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Evaluation and Prediction of Sustained Competitive Advantage of Baijiu Enterprises Based on Entropy Weight-TOPSIS and INGO-BP Neural Network

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Abstract: In-depth scrutiny of the sustained competitive advantage within the liquor industry is paramount for facilitating a comprehensive understanding of market positions, benefiting both enterprises and investors. This study addresses the limitations of the current model, characterized by fewer evaluation indices and incomplete data, leading to lower assessment efficiency. To enhance the objective and effective evaluation of sustained competitive advantage, financial indicators (development ability, profitability, solvency, operating ability, and cash flow) are integrated, alongside non-financial indicators (brand value, environment, and social responsibility), forming a systematic approach for assessing listed liquor companies. Authentic data is sourced from official information disclosure websites. Utilizing the sliding average of each index enhances the reflection of the sustained development advantage of enterprises. The study employs the entropy value method to calculate weighted indicators, followed by the TOPSIS method for a comprehensive evaluation of sustained competitive advantage. The obtained evaluation values are used as a priori samples for the prediction model. An INGO-BP neural network prediction model is proposed in this study. This model, optimized with a sinusoidal algorithm for the exploratory phase of the Northern Goshawk Algorithm (NGO), incorporates a nonlinear reduction strategy to expedite the convergence of the Northern Goshawk. A spiral perturbation stage is added to prevent the NGO algorithm from entering local minima. The improved NGO algorithm (INGO) is employed for BP neural network parameter optimization. Simulation experiments reveal a significant enhancement in the performance of the INGO algorithm. In empirical analysis, a comparative assessment with other models demonstrates that the evaluation and prediction model in this study more accurately reflects the sustained competitive advantage of liquor enterprises, yielding predictions of higher accuracy and enhanced stability in performance.

Keywords: Neural Network; Baijiu; Entropy Weight-TOPSIS; Competitive Advantage; INGO.

1. Introduction

Chinese baijiu, among the traditional liquors, boasts a profound cultural heritage and an extensive production history in the realm of traditional alcoholic beverages. It exhibits distinctiveness not only within the sphere of Chinese culture but also on the global stage of potent spirits, where it demonstrates exceptional brilliance. During the period spanning 2002 to 2011, the baijiu industry experienced rapid growth, marked by a substantial and consistent sevenfold increase in annual production and sales volumes. However, the Chinese economy has experienced a decline since 2012. Market dynamics and regulatory restrictions such as the "Three Public Expenditure Ban" and the "Eight-point Frugality Code" have concurrently impacted the baijiu sector. Consequently, baijiu sales have witnessed a decrease, with other alcoholic beverages emerging as formidable competitors and acquiring market share [1]. The spirits industry has faced significant challenges due to the sudden and drastic market shifts, coupled with a sharp decline in consumer demand; certain liquor companies have, in fact, encountered negative growth in operational revenue. Despite this, certain alcohol companies, like Guizhou Moutai, have increased their share price and operating income by double by actively changing their strategies and strengthening their long-term competitive advantages. China's production of liquor decreased gradually between 2015 and 2022. According to statistics, as of 2022, there were 19 Chinese liquor listed enterprises, 963 liquor enterprises above scale, and approximately 6,712,000 kiloliters of liquor produced, a 5.6% year-over-year decline and a new low in the previous ten years [2]. Currently, the alcohol companies are actively developing sustainable competitive advantage resources, adjusting the initiative's development plan, and working to strengthen sustainable development. Entrepreneurs are now focusing on finding a strategy to achieve a durable competitive advantage in the liquor sector that is specific to its needs.

A corporation's capacity to uphold a lasting competitive advantage is crucial for its prolonged and steady growth. This advantage is intricately connected to the firm's prospective development capabilities, financial outcomes, and market stance [3]. A robust financial position can provide consistent financial backing for the enterprise, ensuring uninterrupted operations and long-term expansion. It serves as the cornerstone and prerequisite for establishing a lasting competitive advantage [4]. Non-financial metrics, such environmental sustainability, have a significant influence on a liquor brewing company's competitive advantage. The future competitive advantage of liquor firms can be assessed and predicted by integrating both their financial and non-financial data [5]. Many scholars have conducted thorough examinations of the liquor industry, exploring various assessment methods and indices that can aid liquor businesses in gaining a competitive edge. For example, Huang [6] employed factor analysis to assess the competitiveness of listed liquor businesses. They selected 13 indicators from four categories: profitability, solvency, operating ability, and growth ability. By condensing a large number of financial indicators into a small number of composite factors that are unrelated to one another, the basic research goal of employing fewer factors to describe many financial indications is accomplished. The same assessment indices were utilized by Chen et al. [7] to thoroughly examine the competitive advantages of four listed liquor companies in Sichuan Province using enhanced gray correlation analysis. By enhancing the conventional DEA evaluation methodology, Long et al. [8] assessed the competitiveness efficiency of 15 listed liquor businesses using four indicators: market share, operational revenue, profitability, and production capacity. Their results showed that there is a wide range in the degree of rivalry among liquor companies, but overall variances are getting smaller. Li et al. [9] developed indices for assessing competitiveness by incorporating variables related to operational capacity and profitability. They further examined the impact of CSR on business competitiveness using the fuzzy set qualitative comparative analysis method. It is evident that while building indicators, contemporary research primarily begins with financial indicators like profitability, solvency, operating capacity, and growth capacity. Furthermore, these models lack comprehensiveness in indicator selection. Indeed, the factors influencing enterprise sustainable competitive advantage are diverse. Therefore, there is a need to judiciously broaden the range of indicators and consider the relationships among them.

To address the aforementioned challenges, this study presents two primary contributions. Firstly, it establishes a competitive advantage evaluation model for liquor enterprises. Commencing from two categories, financial and non-financial indicators, the metrics are classified into seven primary indicators: development capacity, profitability, solvency, operational capacity, cash flow, brand value, and environmental and social responsibility. Further subdivision into 16 secondary indicators is undertaken to provide a more detailed description. In this manner, a competitive advantage evaluation index system for white wine enterprises is formulated. Subsequently, utilizing the established index system, this study gathers annual data from official disclosure platforms for 19 publicly traded liquor companies spanning the years 2014 to 2022. Furthermore, the moving average of various time windows is employed as the assessment criterion to more effectively evaluate the sustainable development capability of liquor enterprises. Subsequently, the entropy method was applied to ascertain the relative weights of each indicator based on the preprocessed data. The weight matrix of the entire evaluation model was then calculated. Following the input of data and weighting matrix, the competitive advantage level for each research subject was computed using the TOPSIS method.

The second contribution of this paper encompasses the training and prediction of a BP neural network, utilizing the composite rating values as prior samples. This process aims to derive appropriate input weights and thresholds for the neural network model. The BP neural network demonstrates robust learning ability and adaptability, excelling particularly in handling multi-indicator predictions. Nevertheless, it is noteworthy that the BP neural network is sensitive to initial parameters and may encounter challenges related to easily falling into local optimization. To prevent the BP neural network from converging to a local optimum, we incorporate a meta-heuristic algorithm, the Northern Goshawk Optimization. Initially, we focus on optimizing the convergence speed of the NGO and mitigating the issue of the algorithm prematurely converging to local extremes. The improved NGO algorithm was applied to optimize the BP neural network, which was then utilized to develop a predictive model for assessing sustained competitive advantage.

The paper is structured as follows. Section 2 briefly describes the results of existing research. Section 3 describes the construction of the index system of sustained competitive advantage of liquor enterprises and the construction of entropy weight-TOPSIS evaluation model. Section 4 shows how the NGO model can be improved and compared with existing models. Section 5 describes the prediction steps based on the INGO-BP neural network model. In Section 6, the validity of our model is demonstrated through empirical analysis by comparing it with other models. Finally, conclusions are drawn in Section 7.

2. Related Work

The sustained competitive advantage of enterprises is a conceptual abstraction, necessitating the use of appropriate methods for measurement and assessment. Currently, prevailing methods for evaluating sustained competitive advantage can be broadly categorized into four types: qualitative evaluation methods, classification evaluation methods, ranking evaluation methods, and quantitative evaluation methods. Scholars have put forth various multi-index comprehensive evaluation methods to comprehensively understand the developmental trends of entities. Based on the determination of evaluation weights, these methods can be classified into subjective evaluation and objective evaluation. Subjective evaluation methods typically rely on expert subjective experience and involve manually setting evaluation weights. Typical methods include Analytic Hierarchy Process (AHP) [10] and Fuzzy Comprehensive Evaluation Method [11]. On the other hand, objective evaluation methods primarily determine weights based on the relationships between evaluation indicators and the coefficients of variation of each indicator. Typical methods include Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [12,13], Grey Relational Analysis (GRA) [14], and Principal Component Analysis (PCA) [15]. Among them, the TOPSIS evaluation model optimized using the entropy weight method has found wide application in various fields. For instance, Chen et al. [16], from the perspective of the high-quality development of Baijiu enterprises, established a high-quality development evaluation index system for Baijiu enterprises consisting of 27 indicators in five dimensions: corporate management, innovative development, product quality, social responsibility and green development, and efficiency benefits. They employed the entropy weight-TOPSIS model for measurement. Li et al. [17] analyzed the comprehensive effects and development capabilities of land use from three aspects: economic benefits, social effects, and ecological security, using the same model. Li [18] evaluated the level of highway traffic development, reflecting the current development status and trends of highway traffic in Luoding City. Mo et al. [19] employed the entropy weight-TOPSIS evaluation method to comprehensively assess agricultural water resource allocation schemes, providing a more objective reflection of agricultural water resource carrying capacity and dynamic change trends. The differences in these research areas fully demonstrate the practicality of the entropy weight-TOPSIS evaluation model. The introduction of the entropy weight method into the TOPSIS model not only reduces subjective judgments of weights but also considers the uncertainty between indicators. This approach allows for the simultaneous consideration of multiple factors, making decision-making more comprehensive. Therefore, this paper chooses to use this evaluation model to conduct a comprehensive assessment of the sustained competitive advantage of listed Baijiu enterprises.

When engaged in predictive modeling, BP neural networks exhibit remarkable proficiency in managing intricate nonlinear interactions and possess a heightened learning capacity. In recent years, there has been a continual surge in research dedicated to BP neural networks. For instance, Cui et al. [20], delving into a comprehensive analysis of rock material characteristics and sedimentation parameters, utilized the BP neural network to classify and predict soil distribution and related geotechnical parameters. Zhang et al. [21] applied the BP neural network algorithm to categorize stock price patterns, presenting a potent tool in the financial domain. Li et al. [22] implemented the BP neural network model in urban green space planning scenarios, optimizing the model with PSO intelligent algorithms to provide a more thorough assessment of urban green space planning solutions. Liu et al. [23] utilized the PSO-BP neural network model to evaluate used car prices, offering robust support for the development of online used car trading platforms. Qin et al. [24] established user personality models based on the five dimensions of the OCEAN personality model, employing the BP neural network for prediction with high efficiency and accuracy. In the realm of business management and risk prediction, Li et al. [25] crafted an early warning model integrating financial and non-financial factors, predicting corporate warnings for listed Chinese manufacturing companies and offering crucial references for business decision-making. These studies enrich the application of BP neural networks across diverse fields, highlighting their versatility and flexibility in addressing complex problems and undertaking predictive tasks. However, the solitary BP neural network has limitations, including a lack of simple and effective parameters leading to BP algorithm instability. Furthermore, the BP neural network exhibits characteristics of local minima and slow convergence speed, necessitating the resetting of initial parameter values to find the global optimal solution, thereby increasing the algorithm's runtime. Therefore, this paper employs a metaheuristic algorithm to optimize the BP neural network, aiming to enhance network accuracy and improve overall algorithm performance.

3. Evaluation System of Sustainable Competitive Advantage of Baijiu Enterprises

3.1. Design of Evaluation System

The analysis of liquor firms' ongoing competitive advantage requires the effective construction of an indicator system. On the other hand, creating sustainable competitive advantage indicators is a methodical, intricate undertaking [26]. A number of guidelines, such as scientificity, comprehensiveness, operability, and data accessibility, must be adhered to while choosing indicators. The selection of evaluation indices for an enterprise's sustainable competitive advantage in this study is done by consulting relevant literature [27-30]. As indicated in Table 1, a total of 16 variables are chosen from both financial and non-financial categories to build the assessment index system of listed liquor firms' sustainable competitive advantage. The "China Wine Cup" liquor brand value ranking, the company's information disclosure platform, and the annual report data of each company provide the fundamental information for the indications of the sustained competitive advantage of listed liquor companies.

-Development capability shows a company's trend of development, shows its potential for scale expansion, and helps determine whether the company's financial and operational choices carry any dangers.

Profitability refers to the ability of a business to generate profits, reflecting not only the efficiency of its investments but also revealing the internal strength of its profit-making capabilities.

Table 1. Assessment Indicator Construction for the Sustainable Competitive Advantage of Listed Chinese Liquor Companies.

Type	Target layer	Indicator layer	Variable
Financial	Development capacity	Increase rate of main business revenue	X1
		Rate of growth in attributable net profit	X2
		Rate of growth in adjusted net profit	X3
	Profitability	Return on total assets (weighted)	X4
		Gross profit margin	X5
		Net profit margin	X6
	Debt-servicing capacity	Current ratio	X7
		Quick ratio	X8
		Debt-to-Asset ratio	X9
	Operational capability	Total assets turnover ratio	X10
		Inventory turnover ratio	X11
	Cash flow	Sales to net cash flow from operations ratio	X12
		Operating cash flow to income ratio	X13
		Cash flow ratio	X14
Non-financial	Brand value	Brand value	X15
	Environmental and social responsibility	Disclosure completeness	X16

Debt-paying ability is a crucial capability for a company to fulfill its obligations on time, playing a decisive role in determining the financial condition of the company. Additionally, it is an important indicator for evaluating the company's ongoing operational capacity and risk level.

Operational capability is the expression of effective business management that shows how well assets are turned over.

Cash flow encompasses the total cash inflow and outflow within a business cycle. Establishing an effective cash flow system is a vital assurance for enhancing a company's competitiveness.

In addition to the aforementioned financial indicators, this study also incorporates non-financial indicators, such as brand value and environmental and social responsibility. Brand value considers elements like brand awareness, brand image, product quality, and innovation capability. Enhancing brand value facilitates companies in attracting consumers, entering new markets, and expanding their business scale. Simultaneously, public disclosure of corporate environmental and social responsibility (CSR) enables companies to comprehensively understand and manage environmental and social risks, thereby improving corporate sustainability. The specific indicators for environmental and social responsibility include six aspects: pollution emission treatment, safe production, employee welfare, participation in social activities, product quality, and consumer rights and interests for liquor enterprises. The assignment method for disclosure is detailed in Table 2, where a value of 0 is assigned for no disclosure, and a value of 1 is assigned for the other five disclosure categories.

Table 2. Disclosure Valuation Method.

Disclosure Status	Score
Not Disclosed	0
Brief Disclosure	+1
Quantitative Disclosure	+1
Comparable to the Previous Year	+1
Comparable to National Standards, Industry Standards, or Competitors	+1
Disclosed Negative Information	+1

3.2. Construction of Comprehensive Evaluation Model

The Entropy Weight-TOPSIS Model [31,32] denotes the process of establishing the entropy value method through objective value assignment in order to determine the weights of the evaluation indicators. Then, the evaluation indicator data is multiplied by the weights determined by the TOPSIS method in order to ascertain the benefits and drawbacks of the comprehensive evaluation model program. This research does a thorough examination using the entropy weight TOPSIS model. The precise method of calculation is as follows：

The original data matrix $X_{ij} = (x_{ij})_{m\times n}$ of the evaluation system can be produced, where x_{ij} is the jth evaluation indicator of the ith evaluation object, assuming that there are m evaluation indicators and n evaluation objects. After standardizing the indicators, the standardized matrix $V_{ij} = (v_{ij})_{m\times n}$ is produced. Next, the information entropy (e_j) of the indicator, the characteristic weight P_{ij} of the ith evaluation object on the jth indicator, and its entropy weight (W_j) are determined using Equation (1).

$$\begin{cases} P_{ij} = \dfrac{v_{ij}}{\sum_{i=1}^{n} v_{ij}} \\ e_j = -\dfrac{1}{\ln n}\sum_{i=1}^{n} P_{ij}\ln\left(P_{ij}\right) \\ W_j = \dfrac{1-e_j}{\sum_{j=1}^{m}\left(1-e_j\right)} \end{cases} \tag{1}$$

To create a weighted decision matrix, apply weights to the normalized matrix V_{ij} :

$$R = \left(r_{ij}\right)_{m\times n} = \left(W_j V_{ij}\right)_{m\times n} \tag{2}$$

Describe the vectors of the positive ideal solution (Z^{+}) and the negative ideal solution (Z^{-}) :

$$\begin{cases} Z^{+} = \left(R_1^{+}, R_2^{+}, \ldots, R_n^{+}\right) = \left\{\max_i R_{ij} \mid j = 1,2,\ldots,n\right\} \\ Z^{-} = \left(R_1^{-}, R_2^{-}, \ldots, R_n^{-}\right) = \left\{\min_i R_{ij} \mid j = 1,2,\ldots,n\right\} \end{cases} \tag{3}$$

Determine the relative closeness (C_i) of the ith evaluation object, representing the sustained competitive advantage of the liquor enterprise. A larger C_i indicates greater proximity to the optimal level or the positive ideal solution of the Euclidean distance. In this context, the letters D^{+} and D^{-} denote the evaluation object and the positive and negative ideal solutions, respectively.

$$\begin{gathered} D^{+} = \sqrt{\sum_{j=1}^{m}\left(R_{ij} - R_j^{+}\right)^2} \\ D^{-} = \sqrt{\sum_{j=1}^{m}\left(R_{ij} - R_j^{-}\right)^2} \\ C_{\mathrm{i}} = \frac{D_i^{+}}{D_i^{-} + D_i^{+}} \end{gathered} \tag{4}$$

4. The Improved Northern Goshawk Optimization Algorithm-INGO

4.1. The Northern Goshawk Optimization Algorithm

The Northern Goshawk Optimization Algorithm (NGO) [33] is a meta-heuristic algorithm designed to emulate the predatory behavior of northern goshawks in the wild. The predation process of the Northern Goshawk is delineated into two primary phases: the prey recognition phase (Exploration phase) and the chase and escape phase (Development phase):

1) Exploration phase: identifying targets and initiating attacks

During the first hunting season, also referred to as the "exploration phase," the northern goshawk chooses its target at random and launches an immediate attack. The NGO algorithm screens any target in the search area at random to enhance the algorithm's overall search performance. When it comes to identifying prey targets and attacking, the Northern Goshawk's traits are best stated as follows:

$$P_i = X_k, i = 1,2,\ldots,N, k = 1,2,\ldots,i-1,i+1,\ldots,N \tag{5}$$

$$x_{i,j}^{new,S1} = \begin{cases} x_{i,j} + r\left(p_{i,j} - I\cdot x_{i,j}\right) F_{P_i} < F_i \\ x_{i,j} + r\left(x_{i,j} - p_{i,j}\right) \quad F_{P_i} \geq F_i \end{cases} \tag{6}$$

$$X_i = \begin{cases} X_i^{new,S1} & F_i^{new,S1} < F_i \\ X_i & F_i^{new,S1} \geq F_i \end{cases} \tag{7}$$

In the formula, P_i is the prey location of the ith northern goshawk; X_k is the location of the kth northern goshawk in the northern goshawk population; N is the number of northern goshawks in the population; and $x_{i,j}^{new,S1}$ is the new location of the ith northern goshawk in the jth dimension; $x_{i,j}$ is the position of the ith northern goshawk in the population in the jth dimension; $p_{i,j}$ is the prey position of the ith northern goshawk in the jth dimension; F_{P_j} is the value of the objective function of the ith northern goshawk; F_i is the value of the objective function of the Nth Nth northern goshawk's own position before updating; $X_i^{new,S1}$ is the new position of the ith northern goshawk during the exploration phase; $F_i^{new,S1}$ is the value of the objective function of the ith northern goshawk's own position after updating during the exploration phase; r is the random number in the interval $[0,1]$; and I is a random number of 1 or 2.

2) Development phase: track and run

The victim attempts to flee as soon as the Northern Goshawk attacks it; this is referred to as the "exploitation phase." With its lightning-fast pursuit pace, the northern goshawk can catch up with nearly all of its victims and eventually bring it to ground. It is possible to enhance the local optimization performance in the search space by algorithmically replicating this behavior. The characteristics of this hunting habit are best characterized as follows:

$$R = 0.02 \times (1 - \frac{t}{T}) \tag{8}$$

$$x_{i,j}^{new,S2} = x_{i,j} + R(2r-1)x_{i,j} \tag{9}$$

$$X_i = \begin{cases} X_i^{new,S2} & F_i^{new,S2} < F_i \\ X_i & F_i^{new,S2} \geq F_i \end{cases} \tag{10}$$

In the formula, R is the radius of the attack position; t is the current number of iterations; T is the maximum number of iterations; $x_{i,j}^{new,S2}$ is the new position of the jth dimension of the ith northern goshawk after the update in the development phase; $X_i^{new,S2}$ is the new position of the ith northern goshawk in the development phase; and $F_i^{new,S2}$ is the value of the objective function of the ith northern goshawk's own position after the update in the development phase.

4.2. The Improved Northern Goshawk Optimization Algorithm-INGO

Despite its robust global search capabilities and rapid convergence speed, the NGO algorithm may encounter situations in later iterations where it converges to a local optimal solution. It is noteworthy that, during the development stage of Northern Goshawk hunting, the actual hunting radius does not diminish linearly with an increase in the number of iterations. This study proposes an improved optimization strategy for the northern goshawk, aiming to tackle the issues mentioned above.

1) Initially, a sinusoidal optimization algorithm is incorporated into the exploration phase to maintain a delicate balance between the NGO algorithm's capacity for global exploration and local exploitation throughout the search process:

$$r_1 = 0.05 \times \cos\left(\frac{\pi}{2} \times \frac{T-t}{T}\right) \tag{11}$$

$$x_{i,j}^{new,S1} = \begin{cases} x_{i,j} + r\left(p_{i,j} - I \cdot x_{i,j}\right) F_{P_i} < F_i \\ x_{i,j} + r \cdot r_1 \cdot \sin\left(r_2\right) \cdot \left|r_3 \cdot X_{best} - X_I\right| \quad F_{P_i} \geq F_i \end{cases} \tag{12}$$

In the formula, r_1 is the control parameter, which mainly controls the amplitude of the sinusoidal function; t is the current number of iterations; T is the maximum number of iterations; r_2 is the random number of $[0,2\pi]$; and r_3 is the random number of $[0,2]$.

2) Following this, an optimization strategy involving nonlinear reduction is applied to refine the hunting radius. This adjustment aims to align the algorithm more closely with the real-world dynamics of a northern goshawk's hunting behavior, resulting in an accelerated convergence speed. The precise expression is:

$$R = 0.02 \times \tan\left(\frac{1-t}{T}\right)^2 \tag{13}$$

3) This study introduces an additional perturbation phase, building upon the initial two phases, to account for the potential scenario where the Northern Goshawk algorithm might converge into a local optimal solution in the later iterations. In order to enhance the algorithm's local search capabilities and convergence speed, this research introduces a spiral search approach and applies it to the northern goshawk's location updating process. Simultaneously, within the perturbation phase, this paper introduces a perturbation factor (d) and a judgment factor (c). In each iteration, d takes a random value within the range of $(0,1)$, and c decreases with the progression of iterations. The specific expression is:

$$d = 1 - \sqrt{\frac{t}{T}} \tag{14}$$

In the formula, t is the current iteration number; T is the maximum iteration number.

A spiral perturbation is needed for that iteration of the algorithm if $d > c$, and the decrease of c is nonlinear as the number of iterations rises from equation (14). Since spiral perturbation is not required at the start of the iteration period, the algorithm is still in the global search state. As a result, the c corresponding to this period is larger, the condition $d > c$ is more difficult to satisfy, and spiral perturbation is performed less frequently. The algorithm may enter the local optimum during the middle and late iterations. In these cases, the spiral perturbation is required to force the algorithm to exit the local optimum solution, resulting in a rapid reduction of the period's coefficient c and an easier time satisfying the condition $d > c$. At this point, the algorithm employs the spiral search perturbation strategy. Equations (15) and (16) can be used to characterize the perturbation update of the northern goshawk position during this phase:

$$x_{i,j}^{new,S3} = x_{i,j} + e^{bl} \cdot \cos\left(2\pi l\right) \cdot \left|x_{i,j} - x_{best}\right| \tag{15}$$

$$X_\mathrm{i} = \begin{cases} X_i^{new,S3} & F_i^{new,S3} < F_i \\ X_i & F_i^{new,S3} \geq F_i \end{cases} \tag{16}$$

In the formula, $x_{i,j}^{new,S3}$ is the new position of the ith northern goshawk in the jth dimension after the update of the perturbation phase; b being 1 corresponds to a logarithmic spiral shape; l is the random number of $[-1,1]$; $X_i^{new,S3}$ is the new position of the ith northern goshawk in the perturbation phase; and $F_i^{new,S3}$ is the value of the objective function for the ith northern goshawk's own position after the update of the perturbation phase.

4.3. The Improved Northern Goshawk Optimization Algorithm-INGO

In order to evaluate the INGO algorithm's performance, this study used six typical classical benchmark functions. These functions include the high-dimensional multimodal function, which is used to test the algorithm's exploration capacity and make sure it doesn't find local optimal solutions, as well as the single-peak function, which is used to assess the algorithm's development capability in quickly locating the ideal answer. In Table 3, the chosen benchmark functions are described in detail.

Table 3. Test function.

Test function	Dimension	limit	Min
$F_1=\sum_{i=1}^{n}x_i^2$	30	[-100,100]	0
$F_2=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert$	30	[-10,10]	0
$F_3=\sum_{i=1}^{n}\left(\sum_{j-1}^{i}x_j\right)^2$	30	[-100,100]	0
$F_{10}=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos\left(2\pi x_i\right)\right)+20+e$	30	[-32,32]	0
$F_{13}=0.1\times\sum_{i=1}^{n-1}\left(x_i-1\right)^2\left[1+\sin^2\left(3\pi x_{i+1}\right)\right]+\left(x_n-1\right)^2\left[1+\sin^2\left(2\pi x_n\right)\right]+\sum_{i=1}^{n}u\left(x_i,5,100,4\right)+0.1\times\sin^2\left(3\pi x_1\right)$	30	[-50,50]	0
$F_{15}=\sum_{i=1}^{11}\left[a_i-\frac{x_1\left(b_i^2+b_ix_2\right)}{b_i^2+b_ix_3+x_4}\right]^2$	4	[-5,5]	0.0003075

To validate the effectiveness of the proposed algorithms, this study compares INGO with Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), and NGO algorithms. Each algorithm is configured with a maximum of 20 individuals and 100 iterations. To mitigate randomness and enhance experimental credibility, each algorithm runs independently 20 times, and the average result is considered the final outcome. The convergence curves for all algorithms are illustrated in Figure 1.

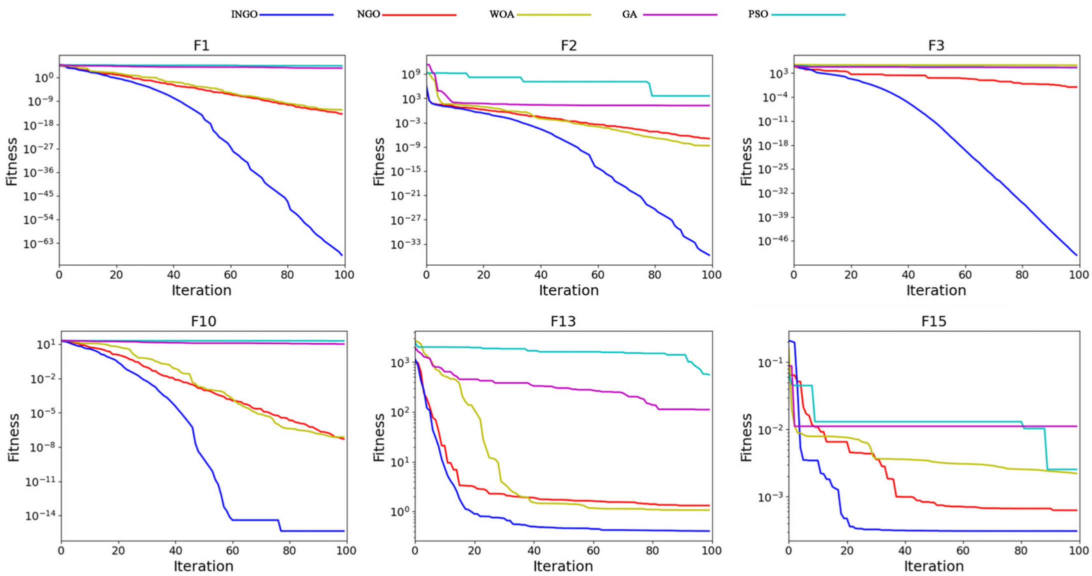

Figure 1. Convergence curves of algorithms

Upon analyzing Figure 1, it becomes evident that, for the single-peak test function, the INGO algorithm proposed in this study demonstrates swifter convergence compared to all the algorithms under consideration. While each algorithm eventually converges to a value near the minimum of the test function, the final outcome of the INGO algorithm distinctly approaches the minimum at a quicker pace than the other algorithms. This indicates its rapid and robust optimization search capability. In the context of the high-dimensional multimodal function, characterized by greater complexity than the single-peak test function and involving multiple local optimal solutions, Figure 1 reveals that certain optimization algorithms may become ensnared in local optima, leading to slower search speeds. Conversely, the INGO algorithm presented in this paper achieves the global optimal solution for the high-dimensional multimodal test function with the utmost speed, underscoring its potent local optimization search capability and superior performance relative to other algorithms.

5. Specific Steps of INGO-BP Neural Network based on Entropy Weight TOPSIS

The BP neural network is a multilayer feedforward neural network that operates on the principle of error backpropagation. This neural network employs a supervised learning method, initially receiving a dataset through the input layer, processing it through the hidden layer, and generating output data in the output layer. Subsequently, the generated data is compared with the desired data to calculate the actual error. Utilizing the gradient descent method, the error is backpropagated, and the weights and thresholds are adjusted layer by layer from the output layer to the input layer. The BP neural network model is gradually optimized through continuous iteration. This iterative process ensures that the neural network's output gradually converges to align with the desired data. By continuously adjusting weights and thresholds, the model's performance can be enhanced to meet the accuracy requirements of data output and desired data. In this context, the initial weights and thresholds are crucial parameters for BP neural networks. This paper employs the INGO optimization algorithm, as proposed in Section IV, to optimize these parameters. The specific steps of the INGO-BP neural network model, based on entropy weight-TOPSIS and introduced in this paper for evaluating the sustained competitive advantage of liquor enterprises, are as follows:

Step 1: Establish the continuous competitive advantage evaluation index system for liquor enterprises and gather relevant data.

Step 2: Preprocess the data to compute the sliding average using multiple windows.

Step 3: Utilize the entropy weight method to calculate the weight coefficients for each index.

Step 4: Based on the results from Step 3, compute the index weight matrix and derive the evaluation outcomes for the sustained competitive advantage of liquor enterprises. Employ the natural discontinuity method to classify the scores.

Step 5: Take the outcomes from Step 4 as input for the BP neural network. Determine the optimal number of hidden layer nodes using the empirical formula (17), and employ the Mean Squared Error (MSE) of the model as an indicator during the training process, as illustrated in formula (18).

$$M = \sqrt{N + L} + \alpha \tag{17}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_r - y_i)^2 \tag{18}$$

In the formula, M is the count of hidden layer nodes; N represents the number of input layer nodes; L denotes the number of output layer nodes; α is an integer within the range [1,10]; $\hat{y}_r$ signifies the predicted value of the sample; y_i represents the actual value of the sample; n is the total number of training samples.

Step 6: Enhance the INGO algorithm as outlined in Section 4.2, determining the dimension of the northern goshawk, the total population size, and the maximum number of iterations. The dimension of the northern pale eagle is influenced by the number of input neurons, hidden neurons, and output neurons in the constructed BP neural network. Attain the optimal individuals of the northern pale eagle as the initial parameters for the BP neural network.

Step 7: In the INGO algorithm's individual fitness function, employ the error function of the BP neural network model as the northern pale eagle individual fitness function, where the fitness function value corresponds to the MSE in Equation (18).

Step 8: Conclude the algorithm upon reaching the maximum number of iterations, where the optimal northern pale eagle individual signifies the optimal initial weights and thresholds for the BP neural network.

Step 9: Integrate the parameters obtained in Step 8 into the BP neural network model established in Step 5. Input data on the sustained competitive advantage of liquor enterprises into the INGO-BP neural network model for validation.

6. An Empirical Analysis of Baijiu Enterprises' Sustainable Competitive Advantage

6.1. Data Selection and Processing

This study selects a total of 19 publicly listed companies involved in liquor brewing in China. It gathers and organizes annual data spanning 9 years from 2014 to 2022. Statistical calculations are conducted based on the 16 indicators of sustained competitive advantage. To enhance the dataset, sliding averages of multiple windows are adopted as evaluation objects. The study ultimately obtains 342 sets of effective initial sample data.

6.2. Evaluation of Baijiu Enterprises' sustainable Competitive Advantage based on Entropy Weight TOPSIS Model

Utilizing the weights and normalized data matrix acquired through the entropy value method, a comprehensive evaluation of liquor enterprises is conducted using the TOPSIS method. The weights assigned to each indicator are detailed in Table 4, while Table 5 presents the sustained competitive advantage scores for each enterprise. We divided all sustained competitive advantage scores into five categories using the natural discontinuity approach [34]. Among them, 1 represents strong sustained competitive advantage, 2 represents stronger, 3 represents moderate, 4 represents weaker, and 5 represents poor. In order to optimize the differences between categories, the natural breakpoint method is a statistical technique for classification based on the rules of numerical statistical distribution. The technique is predicated on the idea that every statistical sequence has a number of inherent turning and distinctive points that can be utilized to divide the research population into clusters based on shared characteristics.

From a holistic perspective, the majority of liquor companies have experienced an upward trajectory in their competitive advantage throughout the study period. Notably, Kweichow Moutai (600519) and Wuliangye (000858) have consistently maintained robust and enduring competitive advantages. Shanxi Fenjiu (600809), Gujing Gongjiu (000596), Yanghe Brewery (002304), and Luzhou Laojiao (000568) also exhibit strong sustained competitive advantages, with Shanxi Fenjiu ascending from the 11th to the 3rd position, holding the highest sustained competitive advantage. Jiugui Liquor (000799), Swellfun (600779), King's Luck Brewery (603369), and Shede Spirits (600702) demonstrate moderate sustained competitive advantages, indicating a relatively stable development. Yingjia Distillery (603198), Laobai gan (600559), Huangtai Liquor (000995), Shunxin Agriculture (000860), Kouzi Jiao (603589), Yilite (600197), TianYouDe (002646), and Jinhui Liquor (603919) exhibit moderate to low sustained competitive advantages, with Yilite dropping from the 9th to the 16th position, and TianYouDe experiencing a significant decline from the 6th to the 17th position. Conversely, Golden Seed Winery (600199) demonstrates a low sustained competitive advantage and consistently holds a poor ranking.

Upon further examination of the current development of these enterprises, and in conjunction with Table 4, it becomes evident that brand value plays a pivotal role in reflecting the competitive advantage of a company. Brands such as Kweichow Moutai and Wuliangye have deeply ingrained themselves in the public consciousness, contributing to their significantly stronger sustained competitive advantage compared to other listed enterprises. Additionally, the enterprise's inventory turnover and gearing ratio exert a substantial impact on its competitive advantage.

Table 4. The weight value for determining the weight of evaluation index based on entropy method.

Type	Target layer	Indicator layer	Variable	Weight
Financial	Development capacity	Increase rate of main business revenue	X1	5.67%
		Rate of growth in attributable net profit	X2	1.07%
		Rate of growth in adjusted net profit	X3	0.59%
	Profitability	Return on total assets (weighted)	X4	1.01%
		Gross profit margin	X5	3.59%
		Net profit margin	X6	0.59%
	Debt-servicing capacity	Current ratio	X7	4.88%
		Quick ratio	X8	8.88%
		Debt-to-Asset ratio	X9	15.24%
	Operational capability	Total assets turnover ratio	X10	4.65%
		Inventory turnover ratio	X11	9.55%
	Cash flow	Sales to net cash flow from operations ratio	X12	2.20%
		Operating cash flow to income ratio	X13	1.58%
		Cash flow ratio	X14	2.92%
Non-financial	Brand value	Brand value	X15	32.84%
	Environmental and social responsibility	Disclosure completeness	X16	4.74%

Given the unique characteristics of the liquor industry, companies are susceptible to inventory backlogs. For instance, Jinhui Liquor is grappling with inventory backlogs while attempting to penetrate new markets. In its latest financial statement in 2022, the inventory of its low-grade, mid-grade, and high-grade products rose by 69.84%, 83.71%, and 90.04%, respectively. This challenge significantly contributes to its sustained competitive advantage consistently lagging behind. Similarly, Golden Seed Winery faces issues as its 2022 white wine products' operating income experienced a 7.23% year-on-year decline, leading to a loss in its main business and limited development due to funding shortages. Moreover, the net interest rate has been negative since 2014, further placing the sustained competitive advantage of the enterprise in an absolute disadvantageous position.

Table 5. Comprehensive score of competitive advantages of Baijiu listed enterprises.

Enterprise share code	Year (ranking)				
	2022	2021	2020	2019	2018
600519	0.6217 (1)	0.5924 (1)	0.5430 (1)	0.5060 (1)	0.4769 (1)
000858	0.5635 (2)	0.5272 (2)	0.4976 (2)	0.4768 (2)	0.4610 (2)
600809	0.4709 (3)	0.4402 (4)	0.4088 (5)	0.3575 (7)	0.3286 (11)
000596	0.4703 (4)	0.4442 (3)	0.4176 (3)	0.3968 (4)	0.3741 (4)
002304	0.4627 (5)	0.4373 (5)	0.4139 (4)	0.4008 (3)	0.3803 (3)
000568	0.4626 (6)	0.4296 (6)	0.4079 (6)	0.3832 (5)	0.3631 (5)
000799	0.3963 (7)	0.3672 (9)	0.3526 (9)	0.3480 (8)	0.3269 (12)
600779	0.3903 (8)	0.3941 (7)	0.3596 (7)	0.3673 (6)	0.3407 (7)
603369	0.3743 (9)	0.3662 (13)	0.3326 (13)	0.3347 (12)	0.3366 (8)
600702	0.3741 (10)	0.3684 (8)	0.3558 (8)	0.3440 (10)	0.3316 (10)
603198	0.3495 (11)	0.3110 (18)	0.3036 (18)	0.3001 (18)	0.2936 (18)
600559	0.3399 (12)	0.3355 (17)	0.3041 (17)	0.3115 (16)	0.3198 (14)
000995	0.3313 (13)	0.3300 (11)	0.3335 (11)	0.3393 (11)	0.3068 (17)
000860	0.3261 (14)	0.3308 (12)	0.3327 (12)	0.3310 (13)	0.3255 (13)
603589	0.3254 (15)	0.3286 (14)	0.3267 (14)	0.3293 (14)	0.3182 (15)
600197	0.3251 (16)	0.3345 (10)	0.3415 (10)	0.3442 (9)	0.3350 (9)
002646	0.3228 (17)	0.3201 (15)	0.3154 (15)	0.3257 (15)	0.3456 (6)
603919	0.3188 (18)	0.3113 (16)	0.3086 (16)	0.3077 (17)	0.3078 (16)
600199	0.2500 (19)	0.2528 (19)	0.2571 (19)	0.2615 (19)	0.2682 (19)

In alignment with the 2022 Hurun Brand List released by the Hurun Research Institute, the results obtained from our model align closely with its ranking. This lends a degree of reliability and accuracy to the application of our chosen model in analyzing sustained competitive advantage within the liquor industry.

6.3. Establishment of INGO-BP Neural Network Model based on Entropy Weight TOPSIS

This section initially outlines the parameter settings for each model. In the BP neural network, the number of nodes in the input layer is set to 16, corresponding to the number of indicators for sustained competitive advantage. The number of nodes in the output layer is set to 5, aligning with the number of evaluation grades for sustained competitive advantage. The optimal number of nodes in the hidden layer is determined through testing the empirical formula (17) and is established as 15. Subsequently, the optimization algorithm is parameterized with an initial population size of 30, a maximum number of iterations set to 100, and dimensions set at 335.

Throughout the training process, data samples undergo a 10-fold test to assess the model's average performance. Given the data imbalance in samples classified using the natural discontinuity method, this paper selects the following evaluation metrics for the classification prediction model: accuracy, Kappa coefficient, and weighted F1 score. The Kappa coefficient is particularly chosen for its ability to offer a more balanced evaluation in the context of unbalanced datasets, taking into account the model's classification performance across each category. The inclusion of the weighted F1 score not only considers individual categories but also integrates precision and recall, contributing to a more objective and accurate evaluation of the model's performance.

$$Accuracy = \frac{\sum_{i=1}^{K} n_{ii}}{N} \tag{19}$$

$$P_e = \frac{\sum_{i=1}^{K}\left(\sum_{j=1}^{K} n_{ij} \cdot \sum_{j=1}^{K} n_{ji}\right)}{N^2} \tag{20}$$

$$Kappa = \frac{Accuracy - P_e}{1 - P_e} \tag{21}$$

$$w\_F1\_score = \frac{\sum_{i=1}^{K} w_i \cdot F1_i}{\sum_{i=1}^{K} w_i} \tag{22}$$

In the formula, $Accuracy$ represents the accuracy of the model, P_e denotes the accuracy of random guessing; K is the number of categories; N is the total number of samples; n_{ii} is the number of samples correctly categorized into category i; n_{ji} is the number of samples categorized into category i but actually belong to category j. The Kappa coefficient has a range of [-1,1], and a higher value indicates better model performance. w_i represents the weight of the category i, and $F1_i$ is the F1-score of each category i. This comprehensive evaluation considers not only individual categories but also integrates precision and recall, contributing to a more nuanced and accurate assessment of the model's performance.

6.4. Experimental Description and Result Analysis

To thoroughly showcase the effectiveness of the enhanced model, this study employs the proposed model to conduct comparative experiments with other models using the same set of test samples. Table 6 illustrates the average scores for each performance metric of the models.

Table 6. Performance evaluation indicators for models.

	Accuracy	Kappa	w_F1_score
BP	92.25%	89.49%	92.60%
GA-BP	93.81%	91.66%	94.00%
NGO-BP	94.11%	92.08%	94.00%
INGO-BP	95.66%	94.19%	95.90%

Upon examining Table 3, it is evident that the INGO-BP neural network proposed in this paper exhibits superior performance in predicting results. Each model is then analyzed individually. The BP neural network, without the utilization of any optimization algorithm, is prone to falling into local minima, resulting in lower prediction accuracy. To address this issue, the paper introduces both the genetic algorithm and the Northern Pale Eagle algorithm to optimize the BP neural network separately, leading to improvements in prediction accuracy for both algorithms. The Northern Pale Eagle algorithm outperforms the genetic algorithm slightly, achieving a greater improvement. Subsequently, the BP neural network is optimized using the more effective INGO model, resulting in an accuracy score of 95.66%, an improvement of approximately 3.4% compared to the general BP neural network. This enhancement allows for a more accurate prediction of the sustained competitive advantage of the enterprise. The Kappa coefficient score reaches 94.19%, further confirming that the model's classification ability is not merely due to random prediction but is genuinely excellent, thereby enhancing the credibility of the INGO-BP model.

In summary, the results of evaluating the sustained competitive advantage of liquor enterprises using the entropy weight-TOPSIS method align closely with the outcomes verified by the actual data in the trained INGO-BP neural network model. The learned and trained INGO-BP neural network model demonstrates a strong learning effect, nonlinear mapping ability for evaluating the sustained competitive advantage of liquor enterprises, and robustness. The retained INGO-BP neural network, when applied to calculate the sustained competitive advantage of liquor enterprises, only requires inputting the index data of each enterprise to obtain the evaluation results. This approach brings considerable convenience to the evaluation and prediction of sustained competitive advantage in the liquor industry.

7. Conclusion

In this study, we present an enhanced NGO algorithm and utilize it to optimize the improved BP neural network through the INGO algorithm. Building upon this, we establish a model for evaluating the sustained competitive advantage of liquor companies, incorporating the entropy weight-TOPSIS method and the INGO-BP neural network method. This model effectively assesses the developmental level of sustained competitive advantage for each listed liquor enterprise in China. Experimental results demonstrate that the sustained competitive advantage of enterprises, as determined by the index system and evaluation model developed in this paper, aligns with the actual development status of current listed liquor enterprises. Moreover, the prediction model proposed herein exhibits higher accuracy and more stable performance compared to alternative models.

While this paper has successfully established a more comprehensive evaluation index system, it is important to note that regional development policies and natural environmental factors significantly influence the sustained competitive advantage of liquor enterprises. In future research, we plan to incorporate additional evaluation indexes and create a more comprehensive evaluation index system to analyze the sustained competitive advantage of liquor enterprises more thoroughly. Although the current enhanced model demonstrates superior predictive efficacy and stability compared to the unimproved model, ongoing efforts will involve further comparisons with advanced artificial neural networks to identify an optimal prediction model.

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