Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 136 (2025) 728–733

www.elsevier.com/locate/procedia

35th CIRP Design 2025

Portfolio Optimization of Electric Vehicles for Design Equilibrium Identification

Weihao Mu[a], Rui Li[a], Alessandro Simeone[b], Jian Zhang[a,c*]

[a]Shantou Key Laboratory for Intelligent Equipment and Technology, Shantou, 515063 China
[b]Department of Management and Production Engineering, Politecnico di Torino, 10129 Turin, Italy
[c] Intelligent Manufacturing Key Laboratory of Ministry of Education, Shantou University, Shantou, 515063 China

* Corresponding author. Tel.: +86-13502724586; fax: +86-0754-8251-8900. E-mail address: jianzhang@stu.edu.cn

Abstract

Portfolio design of electric vehicle can enhance manufacturers' competitiveness by meeting diversified customers preferences using reconfigured manufacturing resources. Electric vehicles are face both external competitions from other companies and internal competitions in the same product portfolio. Identification of design equilibrium by considering both internal and external competitions is needed for enhanced competitiveness. Competition relations and customers preferences are embedded in big sales data of electric vehicle. A method is proposed for the design equilibrium identification of electric vehicle by using big sales data. BYD's mid-range SUV portfolio is investigated as an illustrative example to test the feasibility of the method.

Keywords: Product portfolio; design optimization; design equilibrium; electric vehicle; big sales data;

1. Introduction

With the increasing global green energy transition requirements and rapid technology advancements, development of electric vehicles (EVs) has become the one of the most important trends of the automotive industry [1,2]. The fierce competition of EV companies with both traditional automotive manufacturers and other EV companies requires the development of various EVs to better meet the diversified and personalized market preferences of EV features. A product portfolio refers to a group of products with similar functions, technology platforms, or design features, which typically share the same core technologies or manufacturing resources. A product portfolio usually consists of platforms, customized modules, and personalized modules, which can be reconfigured to better meet the diverse and personalized needs of customers. Designing product portfolios for electric vehicles has been proven in practice to effectively counter market competitions.

The competitiveness of a product is not only related to its own specifications (i.e., features, characteristics, prices etc.) but is also dependent on competing products in the same category [3]. The portfolio design of electric vehicles must consider competition and interactions with other manufacturers, including both electric and combustion powered vehicles. Meanwhile, EVs belongs to the same portfolio also influenced by each other. Therefore, design equilibrium considering both internal and external competitions is needed to facilitate EV portfolio optimization. However, current research on EV portfolio design are focused on market demand analysis and specification determination, and modules division and optimization. There is still insufficient research on the design equilibrium analysis, which leads to irrational EV portfolio design. In addition to the above progress, research efforts have also been devoted for analyzing customer needs by integrating

10.1016/j.procir.2025.08.124

Maslow's hierarchy of needs [4] and the Kano model [5]. Moreover, decision trees [6] has also been employed to model customer behavior and characteristics to identify potential preferences of customers. To capture both the conscious and subconscious preferences of customers, big sales data has also been proposed for customer preference information mining [3, 7-9].

To better meet the diversified demands of the market, many studies have focused on modular design methods, such as module-based product family design, platform design [10-12], and modular design for mass customization, to optimize products and enhance their competitiveness [13,14]. Different methods, such as the Design Structure Matrix and the Modular Function Deployment, have been proposed for product modularization. These methods decompose complex systems into subsystems or modules by decomposing, analyzing, and optimizing the system with the aim of minimizing dependencies [15-17]. Various metrics, including component shape, material selection, and manufacturing capabilities, have been introduced to evaluate modularity in product design [18]. Components and their interfaces standardizing ensures modules can be reused and combined in different configurations. Material selection impacts module durability, interchangeability, and cost. Lastly, manufacturing capabilities affect the manufacturability and economics of the modules. However, such approaches to product optimization typically analyze the physical structure for module segmentation, and rarely focus on reconfiguring modules and optimizing product portfolios by predicting market preferences taking into account interactions between sub-products within the portfolio [19-21].

Although existing design methods product portfolio design methods have been widely applied for enhancing manufacturers competitiveness, the following challenges still need to be solved:

1. The collected information often fails to accurately reflect competition and interaction relationships among competing products in the market, leading to inaccurate estimation of product competitiveness.

2. Product portfolio design decisions are usually made on the basis of structural optimization. Impacts of potential strategies that could be employed by competing manufacturers are often neglected.

3. Potential market overlaps and internal competitions among sub-products in a portfolio, which can impact the overall competitiveness, have not been fully evaluated. Effective balancing of interaction relationships remains an unresolved issue.

In response to the aforementioned issues, this paper proposes a product portfolio design method that meets customer demands while achieving design equilibrium, thereby balancing the mutual influence relationship among sub-products and enhancing the competitiveness of the entire product portfolio. Since big sales data of a product category includes information on customer demand and product competition, it can be used to support rational design decision-making [21-23]. Based on the collection and analysis of big sales data of electric vehicles, this paper proposes a portfolio optimization method for design equilibrium identification. By using the optimized solutions of design equilibrium, a product portfolio with market competitiveness can be achieved considering both internal and external competition.

2. Framework for the EV portfolio optimization considering design equilibrium

Big sales data of EVs are collected for product competitive relationship modeling and their interactive influence estimation. The competitiveness of new products is evaluated by considering both internal and external competitions of a product portfolio. To maximize the competitiveness of an EV portfolio, design equilibrium optimization is carried out by considering interactions among sub-products and other existing EVs in the market. Flow chart and main operations of the proposed method are provided as shown in Fig. 1.

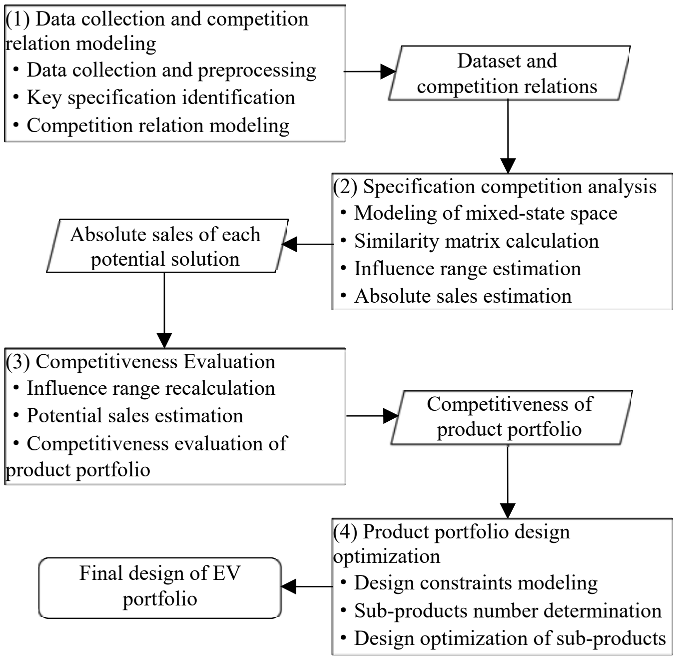

Fig. 1. Flow chart of the proposed method

In the proposed method, raw data of EV sales are firstly collected from public resources such as official websites and reports. The collected raw data including sales number and EV specifications is preprocessed, including redundancy handling and key specification identification, to build an EV dataset in which customers purchase preference and mutual competition relations are embedded. Based on the collected dataset, specification competition analysis is carried out. In this step, potential solutions of specification combination were generated. Mixed design scenarios among potential solutions were identified by analyzing the relative satisfaction of specifications between products, and those specification combinations that could be mixed with existing products were selected to form a mixed-state space [3,24]. Then, by calculating the similarity between the potential solutions in the mixed-state space, the influence range of existing products is estimated. The absolute sales of each potential solution within the mixed-state space is calculated by considering both the influence range and sales number of existing products. When a design candidate is generated, the influence range is recalculated considering the similarities of specifications. Potential design solutions within the influence range of the design candidate can be identified. By calculating the total absolute sales of potential design solutions, the estimated sales for the competitiveness evaluation are obtained. The competitiveness of a product portfolio is evaluated by considering the estimated sales of all the sub-products. The estimated sales of all the sub-products is also used for the design optimization evaluation of product portfolio. By applying a multi-objective optimization using an improved genetic algorithm, the EV portfolio is optimized to identify the design equilibrium with maximum market competitiveness. Detailed procedures and operations of the proposed method is provided in Section 3.

3. Implementation of the proposed method

3.1. Data collection and competition relation modeling

In this Section, design of a portfolio of electric Sport-Utility Vehicle (SUV) is considered for the method implementation. Only Chinese market is considered and the BYD Song PLUS DM-i product portfolio is chosen for the portfolio optimization.

Design specifications and sales data collected in this case study primary from commercial sales websites. Since competitions from combustion vehicles can not be neglected, traditional internal combustion engine SUVs and electric SUVs is considered in the raw data collection. Totally 330 different products are considered in the raw data collection. Missing data were supplemented by consulting SUV official websites, user manuals, and technical documents such as repair manuals, products information as partially displayed in Table 1. In the Chinese SUV market, top 104 products belonging to 41 portfolio account for 60% of the total sales, highlighting that top 104 products can highly reflect the competition relations. To simplify the calculation and discussion, the top 104 products is considered in this work.

Based on automotive information websites and preliminary analysis of the collected raw data, redundant specifications and data were removed, and the data were processed and categorized into five aspects including performance, comfort, safety, economy, and body design of electric vehicles [25-28]. Through raw data pre-processing, 19 key design specifications related to these five aspects were finalized as shown in Table 2. The final dataset includes the BYD Song PLUS DM-i product portfolio and the remaining 99 competing products, and their 19 key specifications.

Before conducting the competition analysis, product specifications were classified into four types based on customer preference on those specifications: non-consistent preference (NCP), larger-the-better (LTB), smaller-the-better (STB), and target-the-best (TTB) [24]. The types of the 19 key specifications are shown in Table 2.

Table 1. collected raw data

ID	Energy Type (-)	Price (CNY)	Driving Range (km)	···	Sales (-)
Byd Song PLUS DM-i	Plug-in	129800	1100	···	4464
Li L7	Range-Extended	301800	1360	···	3509
Galaxy L7	Plug-in	125700	1250	···	1209
Li L6	Range-Extended	249800	1390	···	8897
NIO ES6	Pure Electric	338000	500	···	3708
Model-Y	Pure Electric	249900	554	···	18908
SERES 7	Range-Extended	249800	1300	···	1161
ATTO 3	Pure Electric	119800	430	···	2517
...	...	...	...	...	...

Table 2. key electric vehicle specifications

ID	Specification	Value Range	Unit	Type
S_1	Energy Type	Pure Electric; Range-Extended; Plug-in; Fuel	-	NCP
S_2	Price	[100000,350000]	CNY	STB
S_3	Driving Range	[400,1700]	km	LTB
S_4	Fast Charging Time	[0,1]	h	STB
S_5	Max Engine Power	[0,250]	kw	LTB
S_6	Max Motor Power	[0,450]	kw	LTB
S_7	Max Engine Torque	[0,400]	N·m	LTB
S_8	Max Motor Torque	[0,800]	N·m	LTB
S_9	0-100km/h Acceleration	[0,11]	s	STB
S_{10}	Top Speed	[100,240]	Km/h	LTB
S_{11}	Fuel/Electricity Consumption Equivalent	[1,7.5]	L/100km	STB
S_{12}	Fuel Tank Capacity	[0,90]	L	LTB
S_{13}	Drive Type	Front Wheel; Rear Wheel; All Wheel	-	NCP
S_{14}	Battery Capacity	[0,110]	kWh	LTB
S_{15}	Passive Safety Feature	[4,11]	-	LTB
S_{16}	Active Safety Feature	[4.21]	-	LTB
S_{17}	Smart Feature	[5.20]	-	LTB
S_{18}	Body Structure	5*5;5*6;5*7	-	LTB
S_{19}	Comfort Level	[1,6]	-	LTB

3.2. Specification Competition Analysis

Relative satisfaction, which can be represented by $RS(P_d'S_i/P_xS_i)$, is used to indicate the relative satisfaction of $P_d'S_i$ compared to P_xS_i, thereby measuring the satisfaction comparison results between the two specifications. For LTB specifications, if the value of a product $P_d'S_i$ is greater than that of other products P_xS_i, we say that the relative satisfaction of $P_d'S_i$ is higher, represented by $RS(P_d'S_i/P_xS_i) > 1$. Conversely, if the value of the product is smaller compared to others, we say that the relative satisfaction of $P_d'S_i$ is lower, represented by $RS(P_d'S_i/P_xS_i) < 1$. If the comparison results are the same, it is represented by $RS(P_d'S_i/P_xS_i) = 1$. The STB specifications are the opposite of the specifications. For non-consistent specifications, it refers to those where different customers do not share the same preferences, making it impossible to judge relative satisfaction through comparison. As shown in Table 3, target-the-best specifications are not addressed in this study and will not be discussed further.

Table 3. Relative Satisfaction of Product Specifications

Relative satisfaction	*LTB*	*STB*	*NCP*
$RS(P_d'S_i/P_xS_i) > 1$	$P_d'S_i > P_xS_i$	$P_d'S_i < P_xS_i$	*N/A*
$RS(P_d'S_i/P_xS_i) <1$	$P_d'S_i < P_xS_i$	$P_d'S_i > P_xS_i$	*N/A*
$RS(P_d'S_i/P_xS_i) = 1$	$P_d'S_i = P_xS_i i$	$P_d'S_i = P_xS_i$	$P_d'S_i=P_xS_i$

Based on the relative satisfaction of specifications, four design scenarios are proposed: dominant design, dominated design, equivalent design, and mixed design [3]. Among them, a dominant design product has a relative satisfaction of all its specifications greater than or equal to 1 compared to another product, with at least one specification's relative satisfaction greater than 1; similarly, an dominated design product has a relative satisfaction of all its specifications less than or equal to 1 compared to another product, with at least one specification's relative satisfaction less than 1; an equivalent design product has a relative satisfaction of all its specifications equal to 1 compared to another product; all other cases fall into the mixed design scenario. These design scenarios will be applied in the subsequent derivation of the mixed-state space from a large number of potential solution combinations.

Generating feasible combinations of product specifications requires consideration of the constraints between the specifications. Based on the relevant constraints of the specifications, feasible combinations of product specifications are generated to construct a potential design space as a representation of customer preferences.

Constraints among specifications were defined for this case study, for example:

1. Energy Type = 'Pure electric'→Max Engine Power = 0, Max Engine Torque = 0, Fuel Tank Capacity = 0.
2. Energy Type = 'Range-Extended'→Max Engine Torque = 0.
3. Energy Type = 'Fuel'→Max Motor Power = 0, Max Motor Torque = 0, Battery Capacity = 0, Driving Range = (Fuel Tank Capacity/Fuel Consumption)*100.

To better investigate customers preferences on products with mixed design, mixed-state space which can be denoted as $\boldsymbol{C_{mix}}$ need to be established. Suppose existing 104 competing products can be modeled by $\boldsymbol{C_{exist}}=\{P_1, P_2, ..., P_{104}\}$, potential design of specification combinations that subject to mixed design with any elements in $\boldsymbol{C_{exist}}$ collectively form the mixed-state space $\boldsymbol{C_{mix}}$. Elements in $\boldsymbol{C_{mix}}$ can be considered as mixed design with each other.

In this study, comparison of potential designs with the 104 existing products has been carried out. The dominant designs, dominated designs, and equivalent designs associated to the 104 existing products are excluded from the potential design space, resulting in a mixed-state space that contains 99966 sets of specification combinations, which form the mixed-state space collection set $\boldsymbol{C_{mix}}=\{P'_1, P'_2, ..., P'_{99966}\}$.

After obtaining the mixed-state space, it is necessary to analysis influence ranges of the 104 existing products based on their similarities to the other designs in $\boldsymbol{C_{mix}}$. Considering a product P'_k belonging to $\boldsymbol{C_{mix}}$, the similarity of P'_k with each product in $\boldsymbol{C_{exist}}$ can be calculated by using Euclidean distance. Therefore, the similarity collection {Sim(P'_k, P_1), Sim(P'_k, P_2), ..., Sim(P'_k, P_{104})} can be obtained and the existing product (let's assume that is P_i) which have the highest similarity to P'_k can be identified. This indicates that P'_k falls within the influence range of P_i. If product P'_k has equal similarity with multiple products, then P'_k is located at the intersection of the influence ranges of these products.

Euclidean distance is used to measure the similarity between 99966 potential products in $\boldsymbol{C_{mix}}$ and 104 existing products in $\boldsymbol{C_{ex}}$, to determine the influence range of existing products. After delineating the influence ranges of existing products, the number of potential products within the influence range of each existing product is obtained, and the absolute sales number of each potential product in $\boldsymbol{C_{mix}}$ is determined according to Eq. (1).

$$\overline{P'_kN} = \frac{P_iN}{\sum_{j=1}^{n}\omega_j}, \omega_j = \begin{cases} 0 \\ 1 \\ 1/x \end{cases} \tag{1}$$

where, $\overline{P'_kN}$ is the absolute sales number of a product P'_kS in $\boldsymbol{C_{mix}}$, P_iN represents the sales number of a product P_iS, ω_j is the weight coefficient, and P'_jS represents a product in $\boldsymbol{C_{mix}}$. When P'_jS is outside the influence range of P_iS, $\omega_j = 0$. When P'_jS is within the influence range of P_iS, $\omega_j = 1$. When P'_jS is on the boundary of the influence range of P_iS, $\omega_j = 1/x$, $\boldsymbol{x}$ represents the number of products simultaneously lie on the boundaries of $\boldsymbol{x}$ existing products' influence ranges, $\boldsymbol{n}$ represents the number of products in $\boldsymbol{C_{mix}}$.

The calculation of absolute sales for each product in $\boldsymbol{C_{mix}}$ is aimed at predicting the market competitiveness of the optimized new product portfolio in subsequent optimization steps.

3.3. Competitiveness Evaluation of New Design

To evaluate the competitiveness of a design candidate, the estimated monthly sales are calculated based on the different design scenarios between the design candidate and existing products: if the specifications of the new product outperform or underperform those of an existing product in the market, it can be assumed that the superior product will replace the dominated design in market competition. If both are of equivalent design, the entry of the new product will take away half of the sales of the existing product. If the new product and the existing product are mutually mixed designs, products in $\boldsymbol{C_{mix}}$ must be used to estimate the sales of the new product. The estimated sales of the new product need to be obtained by comparing it competitively with all existing products $\boldsymbol{C_{exist}}$. The addition of the new product will change the influence range of existing products. The new product is included in the existing product set to form a new set $\boldsymbol{C_{new}}$, and the similarity between products in set $\boldsymbol{C_{new}}$ and products in $\boldsymbol{C_{mix}}$ is calculated using Euclidean distance. Products in $\boldsymbol{C_{mix}}$ that will fall within the influence range of the new product can be identified. Finally, by calculating the total absolute sales of all products in $\boldsymbol{C_{mix}}$ that falls into the influence range of the new product, the estimated sales number of the new product are obtained, which serves as an evaluation of its market competitiveness.

In this study, five new sub-products will be added to replace the five sub-products of the existing BYD Song PLUS DM-i product portfolio and to form a new competing product set $\boldsymbol{C_{new}}$. The addition of new products will reshape competition relationships with other existing products. Therefore, the influence range will be recalculated as previously based on the $\boldsymbol{C_{new}}$. The estimated sales for each sub-product can be calculated using Eq. (2).

$$P_iN = \sum_{k=1}^{n}\omega_k\overline{P_kN}, \quad \omega_k = \begin{cases} 0 \\ 1 \\ 1/x \end{cases} \tag{2}$$

where, $\overline{P'_k N}$ is the absolute sales number of a product P'_kS in $\boldsymbol{C_{mix}}$, P_iN represents the sales of a product P_iS in set $\boldsymbol{C_{new}}$, ω_k is the weight coefficient, when P'_kS is outside the influence range of P_iS, $\omega_k = 0$. When P'_kS is within the influence range of P_iS, $\omega_k = 1$. When P'_kS is on the boundary of the influence range of P_iS, $\omega_k = 1/x$, $\boldsymbol{x}$ represents the number of products in $\boldsymbol{C_{mix}}$ that simultaneously lie on the boundary of the influence range of x products in $\boldsymbol{C_{new}}$. $\boldsymbol{n}$ is the number of products within $\boldsymbol{C_{mix}}$.

The sales of a portfolio can be calculated by adding the sales numbers of each sub-product belonging to the portfolio. Since any changes in the sub-products will affect the estimated sales of a portfolio, it is necessary to calculate the estimated sales of product portfolio based on their influence range after each design change in design optimization, thereby assessing the competitive relationships between new products and competing products, as well as the interaction among other sub-products within the same product portfolio.

3.4. Portfolio Optimization of Electric SUVs

The estimated sales number of electric SUV portfolio is considered as the objective function for the portfolio optimization in this section. In this study, genetic algorithm is used to identify the optimal portfolio design solutions which can be represented by specification combinations. By analyzing the specification data collected for the BYD Song PLUS DM-i product portfolio, it is found that its product platform specification data is S_1=Plug-in, S_4=1, S_5=81, S_6=145, S_7=135, S_8=325, S_{10}=170, S_{12}=60, S_{13}=Front-Wheel drive, S_{15}=7, S_{18}=5*5, S_{19}=4. Using the product platform as a constraint, feasible solutions of the product specifications are generated as individuals in the genetic algorithm, and the population is initialized according to the population size.

The parameters for the genetic algorithm are set as follows: population size is set to 50, number of iterations is 100, crossover probability is 0.8, and mutation probability is 0.01. The optimization model for the product specification combination is then solved.

In the optimization process, each solution represented by specification combinations generated by the genetic algorithm is added to the existing product collection $\boldsymbol{C_{new}}$ for evaluating the influence ranges of the sub-products belonging to the new portfolio. Estimated sales of the new portfolio can be calculated according to Eq. (2). The optimization process is shown in Fig. 2 and the optimized specifications for the five sub-products within the portfolio were obtained as shown in Table 4.

From the optimized results in Table 4, it can be seen that these five sub-products form a functionally complementary and clearly positioned product portfolio based on the BYD Song PLUS DM-i product platform. P_{n1} serves as the base model, covering most core functions. The P_{n2} product is an enhanced version of P_{n1}, with improved active safety performance and intelligence. P_{n3} primarily targets customers with a strong demand for intelligence by enhancing the vehicle's level of intelligence, meeting the needs of consumers who focus more on driving experience and smart features, thus further strengthening the product portfolio's image of technological innovation and intelligence. P_{n4} with its high number of active safety features as its core competitiveness, has a strong appeal to customers who prioritize safety, further enhancing the market competitiveness of the product portfolio in terms of safety performance. P_{n5} with its high endurance advantage, targets customers with a higher endurance requirement, further expanding the audience range of the product portfolio. Each sub-product, with its unique technical features and functional focus, targets different customer groups and market demands. Through differentiated functional positioning and clear target market distribution, these five sub-products make up a product portfolio capable of meeting different needs, ultimately achieving the goal of design equilibrium.

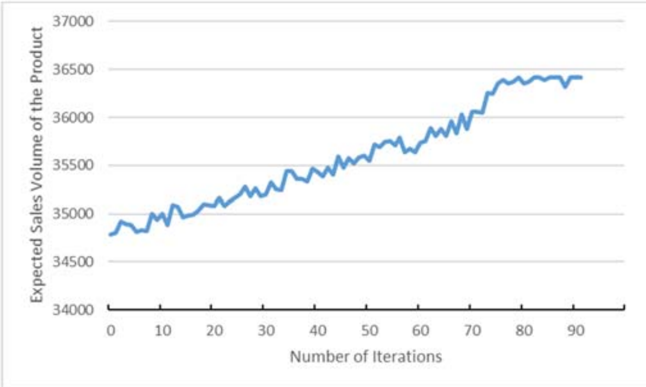

Fig. 2. Electric SUV portfolio optimization

Table 4. The optimized sub-products and their estimated monthly sales

Sub-products in the portfolio	Estimated monthly sales
P_{n1}=[Plug-in, 15.73, 1136, 0.6, 81, 145, 135, 325, 8.6, 170, 1.92, 60, Front-Wheel drive, 14.09, 7, 8, 10, 5*5, 4]	7050
P_{n2}=[Plug-in, 17.55, 1232, 0.7, 81, 145, 135, 325, 8.3, 170, 1.96, 60, Front-Wheel drive, 21.31, 7, 15, 14.5, 5*5, 4]	12070
P_{n3}=[Plug-in, 17.39, 1331, 0.5, 81, 145, 135, 325, 8.4, 170, 1.81, 60, Front-Wheel drive, 25.38, 7, 8, 18, 5*5, 4]	8139
P_{n4}=[Plug-in, 15.25, 1123, 0.6, 81, 145, 135, 325, 8.1, 170, 2.14, 60, Front-Wheel drive, 23.59, 7, 19, 5, 5*5, 4]	3548
P_{n5}=[Plug-in, 16.99, 1393, 0.6, 81, 145, 135, 325, 8.1, 170, 1.45, 60, Front-Wheel drive, 14.83, 7, 8, 6, 5*5, 4]	5610

In order to analyze the sensitivity of portfolio competitiveness to the number of sub-products in the portfolio, design optimization of BYD Song PLUS DM-i portfolio with different number of sub-products is also carried out. Estimated sales number of a portfolio with different sub-products are summarized in Fig. 3.

As shown in Fig. 3, the most significant gains are achieved when the portfolio consists of only two sub-products. Beyond this point, there is a decreasing trend in the return obtained from each additional product. This diminishing return suggests that companies should carefully assess the optimal number of sub-products based on their specific market conditions and strategic goals. While adding more sub-products may still provide incremental benefits, businesses must weigh these gains against the potential complexity and resource allocation required to manage a broader portfolio. Therefore, determining the ideal number of sub-products should be a tailored decision that aligns with both the company’s internal capabilities and the external market environment.

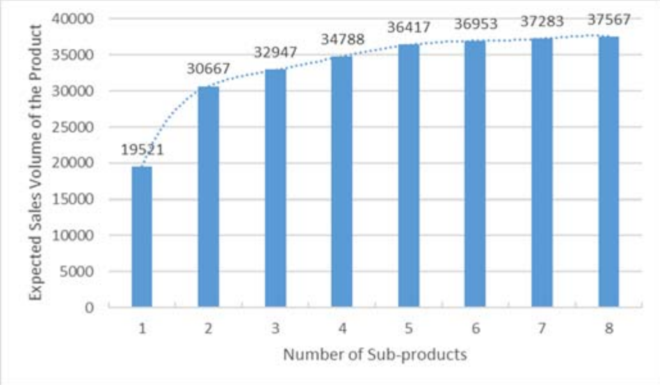

Fig. 3. Estimated monthly sales of the SUV portfolio

4. Conclusions

In order to improve the market competitiveness of EVs, product portfolio optimization needs to consider the competitive interactions among products and the internal competition among sub-products. Based on big sales data of EVs, in this work a portfolio design method is proposed by considering both internal and external competitions. The BYD Song PLUS DM-i product portfolio is selected as an implementation example to illustrate the proposed method. The main research findings include:

- This method can effectively utilize big sales data information to accurately reflect the interaction between products, effectively avoiding the problem of highly overlapping market shares caused by irrational competition between sub-products within the product portfolio, and improving the competitiveness of the product portfolio in the market.
- This paper focuses on the optimization design of the BYD Song PLUS DM-i product portfolio, ultimately resulting in a product portfolio composed of five new products that significantly outperform the original product combination in sales, demonstrating the feasibility and practical significance of this method, and providing recommendations and guidance for the optimization of product portfolio design of electric vehicle companies.

Despite these advances, design equilibrium decisions still need to be explored in light of potential competitor design strategies. In addition, platform design based on the estimated market performance of sub-products in a portfolio is also needed.

References

[1] Kumar M S, Revankar S T. Development scheme and key technology of an electric vehicle: An overview. Renewable and Sustainable Energy Reviews, 2017, 70: 1266-1285.
[2] Huo H, Zhang Q, Wang M Q, et al. Environmental implication of electric vehicles in China. Environmental Science & Technology, 2010, 44 (13): 4856-4861.
[3] Zhang J, Gao J, Simeone A, Gu P. 2023. Game analysis of product specifications for design optimization using big sales data. Journal of Engineering Design, 2023, 34(10): 844-864.
[4] Maslow A H. A theory of human motivation. Psyhological Review. Psychological Review, 1943, 1: 943.
[5] Kano N, Seraku N, Takahashi F, et al. Attractive quality and must-be quality. Journal of the Japanese Society for Quality Control, 1984, 14(2), 39-48.
[6] Tucker C S, Kim H M. Data-driven decision tree classification for product portfolio design optimization. Journal of Computing and Information Science in Engineering, 2009, 9(4):041004
[7] Liechty J, Ramaswamy V, Cohen S H. Choice menus for mass customization: An experimental approach for analyzing customer demand with an application to a web-based information service. Journal of Marketing research, 2001, 38(2): 183-196.
[8] Guo W, Hu M. Methodology of exploring and analyzing the VOC based on extensive web data source. Computer Integrated Manufacturing System, 2004, 10(9): 0.
[9] Zhang J, Xie G, Peng Q, Gu P. 2022. Product evolution analysis for design adaptation using big sales data. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 2023, 237(8): 1241-1253.
[10] Jiao J, Simpson T W, Siddique Z. Product family design and platform-based product development: a state-of-the-art review. Journal of intelligent Manufacturing, 2007, 18: 5-29.
[11] Simpson T W, Siddique Z, Jiao J. Product platform and product family design: methods and applications. Springer Science & Business Media, 2006.
[12] Meyer M H, Lehnerd A P. The power of product platforms: building value and cost leadership. Free Press, 1997.
[13] Newcomb P J, Bras B, Rosen D W. Implications of modularity on product design for the life cycle. ASME Journal of Mechanical Design, 1998, 120(3): 483-490.
[14] Gershenson J K, Prasad G J, Zhang Y. Product modularity: measures and design methods. Journal of Engineering Design, 2004, 15(1): 33-51.
[15] Daniilidis C, Enßlin V, et al. A classification framework for product modularization methods. Product and Systems Design, 2011,15.-19.08.
[16] Browning T R. Applying the design structure matrix to system decomposition and integration problems: a review and new directions. IEEE Transactions on Engineering management, 2001, 48(3): 292-306.
[17] Zhang J, Simeone A, Peng Q, et al. Dependency and correlation analysis of specifications and parameters of products for supporting design decisions. CIRP Annals, 2020, 69(1): 133-136.
[18] Thevenot H J, Simpson T W. A comprehensive metric for evaluating component commonality in a product family. Journal of Engineering Design,2007, 18(6): 577-598.
[19] Tomiyama T, Gu P, Jin Y, Lutters D, Kind Ch, Kimura F. Design Methodologies: Industrial and Educational Application. CIRP Annals-Manufacturing Technology, 2009, 58(2):543-565.
[20] Jiao J and Chen CH. Customer requirement management in product developmnet: a review of research issues. Concurrent Engineering: Research and Applications, 2006, 14(3):173-185.
[21] Zhang J, Li B, Peng Q, Gu P. 2023. Product specifications analysis for modular product design using big sales data. Chinese Journal of Mechanical Engineering, 2023, 36(1): 35-49.
[22] Tseng MM, Kjellberg T, Lu SCY. Design in the New E-commerce Era. CIRP Annals-Manufacturing Technology, 2003, 52(2):509-519.
[23] Ireland R, Liu A. Application of data analytics for product design: sentiment analysis of online proudct reviews. CIRP Journal of Manufacturing Science and Technology, 2018, 23:128-144.
[24] Zhang J, Song X X, Gu P H. Evolutionary state space and adaptability evaluation of complex competing products. Journal of Mechanical Engineering, 60(13): 33-47.
[25] Witten I H, Frank E. Data mining: practical machine learning tools and techniques with Java implementations. Acm Sigmod Record, 2002, 31(1): 76-77.
[26] See-To E W K, Ngai E W T. Customer reviews for demand distribution and sales nowcasting: a big data approach. Annals of Operations Research, 2018, 270: 415-431.
[27] Fan B Y. Analysis of international market competition in power design industry based on Porter's five forces model. Economist, 2013, (6):48-49.
[28] Nicoletti L, Mayer S, Brönner M, Schockenhoff F, Lienkamp M. Design parameters for the early development phase of battery electric vehicles. World Electric Vehicle Journal, 2020, 11(3): 47.