Proceedings of the ASME 2025
International Design Engineering Technical Conferences and
Computers and Information in Engineering Conference
IDETC-CIE2025
August 17-20, 2025, Anaheim, CA

DETC2025-168970

AN EV POWERTRAIN PARAMETER DESIGN FRAMEWORK SUPPORTED BY MARKET SYSTEM SIMULATION AND RELIABILITY-BASED OPTIMIZATION

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ABSTRACT

The selection of powertrain system parameters (e.g., number of battery cells, battery capacity) is critical to the market success of electric vehicles (EVs) as these parameters directly determine the key performance metrics such as the speed and range of an EV, and also greatly affect user experience and manufacturing cost. Automakers need advanced design methods to select optimal powertrain system parameters for gaining higher market dominance. Traditional deterministic design methods often ignore uncertainties in product's engineering attributes as well as market dynamics, limiting their application in real-world use scenarios. To address this gap, we propose an integrated design framework for EV powertrain parameter selection under uncertainty supported by market system simulation and reliability-based optimization. Specifically, we first develop an engineering simulation model to accurately predict vehicle performance metrics with fundamental EV powertrain parameters as input. Then, an Agent-based Model (ABM) is designed to simulate consumers' behaviors in auto market, which can translate consumers' preferences and related market factors (e.g., fluctuations of energy price, entry of new consumers, change of incentive policies) into predicted market share in a dynamic way. A Reliability-Based Design Optimization (RBDO) mechanism is adopted to generate optimal EV powertrain parameters by considering uncertainties in battery performance, consumer usage patterns and driving cycle fluctuations. To validate the proposed framework, a case study is conducted by using real consumer data collected from Shanghai, China. The results demonstrate that the proposed framework achieves superior robustness compared to other ablation methods, highlighting the importance of accounting for both engineering uncertainties and market dynamics.

Keywords: Design optimization, Market system simulation, Reliability-based optimization, Electric vehicle.

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1. INTRODUCTION

With the increasing global emphasis on sustainable transportation, electric vehicles (EVs) have become a central focus in automotive industry. Optimal EV design for both higher engineering performance and market success remains a challenge for many automakers. Particularly, the selection of powertrain system parameters (e.g., number of battery cells, battery capacity as shown in Figure 1) plays a fundamental role in the design process of an electric vehicle. These parameters directly influence the key performance of an EV such as speed and range, and are also closely related to user experience and manufacturing cost. Traditional design approaches primarily focus on improving energy efficiency and reducing manufacturing costs, often neglecting the complexity of consumer behaviors and market dynamics [1, 2]. As a result, engineering advancements do not necessarily lead to higher market adoption or profitability. It is essential to develop a powertrain parameter design framework that considers engineering feasibility and dynamic market acceptance jointly.

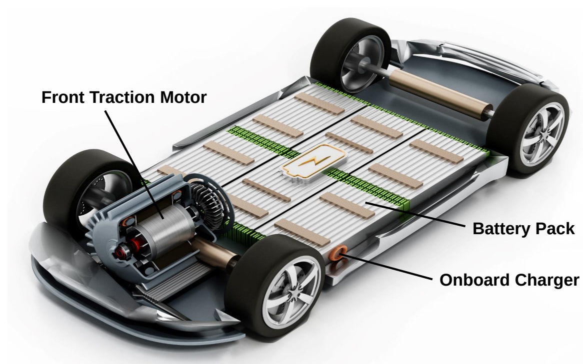

FIGURE 1: THE POWERTRAIN SYSTEM OF AN ELECTRIC VEHICLE

To address this gap, we propose an integrated design framework for EV powertrain parameter selection supported by market system simulation and reliability-based optimization. Specifically, we build an engineering simulation model to translate fundamental powertrain design variables into vehicle attributes that consumers can perceive. To enhance the computational efficiency, a surrogate model is developed to approximate the engineering simulation model, reducing the computational burden of high-fidelity simulations . Then, a market system simulation model is designed by using the Agent-Based Modeling (ABM) technique to capture heterogeneous consumer behaviors, and the impact of social influence and policy incentives to estimate market share more accurately. The Reliability-Based Design Optimization (RBDO) mechanism is eventually adopted to ensure the design robustness under uncertainties such as manufacturing tolerances and material variations. By coupling these models, our framework aims to achieve higher-level market-aware engineering design optimization, ensuring that technical improvements align more closely with consumer preferences and market dynamics. To evaluate the proposed framework, a case study is conducted by using real consumer survey data collected from Shanghai, China. The results demonstrate the effectiveness of our framework and highlight the significant contributions of market system simulation and reliability-based optimization, reinforcing the necessity of integrating both engineering uncertainties and market dynamics in EV design optimization.

The remainder of the paper is structured as follows: Section 2 reviews related work on EV powertrain parameter design and design for market systems in EV design. Section 3 presents the proposed framework, detailing the engineering simulation model, market system simulation model, and the optimization formulation. Section 4 introduces a case study using real-world data to validate the proposed framework and shows the comparison results. Section 5 concludes the study and discusses potential future research directions.

2. RELATED WORKS

2.1. Design of EV Powertrain Parameters

Optimizing the powertrain parameters is a critical aspect of EV design. Previous research has explored various configurations of battery capacity, gear ratio, and battery arrangements (i.e., parallel and series means) to enhance vehicle performance. Traditional studies focused on improving the energy efficiency, maximizing driving range, and optimizing power delivery [3]. Empirical equations and physics-based models are developed to estimate performance metrics such as horsepower and energy consumption [4]. For example, Adegbohun et al. [5] proposed a high-performance Simulink-based EV powertrain modeling approach to simulate and validate real-world vehicle systems, emphasizing reliability and performance metrics like horsepower and energy consumption. More recent approaches integrate optimization algorithms to systematically determine the best powertrain configurations [6]. For example, Dinç and Otkur [7] proposed a genetic algorithm-based design method, in which battery size and gear ratio were optimized to maximize the range and minimize the acceleration time for battery electric vehicles (BEVs). However, these methods often neglect the broader competitive market context. Additionally, existing models often assume static consumer preferences, ignoring how demand shifts due to emerging technologies and regulatory changes [8]. These limitations highlight the need for a more comprehensive framework that integrates powertrain design optimization with market dynamics considerations.

2.2. Design for Market Systems in EV Design

Design for market systems (DMS) seeks to optimize engineering design by incorporating the influence of consumer behaviors and market dynamics. The Decision-based Design (DBD) framework treats engineering design as a decision-making process aimed at maximizing objectives such as product profit, and has been widely employed to support design for market systems [9]. Within the DBD framework, Discrete Choice Analysis (DCA) is often used as a demand modeling technique to estimate consumer preferences and predict purchase decisions [10]. Studies applying DCA in vehicle design typically model consumer preferences using multinomial logit or nested logit models, predicting market demand based on price, range, and charging convenience [4]. For example, Tal et al. [11] proposed a multinomial logit model to quantify consumer preferences for battery electric vehicles (BEVs), incorporating factors like income, gender, and policy incentives. Ling et al. [12] proposed a stated preference survey with a multinomial logit model to predict EV purchase decisions based on consumer's gender and income. While DCA provides valuable insights, it generally assumes static decision-making processes and does not capture how consumer preferences evolve over time or under social influence [13]. Many studies often assume perfect information about competitor strategies and consumer preferences, which limits their practical applicability [14].

Recent research has sought to enhance DBD by integrating market simulation methods such as agent-based modeling (ABM), which can simulate individual consumer behavior in dynamic market environments. Compared to traditional aggregated choice models, ABM can explicitly model individual behaviors and represent complex interactions of stakeholders in auto market, including consumers, auto firms, regulatory agencies as well as the influence of external factors such as policy changes and technological advancements [15]. Some studies have implemented ABM to model EV adoption patterns, showing how social networks and infrastructure developments influence purchasing decisions [16]. For example, van der Kam et al. [17] proposed an agent-based model to simulate EV charging behavior and study the impact of social influence and environmental self-identity on EV adoption rates.

However, these market prediction models often overlook uncertainties in engineering design. Manufacturing tolerances, material inconsistencies, and electrochemical heterogeneity introduce deviations in battery configurations and powertrain parameters, where even minor variations can significantly impact power output, energy efficiency, and driving range [18]. Consumers' usage patterns, such as differences in daily driving distances, charging behaviors, and load conditions, can also result in substantial variations in battery degradation rates, with studies indicating that variations in Depth-of-Discharge (DoD) profiles can shift battery lifespan predictions by up to 0.2, making deterministic lifespan estimates unreliable [19]. Driving cycle fluctuations, where standardized test cycles like UDDS and HWFET fail to capture real-world conditions such as traffic congestion, frequent stops, acceleration profiles, and seasonal temperature variations, can introduce uncertainty into energy consumption and performance predictions [20]. All of these uncertainties can erode consumers' trust and affect market acceptance if not well addressed in design.

To address engineering-level uncertainties and enhance the reliability of electric vehicle performance, significant progress has been made in the field of engineering design. Method such as Reliability-Based Design Optimization (RBDO) has been developed to ensure the reliability of key components design of electric vehicles like battery and electric motors. For instance, RBDO has been applied in optimizing additive manufacturing processes for EV lithium battery silicon anodes [21], reducing performance failure and maximizing the specific energy of lithium-ion batteries by considering manufacturing uncertainties of porous electrodes [22], and in the reliability-based optimal design and tolerancing for complex multibody systems in automotive and aerospace areas [23].

More recently, researchers have explored to connect these methods about reliable design with how products actually sell in the market. For example, Lee et al [24] integrated RBDO and design for market systems (DMS) for an EV design. However, the market model they adopted is macroscopic, and often struggles to fully reflect individual consumer differences (such as varying purchasing preferences or different sensitivities to product reliability), the mutual influences among consumers (like word-of-mouth or social network effects), and how these micro-interactions collectively act and give rise to overall market trends.

In summary, structured design approaches for integrating engineering optimization with market dynamics have emerged. However, existing studies often fail to comprehensively capture the complexity of competitive interactions, evolving consumer behaviors, and technological uncertainties. The need remains for an integrated framework that combines powertrain optimization with dynamic market-driven decision-making while accounting for real-world uncertainties.

3. METHODOLOGY

3.1. Overall Structure

In this study, we propose an integrated design framework to optimize the engineering variables of EV powertrain system for maximizing corporate profit by considering both market dynamics and engineering uncertainties. As shown in Figure 2, the proposed framework consists of three models: an engineering simulation model, a market system simulation model, and a reliability-based optimization model.

The engineering simulation model serves as a bridge between fundamental powertrain design parameters and consumers' perceivable product attributes, i.e., the key performance attributes of an electric vehicle. Typical powertrain design variables include battery capacity, gear ratio, number of batteries in parallel, and number of battery in series. These variables are processed through physical modeling or empirical equations to derive key vehicle performance metrics, such as maximum horsepower and driving range.

The market system simulation model employs the Agent-based Modeling (ABM) technique to simulate consumers' purchasing behaviors over multiple decision cycles, capturing how customer preferences evolve with market dynamics. In this model, consumers are treated as agents whose purchase behaviors are influenced by their own attributes such as income level, travel distance, and charging availability as well as changes in consumers' social network, the car market, regulation policy, electricity price, and fuel price. Discrete Choice Analysis (DCA) is used to link consumer preferences to purchase choices, and then the market share of an EV over a given time period can be predicted.

The optimization model iteratively adjusts powertrain design variables to maximize the manufacturer's profit. Based on the market simulation results, the optimization model identifies the most competitive EV powertrain configurations to enhance both engineering performance and market success. To ensure robust decision-making, the optimization model adopts the reliability-based design optimization (RBDO) mechanism to incorporate uncertainties in battery performance and driving conditions. This optimization process is implemented to refine engineering variables for profit maximization, aiming to align engineering design with both technical performance and long-term market success under uncertainties.

3.2. Engineering Simulation Model

Engineering simulation model translates engineers' concerns (i.e., design variables) into key performance attributes that consumers can perceive, such as driving range and horsepower. These attributes greatly influence consumers' purchase choices and the market acceptance of electric vehicles. To accurately obtain these performance attributes and provide reliable inputs for the subsequent market system modeling, we establish an engineering simulation model using Amesim, a mechatronic system simulation platform that integrates engineering analysis on vehicle dynamics, battery performance, and powertrain simulation with physically interpretable outcomes.

In the engineering simulation model, key design variables include battery configuration (number of cells in series and parallel), gear ratio, battery capacity, and motor parameters. These variables serve as inputs for the simulation model, and the model outputs include critical vehicle performance indicators, such as driving range, motor maximum speed, and required motor power for desired acceleration scenarios. Specifically, the driving range of an electric vehicle is primarily determined by battery capacity and driving cycle conditions. By leveraging the Worldwide Harmonized Light Vehicle Test Procedure (WLTP) standard [25], battery capacity requirements E_{bat} can be approximated using Equation (1):

$$E_{bat} = \frac{1}{SOC_{max} - SOC_{min}} \cdot \frac{d_{range}}{d_{cycle}} \cdot E_{cycle} \qquad (1)$$

where SOC_{max} and SOC_{min} represent the maximum and minimum state-of-charge (SOC) limits of the battery, d_{range} is the target driving range, d_{cycle} is the distance of a single WLTP cycle, and E_{cycle} is the energy consumption per cycle.

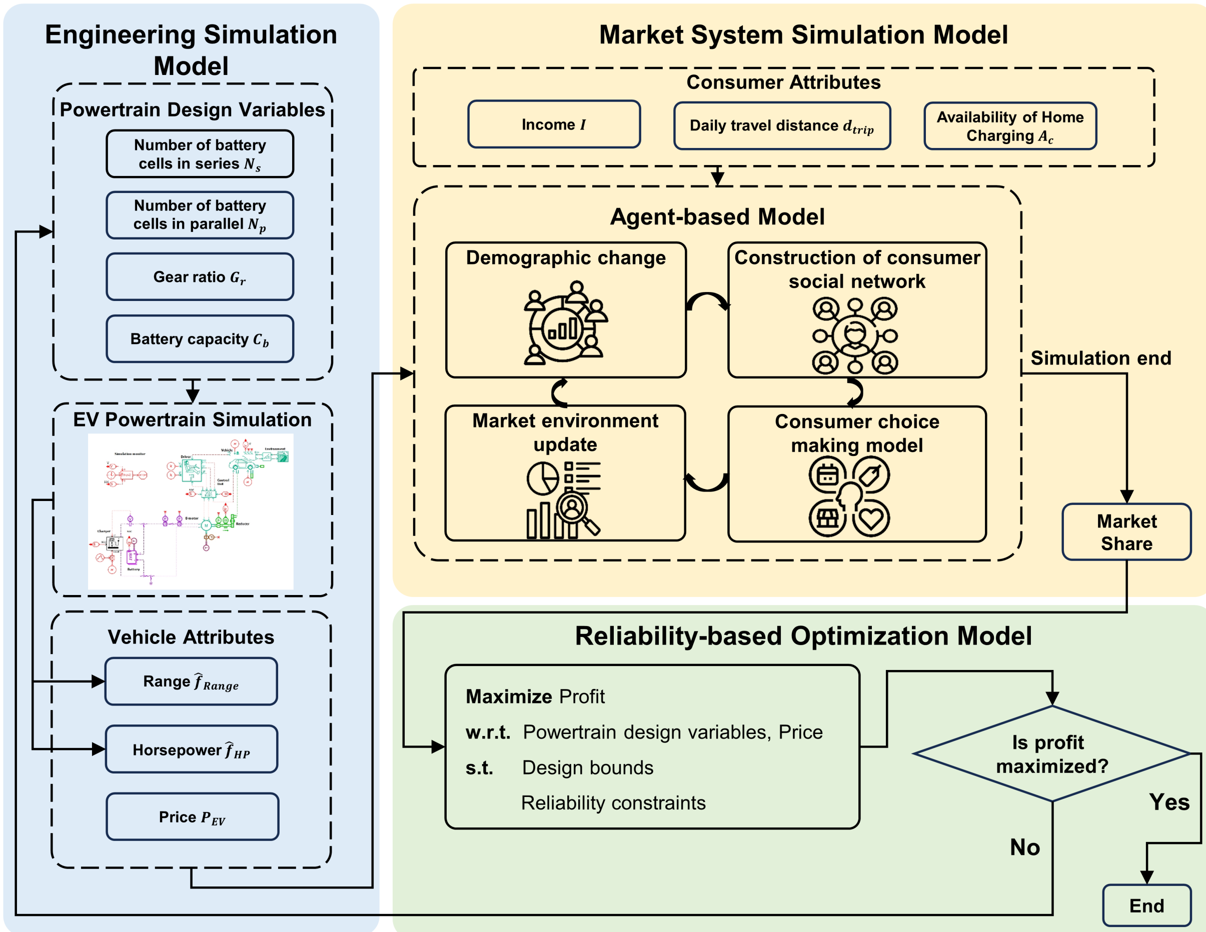

FIGURE 2: THE PROPOSED INTEGRATED EV POWERTRAIN PARAMETER DESIGN FRAMEWORK

The maximum speed of an EV directly relates to the maximum motor rotational speed. Using the vehicle's maximum target speed v_{max}, gear ratio Gr, and wheel radius R_w, the motor maximum rotational speed $\omega_{motor,max}$ can be estimated:

$$\omega_{motor,max} = Gr \cdot \frac{v_{max}}{R_w} \tag{2}$$

The maximum required motor power for specific acceleration performance (e.g., 0-60 km/h acceleration tests) can be analytically approximated by considering inertial forces, rolling resistance, and aerodynamic drag as as shown in Equation (3):

$$\begin{aligned} P_{mot,max} =& \frac{m_{veh}}{2 \cdot t_{req}} \left(v_{req}^2 + \frac{4}{Gr^2} (v_{req}^2 + v_{motor,base}^2) \right) \\ &+ \frac{2}{3} m_{veh} \cdot g \cdot f \cdot v_{req} + \frac{1}{5} \rho \cdot C_x \cdot A \cdot v_{req}^3 \end{aligned} \tag{3}$$

where m_{veh} is vehicle mass, t_{req} is acceleration time required to reach the target speed v_{req}, g is gravitational acceleration, f is rolling resistance coefficient, ρ is air density, C_x is aerodynamic drag coefficient, and A is the vehicle's frontal area.

These equations provide explicit and quantifiable links between engineering design variables and vehicle performance metrics, forming a foundation for subsequent market simulation and design optimization. However, due to the computational intensity associated with repeatedly executing complex simulations, direct incorporating the engineering simulation model within iterative optimization loops can be impractical. To address this challenge, surrogate models—data-driven approximations of the high-fidelity engineering simulations—are needed. By accurately emulating the relationship between design variables and key performance metrics, surrogate models significantly accelerate the optimization process, making the coupled engineering-market optimization computationally feasible without sacrificing engineering simulation accuracy.

3.3. Market System Simulation Model

The market acceptance of electric vehicles is shaped by diverse factors, including consumer demographics, technological advancements, energy prices, policy incentives, and social influence mechanisms. Traditional market forecasting approaches rely solely on historical sales data and static consumer preference assumptions, and often struggle to capture the evolving nature of demand. To address these limitations, we employ the Agent-Based Modeling (ABM) technique developed in our previous work [26] to explicitly model individual consumer's decision-making behaviors influenced by peer social interactions and market conditions. By incorporating heterogeneous consumer behaviors and dynamic market conditions, our model enables the evaluation of long-term adoption trends in EV market and more accurate predictions of market share.

The overall market system simulation flow works as follows: First, initial model parameters include consumer demographics, market environment parameters, and government policies are set. Once these parameters are loaded, the simulation works on a monthly basis (i.e., a simulation cycle). In each cycle, consumer demographics, including age and income, are updated, and new consumers are added to the market to reflect the changes in market capacity. After that, consumer social networks are constructed. Then, each consumer evaluates whether he or she needs to purchase a new car. If there is a need, the consumer will purchase a car based on the probability of the choice making model with updated vehicle ownership information. After all consumers have been updated in a cycle, the market environment is also updated, including the changes in government subsidies, restrictions on city traffic, electricity prices, and fuel prices. By counting the vehicles sold in one simulation cycle, the corresponding market share of an electric vehicle can be predicted. In the following subsections, the major settings of the market system simulation model are briefly introduced.

3.3.1. Setting of the Agents and Change of Consumer Demographics In our market system simulation model, each agent represents an individual consumer with attributes such as income level, mobility needs, home charging accessibility, and social network connections. These consumer data can be collected from surveys or generated randomly based on certain probabilistic distributions from previous research. The model progresses iteratively over a multi-cycle horizon, with each cycle incorporating the following key processes.

In a continuously evolving EV market, consumers' demographic attributes are periodically updated to reflect their age increments and income growth considering these attributes can influence consumers' purchasing power and demand patterns. New consumers, such as recent college graduates or first-time car buyers, enter the market annually with attributes sampled from empirical distributions. This maintains realistic population dynamics and ensures that demand remains representative of evolving market conditions. Existing vehicle owners decide whether to replace, retain, or defer vehicle purchases based on vehicle usage age, maintenance costs, and changing policy incentives. By accounting for these demographic dynamics, our model can simulate realistic market shifts over time.

3.3.2. Construction of Consumer Social Network Consumers' choices can be influenced by peer interactions, including word-of-mouth effects and social learning mechanisms [26]. To capture these interactions, a consumer social network is constructed based on the homophily effect, where individuals with similar income levels, geographic locations, and purchase histories are more likely to form network connections. Social influence plays a critical role in modeling the market penetration of EVs, as early adopters spread usage experiences through peer networks. The strength of peer influence is modeled using a cascading function, where additional recommendations exhibit diminishing marginal effects. The impact of word-of-mouth on a consumer's decision utility is quantified as:

$$U_{w,i} = n_{w,i} \cdot \gamma(n_{w,i}) \cdot \phi \tag{4}$$

where $n_{w,i}$ is the number of positive endorsements received by consumer i, ϕ is the individual's sensitivity to peer influence, and $\gamma(n_{w,i})$ is a diminishing impact function controlling the saturation effect of repeated recommendations.

3.3.3. Consumer Choice-Making Model Consumers' choice-making process follows a two-stage choice model, in which consumers first determine fuel type preferences (EV, hybrid, or conventional vehicle) then select a specific vehicle model. The discrete choice model is used to describe their preferences. The utility function U_{ij} for consumer i selecting vehicle j is structured as:

$$U_{ij} = \sum_k \beta_k X_{k,j} + \epsilon_{ij} \tag{5}$$

where $X_{k,j}$ represents key vehicle attributes such as price, driving range, and charging convenience, β_k denotes consumer sensitivity parameters, and ϵ_{ij} captures unobserved heterogeneity in consumer preferences.

Consumers' purchase probabilities are computed using the multinomial logit model:

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_m \exp(U_{im})} \tag{6}$$

where P_{ij} is the likelihood of a consumer selecting a given vehicle model. The market share of vehicle j is then obtained by aggregating individual purchase probabilities:

$$S_j = \frac{1}{N} \sum_{i=1}^{N} P_{ij} \tag{7}$$

This approach captures heterogeneous consumer preferences, behavioral inertia, and adaptation to policy incentives, ensuring realistic market adoption simulations.

3.3.4. Market Environment Update At each simulation cycle, market conditions are updated to reflect evolving economic and policy landscapes. This ensures that the vehicle adoption responds realistically to changes in energy costs, technology improvements, and government interventions. Key factors influencing the market update process include energy price fluctuations, policy adjustments, and new vehicle introductions.

Electricity prices adjust based on public demand, renewable energy penetration, and seasonal factors, while gasoline prices fluctuate due to global oil supply-demand shifts, geopolitical tensions, and emission taxation policies. These variations introduce price uncertainties, influencing the competitiveness of EVs. Policy interventions, such as government subsidies, tax credits, and vehicle purchase restrictions, further shape the market landscape. Changes in government incentives can significantly alter vehicle affordability, shifting consumer preferences toward EVs. As automakers continuously launch new EV models in the market, these models become available for consumer's selection in subsequent iterations. Technological advancements, such as improvements in battery life, charging speed, and production costs, also enhance the attractiveness of EVs relative to conventional vehicles. To maintain computational efficiency, energy price fluctuations follow a stochastic baseline trajectory, while policy adjustments occur as discrete events based on predefined regulatory timelines.

By integrating these dynamic market factors, the simulation model provides a comprehensive assessment of how consumer choices interact with real-world market conditions. For a more detailed discussion on the modeling procedures, please refer to our previous work [26].

3.4. Reliability-Based Optimization Model

To address the inherent uncertainties in EV engineering attributes and ensure both technical reliability and market competitiveness, we adopt a Reliability-Based Design Optimization (RBDO) mechanism to generate optimal powertrain design solutions. RBDO maximizes system utility while satisfying reliability constraints under uncertainty, offering a robust alternative to deterministic optimization methods. The mathematical formulation of the optimization problem is presented as follows:

Given: Design variables $\mathbf{X} = (N_s, N_p, G_r, C_B)$, price P_{EV}, surrogate-based engineering model $\hat{f}(\cdot)$, and market simulation $f_{MS}(\cdot)$.

$$\{P_{motor}, R_{EV}, C_{mfg}\} \approx \hat{f}(N_s, N_p, G_r, C_B) \tag{8}$$

$$M_s \approx f_{MS}(P_{motor}, R_{EV}, P_{EV}, I, d_{trip}, A_c) \tag{9}$$

$$P_{choice,i} = \frac{e^{U_i}}{\sum_j e^{U_j}}, \quad U_i = \sum_k \beta_k X_{ik} \tag{10}$$

$$D_m = M_s S_{market} \tag{11}$$

The surrogate model $\hat{f}(\cdot)$ predicts key EV performance metrics using the powertrain design variables, including the number of battery cells in series (N_s), the number of battery cells in parallel (N_p), gear ratio (G_r), and battery capacity (C_B). Motor power (P_{motor}) represents the output power of the electric motor in kilowatts. Vehicle range (R_{EV}) is the distance the EV can travel on a single charge, measured in kilometers. Manufacturing cost (C_{mfg}) is the total cost to produce one electric vehicle in Chinese Yuan (CNY).

The market share (M_s) is a fraction between 0 and 1, representing the proportion of the market captured by the EV design. It is obtained through an market system simulation as described in Sec. 3.3, which accounts for EV performance metrics (P_{motor},R_{EV}), vehicle price (P_{EV}, in CNY), and consumer attributes. These attributes include income level (I, in CNY), daily travel distance (d_{trip}, in kilometers), and availability of home charging (A_c, a binary indicator where 1 denotes availability and 0 denotes unavailability). The market system simulation model simulates consumers' decision-making behaviors to estimate M_s under varying market conditions.

Within each round of the market system simulation, the probability of a consumer's selecting a specific EV configuration ($P_{choice,i}$) is calculated by using a utility function U_i. This utility function aggregates product attributes (X_{ik}), each weighted by a consumer preference parameter (β_k). The parameter β_k is a dimensionless coefficient reflecting the importance of each attribute in the consumer's decision-making process.

The demand (D_m) represents the total number of vehicles expected to be sold, computed by multiplying the market share (M_s) with the total market size (S_{market}). Here, S_{market} is the total number of potential buyers in the market.

Find: $\mathbf{X}^* = (N_s^*, N_p^*, G_r^*, C_B^*), P_{EV}^*$

Maximize:

$$\mathbb{E}[\Pi] = D_m(P_{EV} - C_{mfg}) \tag{12}$$

Subject to:

(1) **Design Bounds:**

$$N_s^{\min} \le N_s \le N_s^{\max}, \tag{13}$$

$$N_p^{\min} \le N_p \le N_p^{\max}, \tag{14}$$

$$C_B^{\min} \le C_B \le C_B^{\max}, \tag{15}$$

$$G_r^{\min} \le G_r \le G_r^{\max}, \tag{16}$$

$$P_{EV}^{\min} \le P_{EV} \le P_{EV}^{\max} \tag{17}$$

(2) **Reliability Constraint:**

$$P[G_{\text{eng}}(\mathbf{X}, \mathbf{P}) > 0] \le P_{\text{fail,max}} \tag{18}$$

The objective is to maximize the expected profit ($\mathbb{E}[\Pi]$), measured in CNY, which is the product of demand (D_m), the total number of vehicles expected to be sold, and the unit profit margin, defined as the difference between the vehicle selling price (P_{EV}, in CNY) and the manufacturing cost (C_{mfg}, in dollars). The design variables $\mathbf{X} = (N_s, N_p, G_r, C_B)$ include the number of battery cells in series (N_s) and parallel (N_p), both integers; the gear ratio (G_r), a dimensionless parameter; and the battery capacity (C_B), in Ah. The design bounds (Eqs. (13)-(17)) ensure that these variables and the price (P_{EV}) remain within practical limits.

The reliability constraint (Eq. (18)) ensures that the EV design remains robust under uncertainty by enforcing $P[G_{\text{eng}}(\mathbf{X}, \mathbf{P}) > 0] \le P_{\text{fail,max}}$, where $P_{\text{fail,max}}$ is the maximum allowable failure probability, a predefined threshold ensuring reliability. Here, $\mathbf{X} = (N_s, N_p, G_r, C_B)$ represents the powertrain design variables, while $\mathbf{P}$ denotes the vector of random parameters affecting the power system performance, including manufacturing tolerances (e.g., variations in battery capacity), environmental conditions (e.g., temperature), and usage patterns (e.g., driving cycles). The performance function $G_{\text{eng}}(\mathbf{X}, \mathbf{P})$ evaluates the EV's performance against specified requirements, with failure occurring when $G_{\text{eng}} > 0$. One typical failure scenario is that $\mathbf{X}$ or $\mathbf{P}$ may violate prescribed ranges due to uncertainties, such as production inconsistencies causing N_s or N_p to deviate beyond acceptable bounds. Another failure scenario is that the predicted vehicle range or horsepower from the surrogate model approximating the EV's performance metrics falls below the minimum acceptable levels defined by the design requirements. For instance, G_{eng} can be formulated as $G_{\text{eng}} = R_{\text{req}} - R_{\text{EV}}(\mathbf{X}, \mathbf{P})$, where R_{EV} is the vehicle range computed by the surrogate model, and R_{req} is the required range, with $G_{\text{eng}} > 0$ indicating failure (e.g., insufficient range). The probability $P[G_{\text{eng}}(\mathbf{X}, \mathbf{P}) > 0]$, representing the likelihood of such failures, is thus constrained to ensure both design feasibility and performance adequacy under uncertainty.

Unlike deterministic design methods that assume fixed parameter values and often fail to account for real-world variability, Reliability-Based Design Optimization (RBDO) addresses uncertainties in electric vehicle (EV) design. In RBDO, the reliability constraint $P[G_{\text{eng}}(\mathbf{X},\mathbf{P}) > 0] \leq P_{\text{fail,max}}$ is enforced by computing the failure probability for each design candidate x. In this formulation, the uncertainties in both design variables $\mathbf{X}$ and the random parameters $\mathbf{P}$ are accounted and treated as jointly distributed random variables. The failure probability is expressed as:

$$P_{\text{failure}} = \int_{\Omega_F} f_{\mathbf{X},\mathbf{P}}(\mathbf{x},\mathbf{p})\, d\mathbf{x} d\mathbf{p}, \quad \Omega_F = \{(\mathbf{x},\mathbf{p}) | G_{\text{eng}}(\mathbf{x},\mathbf{p}) > 0\} \tag{19}$$

where $f_{\mathbf{X},\mathbf{P}}(\mathbf{x},\mathbf{p})$ is the joint probability density function of $\mathbf{X}$ and $\mathbf{P}$, describing the combined distribution of design and random parameters, and Ω_F is the failure domain where $G_{\text{eng}}(\mathbf{x},\mathbf{p}) > 0$, indicating failure scenarios (e.g., insufficient vehicle range or power output). Since $\mathbf{X}$ and $\mathbf{P}$ can be high-dimensional and G_{eng} is typically a complex, non-linear function, directly computing this integral analytically is challenging [27]. Therefore, Monte Carlo Simulation (MCS) is employed to estimate the failure probability. MCS approximates the integral by generating a large number of random samples $(\mathbf{x},\mathbf{p})$ from the joint distribution $f_{\mathbf{X},\mathbf{P}}(\mathbf{x},\mathbf{p})$, computing $G_{\text{eng}}(\mathbf{x},\mathbf{p})$ for each sample using an engineering model that evaluates performance metrics (e.g., range or power) based on the sampled design and random parameters, and estimating P_{failure} as the fraction of samples where $G_{\text{eng}} > 0$. This estimated probability is then compared against $P_{\text{fail,max}}$ to ensure the reliability constraint is satisfied. MCS is selected for its simplicity and versatility, as it can handle complex performance functions and arbitrary joint distributions without requiring analytical solutions, making it well-suited for reliability analysis in RBDO. By incorporating uncertainty through RBDO, our framework ensures that the EV design balances technical reliability with market viability leading to a robust and competitive product.

4. CASE STUDY AND RESULTS

4.1. Study Setting

To validate the proposed approach, we conduct a case study using real consumer survey data collected from Shanghai, China, which includes 1,463 valid responses (724 new energy vehicle (NEV) users and 739 conventional vehicle (CV) users) [26]. The survey captures demographic attributes (age, income, gender), vehicle usage patterns (annual mileage, charging conditions), purchasing preferences (price sensitivity, performance priorities), and market conditions (fuel prices, electricity rates, policy incentives). Consumer agents in the Agent-Based Model (ABM) are initialized based on these distributions to ensure realistic behavioral representation. In addition, we choose Tesla Model 3 (standard range version) as a demonstration example EV for powertrain parameter design optimization, whose basic engineering specifications are shown in Table 1. The attributes of other competitive vehicles on the market, including price, driving range, and charging time, are sourced from leading automotive forums, while the fuel prices, electricity rates, and policy incentives are gathered from official government publications.

TABLE 1: BASIC ENGINEERING SPECIFICATIONS OF TESLA MODEL 3

Domain	Attribute	Value
Vehicle	Range (WLTP)	440 km
	Max. Speed	225 km/h
	Mass	1825 kg
	Actual Mass	1861 kg
	Tyres	235/45R18 98Y
	Tyre Radius	346 mm
	Load Coefficient (f0)	9.92 N
Power Unit	Max. Power	239 kW
	30 min Power	100 kW
	Max. Rotations	16,000 rpm
	Max. Torque	420 Nm
	Drive Type	Synchronous
Battery Unit	Pack Energy	58 kWh
	Cell Format	Prismatic

All simulations and computations, encompassing Agent-based Modeling (ABM), Discrete Choice Analysis (DCA), and Reliability-Based Design Optimization (RBDO), are executed over a simulated five-year market horizon using Python on a workstation equipped with an NVIDIA RTX 3060 Ti GPU and Intel i7 processor.

4.2. Discrete Choice Analysis Results

We first employ Discrete Choice Analysis (DCA) to quantify consumer preferences for EVs with the collected consumer data. These results will be used to estimate consumers' purchase probabilities within the market system simulation model. Based on previous research and preliminary tests, car price, horsepower, car range, availability of home charge, income, daily travel distance are selected as the modeling variables in DCA. Their respective estimated coefficients are provided in Table 2.

TABLE 2: ESTIMATION RESULTS OF THE DCA MODEL.

Attribute Type	Explanatory Variables	Coefficient (β)
Vehicle	Price	-0.03**
	Horse Power	0.6102
	Range	1.8652**
Customer	Availability of Home Charge	0.0008
	Income	0.0012**
	Daily Travel Distance	-0.00005
	Constant	-3.4272

Significance levels: ** $p < 0.05$,

The negative coefficient of price (−0.03) indicates that higher vehicle prices significantly reduce consumers' purchase intention. Conversely, the positive coefficients associated with driving range (1.8652) and horsepower (0.6102) suggest that consumers have strong preferences for vehicles with better mobility performance, particularly in terms of extended range and enhanced power capabilities. Additionally, the availability of home charging infrastructure (0.0008) and income level (0.0012) also positively influence purchase decisions, though their effects appear relatively moderate. The negative coefficient for daily travel distance (−0.00005) implies that consumers who have longer daily commutes are slightly less inclined towards EV adoption, potentially reflecting concerns about range anxiety or charging convenience. The negative constant term (−3.4272) captures baseline reluctance or barriers to adoption not explicitly explained by observed attributes. These results underscore the importance of balancing vehicle pricing strategies with performance enhancement to effectively align with consumer preferences in EV market.

4.3. Surrogate Model Selection

To improve the overall computational efficiency of the design optimization flow, we conducted 10,000 engineering simulations across the powertrain design variable space and trained a surrogate model to accelerate the optimization process. To select the best surrogate model, we compared multiple techniques, including Linear Regression (LR), Random Forest (RF), Support Vector Regression (SVR), Gradient Boosting (GB), Extreme Gradient Boosting (XGBoost), and Neural Networks (NN). Table 3 presents the training and prediction time of each model. While the original engineering simulation model requires more than 15 hours (55224 s) for one simulation, surrogate models significantly reduce the computation time.

TABLE 3: TRAINING AND PREDICTION TIME OF DIFFERENT SURROGATE MODELS

Model	Training Time (s)	Prediction Time (s)
Engineering Simulation	-	55224
Linear Regression	0.015142	0.000242
Random Forest	2.706262	0.062547
SVR	1.562517	0.753159
Gradient Boosting	0.842880	0.003499
XGBoost	0.070319	0.002040
Neural Network	17.639420	0.128589

Figure 3 further compares these surrogate models in terms of Mean Absolute Error (MAE) for horsepower and driving range predictions. The results indicate that XGBoost outperforms other models with the lowest MAE and significantly reduced computation time. Specifically, XGBoost achieves lower prediction errors in horsepower and driving range estimation compared to LR and SVR. It is also computationally more efficient than Neural Networks (NN) while maintaining high accuracy, and demonstrates superior generalization ability and better error control compared to RF and GB. One possible explanation is that XGBoost uses gradient boosting with optimized tree-building, which is efficient in handling sparse data, and good at parallel processing. Thus, XGBoost is selected as the surrogate model in our framework to support faster optimization iterations.

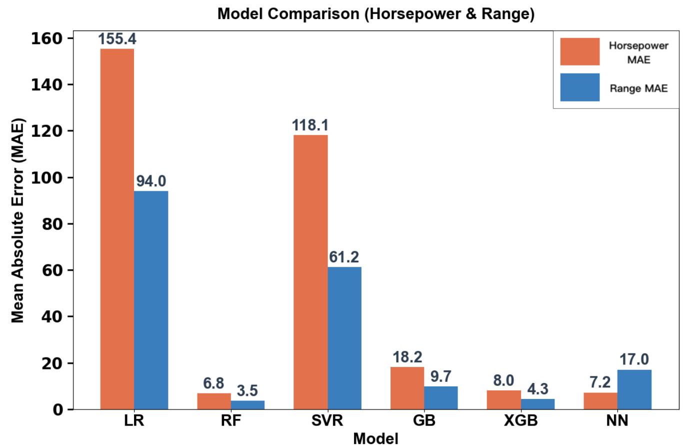

FIGURE 3: COMPARISON OF SURROGATE MODELS IN MEAN ABSOLUTE ERROR (MAE) FOR HORSEPOWER AND DRIVING RANGE PREDICTIONS.

4.4. Optimization Algorithm Selection

To identify the most suitable optimization algorithm for our design framework, a comparative evaluation of four widely used optimization techniques is conducted, including Genetic Algorithm (GA), Differential Evolution (DE), Simulated Annealing (SA), and Particle Swarm Optimization (PSO). Table 4 presents the ranges of design variables in optimization, which are selected based on key battery parameters from mainstream electric vehicles introduced post-2020, including Tesla Model 3, Nissan Leaf e+, Volkswagen ID.4, and BYD Han EV, collected from industry sources and literature. These parameter ranges ensure the optimization procedure accommodates realistic variations in current EV battery technologies and market pricing strategies. Table 5 summarizes the comparative results across the four algorithms. The evaluation criteria include avg iterations, average computational time, and improvement rate (objective gain per second). Each algorithm was run for 20 times. According to the results, Genetic Algorithm (GA) is selected as the primary optimization method for our framework based on its overall balance of solution quality, computational efficiency, and robustness.

TABLE 4: DESIGN VARIABLE RANGES FOR OPTIMIZATION BASED ON MAINSTREAM EV BATTERY PARAMETERS (POST-2020)

Design Variables	Lower Bound	Upper Bound
Gear Ratio (GR)	7.1	13.1
Element Battery Capacity (Ah)	4.8	202
Battery Cells in Series	96	120
Battery Cells in Parallel	1	31
EV Price (CNY)	200,000	400,000

TABLE 5: COMPARISON OF OPTIMIZATION ALGORITHMS FOR POWERTRAIN MARKET OPTIMIZATION

Algorithm	Avg Time (s)	Avg Iterations	Improvement Rate (objective gain/s)
Genetic Algorithm (GA)	**3.23**	**113.6**	**1.18E+10**
Differential Evolution (DE)	16.04	143	2.48E+09
Simulated Annealing (SA)	7.01	300	5.55E+09
Particle Swarm Optimization (PSO)	6.94	300	5.64E+09

4.5. Ablation Experiment

To systematically examine the effect of market system simulation and reliability-based optimization for EV powertrain parameter design, we designed a four-scenario ablation experiment. The main idea is to compare the optimization results when using deterministic or probabilistic design constraints as well as static or dynamic market models. In the deterministic case, all design constraints are assumed to be known with certainty, while in the probabilistic case, the optimization accounts for variations in battery performance, efficiency, and degradation over time. For market models, the traditional static model assumes a fixed consumer preference structure, while the Agent-based model can model individual consumers' evolving interactions and dynamic market conditions.

TABLE 6: ABLATION STUDY SCENARIOS

Scenario	Design Constraints	Market Model
Scenario 1	Deterministic	Static
Scenario 2	Probabilistic	Static
Scenario 3	Deterministic	Dynamic
Scenario 4	Probabilistic	Dynamic

As shown in Table 6, the four ablation settings include: (Scenario 1) a baseline deterministic design constraints with a static market model, (Scenario 2) the introduction of probabilistic design constraints through reliability-based optimization while maintaining a static market model, (Scenario 3) deterministic design constraints combined with market simulation model to capture variable demand, and (Scenario 4) the integration of both market system simulation and reliability-based optimization to evaluate the combined effect of engineering robustness and market adaptation. This setting allows for a structured assessment of how engineering uncertainty and market dynamics influence design optimization outcomes, particularly in terms of profitability, cost efficiency, and market acceptance.

Table 7 presents the optimization outcomes across four ablation scenarios, revealing that lower profits better reflect real-world dynamics. Compared to the baseline (Scenario 1), reliability-based optimization in Scenario 2 improves design efficiency, reducing the optimized EV price from CNY387,146.55 to CNY284,062.90 by prioritizing efficiency over excessive battery capacity. Scenario 2 achieves this with a higher battery cell capacity (89.50 Ah) and more cells in series (178), demonstrating that accounting for engineering uncertainty avoids overly conservative design standards. Consequently, profitability decreases from CNY5.30E+13 in Scenario 1 to CNY3.89E+13 in Scenario 2, indicating reduced financial risks by addressing engineering uncertainties more realistically.

Incorporating a market simulation model with deterministic design constraints (Scenario 3) yields a higher optimized price of CNY392,314.12, reflecting dynamic consumer demand modeling that captures latent market preferences. This leads to a significant profit reduction to CNY2.51E+11, a 99.5% decrease from Scenario 1's CNY5.30E+13, underscoring the agent-based model's (ABM) ability to enhance product positioning by aligning with real-world consumer needs.

Scenario 4, which integrates both market simulation and reliability-based optimization, delivers the most balanced results, with the lowest gear ratio (7.30), reduced battery capacity (14.65 Ah), and increased cells in parallel (5). This combination optimizes cost efficiency and market fit, further lowering profitability to CNY2.50E+11—a 99.5% improvement over Scenario 1—highlighting the critical need to simultaneously address engineering reliability and market dynamics for EV powertrain design.

4.6. Resilience Experiment

To further investigate how our approach performs under extreme product conditions, we designed a resilience experiment. We select battery capacity as the key uncertain parameter, with a significant impact on electric vehicle (EV) market acceptance and cost-effectiveness. We established an extreme scenario by adjusting the EV's battery capacity parameter to a minimal value, significantly below normal design considerations. This setup was intended to simulate severe market conditions where core product performance metrics substantially degrade due to factors such as potential supply chain disruptions or cost control measures. Under this extreme battery capacity condition, we re-evaluated the market performance of Scenario 3 and Scenario 4 as described in Table 6.

In Scenario 3, the estimated profit decreased by CNY7E+9, and in Scenario 4, the estimated profit decreased by CNY4E+9. Therefore, the magnitude of profit reduction for the our approach integrated with RBDO (Scenario 4) was approximately 42.9% less than that for the deterministic approach (Scenario 3). This demonstrates a considerable cushioning effect provided by our approach against extreme design parameter change shocks. The substantial difference in profit preservation underscores our approach's superior capability in navigating severe market uncertainties stemming from critical performance limitations.

5. CONCLUSION

In this study, we propose an integrated design framework for EV powertrain parameter selection supported by market sys-

TABLE 7: OPTIMIZATION RESULTS ACROSS FOUR ABLATION SCENARIOS

Scenario	Gear Ratio	Element Battery Capacity (Ah)	Number of Battery Cells in Series	Number of Battery Cells in Parallel	EV Price (CNY)	Maximized Profit (CNY)
Scenario 1 (Baseline)	11.90	35.78	107	3	387,146.55	5.30E+13
Scenario 2 (Only RBDO)	9.55	89.50	178	1	284,062.90	3.89E+13
Scenario 3 (Only ABM)	11.03	24.15	96	3	392,314.12	2.51E+11
Scenario 4 (RBDO + ABM)	7.30	14.65	96	5	389,811.49	2.50E+11

tem simulation and reliability-based optimization. The proposed framework enables modeling complex interaction between powertrain system design variables and market competition dynamics, offering a robust and market-adaptive approach to EV powertrain design. The case study results indicate that while reliability-based optimization results in slightly lower profitability due to the consideration of engineering uncertainties, it achieves higher design reliability and market prediction accuracy. Meanwhile, the ABM-driven market simulation model demonstrates strong capabilities in dynamic market simulation, effectively capturing shifting consumer preferences and social network effects. The ablation study validates the contributions of reliability-based optimization and market simulation, and underscores the importance of their integration. Relying solely on market simulation or engineering optimization leads to suboptimal results, either in terms of solution reliability or market adaptability. The combination of both models strikes a design balance between technical feasibility and market competitiveness. Additionally, the introduction of surrogate model significantly improves the computational efficiency of solving complex optimization problems.

One limitation of this work is that modeling consumer preferences relies on collecting survey data which costs much time and financial resources. One possible future research direction is to utilize Large Language Model (LLM) to help generate synthetic consumer choices as supplementary data to reduce the need of collecting large-scale consumer data. Furthermore, reinforcement learning from human feedback (RLHF) can also be incorporated to ensure that purchase decision models align more closely with real-world consumer behaviors.

ACKNOWLEDGMENTS

The authors would like to acknowledge the financial support from National Natural Science Foundation of China (52005328) and the National Key R&D Program of China (2022YFB4702400).

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