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Research Article

Automotive Product Portfolio Design from the Perspective of Energy Sustainability: Multicriteria Decision-Making Based on Lotka–Volterra MCGP Model

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Low energy consumption and green transformation of automobile product portfolio is the trend of the times. Automotive manufacturers make product portfolio decisions by setting multiple criteria such as fuel consumption, sales, and volume. It is also important to take into account the symbiotic interaction effects between automotive products. In order to achieve the above research objectives, this paper constructs the Lotka–Volterra MCGP model to make multicriteria decisions on automobile product portfolio design from the perspective of energy sustainability with BMW Brilliance is taken as an example to illustrate the process of using the multicriteria model. The empirical analysis successively measures product growth using the logistic model, analyzes the symbiotic relationship of product portfolios using the Lotka–Volterra model, and finally performs multicriteria evaluation using the MCGP model. In order to verify the reliability of the model, this paper verifies the robustness of the model from the perspectives of parameter dynamics, system boundaries, and model scalability. The results of empirical analysis and robustness analysis show that the Lotka–Volterra MCGP model proposed in this paper is applicable to the multicriteria decision-making of automobile product portfolio design from the perspective of energy sustainability.

1. Introduction

1.1. Research Background. As a major source of carbon emissions, the low-carbon transformation of the automobile industry is crucial. In order to promote the construction of a low-carbon circular development system, more and more transnational automobile enterprises have taken the "road to decarbonization," and the transformation of automobile electrification is imperative. The number of domestic fuel vehicles continues to increase, increasing the pressure on oil self-sufficiency, and the consumption of traditional cars for fuel increases the pressure on the country's oil supply.

In the highly competitive market environment, the increase of automobile sales volume is the premise of profit growth. However, the automobile manufacturing companies might ignore the fact that the rapid growth of automobile sales leads to increased carbon emissions if they simply pursue sales growth. Under the condition of limited market scale, most automobile enterprises, in order to seize market share, take rapid growth as the company's development goal, and pursue the maximization of sales revenue and interests. Under the trend of energy conservation and emission reduction, enterprises are faced with problems caused by increased sales and the multicriteria objectives of energy conservation and emission reduction.

Multicriteria decision-making (MCDM) method is popular in the field of energy sustainability research. The current energy development research focuses on the fields of macroeconomic planning, industrial sustainable development, and regional energy economic analysis. The sustainable development of product portfolio and energy from the perspective of enterprises is an important practical issue. This paper will develop a MCDM method for product portfolio from the perspective of energy sustainable development.

1.2. Literature Review

1.2.1. MCDM Method. MCDM (multicriteria decision-making) method is designed to support decision makers who are faced with multiple decision criteria and multiple decision options. As a unique research field, the research on the MCDM method provide firstly in the 1960s. After the 1980s and 1990s, researchers and practitioners showed exponential growth in their interest in MCDM methods. AHP (analytic hierarchy process), PROMETHEE (preference ranking organization methods for enrichment evaluations), VIKOR (intuitive fuzzy multiattribute decision-making method), ELECTRE (elimination and choice transcribing reality), TOPSIS (technique for order preference by similarity to ideal solutions), and other MCDM methods were proposed and expanded successively. At present, the MCDM method has been widely used in environmental management, socioeconomic ecosystem, manufacturing and energy management, and other fields.

There are many MCDM methods, and each one has its own applicability. In order to facilitate research and application, scholars use different perspectives to classify multiple-criteria decision-making methods. Among them, the most common is the classification of multicriteria decision methods into multiattribute and multiobjective decision methods according to whether the decision space is discrete or not. Multiattribute decision methods are applicable to the selection and ranking of a finite number of options in a discrete decision space, while multiobjective decision methods consider optimization problems with number of alternatives. [1].

Among MCDM methods, multiple attribute decision-making accounts for a large proportion. Paired comparison method calculates the scheme relationship based on the paired comparison of factors (criteria, alternatives) in the decision-making process [2]. Among the paired comparison methods, the most famous is the analytic hierarchy process (AHP), proposed by Saaty, because of its ease of use and transparent procedure for obtaining weights. However, AHP cannot deal with the interdependence between the upper and lower levels. Therefore, Saaty [3] further proposed the analytic network process (ANP), applicable to situations where there is a dependency relationship between factors. Performing the comparison of factors, there may be inconsistency problems. To overcome this problem, Rezaei [4] proposed the best worst method (BWM), which determines the weights of different criteria and the weights of programs under different criteria by comparing two by two on the basis of determining the best and worst criteria. The final score of the scheme is obtained by adding the weights of different criteria and schemes, and the best alternative is selected accordingly. Rezaei pointed out that, the best and worst methods require less comparative data, and the results can be more reliable.

The "outranking method" of decision-making determines the ranking relationship between alternatives by considering the superiority of one alternative relative to another. This approach considers the criteria to be non-compensable with each other while allowing for incomparable relationships between alternatives. Among the "outranking method" of decision-making, ELECTRE and PROMETHEE are the most popular methods. ELECTRE uses a ranking-over-relationship to model preferences, a method that sequentially reduces the number of alternatives without affecting the results by considering less data. PROMETHEE, proposed by Brans, can be used to sort and select a limited range of alternatives from conflicting standards. Compared with other multiple attribute decision-making methods, PROMETHEE is relatively simple in design and implementation [5]. The PROMETHEE method has gradually evolved from a single method to a family of methods as the field of application has expanded. In addition, Roubens also introduced an ORESTE method where quantitative data are lacking and the criterion weights are unknown. The method does not require exact criterion weights to distinguish between better-than, no-difference, and incomparable relationships among solutions [6].

The distance-based method defines a target on each criterion and selects the best scheme by the shortest geometric distance between the scheme and the ideal solution. TOPSIS [7] and VIKOR [8] are the two most commonly used methods in this category. In addition, multiple attribute decision-making methods also include utility-based methods, interaction-based methods, etc. The utility-based method is a MCDM method proposed under the environment of mult-attribute utility theory, including the simple weighting method, MAUT, and MAVT. Among them, the simple additive weighting is the most widely used, and new methods such as WASPAS and SWARA are subsequently introduced [9]. The interaction-based approach is applicable to situations where factors interact in decision-making problems. For example, DEMATEL lets problems be analyzed and solved through visual methods [10].

1.2.2. MCDM in Energy Sustainability. Globally, sustainability is a state of dynamic change [11, 12]. Reasonable and fully selected mathematical models can reliably combine contradiction problems according to preselected criteria. MCDM support tools are useful to make decisions based on several conflicting indicators when faced with the problem of identifying or expressing preferences [13].

As shown in Table 1, the MCDM method has been widely used in the study of sustainable energy development and has achieved good research results. The current research focuses on meso- and macro-areas such as energy development impact factor studies, regional energy project evaluation, and planning. There are few literatures that apply the energy sustainable factor to product portfolio design.

1.2.3. Product Portfolio Design. Choose the right combination of projects to achieve [31], or make strategic adjustments [32]. The main methods used include linear programming [33], fuzzy hierarchical process [34], analytic network process [35], theory of constraints (TOC) [36–38],

Table 1: MCDM method and its application in energy field.

Method (abbreviation)	Field of application (relevant literature)
Analytic hierarchy process(AHP), analytic network process (ANP)	Impact analysis [14–16]
Fuzzy set theory (fuzzy sets)	Impact analysis [15, 17]
Technique for order preference by similarity to ideal solutions (TOPSIS)	Energy policy and energy-related project selection [18, 19]
Weighted aggregated sum product assessment (WASPAS), weighted aggregated sum product assessment with the grey attributes scores (WASPAS-G)	Energy policy, energy related project selection, regional planning, and national planning [20, 21]
PROMETHEE	Power generation technology evaluation [22]
Multicriteria optimization and compromise solution (VIKOR)	Power generation technology evaluation and place selection [23–25]
Elimination and choice transcribing reality (ELECTRE), ELECTRE III	Energy policy, energy related project selection, regional planning, national planning, and power generation technology evaluation [26, 27]
Analysis and synthesis of parameters under information deficiency (ASPID)	Impact analysis [28]
Full multiplicative form of multiobjective optimization by ratio analysis (MULTIMOORA)	Energy policy, energy related project selection, regional planning, national planning, and power generation technology evaluation [29, 30]

intelligent algorithm [39], cross-entropy [40], and the comprehensive algorithm of these methods [41–45]. The product population concept is used to explain the complexity and population balance of the product life cycle model [46, 47].

It is a challenge for companies to increase product categories and expand business services, that is, to maintain the profitability of their product portfolio and manage it throughout the product life cycle. In the view of product structure, effective product portfolio management (PPM) practice may be the key to product profitability in the entire life cycle [48]. Optimal policies smooth the level of aggregate demand and cash flows [49].

Enterprises are faced with important decisions on the product portfolio. The online pattern is beneficial to the average emissions of each product [50]. The product diversification, interdependence, and product scarcity of an enterprise unlock this complexity. For example, research has analyzed the product supply relationship between automobile manufacturers and their suppliers [51]. In order to adapt to changes in the operating environment of enterprises, the latest research focuses on large-scale group decision-making (large scale group decision-making) [52, 53].

At present, in most literatures, MCDM method has been used to study energy sustainable development, but its application is still limited to intermediate level and designing with energy sustainability. The interaction between products in product portfolio design needs to be reflected in the process of portfolio evaluation. The existing research does not specify how the enterprise can achieve energy conservation and emission reduction and maintain a balance in product sales, nor does it extensively consider how development can meet the requirements of multicriteria decision-making. Therefore, the following research objectives are set in this paper: (1) A better automobile product portfolio analysis method that can give consideration to both sales and fuel consumption indicators is to be constructed. (2) This analysis method should reflect the symbiotic effect between products and fully develop the interaction effect between products.

2. Methods and Data

In this section, the idea of building the population growth model of the automobile products is introduced. On the basis of the logistic model and the Lotka–Volterra model, this paper puts forward a model of the enterprise product population relationship and analyzes the equilibrium point of the product portfolio system. The population equilibrium relationship is embedded into the MCGP model, and the Lotka–Volterra MCGP optimization model is constructed. Finally, the model is verified and empirically analyzed through real scenarios. The research framework, method, and process of this paper are shown in the figure below.

As shown in Figure 1, this paper presents a comprehensive analysis framework to evaluate the automobile product portfolio analysis from the perspective of energy sustainability. This research mainly serves for the analysis of product mix of automobile manufacturing enterprises. The product mix analysis of automobile manufacturing enterprises is very suitable for using the population dynamics model. This paper sets the automobile product series as the product population. There is a symbiotic relationship between different automobile products. For example, different automobile products can use the same technology, patent, equipment, and personnel, which is the cooperative relationship between populations. In real life, many different models of automobile products use the same engine and gearbox, and even different automobile brands will have similar cooperation relationships. The cooperative relationship between automobile products is universal, which is conducive to improving the efficiency of automobile manufacturing enterprises and reducing internal friction.

At the same time, there may be competition between automobile products. The talents, production facilities, and financial resources of automobile enterprises are limited. If two automobile products are competing for the internal resources of various enterprises, these two products are typical of internal competition relations. Enterprises need to face the complex symbiotic relationship of product populations when planning their product portfolio.

If sustainable energy constraints such as carbon emissions and fuel consumption are added to the product portfolio analysis, the analysis will become more complex. The analysis of automobile product portfolio from the perspective of energy sustainability is a typical MCDM problem. This paper attempts to construct a convenient and practical framework for product portfolio analysis through the following research methods.

2.1. Population Dynamics Model

2.1. Population Dynamics Model. Internal system of PP_1 (product population 1, PP_1) is build based on the logistic model as follows:

$$\begin{cases} \Delta N_1(t) = \alpha_1 N_1\left(1 - \dfrac{N_1}{K_1}\right), \\ N_1(t)\text{: population size}, \\ K_1\text{: largest population size}, \\ \alpha_1\text{: intrinsic growth rate}, \\ \left(1 - \dfrac{N_1}{K_1}\right)\text{: growth retardation factor}. \end{cases} \tag{1}$$

Set $\gamma_1 = -(\alpha_1/K_1)$.

Regression model can be obtained:

$$\Delta N_1(t) = \alpha_1 N_1(t-1) + \gamma_1 N_1^2(t-1). \tag{2}$$

The extended logistic model can be obtained based on the above formula.

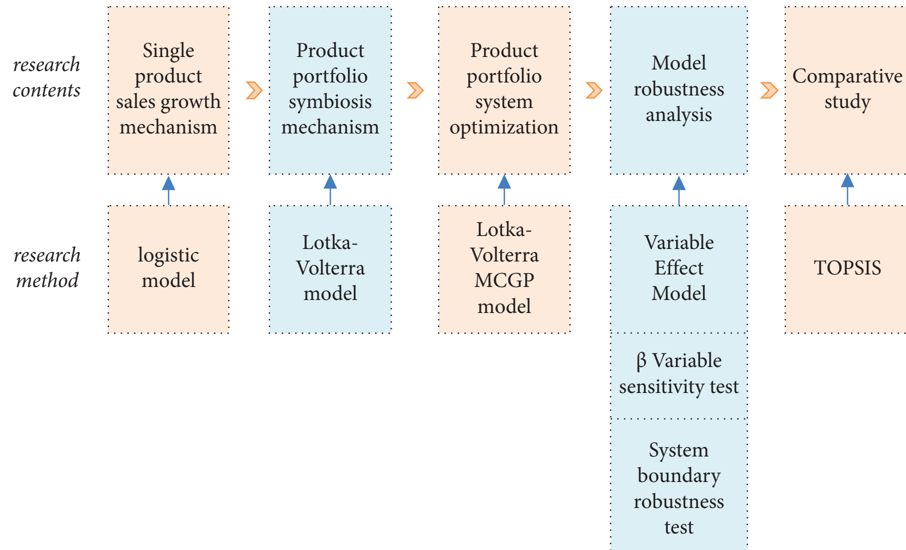

Figure 1: Research technology route.

$$\Delta N_1(t) = \alpha_1 N_1(t-1) - \frac{\alpha_1 N_1^2(t-1)}{K_1} + \frac{\alpha_1 \beta_{12} N_1(t-1) N_2(t-1)}{K_2}. \tag{3}$$

The influence of population 2 on population 1 is added to the above model. This is an asymmetric and skewed system.

The system made up of IP_1 and IP_2 is a Lotka–Volterra system. The regression model is

$$\begin{cases} \Delta N_1(t) = \alpha_1 N_1(t-1) - \dfrac{\alpha_1 N_1^2(t-1)}{K_1} + \dfrac{\alpha_1 \beta_{12} N_1(t-1) N_2(t-1)}{K_2}, \\ \Delta N_2(t) = \alpha_2 N_2(t-1) - \dfrac{\alpha_2 N_2^2(t-1)}{K_2} + \dfrac{\alpha_2 \beta_{21} N_1(t-1) N_2(t-1)}{K_1}. \end{cases} \tag{4}$$

Of them, $1 > \beta_{12} > 0$ and $1 > \beta_{21} > 0$. Based on stability analysis, the equilibrium point of the symbiotic relationship is

$$Pe\left(\frac{K_1(1+\beta_{12})}{1-\beta_{12}\beta_{21}}, \frac{K_2(1+\beta_{21})}{1-\beta_{12}\beta_{21}}\right). \tag{5}$$

It is the equilibrium state of the Lotka–Volterra system (PP_1 and PP_2).

2.2. Multichoice Goal Programming. Multichoice Goal Programming (MCGP) has been widely used in MCDM issue [54].

Multichoice Goal Programming is suitable for analyzing automotive product portfolio design from the perspective of energy sustainability, mainly reflected in the following points: (1) Automotive product design is a multiobjective process, which comprehensively considers issues such as product handling, safety, comfort, and economy. Multidimensional goals run through the entire process of automotive product design. (2) Product portfolio design makes goal setting more complex. (3) When considering energy sustainability issues, automobile manufacturing companies cannot only consider their own operational and profit goals but also incorporate energy sustainability goals into product development standards. Therefore, the combination of the Lotka–Volterra model and the MCGP model is beneficial for solving the complex multiobjective problems mentioned above. Embedding the MCGP model and the Lotka–Volterra model, we can get the Lotka–Volterra MCGP model [55]:

$$\text{Objective function: } \operatorname{Min} \sum_{i=1}^{n} \left(d_i^+ + d_i^-\right) + \sum_{i=1}^{n} \left(e_i^+ + e_i^-\right),$$

$$\text{Constraints: } \begin{cases} f_i(x) - d_i^+ + d_i^- = g_i, & i = 1, 2, \cdots, n, \\ x \in X = \{x_1, x_2, \cdots, x_m\} & \\ g_i - e_i^+ + e_i^- = g_{i,\max}, & i = 1, 2, \cdots, n, \\ g_{i,\min} \le g_i \le g_{i,\max}, & i = 1, 2, \cdots, n, \\ d_i^+, d_i^-, e_i^+, e_i^- \ge 0, & i = 1, 2, \cdots, n, \\ X \in F, & (F \text{ is the set of feasible solutions}), \\ x_1 = \dfrac{K_1(1+\beta_{12})}{1-\beta_{12}\beta_{21}}, & x_2 = \dfrac{K_2(1+\beta_{21})}{1-\beta_{12}\beta_{21}}, \quad \dfrac{x_1}{x_2} = \dfrac{K_1(1+\beta_{12})}{K_2(1+\beta_{21})}, \\ -1 < \beta_{12} < 1, & -1 < \beta_{21} < 1. \end{cases} \tag{6}$$

The Lotka–Volterra MCGP model (equation (6)) can consider the interaction between products and the multi criteria requirements of product portfolio decision-making.

2.3. Entropy Weight TOPSIS. This method can make the evaluation weight of each index in TOPSIS more objective [56–59]. In this paper, the method is studied as a main comparison method.

$$\text{Evaluation matrix: } A = \left[a_{\text{ij}}\right]_{m\times n}, \tag{7}$$

where a_{ij} represents the evaluation scores of different product combinations on different criteria.

Then, the initial evaluation matrix is

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{\text{mn}} \end{bmatrix} = \left[a_{\text{ij}}\right]_{m\times n}. \tag{8}$$

Step 1. Standardize the evaluation matrix.

$$r_{\text{ij}} = \frac{a_{\text{ij}}}{\sqrt{\sum_{i=1}^{m} a_{\text{ij}}^2}}. \tag{9}$$

Step 2. Calculate entropy.

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} r_{\text{ij}} \text{In}\, r_{\text{ij}}, \quad j = 1, 2, \cdots, n. \tag{10}$$

Step 3. Calculate weights.

$$w_j = \frac{1 - e_j}{\sum_{i=1}^{n}\left(1 - e_j\right)}, \quad j = 1, 2, \cdots, n. \tag{11}$$

The TOPSIS steps are shown as follows:

$$
\begin{cases}
\text{Step 1, normalized matrix:} \\
r_{\mathrm{ij}} = \dfrac{a_{\mathrm{ij}}}{\sqrt{\sum_{i=1}^{m} a_{\mathrm{ij}}^2}}, \\
\text{Step 2, weighted normalization matrix:} \\
v_{\mathrm{ij}} = w_j r_{\mathrm{ij}}, \sum_{j=1}^{n} w_j = 1, \\
\text{Step 3, calculate } A^+ \text{ and } A^-: \\
A^+ = \left\{ \left(\max v_{\mathrm{ij}} \mid j \in J \right) \mathrm{or} \left(\min v_{\mathrm{ij}} \,\middle|\, j \in J' \right) \right\}, \\
i = 1, 2, \cdots, m, \\
= \left\{ v_1^+, v_2^+, \cdots, v_n^+ \right\}, \\
A^- = \left\{ \left(\min v_{\mathrm{ij}} \mid j \in J \right) \mathrm{or} \left(\max v_{\mathrm{ij}} \,\middle|\, j \in J' \right) \right\}, \\
i = 1, 2, \cdots, m, \\
= \left\{ v_1^-, v_2^-, \cdots, v_n^- \right\}, \\
\text{Step 4, calculate PIS \& NIS:} \\
S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{\mathrm{ij}} - v_j^+ \right)^2}, i = 1, 2, \cdots, m, \\
S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{\mathrm{ij}} - v_j^- \right)^2}, i = 1, 2, \cdots, m, \\
\text{Step 5, sort the order:} \\
C_i^+ = \dfrac{S_i^-}{S_i^+ + S_i^-}, 0 < C_i^+ < 1, i = 1, 2, \cdots, m.
\end{cases} \tag{12}
$$

Here is $Ci+ \in (0, 1)$, where $i = 1, 2, \ldots, M$. Therefore, the best enterprise should be found in the order of $Ci+$. The larger is the value of $Ci+$, the better. If $Ci+$ is close to 1, the alternative Ai is closer to PIS.

3. Empirical Analysis

BMW Brilliance, a joint venture, was selected as the research sample for this study. BMW Brilliance's sales have been among the top in the Chinese luxury car market. At the same time, BMW has only a few product models, and the main product models are the BMW 5 Series, BMW 3 Series, BMW X1, and BMW X3. These four products have significant differences in market positioning, pricing, and fuel consumption. The sales data are selected from the actual sales data of each different model of BMW cars [60].

3.1. Empirical Analysis Cases. The study set up a research scenario in which companies replan the dominant product portfolio design guided by the concept of energy sustainability. Sales and total fuel consumption are used as the main discriminatory criteria in the product portfolio design for multicriteria product portfolio planning and design.

The average price and fuel consumption per hundred kilometers of relevant vehicle models are as follows:

BMW 5 Series, with an average price of 449,900 RMB and fuel consumption of 11.13 liters per 100 km

BMW 3 Series, with an average price of 326,400 RMB and a fuel consumption of 10.18 liters per 100 km

BMW X1 series, with an average price of 225,600 RMB and a fuel consumption of 11.06 liters per 100 km

BMW X3 series, with an average price of 380,200 RMB and a fuel consumption of 10.17 liters per 100 km

3.1.1. Evaluation of Single Product Growth Mechanism. As shown in Table 2, the regression results of the logistic regression model have a good fit. From the perspective of the internal growth rate of the product population, the BMW 5 Series and X1 are obviously better than the BMW 3 Series and X3. From the perspective of the maximum scale value of the product population, the BMW 5 Series and BMW 3 Series are obviously better than the X3 and X1. The market performance of BMW 5 Series products conforms to its market positioning and product advantages of the BMW automobile brand. BMW is a luxury brand that pays attention to driving quality and driving pleasure, which is also confirmed by consumers' preference for the BMW 5 Series. The disadvantage of logistic model is that it can only study the market growth characteristics of products in isolation and cannot reflect the mutual influence and interaction effects between products.

3.1.2. Analysis of Product Portfolio Symbiosis Mechanism. The Lotka–Volterra model can better analyze the symbiotic relationship within the product portfolio. The regression model can obtain the intrinsic growth rate, population inhibition coefficient, product interaction influencing factors, and population size (sales volume scale). On this basis, the total sales volume, total sales volume, and total fuel consumption of the product portfolio can be calculated.

As shown in Table 3, the Lotka–Volterra model can better show the symbiosis between two products in the product portfolio. It is also difficult to capture the multicriteria feature of product portfolio decisions in the regression results of the Lotka–Volterra model. Table 3 shows

Table 2: Single product sales growth mechanism.

Product model	α	γ	K
5	1.025 (5.121)***	-7.102×10^{-05} (−5.492)***	14434
3	0.963 (4.211)***	-6.925×10^{-05} (−4.721)***	13907
X1	1.018 (3.953)***	-1.242×10^{-04} (−4.244)***	8205
X3	0.847 (4.087)***	-7.909×10^{-05} (−4.403)***	10708

() t value, *** p value <0.01.

the interaction between products within different product portfolios. There is a symbiotic relationship between different types of automobile products. This symbiotic relationship can be expressed as synergy, like in the case where different product models can share a development platform or an engine model. At the same time, the symbiotic relationship can also be expressed as a competitive relationship, like in the case where companies need to allocate R&D and marketing expenses among different products. A good internal relationship can bring more synergy and reduce internal consumption.

We can get the good and bad order of the product portfolio. For example, from the perspective of sales volume, product portfolio 3 has the best sales prospects, while product portfolio 6 has the worst sales prospects. From the perspective of sales, portfolio 3 has the best prospects, and portfolio 6 has the worst prospects. From the perspective of total fuel consumption, portfolio 6 has the lowest total unit fuel consumption, while portfolio 3 has the highest total unit fuel consumption. Based on the regression data in this section, traditional evaluation methods (such as the TOPSIS method and the VIKOR method) can be used for in-depth analysis. However, traditional methods are difficult to reflect the mechanism of system evolution. This paper will use the Lotka–Volterra MCGP model to describe the evolution and optimization of the product portfolio symbiosis system.

3.1.3. Product Portfolio Symbiosis System Optimization. The authors take product portfolio 1 as an example. Set the turnover target as no less than 10,000,000,000 Yuan, and the total unit fuel consumption shall not be more than 30000 liters per hundred kilometers. The following Lotka–Volterra MCGP model can be obtained:

$$
\begin{aligned}
&\text{Objective function:}\ \ \mathrm{Min}\sum_{i=1}^{2}\left(d_i^{+}+d_i^{-}\right)+\sum_{i=1}^{2}\left(e_i^{+}+e_i^{-}\right),\\
&\text{Constraints:}\ \begin{cases}
f_1(x)-d_1^{+}+d_1^{-}=g_1=44.99x_1+32.64x_2-d_1^{+}+d_1^{-},\\
f_2(x)-d_2^{+}+d_2^{-}=g_2=11.13x_1+10.18x_2-d_2^{+}+d_2^{-},\\
x\in X=\left\{x_1,x_2,\cdots,x_m\right\}(X\ \text{is the set of feasible solutions}),\\
g_1-e_1^{+}+e_1^{-}=g_{1,\max},g_1\leq g_{1,\max}=1000000,\\
g_2-e_2^{+}+e_2^{-}=g_{2,\max},g_2\leq g_{2,\max}=300000,\\
d_i^{+},d_i^{-},e_i^{+},e_i^{-}\geq 0,i=1,2,\\
x_1=\dfrac{K_1\left(1+\beta_{12}\right)}{1-\beta_{12}\beta_{21}},x_2=\dfrac{K_2\left(1+\beta_{21}\right)}{1-\beta_{12}\beta_{21}},\dfrac{x_1}{x_2}=\dfrac{K_1\left(1+\beta_{12}\right)}{K_2\left(1+\beta_{21}\right)},\\
\beta_{12}=-0.038,\beta_{21}=0.230.
\end{cases}
\end{aligned}
\tag{13}
$$

The above model is a fixed effects model, which means that the concerns between products in the product portfolio are fixed (the β value is a constant). The construction idea is to give priority to the product portfolio with the lowest fuel consumption coefficient for production and sales when the sales volume of the product portfolio remains unchanged. The MCGP model results are shown in the following table.

As shown in Table 4, the MCGP model gives better results of system optimization under the dual criteria of sales and fuel consumption. There are significant differences in the optimization results of MCGP. In this paper, a simple method to select and judge the quality of a product portfolio is given.

Selection criteria are as follows: (1) When the total sales amount is the same, the product portfolio with a low fuel

Table 3: Product portfolio symbiosis mechanism.

Portfolio	Product model	α	γ_1	γ_2	β	K	Total sales	Total selling price	Total unit fuel consumption
1	5	1.031 (5.086)***	-6.84×10^{-05} (−4.666)***	-3.41×10^{-06} (−0.385)	−0.038	15061	26503	1051061	284108
	3	0.869 (3.301)***	-7.60×10^{-05} (−4.369)***	1.33×10^{-05} (0.730)	0.230	11442			
2	5	1.111 (4.944)***	-6.80×10^{-05} (−5.063)***	-1.62×10^{-05} (−0.849)	−0.114	16325	24139	910746	268120
	X1	0.993 (3.492)***	-1.27×10^{-04} (−3.918)***	3.56×10^{-06} (0.222)	0.059	7814			
3	5	1.060 (4.842)***	-6.76×10^{-05} (−4.381)***	-7.92×10^{-06} (−0.409)	−0.092	15664	27950	1171837	299289
	X3	0.902 (3.852)***	-7.34×10^{-05} (−3.472)***	-8.14×10^{-06} (−0.520)	−0.141	12286			
4	3	0.995 (3.646)***	-6.85×10^{-05} (−4.508)***	-5.21×10^{-06} (−0.217)	−0.041	14514	22406	651780	235038
	X1	1.011 (3.868)***	-1.28×10^{-04} (−3.979)***	3.24×10^{-06} (0.312)	0.046	7892			
5	3	0.805 (2.988)***	-7.65×10^{-05} (−4.771)***	2.47×10^{-05} (1.106)	0.325	10519	21095	875349	214641
	X3	0.845 (3.994)***	-7.99×10^{-05} (−3.961)***	8.41×10^{-07} (0.087)	0.010	10576			
6	X1	1.097 (3.822)***	-1.20×10^{-04} (−3.997)***	-1.06×10^{-05} (−0.638)	−0.067	9124	16054	469316	171390
	X3	0.700 (3.271)***	-1.01×10^{-04} (−4.900)***	4.85×10^{-05} (1.981)*	0.632	6930			

() t value, $^{*}p$ value <0.1, $^{***}p$ value <0.01.

consumption coefficient is preferred. (2) When the sales volume and fuel consumption are the same, the product portfolio with a high total sales volume is preferred.

According to the above criteria, the product portfolio rankings can be obtained as: portfolio 3, portfolio 1, portfolio 5, portfolio 4, portfolio 6, and portfolio 2.

3.2. Robustness Analysis

3.2.1. Product Portfolio Variable Effect Model. The researchers take product portfolio 1 as an example and set the turnover target as no less than 10,000,000,000 Yuan, and the total unit fuel consumption shall not be more than 30000 liters per hundred kilometers. The following variable effect model is obtained:

$$\text{Objective function: } \operatorname{Min}\sum_{i=1}^{2}\left(d_i^{+}+d_i^{-}\right)+\sum_{i=1}^{2}\left(e_i^{+}+e_i^{-}\right),$$

$$\text{Constraints: }\begin{cases} f_1(x)-d_1^{+}+d_1^{-}=g_1=44.99x_1+32.64x_2-d_1^{+}+d_1^{-}, \\ f_2(x)-d_2^{+}+d_2^{-}=g_2=11.13x_1+10.18x_2-d_2^{+}+d_2^{-}, \\ x\in X=\{x_1,x_2,\cdots,x_m\}\ (X \text{ is the set of feasible solutions}), \\ g_1-e_1^{+}+e_1^{-}=g_{1,\max},\ g_1\le g_{1,\max}=1000000, \\ g_2-e_2^{+}+e_2^{-}=g_{2,\max},\ g_2\le g_{2,\max}=300000, \\ d_i^{+},d_i^{-},e_i^{+},e_i^{-}\ge 0,\ i=1,2, \\ x_1=\dfrac{K_1(1+\beta_{12})}{1-\beta_{12}\beta_{21}},\ x_2=\dfrac{K_2(1+\beta_{21})}{1-\beta_{12}\beta_{21}},\ \dfrac{x_1}{x_2}=\dfrac{K_1(1+\beta_{12})}{K_2(1+\beta_{21})}, \\ -1<\beta_{12}<1,\ -1<\beta_{21}<1. \end{cases} \tag{14}$$

The idea of this variable effects model is to explore the optimal state of the product portfolio symbiosis system. The similarities and differences between the optimized symbiotic system and the original symbiotic system can be further compared.

As shown in Table 5, the variable effects model is different from the data in Table 4. However, the ranking of product portfolio is still: portfolio 3, portfolio 1, portfolio 5, portfolio 4, portfolio 6, and portfolio 2.

Table 4: Optimization results of the MCGP model of product portfolio (fixed effect model).

Portfolio	Sales volume	Product 1 sales	Product 2 sales	Total unit fuel consumption	Total sales
1	1000000	13038	12665	274051	25703
2	1000000	17272	9881	300000	27153
3	1000000	13660	10136	255135	23796
4	1000000	21729	12887	300000	34616
5	1000000	16186	12405	290947	28591
6	1000000	13685	18181	300000	31866

Table 5: Optimization results of the product portfolio MCGP model (variable effect model).

Portfolio	Sales volume	Product 1 sales	Product 2 sales	Total unit fuel consumption	β_{12}	β_{21}	Total sales
1	1000000	11860	14289	277477	0.000	0.585	26149
2	1000000	17412	9602	300000	0.054	0.214	27014
3	1000000	13367	10484	255401	0.000	0.000	23851
4	1000000	25182	7892	300000	0.735	0.000	33074
5	1000000	18318	10576	294035	0.741	0.000	28894
6	1000000	12450	18913	300000	0.000	1.000	31363

3.2.2. β Variable Sensitivity Test. In order to test the dynamic stability of the interaction influence factor in Lotka–Volterra MCGP, a β variable sensitivity test is conducted in this paper. The skewness of the original model is followed in the test. The values of β_{12} and β_{21} are set, and the optimization results are shown in the following table for portfolio 1 as an example.

As shown in Table 6, the model optimization results vary with the interaction coefficient β. Within the theoretical bound of β, the corresponding optimization results change accordingly.

3.2.3. Robustness Test of System Boundary. This section tests the stability of the model from the perspective of variable sales target criteria and fuel consumption target criteria. Taking portfolio 5 as an example, the system boundary stability results are as follows.

As shown in Table 7, with the boundary expansion of the objective criteria, the model can still work normally and the calculation results are valid.

3.3. TOPSIS Evaluation. The data in Table 4 are used for TOPSIS evaluation of entropy weight and TOPSIS under the condition of subjective weight setting. The analysis results are shown in the following table.

As shown in Table 8, the Lotka–Volterra MCGP proposed in this paper can be better used in combination with the traditional TOPSIS method. The idea of setting weights based on entropy values is based on the difference in the richness of the information contained in the data. However, under the guidance of sustainable energy development, the weight of the energy index can be adjusted. In this paper, several different energy index weights are set for comparative analysis of TOPSIS results. When the weight of the energy index is set high enough (0.9), the TOPSIS results are the same as the previous research results.

3.4. Expand Multidimensional Model. The two-species Lotka–Volterra MCGP model can better evaluate the combination of two products using multiple criteria. At the same time, the model itself has certain scalability. For example, when the enterprise's product portfolio is multiple choice and four combinations—that is, four products from multiple products—are selected as the leading product portfolio. In this situation, the first step is to calculate the evaluation data of the two product combinations and then conduct the second round of evaluation of the two product combinations. This multistage expansion is difficult to apply to odd product portfolio measurement. This section proposes a three-dimensional Lotka–Volterra MCGP model to solve similar problems. The case analysis data still adopts the

Table 6: β variable sensitivity test.

β_{12}	β_{21}	Sales volume	Product 1 sales	Product 2 sales	Total unit fuel consumption	Total sales
0	0.9	1000000	10857	15671	280381	26528
0	0.8	1000000	11157	15257	279509	26414
0	0.6	1000000	11811	14357	277613	26168
0	0.4	1000000	12546	13344	275480	25890
0	0.2	1000000	13378	12196	273065	25574
0	0	1000000	14329	10886	270306	25215
0	−0.2	1000000	15425	9375	267125	24800
0	−0.4	1000000	16703	7613	263417	24316
0	−0.6	1000000	18212	5534	259039	23746
0	−0.8	1000000	20020	3041	253792	23061
0	−0.9	1000000	21066	1600	250757	22666

Table 7: System boundary robustness test.

β_{12}	β_{21}	Sales volume	Product 1 sales	Product 2 sales	Total unit fuel consumption	Total sales
0.325	0.010	1000000	16186	12405	290947	28591
0.325	0.010	1100000	17805	13646	320042	31451
0.325	0.010	1200000	19424	14886	349136	34310
0.325	0.010	1300000	21042	16127	378231	37169
0.325	0.010	1400000	22661	17367	407326	40028
0.100	0.300	1500000	19276	22904	429169	42180
0.100	0.300	1600000	20561	24431	457780	44992
0.200	0.300	1700000	22956	25004	488001	47960
0.300	0.300	1800000	24307	26475	500000	50782

relevant data of BMW Brilliance given in the article. The extended Lotka–Volterra model is as follows:

$$\begin{cases} N_1(t) = \dfrac{\alpha_1\beta_{12}N_1(t-1)N_2(t-1)}{K_2} + \dfrac{\alpha_1\beta_{13}N_1(t-1)N_3(t-1)}{K_3} + \dfrac{\alpha_1\beta_{14}N_1(t-1)N_4(t-1)}{K_4}, \\ N_1(t) = N_2(t) + N_3(t) + N_4(t), \end{cases}$$
$$\Longrightarrow N_1(t) = \gamma_1 N_1(t-1)N_2(t-1) + \gamma_2 N_1(t-1)N_3(t-1) + \gamma_3 N_1(t-1)N_4(t-1). \tag{15}$$

Based on the above multidimensional population dynamics model, the following regression model results can be obtained.

As shown in Table 9, the multidimensional extended Lotka–Volterra deformation model can express the internal influence relationship of the three product portfolios. Among them, the internal relationship of product portfolio 3 is the most harmonious, and the impact of the three products on the total product portfolio is positive. There is no internal friction in the product portfolio, which is more reflected in synergy. In this paper, the Lotka–Volterra MCGP model is optimized based on the internal relationships among the above three product combinations. In this section, portfolio 1 (5, 3, X1) is used as an example to illustrate Lotka–Volterra MCGP after dimension expansion, and the following model can be obtained:

Table 8: TOPSIS ranking of product portfolio.

Portfolio	Total unit fuel consumption	Total sales	TOPSIS result	RANK	TOPSIS result	RANK	TOPSIS result	RANK	TOPSIS result	RANK	TOPSIS result	RANK
1	0.087	0.007	0.401	4	0.460	2	0.489	3	0.515	2	0.573	2
2	0.000	0.023	0.200	6	0.158	6	0.229	6	0.113	6	0.033	6
3	0.259	0.000	0.509	1	0.600	1	0.594	1	0.700	1	0.900	1
4	0.000	0.241	0.491	2	0.400	3	0.561	2	0.300	3	0.100	4
5	0.011	0.047	0.330	5	0.289	5	0.377	5	0.250	4	0.206	3
6	0.000	0.134	0.412	3	0.329	4	0.475	4	0.241	5	0.077	5
	Index weight		W_j (0.509, 0.491)		W_1 (0.6, 0.4)		W_2 (0.65, 0.35)		W_3 (0.7, 0.3)		W_4 (0.9, 0.1)	

Table 9: Results of the expanded multidimensional model.

Portfolio	γ_1	γ_2	γ_3
1 (5, 3, X1)	0.0000414 (2.160)**	−0.0000082 (−0.507)	0.0000478 (2.160)*
2 (5, 3, X3)	0.0000292 (1.331)	−0.0000093 (−0.571)	0.0000535 (1.907)*
3 (5, X1, X3)	0.0000228 (1.038)	0.0000506 (1.564)*	0.0000140 (0.475)
4 (3, X1, X3)	−0.0000055 (−0.374)	0.0000584 (1.863)*	0.0000447 (1.746)*

() t value, $^{*}p$ value <0.1, $^{**}p$ value <0.05.

$$\text{Objective function:}\ \ \text{Min}\sum_{i=1}^{2}\left(d_i^{+}+d_i^{-}\right)+\sum_{i=1}^{2}\left(e_i^{+}+e_i^{-}\right),$$

$$\text{Constraints:}\ \begin{cases} f_1(x)-d_1^{+}+d_1^{-}=g_2=11.13x_2+10.18x_3+11.06x_4-d_1^{+}+d_1^{-}, \\ x_1=\gamma_1x_1x_2+\gamma_2x_1x_3+\gamma_3x_1x_4, \\ x_1=x_2+x_3+x_4, \\ g_1-e_1^{+}+e_1^{-}=g_{1,\max}, g_1\le g_{1,\max}=300000, \\ d_i^{+},d_i^{-},e_i^{+},e_i^{-}\ge 0,\quad i=1,2. \end{cases} \tag{16}$$

The optimization results are shown in the following table.

As shown in Table 10, the expanded model can still achieve an effective evaluation of the product portfolio. The advantages and disadvantages of three product portfolio analyses are ranked as follows: portfolio 4, portfolio 2, portfolio 1, and portfolio 3. Most of the three product combinations are unbalanced systems, so there is an unbalanced distribution of product optimization results, and some models are difficult to get a place in the product combination.

4. Results and Discussion

4.1. Results. This article achieves the research objectives by using the population dynamics model to make regression analysis on the single population growth mechanism and the double population symbiosis mechanism of automobile enterprises. Based on the Lotka–Volterra symbiosis mechanism, the Lotka–Volterra MCGP optimization model is constructed. In the MCGP model, two main criteria are set: total sales and total fuel consumption of products sold. Based on the analysis results of the MCGP model, a simple product portfolio evaluation process is given. In order to test the robustness of the Lotka–Volterra MCGP model, this paper verifies that the model is applicable and effective from the perspectives of fixed effects model, the variable effects model, the boundary adjustment model, and comparative analysis. Finally, the research combines the results of the Lotka–Volterra MCGP model and the entropy weight TOPSIS method for analysis and evaluation, demonstrates the extensibility of the Lotka–Volterra MCGP model, and proves that the Lotka–Volterra MCGP model can be better combined with other traditional methods for multicriteria analysis of product portfolio.

4.2. Discussion. The Lotka–Volterra MCGP model provides a new research perspective and theoretical foundation, viewing the automotive product portfolio as a symbiotic ecosystem from the perspective of population symbiosis. The Lotka–Volterra model provides a symbiotic relationship. The MCGP model provides a multiobjective product design solution that includes energy consumption. From a methodological perspective, the Lotka–Volterra MCGP model has better adaptability and highlights. Compared with the traditional analytic hierarchy process [14–16], this research method does not need to set the weight of evaluation variables. Compared with traditional TOPSIS [18, 19] and VIKOR [23–25] research methods with heavy subjective impact, this research method can be analyzed based on objective data to find the symbiotic mechanism between products from the objective data. WASPAS [20, 21] and ELECTRE [26, 27] methods are suitable for regional energy economic planning and other fields, but not for automobile product portfolio analysis and decision-making under the guidance of low fuel consumption. The method provided in the paper can be seen as a development of a traditional product portfolio analysis method. The Lotka–Volterra MCGP optimization model comprehensively uses the ideas of linear programming [33], the theory of constraints [36–38], and embedded constraints [45]. Compared with these traditional methods, Lotka–Volterra can fully reflect the symbiotic relationship between products, and the MCGP model can realize multicriteria evaluation.

There is no mature and comprehensive evaluation method for designing automotive product combinations from the perspective of energy sustainability. The evaluation method that this article aims to explore needs to meet the following conditions: (1) The new evaluation method proposed in this article can achieve multiobjective and multicriteria evaluation standards. The evaluation criteria should

Table 10: Results of the expanded multidimensional Lotka–Volterra MCGP model.

Portfolio	Sales volume	Product 1 sales	Product 2 sales	Product 3 sales	Total unit fuel consumption
1 (5, 3, X1)	27168	24652	2516	0	300000
2 (5, 3, X3)	27639	19699	0	7939	300000
3 (5, X1, X3)	27040	13247	13793	0	300000
4 (3, X1, X3)	27995	9665	17076	1262	300000

include both traditional economic evaluation indicators and energy sustainable development indicators. (2) The evaluation method should be able to accurately distinguish and clearly evaluate and rank the evaluation values of different automotive product combinations. (3) The evaluation method should be simple and feasible and should not be too complex. The research results indicate that the Lotka–Volterra MCGP method proposed in this paper meets the above conditions well and successfully achieves the research objectives. The Lotka–Volterra MCGP method effectively integrates the advantages of the Lotka–Volterra model and the MCGP method. The MCGP method can achieve multiobjective optimization. The Lotka–Volterra model views multiple attributes of automotive products as a symbiotic system from an ecological perspective. The economy, safety, handling, and energy sustainability of automotive products are all different elements in a symbiotic system. The symbiotic mechanism can effectively balance the diversity standards of product performance.

4.3. Management Enlightenment

4.3.1. Enterprise Perspective. From the perspective of long-term development, automobile manufacturers must carry out technological innovation and improve the cost performance and differentiation of low-carbon automobile products if they want to gain competitive advantages in the low-carbon automobile market. They must make full use of low-carbon technology research and development achievements, improve their independent research and development capabilities in the fields of platform modularization, lightweight, electronic control technology, intelligence, etc., and provide technical support for the development of low-carbon vehicles. In addition to improving technology R&D and innovation capabilities and further enriching the product categories of the platform, it is also necessary to gradually develop the corresponding new energy vehicles as well as the maturity and acceptance of power battery technology. At the same time, automobile manufacturers should pay attention to the improvement of lightweight automobile. In terms of vehicle lightweight improvement, automobile manufacturers should further cooperate with suppliers to carry out research, development, and application of high-strength steel, aluminum magnesium alloy, glass fiber, carbon fiber, and other lightweight materials for automobiles so as to reduce fuel consumption and emissions by reducing vehicle weight. Automobile manufacturing companies should aim to display an energy-saving and environmentally friendly image, as brand image is formed by consumers' perception of the company's products. Establishing a brand is intended to improve corporate awareness and consumer loyalty to the product, so a good brand image always plays an important role in the development process of the company. Automobile manufacturing companies must establish the brand image of quality first, energy saving, and low carbon so as to improve the attractiveness of products and customer loyalty. Analyzing and designing the development direction of automobile products from the perspective of sustainable energy development will contribute to the healthy development of the automobile industry. The new energy vehicle (NEV) manufacturers should give full play to the power of the market, improve consumer satisfaction, encourage competition and cooperation among NEV manufacturers, and break the local protection in the promotion of NEVs. We should improve the access management rules for NEVs, especially the market cultivation of low-cost pure electric vehicles.

4.3.2. Policy Perspective. From a macroperspective, we should enhance consumers' personal awareness of environmental protection, improve product technology, strengthen product quality, guide key infrastructure construction, promote the urban economy, and improve public transport facilities and other policies. At the medium level, it proposes policies such as strengthening brand image and influence, encouraging industrial technological innovation, and adjusting and changing industrial subsidies. From a microperspective, enterprises should fully study consumer behavior to accurately position products and markets and encourage enterprises to increase investment in product core technologies. In view of the existing problems in the current new energy automobile industry, it proposes policies such as building a collaborative innovation platform, improving the industrial chain coordination mechanism, and breaking regional barriers to enhance industrial competitiveness.

4.4. Conclusion. The research goal of this paper is to construct a better analysis method of automobile product portfolio that can give consideration to both sales and fuel consumption indexes. This analysis method should reflect the symbiotic effect between products and fully develop the interaction effect between products. The Lotka–Volterra MCGP method proposed in this paper has better achieved the above research objectives.

The research highlights of this paper are as follows: (1) This paper constructs the Lotka–Volterra MCGP model and applies it to the evaluation of automobile product portfolio from the perspective of energy sustainability. (2) The application scenarios of Lotka–Volterra MCGP model are expanded through the expansion of model dimensions. (3) The criterion of energy sustainable development is introduced into the research of automobile product portfolio, which expands the perspective of energy sustainable research. The main disadvantage of this paper is that the Lotka–Volterra model set in the research is two-dimensional. In future research, the dimensions of the Lotka–Volterra model need to be expanded to make it more widely used.

Data Availability

All relevant data sources have been provided within this manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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