Research Article

Competition Analysis on Industry Populations Based on a Three-Dimensional Lotka–Volterra Model

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The classical Lotka–Volterra model is mainly a two-dimensional configuration. The two-dimensional form limits the application scenarios of the Lotka–Volterra model. The research objective of this paper is to develop a feasible three population equilibrium model to analyze the industry competition. In order to expand the Lotka–Volterra model to empirical analysis, this paper proposes a symbiosis model of enterprise population based on a three-dimensional Lotka–Volterra model. This paper analyzes the symbiotic system from two aspects: the balanced development of three species and the competitive evolution of the three species, taking the sales volume of three local automobile enterprises in China as the sample for empirical analysis. The symbiotic optimization under the equilibrium state of three populations indicates that there is the possibility of equilibrium and reciprocity in the growth of three automobile product populations. The empirical analysis fully explains the feasibility of this research paradigm. The analysis of competition evolution shows that cooperative action is better than competitive strategy and that comprehensive cooperation is the ideal state of a three-population symbiotic system.

1. Introduction

Research for competing for interacting networks takes into account real-world networks [1–6]. However, the researchers ignored the competitors competing not only to survive but also to defeat their competitors [7]. An incursion between species can alter the dynamics of the predator-prey interaction [8], which is a widespread phenomenon. The theoretical framework that measures the feedback mechanisms and resilience dynamics between two competing dynamic networks was developed to identify the factors in a network [9, 10]. However, the competition network in the real world is more complex compared with the relationship between two species. The complex symbiotic relationship in the industrial ecosystem can be taken as an example.

The industrial ecosystem, which emerged in the 1990s, is an interdisciplinary applied discipline. Its main purpose is to explore the interaction between industry and its products and the natural environment. Traditional industrial activities

should be transformed into an industrial ecosystem [11]. In this system, the consumption of energy and material is optimized, the output of waste is minimized, and the waste of one industrial process can be used as the raw material of another process. The theory of industrial ecology studies how the industrial system operates, regulates, and interacts with the biosphere and decides how to adjust the industry to make it compatible with the biosphere based on the cognition of the ecosystem [12]. The research of the industrial ecosystem is rich and diversified. Carayannis and Alexander [13] propose a dynamic- and learning-driven framework to study the process of knowledge generation and how to maximize organizational value by using game theory. Carayannis et al. [14] believe that knowledge sharing and knowledge management across organizational boundaries have provided a good analytical framework for the research cooperation between industry and university and promoted the trust relationship and social capital between organizational cooperation. Korhonen et al. [15] point out that the concept of sustainable development of

industrial ecosystem provides a new way of thinking and an innovation path for the current industrial system construction, and the theory of industrial ecosystem and interorganizational management can supplement the shortcomings of the traditional theory of intraorganizational environmental management and guide human behavior to achieve the goal of industrial ecological balance.

Many scholars have made in-depth research on the practical application of the industrial ecosystem. Cabezas et al. [16] hold that the development of industrial ecology should not only stay at the stage of concept proposal but also be realized in practice. Therefore, simulated ecological and technological experiments have been conducted, and it is further pointed out that the industrial ecosystem is a complex sustainable system and that a complex “generalized food web” is formed in industry, agriculture, and natural organisms of human social activities. Korhonen and Snakin [17] scientifically analyze the application of industrial ecology to the ecological economy, environmental planning, and organization management by establishing various models of resource utilization, energy cycle, and industrial diversification. They emphasize that industrial ecology and industrial ecological evolution theory will play an important role in the future development of the industrial economy. In addition, Basu and van Zyl [18] further combine the theory of industrial ecology and the theory of cleaner production and point out that the degree of cleaner production depends on the degree of industrial ecology. The research findings of these scholars enrich the theoretical system of industrial ecology and provide a new research perspective for the harmonious development of the economy and environment.

The industrial ecosystem provides a systematic analysis and a synthetic method to examine the whole life cycle of a product or a process, not just the impact of a part of a certain stage. Lotka–Volterra model (LV model) is a classical model for the study of coevolution among species in natural ecology. It is proposed by Lotka [19] and Volterra [20] to analyze the competition mechanism between two species. Lotka–Volterra model is based on the logistic curve, which is an extension of the logistic model under the condition of nonsingle species competition. Based on the logistic growth curve of a single species, the dynamic competitive growth of multiple agents in the system is considered. Lotka–Volterra model was successfully spread to the research fields of the social and economic system to interpret the competition behavior between organizations [21]. The model is widely used in the research fields of industrial competition, enterprise competition, and market competition [22–25]. Some researchers use the Lotka–Volterra model to analyze innovation activities among competitors [26–29] or technology substitution among competitors [30, 31]. Some researchers focus on the transformation path [32].

At present, the application of the multidimensional Lotka–Volterra model is rare. In fact, the classical Lotka–Volterra model mainly explains the symbiotic relationship between two populations. The interpretation of symbiotic relationships in the real world needs the help of more complex models. As a result, this paper provides a three-dimensional Lotka–Volterra approach to analyze the competition evolution dynamic among the firms. Ecological populations and communities in

nature are composed of organisms with different life characteristics. There are various complex organic relations between different populations, groups, and organisms and the natural environment. Under the comprehensive effect of the external environment, the ecological community develops and evolves continuously, thus forming an ecosystem. Similar to the evolution of the natural ecological community, the industrial ecological innovation system is also an open and dynamic system. There are many similarities between them in selection mechanism, environmental function, evolution, and development. The evolution process of industrial ecological innovation system can be analyzed and illustrated by referring to the evolution phenomenon among biological populations. Geroski and Mazzucato [33] explored four models for industry population dynamics: market size model, negative feedback model, contagion model of entry and exit, and density-dependent model.

At present, few researchers focus on the application of industrial ecosystem theory to a certain industry. This paper attempts to study the evolution path of specific industrial ecological innovation systems from the perspective of ecology through a combination of the theory of industrial ecosystem and specific industries and to make some tentative exploration on the evolution and development of industries. The research objective of this paper is to develop a feasible three population equilibrium model to analyze the industry competition. The benefits of the three-dimensional Lotka–Volterra system are as follows: we successfully develop a feasible three population equilibrium model to analyze the industry competition, and that expands the research situation of the two-dimensional model and has a broader application field. The three-dimensional Lotka–Volterra model is closer to the real-world population competition relationship. The two-dimensional Lotka–Volterra model can be regarded as a special case of the three-dimensional Lotka–Volterra model. It is an ideal state that there are only two competitors in an industry. This paper proves the value of the three-dimensional Lotka–Volterra model from both theoretical and empirical perspectives and successfully expands the system dimension of the Lotka–Volterra model in the analysis of the competitive relationship.

2. Materials and Methods

In this section, we will describe the three-dimensional Lotka–Volterra model and its equilibrium state. These theorems will be used to discuss the case of industrial competition analysis. This paper selects BYD, Great Wall Motor, and ChangAn Motor as the research objects. These three companies have the same market segment and are among the top domestic auto companies in this market segment.

As shown in Figure 1, this paper provides the deduction of the LV-MCGP model. The specific model construction process is as follows.

2.1. Dynamics Analysis of Logistic and Lotka–Volterra Models. According to the logistic model, we constructed an internal dynamic system of population 1 (P_1).

FIGURE 1: Research flow chart.

$$g_1(t) = \frac{dN_1(t)}{dt} = \alpha_1 N_1 \left(1 - \frac{N_1}{K_1} \right), \quad (1)$$

where $g_1(t)$ is the growth rate in phase t . $N_1(t)$ is the population size of period t . K_1 is the maximum population

scale. α_1 is the intrinsic growth rate. $(1 - (N_1/K_1))$ is the retardation of growth.

The measurement model is as follows:

$$\begin{aligned} \text{because } N_1(t) &\approx \Delta N_1(t), \Delta N_1(t) = N_1(t) - N_1(t-1), dt \approx \Delta t = t - (t-1) = 1, \\ \text{so } g_1(t) &\approx \Delta N(t) = \gamma_1 N_1(t-1) + \gamma_2 N_1^2(t-1). \end{aligned} \quad (2)$$

Among them, $\gamma_1 = \alpha_1$; usually, $\gamma_1 > 1$. It usually represents the synergy within a population. $\gamma_2 = -(\alpha_1/K_1)$; usually, $\gamma_2 < 0$. It refers to the competition effect within a population. It is called the internal competition coefficient or population density inhibition coefficient.

Similarly, the internal relation model of population 2 (P_2) can be obtained:

$$g_2(t) = \frac{dN_2(t)}{dt} = \alpha_2 N_2 \left(1 - \frac{N_2}{K_2} \right). \quad (3)$$

The following system shows the impact of the P_2 on P_1 :

$$g_1(t) = \frac{dN_1(t)}{dt} = \alpha_1 N_1 \left(1 - \frac{N_1}{K_1} + \frac{\beta_{12} N_2}{K_2} \right), \quad (4)$$

where β_{12} is the influence of population 2 on population 1 ($\beta_{12} > 0$, synergistic effect, $\beta_{12} < 0$, competitive effect). Similarly, the following system shows the impact of P_1 on P_2 :

$$g_2(t) = \frac{dN_2(t)}{dt} = \alpha_2 N_2 \left(1 - \frac{N_2}{K_2} + \frac{\beta_{21} N_1}{K_1} \right), \quad (5)$$

where β_{21} is the impact factor of population 1 on population 2. The dynamic system of P_1 and P_2 is

$$\begin{cases} g_1(t) = \frac{dN_1(t)}{dt} = \alpha_1 N_1 \left(1 - \frac{N_1}{K_1} + \frac{\beta_{12} N_2}{K_2} \right), \\ g_2(t) = \frac{dN_2(t)}{dt} = \alpha_2 N_2 \left(1 - \frac{N_2}{K_2} + \frac{\beta_{21} N_1}{K_1} \right). \end{cases} \quad (6)$$

Equation (6) is called the Lotka-Volterra (LV) system. The LV model, based on the logistic model of a single species, considers the dynamic growth of competition and

symbiosis of two or more entities simultaneously in the ecosystem [20], which can accurately describe the competition and symbiosis between corporate populations. The LV system can determine the influence of the core population in the evolution of the entire ecosystem [34] and thus has better data fitting and prediction expression [35].

The classical Lotka-Volterra model, a differential dynamic system, was used to simulate the dynamic relationship of populations in ecology. Later, economists introduced it into the fluctuation of macroeconomic growth and the market competition of medium scale and scope. According to the principle of biology, there are many kinds of functional relationships among biological populations: promotion or inhibition. For their own survival and development, there is also a relationship between market competition subjects: the existence of one subject can promote or inhibit the diffusion process of another. The LV model of dual-population or multipopulation growth is a differential dynamic system to simulate the dynamic relationship between populations. Based on the numerical value of β , the type of interaction between species can be judged [36]:

- (1) When $\beta_{12} = 0$ and $\beta_{21} = 0$, the populations develop independently and do not affect each other. At this time, the LV model expresses no symbiotic relationship.
- (2) When $\beta_{12} < 0$ and $\beta_{21} < 0$, the two populations compete with each other. One party grows while the other declines. There is no symbiotic relationship between the two.
- (3) When $\beta_{12} > 0$ and $\beta_{21} < 0$ or $\beta_{21} < 0$ and $\beta_{12} > 0$, one population is attached to the other during the symbiotic evolution of the innovative population, showing a parasitic mode of constantly requesting

resources from the other population to maintain its own growth.

- (4) When $\beta_{12} > 0$ and $\beta_{21} = 0$ or $\beta_{12} = 0$ and $\beta_{21} > 0$, both sides have obtained extra high-quality resources in the evolution process, but the symbiosis coefficient of one of them is zero, indicating that it has not obtained extra resources, suffering from no loss, and the innovation ecosystem is now in a symbiotic mode of partial benefit.
- (5) When $\beta_{12} > 0$ and $\beta_{21} > 0$, the population is in a mutually beneficial symbiosis mode. Among them, if $\beta_{12} \neq \beta_{21}$, the symbiotic relationship between the two populations is asymmetric and mutually beneficial symbiosis; when $\beta_{12} = \beta_{21}$, the populations have obtained equal benefits in the process of symbiotic evolution, and the resources are exchanged in equal amounts, forming a symmetric and mutually beneficial symbiosis.

In business activities, competition can occur between populations that use common resources. Symbiosis in the industry ecosystem does not exclude competition. Populations in completely or partially the same living space need to conduct technology, talent, and market interaction in the factor market. However, when one population in the ecosystem relies on another core or dominant population to obtain resources and living space, a parasitic relationship is formed. In a parasitic relationship, the symbiotic subject has a one-way exchange of interests. The state is not extensive because of this asymmetric one-way exchange. Therefore, the system will gradually develop in the direction of symbiosis conducive to mutual dependence and mutual benefit.

2.2. Analysis of Equilibrium Point Stability. The equilibrium point of the evolution of the populations means that the output of both parties has reached the maximum and has remained stable. The following does the stability analysis. In a stable state, the equations are

$$\begin{cases} f_1(N_1, N_2) \equiv \frac{dN_1(t)}{dt} = \alpha_1 N_1 \left(1 - \frac{N_1}{K_1} + \frac{\beta_{12} N_2}{K_2} \right) = 0, \\ f_2(N_1, N_2) \equiv \frac{dN_2(t)}{dt} = \alpha_2 N_2 \left(1 - \frac{N_2}{K_2} + \frac{\beta_{21} N_1}{K_1} \right) = 0. \end{cases} \quad (7)$$

The equilibrium points are $P_1(0, 0)$, $P_2(N_1, 0)$, $P_3(0, N_2)$, $P_4((K_1(1 + \beta_{12})/(1 - \beta_{12}\beta_{21})), (K_2(1 + \beta_{21})/(1 - \beta_{12}\beta_{21})))$.

The Jacobian matrix is used to solve the equilibrium point. We obtain the determinant $\text{Det}(J)$ and trace $\text{Tr}(J)$ of the Jacobian matrix. When $\text{Det}(J) > 0$ and $\text{Tr}(J) < 0$, the local equilibrium point is in a stable state; otherwise, it is not a stable equilibrium point. Table 1 shows a comparative analysis of the determinants and traces of the Jacobian matrix. On this basis, stable equilibrium points are obtained.

As shown in Table 1, the condition in which the local equilibrium point is stable is obtained. Through comparison,

the symbiosis evolution mode under different values corresponds to different stable equilibrium points, but the equilibrium points of partial benefit, asymmetric reciprocity, and symmetric reciprocity symbiosis are all the same P_4 . The parasitic equilibrium point may be P_2 , P_3 , or P_4 (Table 2).

As shown in Table 2, the symbiosis evolution equilibrium point of the population is related to the symbiosis model and is affected by the size of the mutual competition coefficient between the innovation populations and the maximum capacity of the respective populations.

Because of the interdependence between the two populations, the size of the population should not be zero. P_4 point corresponds to the scale of population 1 (P_1) and population 2 (P_2), respectively $((K_1(1 + \beta_{12})/(1 - \beta_{12}\beta_{21})), ((K_2(1 + \beta_{21})/(1 - \beta_{12}\beta_{21})))$. At the same time, the conditions for meaningful P_4 are

$$\begin{cases} \frac{K_1(1 + \beta_{12})}{1 - \beta_{12}\beta_{21}} > 0, \\ \frac{K_2(1 + \beta_{21})}{1 - \beta_{12}\beta_{21}} > 0. \end{cases} \quad (8)$$

With the solution of the above equations, the only nonnegative solution can be obtained. That is, the equilibrium solution is $((K_1(1 + \beta_{12})/(1 - \beta_{12}\beta_{21})), ((K_2(1 + \beta_{21})/(1 - \beta_{12}\beta_{21})))$. This equilibrium solution represents the equilibrium state of the LV system.

2.3. Three-Dimensional Lotka-Volterra Model. In a symbiotic system composed of population 1 (P_1), population 2 (P_2), and population 3 (P_3), the mathematical model is

$$\begin{cases} g_1(t) = \frac{dN_1(t)}{dt} = \alpha_1 N_1 \left(1 - \frac{N_1}{K_1} + \frac{\beta_{12} N_2}{K_2} + \frac{\beta_{13} N_3}{K_3} \right), \\ g_2(t) = \frac{dN_2(t)}{dt} = \alpha_2 N_2 \left(1 - \frac{N_2}{K_2} + \frac{\beta_{21} N_1}{K_1} + \frac{\beta_{23} N_3}{K_3} \right), \\ g_3(t) = \frac{dN_3(t)}{dt} = \alpha_3 N_3 \left(1 - \frac{N_3}{K_3} + \frac{\beta_{31} N_1}{K_1} + \frac{\beta_{32} N_2}{K_2} \right). \end{cases} \quad (9)$$

Among them, β_{ij} ($i = 1, 2, 3, j = 1, 2, 3$) is the interaction coefficient between populations. When β_{ij} is greater than zero, there is a synergetic relationship among populations. When β_{ij} is less than zero, there is competition among populations.

Objective programming is an effective way to solve the problem of multiobjective programming. The basic idea is to determine the expected value of each objective function of the multiobjective programming problem. The goal programming method is more flexible, more effective, and easier to use and implement in dealing with multiobjective problems. In recent years, multichoice goal programming (MCGP) has been widely used to solve many practical decision problems [37]. Chang [38] proposes the multiple-choice goal programming (MCGP) method as

TABLE 1: Equilibrium point and stability condition of symbiotic evolution in the ecosystem.

Equilibrium point	Det (J)	Tr (J)	Stability conditions
$P_1(0, 0)$	$\alpha_1 \alpha_2$	$\alpha_1 + \alpha_2$	Unstable
$P_2(N_1, 0)$	$-\alpha_1 \alpha_2 (\beta_{21})$	$-(\alpha_1 + \alpha_2)(1 + \beta_{21})$	$\beta_{21} < -1$
$P_3(0, N_2)$	$-\alpha_1 \alpha_2 (\beta_{12})$	$-(\alpha_1 + \alpha_2)(1 + \beta_{12})$	$\beta_{12} < 0$
$P_4((K_1(1 + \beta_{12})/(1 - \beta_{12}\beta_{21})), (K_2(1 + \beta_{21})/(1 - \beta_{12}\beta_{21})))$	$(\alpha_1 \alpha_2 (1 - \beta_{12})(1 - \beta_{21}))/((1 - \beta_{12}\beta_{21}))$	$(\alpha_1 \alpha_2 (1 - \beta_{12})(1 - \beta_{21}))/((1 - \beta_{12}\beta_{21}))$	$\beta_{12} < 1, \beta_{12} < 1$

TABLE 2: Symbiotic evolution model and equilibrium point of the ecosystem.

Value combination of influencing factor	Symbiotic evolution model among populations	Stable equilibrium point
$\beta_{12}\beta_{21} < 0$	Parasitic relationship	P_2, P_3, P_4
$\beta_{12} = 0, \beta_{21} < 0$ or $\beta_{21} = 0, \beta_{12} < 0$	Favor symbiosis	P_4
$\beta_{12} > 0, \beta_{21} > 0, \beta_{12} \neq \beta_{21}$	Asymmetric symbiosis	P_4
$\beta_{12} > 0, \beta_{21} > 0, \beta_{12} = \beta_{21}$	Symmetry symbiosis	P_4

$$c \begin{cases} \text{objective function,} \\ \text{Min } \sum_{i=1}^n (d_i^+ + d_i^-) + \sum_{i=1}^n (e_i^+ + e_i^-), \\ \text{constraints,} \\ g_i = f_i(x) - d_i^+ + d_i^-, \quad i = 1, 2, \dots, n, \\ x \in X = \{x_1, x_2, \dots, x_m\}, \\ X \in F, \text{ (} F \text{ is the set of feasible solutions),} \\ g_{i,\max} = g_i - e_i^+ + e_i^-, \quad i = 1, 2, \dots, n, \\ g_{i,\max} \geq g_i \geq g_{i,\min}, \quad i = 1, 2, \dots, n, \\ e_i^+, e_i^-, d_i^+, d_i^- \geq 0, \quad i = 1, 2, \dots, n. \end{cases} \quad (10)$$

Here, d_i^+ and d_i^- indicate the value of the i -th goal exceeding and not reaching the expected value of the goal. $f_i(x)$ is the formula of the i -th objective. X is the decision variable. g_i indicates the expected goal of i -th. e_i^+ are close to the positive deviation of $|g_i - g_{i,\max}|$. e_i^- are close to the negative deviation of $|g_i - g_{i,\max}|$. $g_{i,\min}$ and $g_{i,\max}$ are the lower and upper limits for the goal of g_i . Having studied the relevant research [39], the authors embed the equilibrium condition of the LV system into the MCGP model to obtain the Lotka–Volterra-MCGP model in this paper:

$$\text{objective function, Min } \sum_{i=1}^n (d_i^+ + d_i^-) + \sum_{i=1}^n (e_i^+ + e_i^-),$$

constraints,

$$g_i = f_i(x) + d_i^+ - d_i^-, \quad i = 1, 2, \dots, n,$$

$$x \in X, \quad X = \{x_1, x_2, \dots, x_m\},$$

$$X \in F \text{ (} F \text{ is the set of feasible solutions),}$$

$$g_{i,\max} = g_i + e_i^- - e_i^+, \quad i = 1, 2, \dots, n,$$

$$g_{i,\min} \leq g_i \leq g_{i,\max}, \quad i = 1, 2, \dots, n,$$

$$d_i^+, d_i^-, e_i^+, e_i^- \geq 0, \quad i = 1, 2, \dots, n,$$

$$g_1(t) = \frac{dN_1(t)}{dt} = \alpha_1 N_1 \left(1 - \frac{N_1}{K_1} + \frac{\beta_{12}N_2}{K_2} + \frac{\beta_{13}N_3}{K_3} \right),$$

$$g_2(t) = \frac{dN_2(t)}{dt} = \alpha_2 N_2 \left(1 - \frac{N_2}{K_2} + \frac{\beta_{21}N_1}{K_1} + \frac{\beta_{23}N_3}{K_3} \right),$$

$$g_3(t) = \frac{dN_3(t)}{dt} = \alpha_3 N_3 \left(1 - \frac{N_3}{K_3} + \frac{\beta_{31}N_1}{K_1} + \frac{\beta_{32}N_2}{K_2} \right),$$

$$-1 < \beta_{ij} < 1, \quad i = 1, 2, 3, j = 1, 2, 3,$$

$$\sum g_i = K, \text{ (} K \text{ is the sum of market capacity).}$$

(11)

As a linear form for goal programming, multichoice goal programming embedded with Lotka–Volterra equilibrium (LV-MCGP) can be easily resolved by common software.

3. Results and Discussion

This paper takes competitive enterprises in the automobile industry as an example. The automobile industry is one of the largest and most important industries in the world. In a sense, the development level and strength of the automobile industry reflect the comprehensive national strength and competitiveness of a country. China's automobile production and sales have ranked first in the world for many years in a row, and India, Russia, and other countries have also developed rapidly in recent years. The emerging market is characterized by low car ownership per capita and large potential demand, so it is still the most potential market for the world automobile industry in the future. China Industry Information Network (CIIN) shows that auto production increased from 2.07 million to 24.5 million during 2000–2015, with an average annual growth rate of 17.92% [40]. After years of rapid development, the growth state of China's vehicle industry has returned stable [41].

In the medium and long term, the impact of national policy-oriented market consumption demand is relatively short-lived, and the automobile industry has a huge pulling effect on the economy because it has a high contribution to GDP growth. Under the premise of stable growth, it is difficult to introduce policies to stimulate or inhibit the automobile industry. The influence of local purchase restriction policy on the overall sales of the automobile industry is limited, so the sustainable development of the social economy is the decisive factor for the sustainable growth of the automobile industry.

This study selects the independent brands in China's automobile market (providing average quality and low-end products) as the market segment for analysis. Three major manufacturers in the market segment are taken as the research samples. The products of three enterprises are regarded as three product groups. The scale of product population is expressed by the sales volume of automobile products in each quarter. The three-dimensional LV system is used to study the symbiotic and interaction mechanism among three enterprises (three enterprise product populations). The status of the automobile industry in China's national economy is constantly improving, but it is also facing increasingly fierce and cruel global competition. Given the coexistence of opportunities and challenges, it has become a realistic proposition how to comprehensively, correctly, and timely evaluate the competitive situation of

automobile manufacturing enterprises, so as to achieve the purpose of promoting the sustainable and healthy development of the automobile industry. The development level of the automobile industry depends on the level of automobile manufacturing to a certain extent. With the characteristics of a long industrial chain, high relevance, strong driving force, and integration of various high and new technologies, automobile manufacturing enterprises have become one of the important symbols to measure the industrial level, economic strength, and the ability in technological innovation of a country.

Founded in 1995, BYD is listed on Shenzhen Stock Exchange and Hong Kong stock exchange. It is mainly engaged in the business of rechargeable batteries and the automotive industry including traditional fuel vehicles and new energy vehicles.

Great Wall Motor Co., Ltd., is the largest SUV manufacturing enterprise in China. It was listed in Hong Kong H-share. At present, it has three brands of Haval, Great Wall, and Wey, and its products cover three categories of

SUV, car, and pickup truck. It has four vehicle production bases and has the independent supporting ability of engine, transmission, and other core parts.

ChangAn automobile is a camp enterprise of four major groups of Chinese automobiles. It has 159 years of history and 37 years of vehicle manufacturing accumulation.

3.1. Three-Species System Analysis. Automobile sales have significant seasonal characteristics, so this paper gets the smoothing data firstly. In this paper, the four-period simple moving average method is used to process the observation data, and the later research is mainly based on the moving average data. Auto sales data comes from the public database of related enterprise websites.

As shown in Table 3, the data provided the official website of the China Automobile Industry Association [42]. By substituting the seasonal smoothing data in Table 3 into the following econometric model and making regression analysis, Table 4 can be obtained.

$$\begin{cases} g_1(t) = \gamma_{11}N_1(t-1) + \gamma_{12}N_1^2(t-1) + \gamma_{13}N_1(t-1)N_2(t-1) + \gamma_{14}N_1(t-1)N_3(t-1), \\ g_2(t) = \gamma_{21}N_2(t-1) + \gamma_{22}N_2^2(t-1) + \gamma_{23}N_2(t-1)N_1(t-1) + \gamma_{24}N_2(t-1)N_3(t-1), \\ g_3(t) = \gamma_{31}N_3(t-1) + \gamma_{32}N_3^2(t-1) + \gamma_{33}N_3(t-1)N_1(t-1) + \gamma_{34}N_3(t-1)N_2(t-1). \end{cases} \quad (12)$$

Among them, $\gamma_1 = \alpha_1$. Generally, $\gamma_1 > 0$, meaning the synergy effect within the population. $\gamma_2 = -(\alpha_1/K_1)$, and generally $\gamma_2 < 0$, meaning the competition effect within the population. It is called the internal competition coefficient or the population density inhibition coefficient.

The results of the regression are shown in Table 4.

As shown in Table 4, the regression effect is not very good, the P value is high, and the correlation coefficient value does not meet the requirements of the theoretical hypothesis.

Among them, $\alpha_1 = -0.103$, $K_1 = 107015$. $\alpha_2 = -0.220$, $K_2 = 206861$. $\alpha_3 = 0.773$, and $K_3 = 185888$.

In order to deal with the above problem, a step-by-step measurement method is provided to reduce the dimension of the measurement model.

Step 1. Calculate α_i and K_i based on the population growth model.

As shown in Table 5, the effect of regression is better, which meets the requirements of the theoretical hypothesis. Substitute the above parameters into equation (12).

Step 2. Deform the model (12) as model (13). In the transformed equations, the left side of the equal sign is the known value, and the right side of the equal sign is the parameter equation waiting to be solved.

$$\begin{cases} g_1(t) - \gamma_{11}N_1(t-1) - \gamma_{12}N_1^2(t-1) = \gamma_{13}N_1(t-1)N_2(t-1) + \gamma_{14}N_1(t-1)N_3(t-1), \\ g_2(t) - \gamma_{21}N_2(t-1) - \gamma_{22}N_2^2(t-1) = \gamma_{23}N_1(t-1)N_2(t-1) + \gamma_{24}N_2(t-1)N_3(t-1), \\ g_3(t) - \gamma_{31}N_3(t-1) - \gamma_{32}N_3^2(t-1) = \gamma_{33}N_1(t-1)N_3(t-1) + \gamma_{34}N_2(t-1)N_3(t-1). \end{cases} \quad (13)$$

TABLE 3: Sample data and seasonal smoothing data of car sales.

Year	Quarter	Sample data			Seasonal smoothing data		
		BYD	Great Wall	ChangAn	BYD	Great Wall	ChangAn
2020	3	98819	182765	225284	92732	173252	184340
	2	91360	156011	181133	93678	169556	163993
	1	59659	106427	121559	96856	173549	148508
2019	4	121090	247806	209384	110452	198452	161753
	3	102602	167978	143895	119314	211231	144593
	2	104071	171985	119194	124315	204440	145866
	1	114044	206038	174539	125858	197640	152508
2018	4	156538	298924	140742	125007	191261	165956
	3	122607	140812	148988	118849	183444	194455
	2	110244	144786	145761	110795	195656	202495
	1	110639	180523	228332	106187	202382	197748
2017	4	131904	267655	254739	101197	212539	203302
	3	90391	189660	181146	108212	232547	195767
	2	91812	171689	126775	115218	238035	194257
	1	90681	221152	250547	119637	241703	197278
2016	4	159963	347688	224598	122254	234505	190065
	3	118414	211612	175106	116883	200851	182063
	2	109491	186361	138860	105920	182496	177858
	1	101149	192358	221696	104079	173141	189035
2015	4	138477	213071	192588	110110	165619	181415
	3	74562	138192	158287	110433	151124	166541
	2	102126	148941	183568	114427	142207	152951
	1	125273	162271	191218	114969	127553	132417
2014	4	139769	155092	133092	109431	107331	108318
	3	90540	102524	103924	108174	88897	94418
	2	104295	90325	101433	113155	82093	82161
	1	103121	81384	94823	116615	75343	71124
2013	4	134741	81355	77491	126547	69930	64589
	3	110464	75308	54898	—	—	—
	2	118133	63325	57283	—	—	—
	1	142851	59733	68684	—	—	—

Unit: vehicle.

TABLE 4: Regression results of the three-species Lotka-Volterra model.

$g_i(t)$	γ_{i1}	γ_{i2}	γ_{i3}	γ_{i4}
$g_1(t)$	$-0.103 (P = 0.505)$	$2.823 * 10^{-7} (P = 0.820)$	$-1.094 * 10^{-6} (P = 0.011)$	$1.581 * 10^{-6} (P = 0.004)$
$g_2(t)$	$-0.220 (P = 0.280)$	$-1.851 * 10^{-6} (P = 0.002)$	$3.788 * 10^{-6} (P = 0.025)$	$9.563 * 10^{-7} (P = 0.175)$
$g_3(t)$	$0.773 (P \leq 0.001)$	$-2.314 * 10^{-6} (P = 0.003)$	$-4.046 * 10^{-6} (P = 0.019)$	$5.386 * 10^{-7} (P = 0.326)$

Let α_i and K_i be substituted into the model. The value of Y_i can be obtained by calculating the following equations:

$$\begin{cases} Y_1 = g_1(t) - \gamma_{11}N_1(t-1) - \gamma_{12}N_1^2(t-1), \\ Y_2 = g_2(t) - \gamma_{21}N_2(t-1) - \gamma_{22}N_2^2(t-1), \\ Y_3 = g_3(t) - \gamma_{31}N_3(t-1) - \gamma_{32}N_3^2(t-1). \end{cases} \quad (14)$$

Equation (14) gives the value of Y_i . The model can then continue to calculate the variables of the relationship between populations. A new econometric model (15) can be obtained.

$$\begin{cases} Y_1 = \gamma_{13}N_1(t-1)N_2(t-1) + \gamma_{14}N_1(t-1)N_3(t-1), \\ Y_2 = \gamma_{23}N_1(t-1)N_2(t-1) + \gamma_{24}N_2(t-1)N_3(t-1), \\ Y_3 = \gamma_{33}N_1(t-1)N_3(t-1) + \gamma_{34}N_2(t-1)N_3(t-1). \end{cases} \quad (15)$$

Step 3. Get the relevant parameters through regression analysis. The research replaces γ_{ij} in the equations with β_{ij} and K_i , and then the value of β_{ij} can be obtained by regression operation.

TABLE 5: Calculation results of α_i and K_i values.

Variable	Regression coefficient
α_1	0.181 ($P = 0.109$)
$-(\alpha_1/K_1)$	$-1.697 * 10^{-6}$ ($P = 0.107$)
K_1	107015
α_2	0.231 ($P = 0.002$)
$-(\alpha_2/K_2)$	$-1.119 * 10^{-6}$ ($P = 0.003$)
K_2	206861
α_3	0.301 ($P = 0.001$)
$-(\alpha_2/K_2)$	$-1.621 * 10^{-6}$ ($P = 0.001$)
K_3	185888

As shown in Table 6, the regression results are provided. The regression coefficients of some parameters are not significant. This shows that there is a difference between the symbiosis model and the ideal state in the real world.

Step 4. Put the regression results into the three-species symbiosis system. The results are as follows:

$$\begin{cases} g_1(t) = 0.181N_1(t-1) - \frac{0.181}{107015}N_1^2(t-1) + \frac{0.181 \times (-1.069)}{206861}N_1(t-1)N_2(t-1) + \frac{0.181 \times 0.944}{185888}N_1(t-1)N_3(t-1), \\ g_2(t) = 0.231N_2(t-1) - \frac{0.231}{206861}N_2^2(t-1), \\ g_3(t) = 0.301N_3(t-1) - \frac{0.301}{185888}N_3^2(t-1). \end{cases} \quad (16)$$

By observing the above formula, we can find that this is a typical asymmetric three-species symbiosis model. Product group 2 (Great Wall Motor) has a competitive (negative) impact on product group 1 (BYD), while product group 3 (ChangAn Motor) has a cooperative (positive) impact on product group 1 (BYD). In order to understand the interaction mechanism of this symbiotic system, we will analyze

the evolution from the perspectives of three-species equilibrium development and three-species dynamic game.

3.2. *Balanced Development of Symbiotic System Analysis.* The three-species equilibrium system can be obtained by modifying the actual system (formula (16)).

$$\Rightarrow \begin{cases} g_1(t) = 0.181N_1 - \frac{0.181}{107015}N_1^2 + \frac{0.181 \times \beta_{12}}{206861}N_1N_2 + \frac{0.181 \times \beta_{13}}{185888}N_1N_3, \\ g_2(t) = 0.231N_2 - \frac{0.231}{206861}N_2^2 + \frac{0.231 \times \beta_{21}}{107015}N_2N_1 + \frac{0.231 \times \beta_{23}}{185888}N_2N_3, \\ g_3(t) = 0.301N_3 - \frac{0.301}{185888}N_3^2 + \frac{0.301 \times \beta_{31}}{107015}N_3N_1 + \frac{0.301 \times \beta_{32}}{206861}N_3N_2. \end{cases} \quad (17)$$

The equilibrium point of the three-species symbiosis system is as follows:

$$\begin{cases} g_1(t) = 0.181N_1 - \frac{0.181}{107015}N_1^2 + \frac{0.181 \times \beta_{12}}{206861}N_1N_2 + \frac{0.181 \times \beta_{13}}{185888}N_1N_3 = 0, \\ g_2(t) = 0.231N_2 - \frac{0.231}{206861}N_2^2 + \frac{0.231 \times \beta_{21}}{107015}N_2N_1 + \frac{0.231 \times \beta_{23}}{185888}N_2N_3 = 0, \\ g_3(t) = 0.301N_3 - \frac{0.301}{185888}N_3^2 + \frac{0.301 \times \beta_{31}}{107015}N_3N_1 + \frac{0.301 \times \beta_{32}}{206861}N_3N_2 = 0. \end{cases} \quad (18)$$

TABLE 6: Regression results of interaction coefficient.

Interaction coefficient	Regression value	P value	Significance
β_{12}	-1.069	(0.019)	Significant
β_{13}	0.944	(0.037)	Significant
β_{21}	0.199	(0.523)	Not significant
β_{23}	-0.358	(0.307)	Not significant
β_{31}	0.022	(0.940)	Not significant
β_{32}	-0.011	(0.972)	Not significant

The equivalent change can be obtained as follows:

$$\Rightarrow \begin{cases} N_1 - \frac{1}{107015}N_1^2 + \frac{\beta_{12}}{206861}N_1N_2 + \frac{\beta_{13}}{185888}N_1N_3 = 0, \\ N_2 - \frac{1}{206861}N_2^2 + \frac{\beta_{21}}{107015}N_2N_1 + \frac{\beta_{23}}{185888}N_2N_3 = 0, \\ N_3 - \frac{1}{185888}N_3^2 + \frac{\beta_{31}}{107015}N_3N_1 + \frac{\beta_{32}}{206861}N_3N_2 = 0. \end{cases} \quad (19)$$

Divide both sides of the equation by N_i ($i = 1, 2, 3$).

$$\Rightarrow \begin{cases} 1 - \frac{1}{107015}N_1 + \frac{\beta_{12}}{206861}N_2 + \frac{\beta_{13}}{185888}N_3 = 0, \\ 1 - \frac{1}{206861}N_2 + \frac{\beta_{21}}{107015}N_1 + \frac{\beta_{23}}{185888}N_3 = 0, \\ 1 - \frac{1}{185888}N_3 + \frac{\beta_{31}}{107015}N_1 + \frac{\beta_{32}}{206861}N_2 = 0. \end{cases} \quad (20)$$

The following formula can be obtained by equivalent transformation of the equations:

$$\Rightarrow \begin{cases} N_1 = 107015 + \frac{107015}{206861}\beta_{12}N_2 + \frac{107015}{185888}\beta_{13}N_3 \\ = 107015 + 0.517\beta_{12}N_2 + 0.575\beta_{13}N_3, \\ N_2 = 206861 + \frac{206861}{107015}\beta_{21}N_1 + \frac{206861}{185888}\beta_{23}N_3 \\ = 206861 + 1.933\beta_{21}N_1 + 1.112\beta_{23}N_3, \\ N_3 = 185888 + \frac{185888}{107015}\beta_{31}N_1 + \frac{185888}{206861}\beta_{32}N_2 \\ = 185888 + 1.737\beta_{31}N_1 + 0.898\beta_{32}N_2. \end{cases} \quad (21)$$

By substituting the above symbiotic relationship into the MCGP model, the following results are obtained:

$$\text{objective function, Min } \sum_{i=1}^n (d_i^+ + d_i^-) + \sum_{i=1}^n (e_i^+ + e_i^-),$$

constraints,

$$g_i = f_i(x) + d_i^- - d_i^+, \quad i = 1, 2, \dots, n,$$

$$x \in X, \quad X = \{x_1, x_2, \dots, x_m\},$$

$$X \in F, \quad (F \text{ is the set of feasible solutions}),$$

$$g_{i, \max} = g_i + e_i^- - e_i^+, \quad i = 1, 2, \dots, n,$$

$$g_{i, \min} \leq g_i, g_i \leq g_{i, \max}, \quad i = 1, 2, \dots, n,$$

$$e_i^+, e_i^-, d_i^+, d_i^- \geq 0, \quad i = 1, 2, \dots, n,$$

$$N_1 = 107015 + \frac{107015}{206861}\beta_{12}N_2 + \frac{107015}{185888}\beta_{13}N_3 = 107015$$

$$+ 0.517\beta_{12}N_2 + 0.575\beta_{13}N_3,$$

$$N_2 = 206861 + \frac{206861}{107015}\beta_{21}N_1 + \frac{206861}{185888}\beta_{23}N_3$$

$$= 206861 + 1.933\beta_{21}N_1 + 1.112\beta_{23}N_3,$$

$$N_3 = 185888 + \frac{185888}{107015}\beta_{31}N_1 + \frac{185888}{206861}\beta_{32}N_2$$

$$= 185888 + 1.737\beta_{31}N_1 + 0.898\beta_{32}N_2,$$

$$-1 < \beta_{ij} < 1, \quad i = 1, 2, 3, j = 1, 2, 3,$$

$$\sum g_i = K, \quad (K \text{ is the sum of market capacity}).$$

(22)

The problem is solved using the LINGO [43] software. The results of β_{ij} value optimization of the equilibrium symbiosis model are shown in Table 7.

As shown in Table 7, with the expansion of the market scale, more cooperative behaviors among populations are required. Cooperation behavior is comprehensive, and the intensity of cooperation is similar, not the greater the better. The intensity of cooperation between enterprises is close to equilibrium.

TABLE 7: Simulation of symbiotic relationship of balanced growth of three populations.

Market size (K)	499764	550000	600000	650000	700000	750000	800000
β_{12}	0.000	0.000	0.000	0.000	0.181	0.181	0.186
β_{13}	0.000	0.000	0.000	0.000	0.181	0.181	0.186
β_{21}	0.000	0.000	0.181	0.181	0.171	0.181	0.188
β_{23}	0.000	0.067	0.302	0.113	0.000	0.104	0.188
β_{31}	0.000	0.181	0.000	0.181	0.181	0.181	0.188
β_{32}	0.000	0.000	0.000	0.181	0.181	0.181	0.188

3.3. *Three-Species Evolutionary and Strategic Analysis.* In order to illustrate the evolution trend of the three-species game, this paper selects several representative symbiotic relationships for data simulation:

- (1) Comprehensive cooperation: the three enterprises adopt the strategic behavior of mutual cooperation ($\beta = 0.5$)
- (2) Overall competition: the three enterprises take the strategic behavior of competing with each other ($\beta = -0.5$)
- (3) The combination of the two powers: the interaction coefficient between them is 0.5. At the same time, they take the competitive strategy against the third enterprise, and the interaction coefficient is -0.5 . In this study, Great Wall Motor and ChangAn Motor are the relative advantage enterprises. For example, in 2020, the total sales of the Great Wall and ChangAn Automobile ranked 7th and 8th in the Chinese market. BYD, meanwhile, ranked 16th in sales [42]
- (4) The combination of the two weak enterprises: the interaction coefficient between them is 0.5. At the same time, they take the competitive strategy against the third enterprise, and the interaction coefficient is -0.5 . In this study, Great Wall Motor and BYD motor are relatively inferior enterprises
- (5) Isolated mode: the three enterprises have no influence on each other and develop separately
- (6) Parasitic mode: one enterprise gets help from two other enterprises. BYD is an example to illustrate the parasitic mode
- (7) Malicious parasitism mode: one enterprise gets help from two other enterprises and takes competitive activities against them. BYD is an example to illustrate the malicious parasitism model

The statistical characteristics of data simulation results are shown in Table 8.

As shown in Table 8, under different models, the simulation data are significantly different. In this paper, the simulation results will be compared and evaluated.

3.4. *Model Evaluation.* This paper evaluates the population growth of different modes based on the similarity between ideal solution and simulation data. The higher the similarity, the better the growth. The evaluation matrix is A .

$$A = [a_{ij}]_{27 \times 3}, \quad (23)$$

This study determines the weight by entropy method for the three populations in the evaluation. A technique for order preference by similarity to an ideal solution (TOPSIS) was used to evaluate the similarity. The ideal scale (max scale) of the three populations can be regarded as three criteria for evaluating the three-species Lotka–Volterra system.

Entropy weight is an objective method [44]. It is a popular method and always combined with other methods, for example, entropy combined with fuzzy VIKOR [45], entropy combined with GIS and AHP [46], and entropy combined with subjective weight [47].

The entropy weight method is provided as follows [48]. Suppose that m is alternatives ($A_1, A_2, \dots, A_m$) and n is criteria ($C_1, C_2, \dots, C_n$) for a decision problem. Then initial decision matrix is

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} = [a_{ij}]_{m \times n}. \quad (24)$$

Step 1: normalize the evaluation matrix.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}}. \quad (25)$$

Step 2: compute entropy.

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m r_{ij} \ln r_{ij}, \quad j = 1, 2, \dots, n. \quad (26)$$

Step 3: calculate weights.

$$w_j = \frac{1 - e_j}{\sum_{i=1}^n (1 - e_j)}, \quad j = 1, 2, \dots, n. \quad (27)$$

Calculated based on the data in the example, $w_1 = 0.346$, $w_2 = 0.325$, and $w_3 = 0.329$.

Hwang and Yoon [49] proposed the popular method TOPSIS to determine the best alternative. TOPSIS method is presented as follows:

Step 1: build the normalized matrix R .

TABLE 8: Statistical characteristics of population growth.

	Moving average of observations			Comprehensive cooperation			Overall competition		
	BYD	Great Wall	ChangAn	BYD	Great Wall	ChangAn	BYD	Great Wall	ChangAn
Average	-1252	3827	4435	15913	87556	99109	-18402	-6162	-1425
Min	-13596	-24903	-28499	3670	28181	33222	-27006	-26034	-20039
Max	10963	33654	24099	21587	136006	132616	-9392	10289	14733
Std.	5905	12998	12482	4730	30826	29681	5284	10990	9779
	Combination of two powers			Combination of two weak firms			Isolated mode		
	BYD	Great wall	ChangAn	BYD	Great wall	ChangAn	BYD	Great wall	ChangAn
Average	-18402	18031	24399	-1368	63363	-1425	-1245	40697	48842
Min	-27006	6366	13589	-4288	17184	-20039	-4181	17404	21408
Max	-9392	25217	32455	2015	100071	14733	2113	55833	61194
Std.	5284	5132	4818	1522	23527	9779	1655	10586	11001
	Parasitic mode			Malicious parasitism mode					
	BYD	Great wall	ChangAn	BYD	Great wall	ChangAn			
Average	15913	40697	48842	15913	5935	11487			
Min	3670	17404	21408	3670	-9270	-3225			
Max	21587	55833	61194	21587	17031	23357			
Std.	4820	10788	11210	4820	7864	7080			

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}} \quad (28)$$

Step 2: build weighted normalized matrix V .

$$v_{ij} = w_j r_{ij}, \sum_{j=1}^n w_j = 1, \quad w_j \text{ is the weight of } j \text{ th criterion.} \quad (29)$$

Step 3: calculate A^+ and A^- .

A^+ and A^- are defined in the following way:

$$\begin{aligned} A^+ &= \{(\max v_{ij} | j \in J) \text{ or } (\min v_{ij} | j \in J')\}, \quad i = 1, 2, \dots, m \\ &= \{v_1^+, v_2^+, \dots, v_n^+\}, \\ A^- &= \{(\min v_{ij} | j \in J) \text{ or } (\max v_{ij} | j \in J')\}, \quad i = 1, 2, \dots, m \\ &= \{v_1^-, v_2^-, \dots, v_n^-\}. \end{aligned} \quad (30)$$

The positive-ideal solution (PIS) and negative-ideal solution (NIS) are determined, where J and J' are sets of benefit and cost criteria, respectively.

Step 4: calculate the distances of each alternative from positive-ideal solution (PIS) and negative-ideal solution (NIS).

$$\begin{aligned} S_i^+ &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad i = 1, 2, \dots, m, \\ S_i^- &= \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, \quad i = 1, 2, \dots, m. \end{aligned} \quad (31)$$

Step 5: rank the order of alternatives.

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}, \quad 0 < C_i^+ < 1, i = 1, 2, \dots, m. \quad (32)$$

Here, $C_i^+ \in [0, 1]$ with $i = 1, 2, \dots, m$. Therefore, the best alternative should be found with the order of C_i^+ . The more value of C_i^+ , the better. If C_i^+ is close to 1, the alternative A_i is closer to the PIS.

As shown in Table 9, this paper can successfully get the evaluation ranking of populations in different modes. For the three-species symbiosis system, the comprehensive cooperation mode is the best symbiosis mode, and the comprehensive competition mode is the worst symbiosis mode. In the comprehensive cooperation mode, the three enterprises can occupy more market share. The three enterprises have a certain advantage in the market segmentation, and their cooperation can strengthen the core competitiveness. The three enterprises can strengthen their market position by establishing strategic alliances, product development cooperation, and even price collusion.

The simple parasitic mode is better than the malicious parasitic mode. The two-weak-joint mode is better than the two-strong-joint mode. The simple parasitic mode is better than the two-weak-joint mode and the two-strong-joint mode. Cooperative behavior is always better than competitive behavior. The more cooperative behavior, the better. And the less competitive behavior, the better.

3.5. Discussion. The result shows that there is a typical asymmetric three-species symbiosis system. Product group 2 (Great Wall Motor) has a competitive (negative) impact on product group 1 (BYD), while product group 3 (ChangAn Motor) has a cooperative (positive) impact on product group 1 (BYD). For the three-species symbiosis system, the comprehensive cooperation mode is the best symbiosis mode, and the comprehensive competition mode is the worst symbiosis mode. The simple parasitic mode is better than the malicious parasitic mode. Cooperative behavior is always better than competitive behavior.

The classical Lotka-Volterra model is used to discuss the symbiosis of two species. With the extensive development of related research, the two-species model is difficult to solve

TABLE 9: Result of TOPSIS.

Mode	β_{12}	β_{13}	β_{21}	β_{23}	β_{31}	β_{32}	C_i^+	Rank
Moving average of observations	-1.069	0.944	0	0	0	0	0.229	7
Comprehensive cooperation	0.5	0.5	0.5	0.5	0.5	0.5	0.714	1
Overall competition	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	0.160	8
Combination of two powers	-0.5	-0.5	-0.5	0.5	-0.5	0.5	0.297	5
Combination of two weak	0.5	-0.5	0.5	-0.5	-0.5	-0.5	0.389	4
Isolated mode	0	0	0	0	0	0	0.451	3
Parasitic mode	0.5	0.5	0	0	0	0	0.469	2
Malicious parasitism mode	0.5	0.5	-0.5	0	-0.5	0	0.281	6

practical problems. Scholars began to pay more attention to the three-species LV model. Dong et al. deal with bistable solutions for a three-species competition model with nonlocal anisotropic dispersal [50]. They demonstrate the asymptotic behavior of traveling waves and have constructed a class of front-like entire solutions. Liu et al. have found the spreading properties of a three-species competition-diffusion system, which is noncooperative [51]. That is an important theoretical result for the three-species competition system in unbounded domains. The above researchers are the forerunner of the three-species Lotka–Volterra model. The current research mainly focuses on the mathematical analysis, feasible solution, and its conditions of the three-species Lotka–Volterra model. The research of the three-species Lotka–Volterra model for empirical and applied analysis has just got off the ground. This paper provides a feasible analysis paradigm for LV symbiosis analysis of three populations, which is a meaningful attempt.

The evolution of the industrial innovation ecosystem is a complex process. The model, method, and data studied in this paper are simple and have some shortcomings in the following aspects. Firstly, the evolution of the industrial innovation ecosystem is complex in organizational evolution, science and technology, economic development, innovation culture, innovation policy, and so on. A more in-depth research process needs to consider the influence of the above complex factors. Researchers need to summarize the evolution characteristics of the industrial innovation ecosystem, such as creativity, diversity, dependence, environmental selectivity, and self-organization. This study does not explore the life cycle characteristics of industry and enterprise development. According to the life cycle theory of ecosystem, the follow-up research needs to deeply explore the evolution process of the industrial innovation ecosystem, determine four evolution stages: germination stage, growth stage, stable stage, and decline stage, and analyze the main characteristics of each stage. In the process of the formation, operation, and evolution of the industrial ecosystem, we will encounter many problems about risk, including risk identification, risk management, and risk control. In future research, researchers should strengthen the management of the operation and evolution process of the industrial innovation ecosystem, reduce the risk, and strictly control the incidence of system risk. We can quantify the operation process and evolution process of the system and establish a scoring and management system, which will help to control the system risk. In terms of case study, we should appropriately select industries other than the automobile industry

to study the industrial ecosystem, such as the telecommunications industry, clothing industry, and food industry. According to the characteristics of different industries, we should explore the formation and development rules of different industrial ecosystems and expand the research field.

4. Conclusion

The three-dimensional Lotka–Volterra model has been successfully built with the sales data of three local automobile enterprises in China. Based on Three-Species System Analysis, it can be found that there is a symbiotic relationship among automobile enterprises and that the three-species model can be adopted in analyzing the competition and cooperation among enterprises. Through the balanced development of Symbiotic System Analysis, the result of symbiotic optimization under the equilibrium state of three populations is obtained. Equilibrium is possible in the growth of three populations. Three-Species Evolutionary Analysis shows that cooperative action is better than competitive strategy and that this method is more practical in the analysis of enterprise competitive strategy. The findings reveal that this approach is feasible and effective in analyzing competition, evolution, and balanced development of enterprise population. It is of great importance to study the relationships among enterprises as it is helpful for enterprises to make policies of strategy. Future studies could analyze the life cycle of competition among enterprises with the three-species Lotka–Volterra model.

Data Availability

The experimental data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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