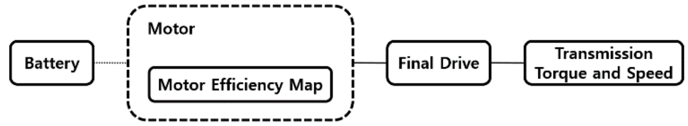

Fig. 1 EV powertrain systems with components

2.1.1. EV performance model.

The EV's 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 connecting to wheels along with a final drive. In order to simulate such a model, we utilize the specifications of EV including Li-ion battery from the Nissan Leaf for the EV model, which is listed in Table 1 [30,31]. The powertrain systems of the Nissan Leaf with powertrain components, which are presented in Fig. 1, are also used in the EV performance model. AMESIM software and other simulation models are combined to modify our analytical EV performance model [32].

In the battery pack, the cells connected in series form a branch, and several such branches are connected in parallel. The number of cells in series and parallel connections are used as decision variables. The battery capacity is determined by the variables, 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 affects the output power of the motors. In addition, the weight of the battery pack, which is proportional to the number of cells, influences the total weight of EV, and in turn affects the EV's acceleration and MPGe.

The 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 the input speed and the output speed. Larger torque is achieved from the higher ratio that in turn leads to a higher acceleration performance but with lower maximum speed, while the smaller torque is achieved from the lower ratio that in turn leads to a lower acceleration performance with higher maximum speed. The fuel economy, MPGe, is also related to the final drive ratio in terms of different energy consumptions.

2.1.2. Battery degradation model.

The battery lifetime highly depends on the daily driving distance, and in order to reflect the various daily driving distance of users, the battery degradation model takes crucial part in this study. Because of cycling, the Li-ion battery capacity decreases due to increased cell impedance caused by solid-electrolyte interface (SEI) growth, loss of accessible lithium ions, and degradation of electrical parts [29,33]. State of charge (SoC) is the amount of useful remaining charge compared to its initial fully charged state:

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

Table 2 Characteristics of standard driving cycles

Statistics	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

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

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

$$\mathbf{DoD} = \mathbf{SoC}_{\boldsymbol{initial}} - \mathbf{SoC}_{\boldsymbol{final}} \tag{2}$$

The capacity fade is related to the number of cycles and the DoD that the battery experienced [34]. Generally, the EV battery should be replaced when the capacity decreased to 80 % of its initial capacity [28]. The cycle life, which resulted from the capacity fades with regards to DoD that the battery experienced, has been theoretically and experimentally presented by Thaller [35] as

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

where D is the DoD of the battery, F is the additional fraction of the nominal capacity, P is the penalty factor for the deeper DoD, A is the capacity loss factor, and σ is the standard deviation of $(1 - A)$. The distribution of capacity loss factor has its origin in the connection between cells. In this study, the battery life is considered as the cycle life on the assumptions that the individual drives every day and the 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 the specific battery chemistry, temperature, c-rate, and storage conditions, these factors are ignored in this paper.

In this battery degradation model, the DoD is calculated using the initial battery capacity and the driving distance. By utilizing MPGe, which is predetermined at 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, the DoD is determined by Eqs. (1) and (2).

2.2. Engineering uncertainty

2.2.1. Battery capacity, voltage, and weight. A 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]. Because of the Li-ion battery's hypersensitivity to uncertainties, the uniformity at the component level is highly required [39]. However, there exist some deviations of material and physical properties between cells, which is caused during the manufacturing process [38]. Dubarry et al. [40] conducted an experiment with statistical and electrochemical analysis on 100 $\mathbf{LiCoO_2}$ Li-ion battery cells using an equivalent circuit model and displayed the distributions of capacity, open circuit voltage, and weight of cells. The uncertain cell properties, e.g., solid particle size and porosity, may lead to variations in cell characteristics [41]. The distributions of these uncertainties are adapted to our engineering model: the mean and the standard deviation of cell capacity is 33.1 Ah and 0.5 Ah; the mean and the standard deviation of cell voltage is 3.8 V and 0.02 V; and the mean and the standard deviation of cell weight is 0.7864 kg and 0.0149 kg.

2.2.2. Driving distance. The DoD of the battery used is directly related to the daily driving distance because the DoD differs with the energy consumptions, although it has the same battery capacity [29]. For example, an EV with a battery capacity of 80 miles will experience 100 % DoD for driving 80 miles, while the same EV will experience only 50 % DoD for driving 40 miles.

To deal with the uncertainty of the daily driving distance of users, we used the daily vehicle miles of travel (VMT) data of the 2009 national household travel survey (NHTS) [42]. The daily trip level data for 150,147 households are contained in the NHTS dataset, which are obtained through surveys. After post processing, only the data of cars, station wagons, SUVs, and trucks that traveled more than 10 miles are included in the dataset and the average daily VMT is found to be 34.4 miles.

To determine the actual lifetime of the battery, Eq. (3) are integrated over the distribution of DoD for 5 years, which originates from random sampling of the daily VMT data.

2.2.3. Driving cycle. Various driving patterns affect the 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 the fuel consumption of vehicles in US environment protection agency (EPA). Likewise, in order to reflect the real driving pattern into the engineering model, the representative standard driving cycles provided by EPA are applied when calculating the driving range: the urban dynamometer driving schedule (UDDS) represents driving conditions in the city for light duty vehicles with characteristics of low speed; the New York city cycle (NYCC) represents frequent stop-and-go traffic conditions with low speed; LA92 represents aggressive driving with high speed in city conditions; the highway fuel economy test (HWFET) are driving conditions on a highway under 60 mph; and the US06 represents an aggressive driving pattern, which involves high acceleration and extreme engine loads. The characteristics of standard driving cycles are presented in Table 2 [44]. Since the combination of distinct types of driving cycles are frequent and natural in actual driving conditions, an average driving range, which is calculated from five random standard driving cycles with the given input variables, is used as the driving range of the designed vehicle in this paper.

3. MARKETING MODEL AND HETEROGENEITY

A marketing model estimates market demand by predicting consumer purchase decisions or consumer preferences toward the designed product's characteristics and price. In this section, explanations of estimating the market demand from consumer preference and heterogeneity, which influences the final optimal design and profit of the company, are presented.

3.1. Marketing model

In market systems, the product design problem can be formulated as a mathematical optimization problem, which maximizes the profit while satisfying various constraints. The mathematical optimization problem contains an economic model, which has its base on the market demand and cost of the product.

To express the demand of the customer as a function of attributes, the characteristics of the product assessed by the customer, representing the design attributes with respect to decision variables must be preceded. As the designer or company decide the decision variables, the product attributes are determined or calculated through simulation. Therefore, the values of the designed product perceived by the customer are also determined, which results in choice probability (market share). Then, the market demand is calculated as the product of market share and market potential (market size).

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

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

where $\boldsymbol{\beta}_{ikl}$ are the part-worths of level l of attribute k for individual i, and z_{jkl} is the binary dummy number, which is equal to 1 if the level l of attribute k is chosen for alternative j and 0 otherwise. For the given utilities of competing products, the market share is calculated as

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

which is similar to the probability of individual i choosing option j from a set of alternatives J. By using the part-worths data of an 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 the potential market size s. Accordingly, the predicted profit is defined as the product of the market demand and margin, which is the price after unit production cost and warranty cost. In this paper, the fixed cost for an electric vehicle body and battery cost, which is decided by the number of battery cells in series and parallel, are included in the unit production cost.

The data needed for the market share estimation above can be obtained from sales data of existing markets, which reveal customer responses or questionnaires answered by customers. The method of using questionnaires is more general and suitable for studying customer preferences toward the new product concept 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 displayed to the respondent. The respondent then chooses the most preferred design. If there are no satisfactory designs, the respondent may choose none of the options.

Table 3 Attribute levels

	Level			
Attributes	1	2	3	4
Warranted battery lifetime	3 year	7 year	11 year	15 year
MPGe	90	100	110	120
Top speed	70 mph	90 mph	110 mph	130 mph
0 to 60 (acceleration)	6 sec	8 sec	10 sec	12 sec
Range	80 mi	130 mi	180 mi	230 mi
Price	\$15,000	\$25,000	\$35,000	\$45,000

To obtain individual-level posterior part-worth distribution, the actual respondent results collected from the choice-based conjoint (CBC) study and prior characteristic of the type of consumer are then used. The estimation of individual part-worths can be performed by either hierarchical Bayes estimation [45-47], and the details are provided in the following section.

3.2. Market heterogeneity

Since there are various customer preferences toward attributes of the product, the part-worths for similar attributes are different. Hierarchical Bayesian (HB) approach and CBC analysis are used to build a heterogeneous market in this paper. Based on the results of the survey conducted using Mturk [48], which was targeted for the US, the individual-level part-worth distribution is derived. Responses were drawn from 249 subjects living in the US: 49 % were male and 51 % were female; 13 % were 15 to 24 years of age, 41 % were 25 to 34 years of age, 24 % were 35 to 44 years of age, 13 % were 45 to 54 years of age, and 9 % were 55 to 64 years of age.

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

The result of optimization can explain a heterogeneous market since an individual-level market demand, sP_{ij}, is used for calculating profit in system-level optimization. The average profit of all individual market scenarios can then be used as the objective.

Though the achieved part-worth coefficients are discrete, interpolation of the intermediate attributes values using a nature cubic spline enables individual-level utility models to cope with continuous attributes. The resulted part-worths distributions are shown in Fig. 2 with the value of part-worth (beta) on the y-axis. The wide variance of part-worths with high and low prices clearly demonstrates that heterogeneous preferences should be considered for market system design.

4. RBDO FOR MARKET SYSTEMS

From the decision variables provided, the performances of EV and the warranted battery lifetime can be determined; thus, the utility of the product can be calculated by the part-worths drawn from the results of the survey. The final product then competes against other conventional EVs, and the market share can be estimated from the result of choice probability. Once the predicted market demand is derived from the market share and market size, the profit of the manufacturing company will be the product of market demand and margin, which subtracts manufacturing cost and warranty cost from the price. To estimate feasible range of decision variables, extensive simulation with a set of constraint functions and specifications of EV in the real world are included. The range of decision variables are listed in Table 4.

Table 4 Decision variables

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

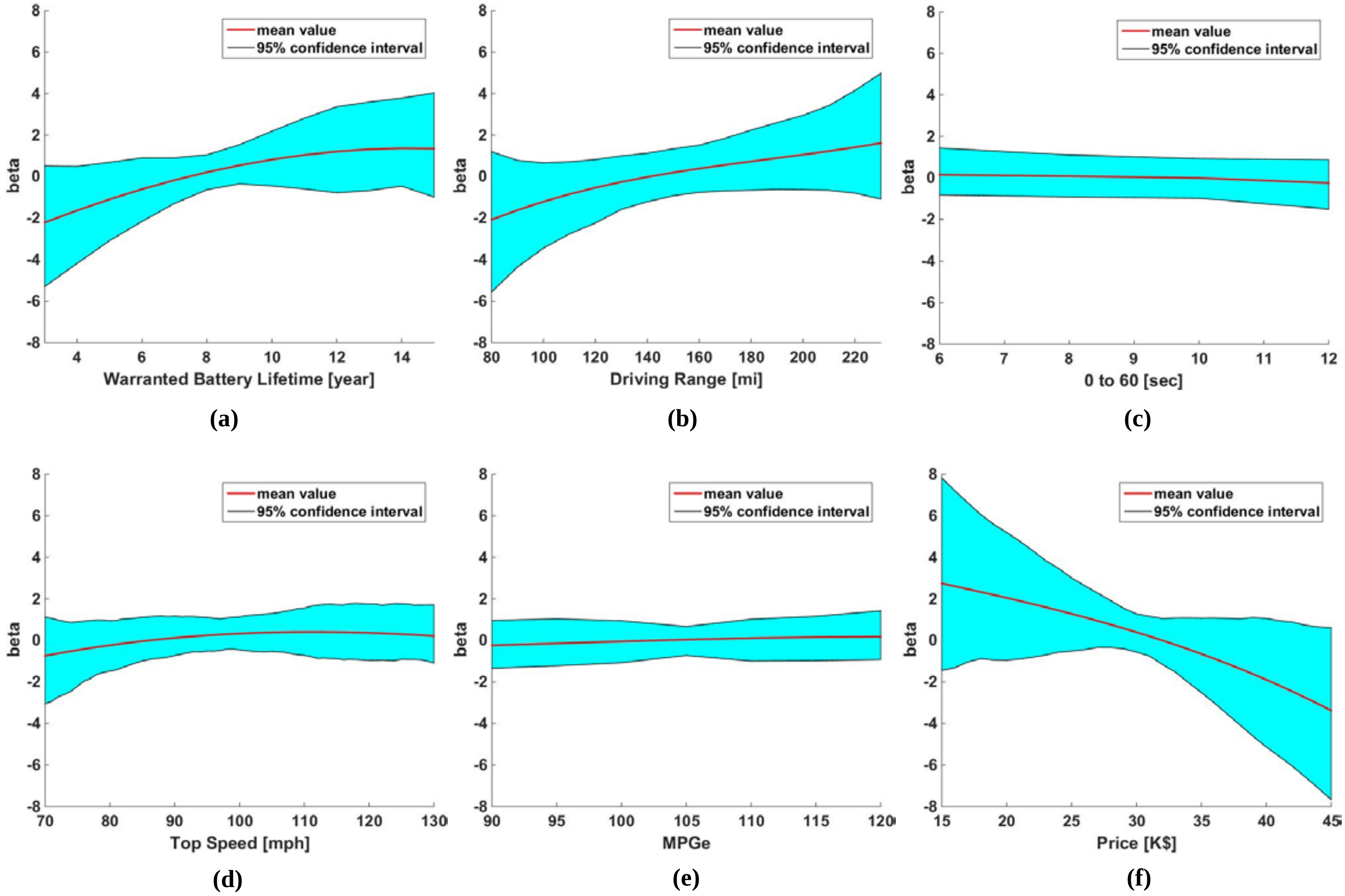

Fig. 2 Mean and 95 % confidence interval of the part-worths distributions for: (a) warranted battery lifetime; (b) driving range; (c) 0 to 60; (d) top speed; (e) MPGe; (f) price

4.1. MODELING ASSUMPTION

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

- The integrated model, which embraces both the engineering and marketing model, assumes that the size of the battery pack is changeable. Further, the EV manufacture company determines the designs of powertrain and battery, warranted battery lifetime, and selling price, which are designated as decision variables.
- In computing the market share in the market system model, two competitors were used: 2017 Nissan Leaf and 2017 Chevrolet Bolt. They are competitive in terms of reasonable price and good performance, which have possibility to take high market shares. The part-worths of their MPGe, range, 0 to 60 mph, top speed, warranted battery lifetime, and price determines the utilities of the competitors, which affect market share whileEV market size of US is used to determine the market demand.
- In deterministic engineering model, the mean of cell capacity, cell voltage, cell weight, daily driving distance, and driving cycles are used to solve the optimization problem. Further, the mean of part-worths are utilized in homogeneous marketing model.
- In order to satisfy the minimum performances of EV to drive in the real world, constraints are applied for performances of EV to all scenarios: driving range should be more than 80 miles; 0 to 60 mph should be smaller than 12 s; and top speed should be more than 70 mph.

4.2. FOUR MARKET SCENARIOS

To investigate the influence of uncertain and heterogeneous factors in the EV market systems, four different scenarios are examined (shown in Fig. 3): scenario 1 is deterministic optimization with no uncertain and heterogeneous factors; in scenario 2, the market is homogeneous, but the uncertainties in the engineering level are considered; in scenario 3, uncertain factors in the engineering level are not considered, instead a heterogeneous market is considered; and in scenario 4, all the uncertainties in the engineering level and heterogeneity in the market system level are considered. The following section explains the formulation of RBDO for scenario 4.

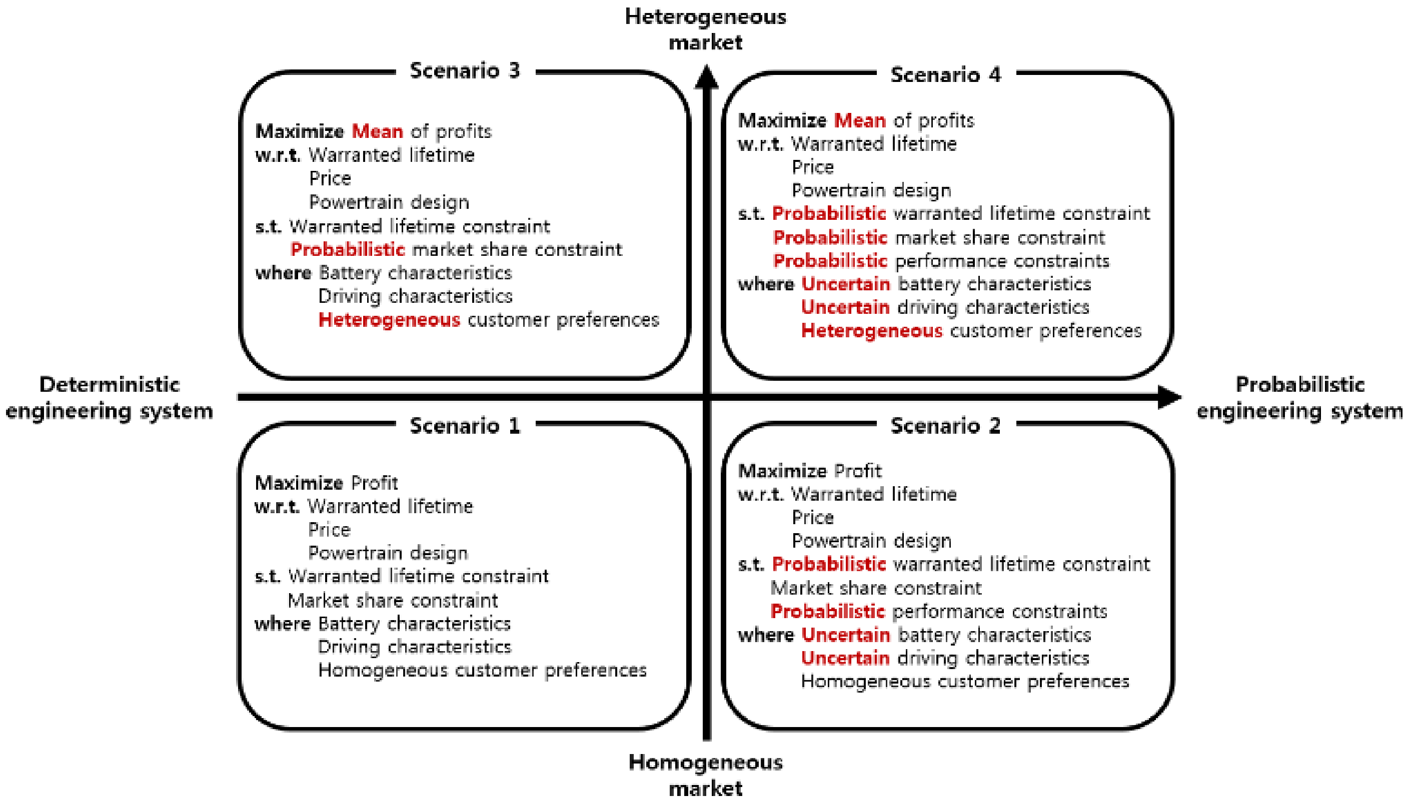

Fig. 3 Four scenarios for decision making

4.3. RBDO FORMULATION

A general expression of the RBDO problem is applied [49] to scenario 4, where powertrain design (battery and gear) and the market system considers all the engineering uncertainties and market heterogeneity, which maximizes the mean of profit and satisfies the required level of reliability in both declared performance and market share. In this scenario, the RBDO can be formulated to

$$\text{Maximize} \quad \mu(Profit(\mathbf{X},\mathbf{P})) \tag{6}$$

subject to

$$P[G_j(\mathbf{X},\mathbf{P})>0] \le P_{F_j}^{\mathbf{Target}}, \qquad j=1,\cdots,n_c \tag{7}$$

$$P[G_m(\mathbf{X},\mathbf{P})>0] \le P_{F_m}^{\mathbf{Target}} \tag{8}$$

$$\mathbf{X}^{\mathrm{L}} \le \mathbf{X} \le \mathbf{X}^{\mathrm{U}},\ \mathbf{X}\in\mathbf{R}^{n_d},\ \ \mathbf{P}\in\mathbf{R}^{n_{rp}} \tag{9}$$

where $\mathbf{X}=\{X_i\},\ i=1\sim n_d$ is the deterministic decision variable vector; $\mu(\cdot)$ is the mean value; $P[\cdot]$ is the probability measure; $\mathbf{P}=\left\{P_1,P_2,\cdots,P_{n_{rp}}\right\}$ denotes the vector of random parameter; $P_{F_j}^{\mathbf{Target}}$ is the target probability of failure for jth performance constraint; $P_{F_m}^{\mathbf{Target}}$ is the target probability of failure for market share constraint; and n_c, n_d and n_{rp} are the number of probabilistic engineering constraints, decision variables, and random parameters, respectively. From the market demand which can be expressed as $q(\mathbf{X},\mathbf{P})$, the profit can be stated as

$$Profit = q(\mathbf{X},\mathbf{P})(price - c(\mathbf{X})) \tag{10}$$

where $c(\mathbf{X})$ is the sum of the manufacturing cost and warranty cost.

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

$$P_F = P[G(\mathbf{X})>0] = \int_{\Omega_F} f_{\mathbf{X}}(\mathbf{x})\,\mathrm{d}\mathbf{x} \tag{11}$$

where $f_{\mathbf{X}}(\mathbf{x})$ represents the joint probability density function; and Ω_F is the failure set defined as $\{\mathbf{x}:\ G(\mathbf{X})>0\}$. The integral calculation in Eq. (1) is difficult to perform because the integration domain Ω_F is usually unknown, and multidimensional integration is difficult or almost impossible.

The general reliability analysis methods are statistical sampling or simulation such as Monte Carlo simulation (MCS), and most probable point based methods including the first order reliability method and the second order reliability method. In this study, the Monte Carlo simulation was used to perform the reliability analysis of the probabilistic design problem because the MCS method is accurate even with a large sample size, robust, and easy to perform. Randomly generated samples from the statistical distributions or data distributions of random variables are used in the Monte Carlo simulation.

The probability of failure can be calculated from the statistics of the sample simulation. In the above probabilistic design problem, the probability of failure is regarded as the ratio of the number of samples that do not satisfy the declared EV performances or warranted battery lifetime. From the EV survey results, 64 % of its actual performance is expected to satisfy the declared performance and 67 % of the actual batteries' lifetime are expected to satisfy the warranted battery lifetime. Therefore, the target probability of failure for the EV performances and the warranted battery lifetime are 36 % and 33 %, respectively (further parametric study will be provided). Among all produced vehicles, less than 36% of them show lower performances than declared values, and less than 33 % of them show a lower actual battery lifetime than the warranted battery lifetime, regardless of any condition.

In the case of the heterogeneous marketing model, market share distribution exists due to various customer preferences. Therefore, the market share constraint should contain probability: the final design ensures markets to take more than 28 % market share, the EV market share of Tesla Model S, which is the second largest in US [50], with 60 % reliability (arbitrary value, further parametric study will be provided).

For the probabilistic engineering model, many samples are needed to find the EV performances or the warranted battery lifetime that needs to be declared. This is so that the specific percentage of the actual performances or the battery lifetime of EVs can satisfy the declared value. Each sample stands for various performances and battery lifetime for the same EV powertrain systems and Li- ion battery design. After performing pretest with a variety of sample sizes, 500 samples are used because this number provides relatively fair reliability while still being practically reasonable.

The information flow of RBDO for EV market systems with all the uncertain and heterogeneous factors from the view point of the manufacturer is illustrated in Fig. 4.

5. RESULTS AND DISCUSSION

This section compares the results of the four scenarios: (1) Deterministic engineering model with homogeneous market; (2) probabilistic engineering model with homogeneous market; (3) deterministic engineering model with heterogeneous market; and (4) probabilistic engineering model with heterogeneous market. The probability of failure for EV performances and warranted battery lifetime is calculated using MCS with a million samples at the optimum design. Probabilistic market share constraint is also applied in the heterogeneous marketing model.

In all four scenarios, we vary the number of battery cells in parallel with respect to discrete variables, we regard the number of battery cells in series as continuous variables, and solve the continuous optimization problem using sequential quadratic programming with multiple initial points. The optimal values of the number of battery cells in series is then rounded to a discrete value. The computation requires 17 h on average using a standard desktop (Intel i7 6900 CPU @ 3.20 GHz and 64.0 GB RAM).

Table 5 summarizes the optimal design and outcomes of four scenarios. For scenarios 3 and 4, market share has distribution because various customer preferences exist in the heterogeneous marketing model. The mean and standard deviation of the market share is shown in the table. For the probabilistic engineering model in scenarios 2 and 4, the mean and standard deviation of actual battery lifetime and real performance are also provided in the table. For a comparison between homogenous and heterogeneous market scenarios, through post-analysis, we calculated both the deterministic profits and market shares for the optimal decisions in heterogeneous scenarios as well as the probabilistic profits and market shares for the optimal decisions in heterogeneous scenarios (see bold and italic values in Table 5). The declared performance is the performance that customers see when purchasing EVs, and the actual performance are the results affected by engineering uncertainties.

Several observations on the results of optimization are as follows.

First, the company's profit decreases when the uncertain factors in the engineering model are considered. The probabilistic engineering model should sacrifice or lower the warranted battery lifetime and declared performances to secure its reliability. Therefore, it can be verified that the warranted battery lifetime and declared performances of probabilistic engineering model fall behind the mean of actual battery lifetime and real performances.

When comparing scenarios 1 and 2, it is found that the battery capacity in the optimum design of scenario 2 is much higher as the battery lifetime indicates in the actual performance. The ranges are slightly different and

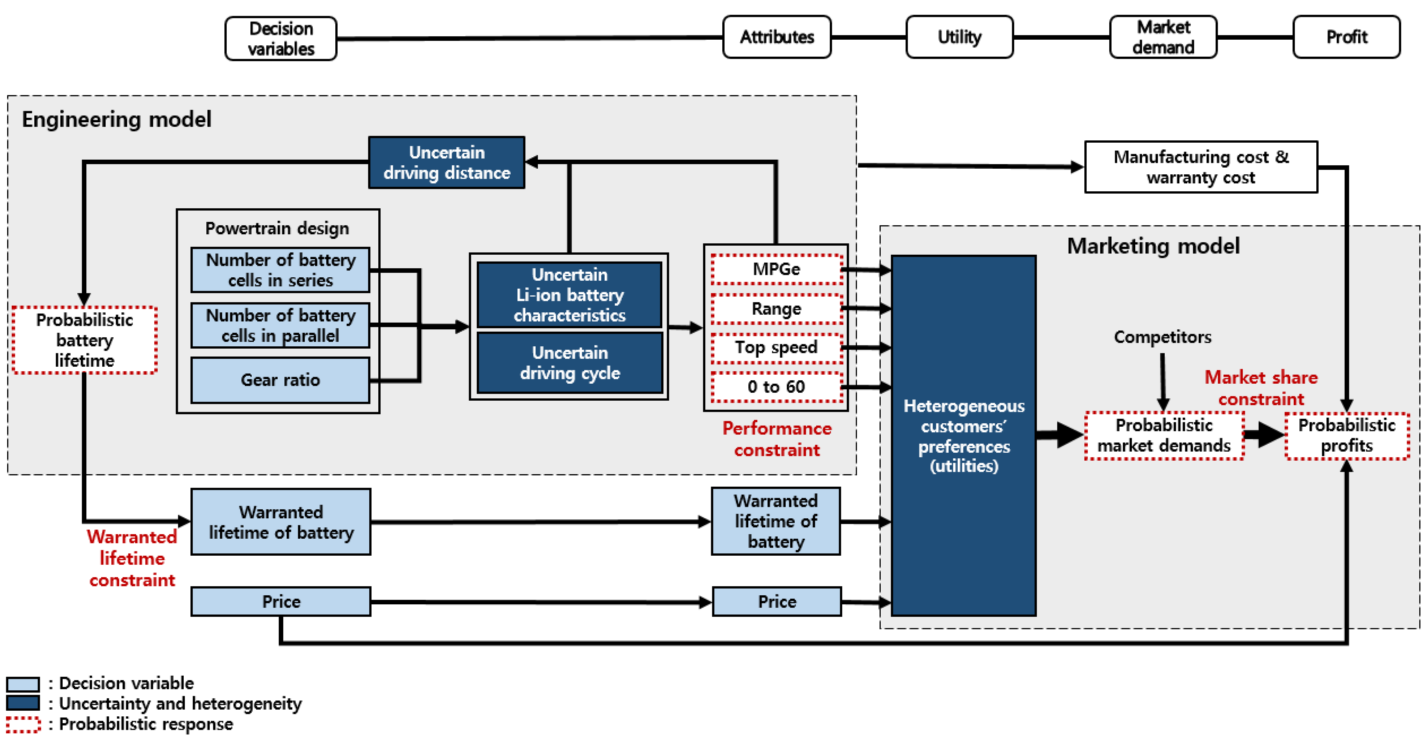

Fig. 4 Information flow of RBDO for EV market systems

Table 5 Optimal design and outcomes of four scenarios

		Scenario 1	Scenario 2	Scenario 3	Scenario 4
Decision variable	Warranted battery lifetime	9.0 year	8.9 year	9.4 year	9.2 year
	Price	$36,161	$36,548	$35,312	$35,330
	Number of battery cells in series	186	191	195	197
	Number of battery cells in parallel	2	2	2	2
	Gear ratio	8.7	8.7	8.7	8.7
Profit	Homogeneous market	$284M	$262M	***$260M***	***$243M***
	Heterogeneous market	***$270M***[*] ***($221M)***[**]	***$259M*** ***($215M)***	$227M ($169M)	$220M ($163M)
Market share	Homogeneous market	37.6 %	36.0 %	***48.7 %***	***47.9 %***
	Heterogeneous market	***35.8 %*** ***(29.3 %)***	***35.6 %*** ***(29.5 %)***	42.6 % (31.7 %)	43.2 % (32.1 %)
Declared performance	Battery lifetime	9.0 year	8.9 year	9.4 year	9.2 year
	MPGe	114.6	111.9	114.1	111.5
	Range	159.9 mi	160.6 mi	165.8 mi	165.1 mi
	0 to 60	6.6 sec	6.5 sec	6.4 sec	6.4 sec
	Top speed	100 mph	100 mph	100 mph	100 mph
Actual performance	Battery lifetime	9.0 year	9.33 year (0.97 year)	9.4 year	9.65 year (0.99 year)
	MPGe	114.6	114.45 (5.85)	114.1	114.08 (5.81)
	Range	159.9 mi	164.29 mi (8.56 mi)	165.8 mi	168.91 mi (8.79 mi)
	0 to 60	6.6 sec	6.49 sec (0.036 sec)	6.4 sec	6.34 sec (0.035 sec)
	Top speed	100 mph	100 mph (0 mph)	100 mph	100 mph (0 mph)

[*] Calculated from post-analysis for comparison between scenarios.
[**] Standard deviation is shown in parenthesis

the warranted battery lifetime of scenario 1 is even smaller than of scenario 2. Further, despite the higher selling price in the optimum design of scenario 2, due to the higher production cost for the larger battery size and the lower market share, the profit was lower when compared to scenario 1.

Some engineering mechanisms support the comparison between outcomes of deterministic and probabilistic engineering model. 0 to 60 is improved in probabilistic engineering model because the acceleration tends to improve as the voltage of the battery increases. The deterioration of MPGe can be explained by an increase in battery cell weight. Top speed shows no change because it is insensitive to the voltage of the battery when the number of battery cells in series exceeds a certain threshold.

Second, in the heterogeneous marketing model, the performances and warranted battery lifetime should be enhanced, and price should be decreased to achieve a certain degree of fair market share regardless of various customer preferences. By comparing scenarios 1 and 3, and scenarios 2 and 4, we can verify that the number of battery cells in series is larger on the heterogeneous marketing model, which resulted in enhanced engineering performances and warranted battery lifetime. The price decrease is also advantageous in terms of small part-worths variation, which is shown in Fig. 2(f).

Lastly, market heterogeneity and increasing the reliability of market share deteriorates the company's profit. To ensure the reliability of market share when heterogeneity of market systems is considered, the product should be designed to be more beneficial for the customers, which can be a damage to the company. In the profit and market share results of the heterogeneous market, the mean market share in scenarios 3 and 4 are higher than those of scenarios 1 and 2. In securing the reliability of the market share, scenarios 3 and 4 displayed a lower mean profit.

When excluding the market share constraint in scenario 4, the optimization result shows that only 35 % of the markets can have more than 28 % market share constraint. Negative mean profit is drawn when the required reliability for 28 % market share constraint is over 65 %. This result means that no design can satisfy 28 % of market share with 65 % reliability due to the presence of severe heterogeneity in the market.

Further, note that the probabilistic market share constraint in scenarios 1 and 2 is not active, and it does not affect the optimization result because the resulted market share is higher than the constraint.

Regarding the results of our target, scenario 4, probabilistic engineering constraints and probabilistic market share constraint should be satisfied at the same time. We can see that when the probabilistic market share constraint is active, 59.4 % of markets occupy more than 28 % market share, which is presented in Fig. 5.

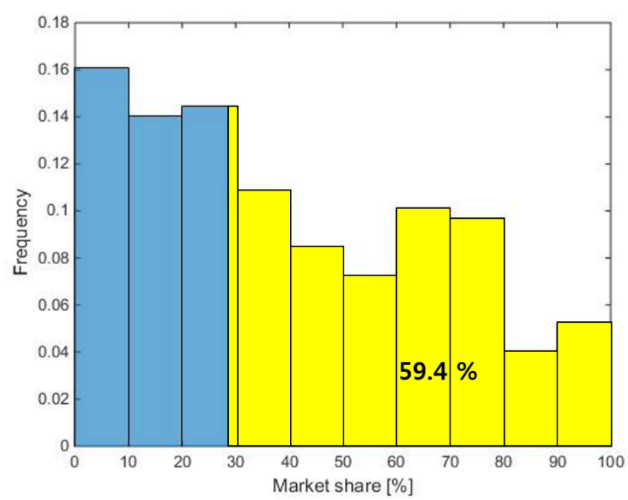

Fig. 5 Market share distribution for result of scenario 4

Table 6 Monte Carlo simulation results

	$P_F^{\mathbf{Target}}$	MCS (1,000,000)	
		Scenario 2	Scenario 4
MPGe	36 %	36 %	36.1 %
Range	36 %	38.18 %	37.33 %
0 to 60	36 %	36.82 %	36.09 %
Warranted battery lifetime	33 %	33.97 %	33.64 %

The probability of failure for warranted battery lifetime and performance, except for top speed, are presented in Table 6. Top speed shows no variations because the uncertainties in the engineering level do not significantly affect top speed. The results show that the probability of failure is close to the target probability of failure, and these can be enhanced by increasing the number of samples.

In summary, the reliability of the declared values is secured and the probabilistic market share constraint is satisfied under uncertainties in the engineering model and heterogeneity in the marketing model.

The same concept of the research presented can be applied to other problems. For example, the Volkswagen emissions scandal raised the problem that the emissions can vary, can be prone to exceed legal emission limits under real world driving conditions, and the fine may lower the profit of the vehicle manufacturing company. In a comparable way suggested in this paper, the company can maximize the profit while satisfying emission constraint regardless of any driving conditions.

6. CONCLUSION

The presented work enables the manufacturer to achieve maximum profit while securing some extent of reliability on engineering performances and market share despite the uncertain factors in engineering level, which interact with the heterogeneous factors in the market system level.

One of the main contributions of this research is that we introduced the integrated RBDO problem considering uncertainties and heterogeneities in both engineering and market system levels. The research can be considered a stepping stone for RBDO problems within various fields. Other contribution is the suggestion of a design methodology that can satisfy both the manufacturer and the customers with its optimization result. The manufacturer can achieve maximum profit and fair market share, while the customer can have a product with reasonable reliability of performances. Therefore, customers do not have to suffer from using faulty or defective product regardless of any usage conditions.

Future work should revise some assumptions and reflect more fidelity on engineering model and its uncertainties. Parametric study and sensitivity analysis should also be added.

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