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Combined soft measurement on key indicator parameters of new competitive advantages for China's export

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Abstract

The estimation of the difference between the new competitive advantages of China's export and the world's trading powers have been the key measurement problems in China-related studies. In this work, a comprehensive evaluation index system for new export competitive advantages is developed, a soft-sensing model for China's new export competitive advantages based on the fuzzy entropy weight analytic hierarchy process is established, and the soft-sensing values of key indexes are derived. The obtained evaluation values of the main measurement index are used as the input variable of the fuzzy least squares support vector machine, and a soft-sensing model of the key index parameters of the new export competitive advantages of China based on the combined soft-sensing model of the fuzzy least squares support vector machine is established. The soft-sensing results of the new export competitive advantage index of China show that the soft measurement model developed herein is of high precision compared with other models, and the technical and brand competitiveness indicators of export products have more significant contributions to the new competitive advantages of China's export, while the service competitiveness indicator of export products has the least contribution to new competitive advantages of China's export.

Keywords: China's export, New competitive advantages, Export competitive advantage, Core competitiveness, Fuzzy least squares support vector machine, Soft measurement

Introduction

Since China's accession to the World Trade Organization, it's total export volume has increased rapidly, while its status as a major trading country has been further consolidated. However, most of China's export products are at the low end of the global value chain. There is a significant difference between China's export products and those of other powerful trading countries in terms of product technology content, brand value, quality level, core competitiveness, as well as innovation and marketing abilities (Smirnov et al. 2016; Suroso and Fakhrozi, 2018). With the increasing cost of labor, energy, and other resources, as well as the profound changes in domestic and foreign conditions and environment (Romero et al. 2015), China's competitive advantages of rapid export growth is gradually

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weakening and unsustainable. Thus, accelerating the development of China's new export competitive advantages in China-related studies has become a major issue that the Chinese government, enterprises, and academia pay close attention to and urgently need to solve. Moreover, China's Belt and Road Initiative (also known as One Belt One Road) is one of the measures to establish such advantages.

Regarding the novel concept of "new advantages in export competition," there is no clear definition at present (Wang 2013). The surveys (World Brand Lab) of 257 companies in the world trade 500 have shown that the pricing basis of their export products and their unique competitive advantages are responsible for the high-end position of their companies and products in the international division of labor rather than the cost-plus pricing principle. Notably, the pricing basis of the export products of the 257 companies does not rely on the comparative cost advantage and factor endowment from the traditional trade theory nor the scale economy and production efficiency advantages from the new trade theory, but it depends on the technical content, quality level, brand reputation, and continuous high-quality service of its products to win the loyalty of customers worldwide and share of the international market. Moreover, research results (Hausmann et al. 2007; Hallak and Schott 2011; Chu 2014) show that the different products exported by powerful world trading nations have some common characteristics: their products are top-ranked globally in terms of technical content, quality level, brand reputation, and continuous high-quality service.

New export competitive advantages (Wang and Huang 2015) refer to the new export advantages of a country (region) based on the accumulation of knowledge capital, independent innovation ability and innovation-driven mechanism, as well as the core competitiveness of high-end technology, brand, quality, and global value chain service. The definition can clarify three ideologies: (1) the core source of "new advantages in export competition" is a country's knowledge capital accumulation, independent innovation ability, and innovation-driving mechanism, thus overcoming the limitations of the traditional resource endowment theory; (2) the core connotation of "new advantage in export competition," which is the integration of four core competitiveness variables: technology, brand, quality, and service, and this is beyond the traditional comparative cost advantage; and (3) the basic characteristics of the "new export competitive advantage" can be clarified: the products at the high end of the global value chain, i.e., the "four high" products with high technical complexity, brand value, quality, and service content, can surpass the general competitive advantages based on production cost, scale economy, and production efficiency.

The rest of the paper is organized as follows: the literature review is presented in Sect. 2, while the soft measurement model establishment of key indicators of new competitive advantages in China's export is discussed in Sect. 3. The empirical analysis and the results of the soft measurement model of the key index parameters of the new competitive advantages of China's export are provided in Sect. 4, while the conclusions are given in Sect. 5.

Literature review

Research on the technical competitiveness of export products is mainly based on the measurement of the technical complexity of export products (Waugh and Ravikumar 2016; Zhao et al. 2018) and the exploration of its influencing factors (Sasahara 2019; Tian and Lin 2017). In recent years, Zhu et al. (2019) have investigated the international market power of China's tungsten export market from the perspective of tungsten export

policies, and they have analyzed the reasons for China's rising market power and the effectiveness of its export policies, while proposing corresponding policy recommendations. Weldemicael (2014) analyzes the relative importance of technology and trade costs for export sophistication and welfare in a general equilibrium framework, and the research results show that export sophistication is highly correlated with gross domestic product (GDP) per capita. Moreover, Du and Zhang (2013) use an international vertical specialization perspective to investigate the measurement and dynamic change of domestic technical complexity of China's industrial manufactured product export. Zhang et al. (2019) investigate the economic gains and environmental costs from China's exports based on regional inequality and trade heterogeneity, whereas Yu and Luo (2018) measure domestic value added in China's manufactured exports to explain China's real gains within global value chains. Kou et al. (2012, 2014) also evaluate a multiple criteria decision-making-based approach and use it to investigate uncertain financial risks. Yang et al. (2020) consider the relationship between financial and innovation performance, while Tsai and Lasminar (2021) study the relationship between supply chain information integration and performance. Liu et al. (2021) analyze opportunistic behaviour in supply chain finance. The aforementioned researchers have designed a variety of methods to measure the technical content of export products by examining changes in the technical level of export products in trading countries (especially China), studying financial factors, and trying to explore the reasons for this technological level change; however, they disagree on the measurement of the technical content of Chinese exports.

Research on the competitiveness of export brands are mainly based on the evaluation of the value of brand assets of export products and the identification of their main influencing factors. Among them, the most influential assessment methods are: (1) Regarding the financial orientation-based brand equity valuation method, Leung et al. (2019) analyze the effects of bank stakeholder orientation on financial stability enhancement; Yu et al. (2019) study the dynamism, disruption orientation, and resilience in the supply chain, as well as the impacts on financial performance based on a dynamic capabilities perspective; while Yu and Huo (2019) analyze the impact of environmental orientation on supplier green management and financial performance owing to the moderating role of relational capital. (2) For the brand equity valuation method based on market performance, Ricca and Robins (2017) study the value of brands based on measuring brand equity and the economy of meta-luxury, while Downer (2016) employs a new brand-oriented party model to investigate the importance of partisan brand equity or voter-perceived value, and the results show that it is the equity stupid for protecting the value of the partisan brand. (3) Mazurek (2014) studies a brand value evaluation method based on customer orientation and branding paradigms, as well as the shift of methodological approaches to branding. Consequently, a hybrid evaluation method, using different combinations, is derived, although it has various advantages and disadvantages (Leung et al. 2019).

The latest studies on export quality competitiveness are mainly based on the assessment of the quality of export products, the main influencing factors, and the trade effect of export quality (Ismail et al. 2014; Baiardi and Bianchi 2019). A quality competitiveness assessment framework based on supply factors and the Quality Competitiveness Index is created as an analytical tool to measure and enhance the quality

competitiveness of enterprises to identify and improve on their weaknesses. Domestic scholars have subsequently started researching on the quality of export products, and the main aspects are: (1) The quality of Chinese export products is measured using a variety of methods. For example, Wang (2013) measures the quality of Chinese export products using new advantages of export competition, while Sun et al. (2014) investigate the quality of China's export products and upgrading of quality, but there is no consensus on the measurement of the quality of Chinese export products, which may be related to measurement methods, data sources, and processing accuracy. (2) The empirical method is used to explore the influencing factors of the quality of China's export products. The relevant empirical results show that foreign direct investment, income gap, research and development density, financial development, learning by doing, export subsidies, RMB real appreciation, import country tariff reduction, import intermediate product quality, and labor productivity have a positive effect on the improvement and upgrading of China's export quality (Li and Wang 2013). However, the factor market distortion has a negative impact on the quality of export products (Geng 2014).

Research on export integration (integration of products and services) is a new area of development in trade theory. The implementation path of export integration can be divided into service- and product-oriented approaches. Recently, some studies have introduced certain technologies, such as cloud computing, Internet of things, and mobile Internet, into product and service integration systems in some foreign literature to promote innovation in integrated modes (Chen 2014). With the intensification of integration theory research, relevant empirical studies, such as the exploration of the integration of products and services as well as service-oriented manufacturing systems, have gradually begun.

Based on the aforementioned research status, previous studies have developed a variety of methods to measure the technical content and quality level of export products; however, an effective method for measuring the brand value of export products and the degree of service integration remains elusive. For example, market survey remains the main method to obtain brand measurement data. However, it only adapts to the small product variety and small-scale brand value measure (Paul 2019), and it is difficult to adapt it for the measurement and comparative analysis of the brand value of a large-scale and wide variety of export products between countries (Gilani and Cunningham 2017). A method for measuring service integration degree is yet to be developed, while that for technical content and quality level is still being preliminarily explored. Because the per capita GDP of each country is used as the main measurement technology content, and the weight does not reflect the inherent determinants of the technical content of export products, it is easy to obliterate the difference in technical content between different industries, enterprises, and products in a country. Therefore, taking price as the main basis to measure the quality level cannot reflect the influence of key factors, such as technology, branding, cost, supply, and demand relationship, on price. Meanwhile, the evaluation method of comprehensively measuring the new advantages of export competition from a holistic perspective is rather blank. Therefore, the measurement of the technology, brand, quality, and integration competitiveness of export products, as well as

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the estimation of the difference between the new competitive advantages of China's export and those of the world's trading powers are the key measurement problems that remain to be resolved.

Evidently, former theories fail to capitalize on the new advantages of export competition as the research object and mostly ignore research on the new advantages of export competition with technology, brand, quality, and service as the core. Therefore, it is essential to develop new international trade and competition theories. This study is in line with the development of the international trade discipline, focusing on the basic theoretical issues of new advantages in export competition.

Notably, regarding support vector regression (Zuo et al. 2018), fuzzy support vector machines (SVMs) (Abe 2015; Fan et al. 2017) improve support vector regression (Dong et al. 2018; Zhang and Hong 2019; Zhang et al. 2020), and fuzzy least squares (FLS) SVMs (Wang and Zuo 2014) can reflect the uncertainty of samples in the system objectively and accurately, while exhibiting unique advantages, such as requiring less sample data, apt at relearning online, and having good anti-noise performance (Zuo et al. 2014; Jiaqiang et al. 2017) in resolving the above-mentioned nonlinearity and multifactor coupling problems in relation to measuring the new competitive advantages of China's export. The main objectives and ideas are expressed as follows: according to the sensitivity of SVM to noise and outliers in training samples, fuzzy parameters are introduced into the LS-SVM to ensure that various samples have different contributions when constructing the objective function to weaken the influence of noise and outliers on classification, thereby embellishing the FLS-SVM for cost-sensitive or noisy data. Therefore, a comprehensive evaluation model for the new competitive advantage of China's export will be established, and the obtained evaluation value of new competitive advantage indicator of China's export will be used as the input variable of the FLS-SVM to construct the soft measurement model of the corresponding parameters of China's export competition. Furthermore, the effect of the soft measurement on the new advantage indicator will be realized, as well as the export product technical, brand, quality, and service competitiveness indicators of China's export competition, which can provide a better theoretical method and reference basis to enhance the core competitiveness of China's export.

Soft measurement model of key indicators of new competitive advantage in China's export

A soft measurement flow chart of four key indicator parameters for the new competitive advantages of China's export is shown in Fig. 1.

The high-tech products include some categories as follows:

(1) Computer and communication/electronic technology, (2) Life science and technology, (3) Computer integrated manufacturing technology, (4) Aerospace technology, (5) Photoelectric technology, (6) Biotechnology, and (7) Material technology.

Moreover, the export share of high-tech products is the key index of technical competitiveness of export products, and it accounts for approximately 25–30% of the total export volume based on data released by the National Bureau of Statistics in China from 2016 to 2020.
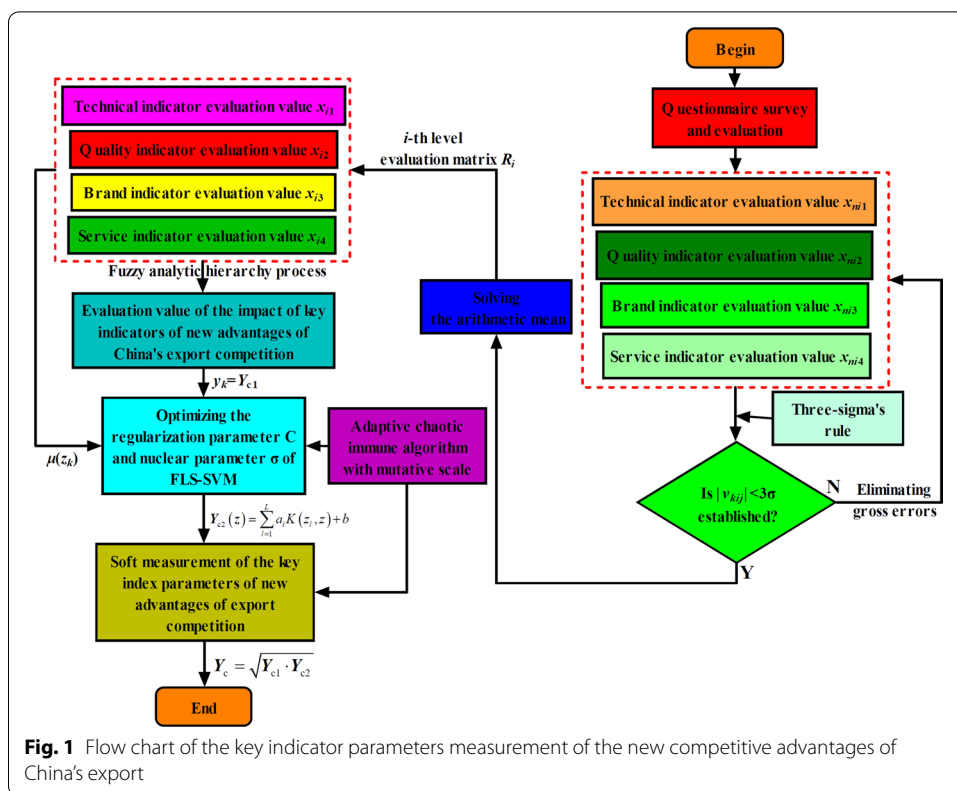
Fig. 1 Flow chart of the key indicator parameters measurement of the new competitive advantages of China's export

Soft measurement model of the key indicators of the new competitive advantages in China's export based on the fuzzy entropy weight analytic hierarchy process

The specific steps of key indicator parameter measurement of new competitive advantages of China's export are expressed as follows:

Step 1 Data collection method.

The experts that conduct this questionnaire survey are composed of 17 reputable professors in the export trade and international trade finance field, drawn from famous universities at home and abroad, 15 industry management experts from the International Chamber of Commerce, as well as 18 directors of large multinationals and trading companies.

The research group collects data through a questionnaire survey, in-depth interview, forum, and literature analysis. The key indicator evaluation table (Table 1) of the new competitive advantages of China's export is distributed to the experts in the export trade field (50 copies), and the key indicators of the new competitive advantages of China's export are graded and answered anonymously. After the test, the 50 questionnaires are immediately recovered.

Step 2 China's export competition new advantage evaluation indicator data collection.

Step 2.1 Construction of China's export competition new advantage evaluation indicator system.

The technical competitiveness indicator x_1 of export products given by the n-th expert (product export technology complexity x_{n11}, intermediate input ratio x_{n12}, high-tech product export share x_{n13}), export product brand competitiveness indicator

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Table 1 Key indicator evaluation of the new competitive advantages of China's export (the *n*th expert)

Judge factors of Level 1	Judge factors of Level 2	Evaluation grade of the key indicators of competitiveness of new competitive advantages of China's export				
		Excellent	Good	Medium	Less inferior	Inferior
x_1	x_{11}					
	x_{12}					
	x_{13}					
x_2	x_{21}					
	x_{22}					
	x_{23}					
	x_{24}					
x_3	x_{31}					
	x_{32}					
	x_{33}					
x_4	x_{41}					
	x_{42}					
	x_{43}					

x_2 (classified brand product export flow structure x_{n21}, brand product profitability x_{n22}, brand product market share x_{n23}, importing country consumer demand intensity and evaluation x_{n24}), export product quality competitiveness indicator x_3 (excluding the export price indicator x_{n31} after the influence of quality factors, the ratio of added value of export products x_{n32}, quality reputation x_{n33}), and export product service competitiveness indicator x_4 (the proportion of export product service income to the total sales volume of its export products x_{n41}, the proportion of manufacturing service income to the total income of similar products in the world x_{n42}, service quality satisfaction x_{n43}) are taken as an evaluation indicator system for Levels 1 and 2 (as shown in Table 1).

Step 2.2 Expert evaluation of key indicators of the new competitive advantages of China's export.

The obtained key indicator data collection tables of the new competitive advantages of China's export are uniformly numbered as n ($n = 1, 2, ..., 50$), and the 50 main index evaluation value groups of the key index parameters, such as the technical, brand, quality, and service competitiveness indicators of the export product, affecting the new competitive advantages of China's export are obtained.

Step 2.3 Key indicator evaluation data processing of the new competitive advantages of China's export.

Step 2.3.1 Based on the need to measure the evaluation index of China's new advantages in export competition, the relevant data of China's import and export products are obtained.

Step 2.3.2 According to the three-sigma rule (Dileep and Danti 2018), in the competitiveness measure impact data column of a year of China's export competitiveness new advantage, if the residual evaluation value r_{nijk} of the *i*-level and *j*-item indicator given by the *n*-th ($n = 1, 2, ...,50$) expert is that the absolute value of $v_{nijk} = r_{nijs} - r_{\mu ijs}$ [i.e., the difference of the arithmetic mean value $r_{\mu ijs}$ of the evaluation value r_{nijk} and

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the evaluation value r_{nijs} ($n=1, 2, ...,50;\ i=1, 2, ..., 4;\ j=1, 2, ..., J;\ s=1, 2, ..., 5$)] is three times larger than the standard error of the evaluation column (i.e., $|v_{nijs}| > 3\sigma$), it can be considered as a gross error, and then r_{nijs} is eliminated.

Step 2.3.3 Thereafter, the arithmetic mean value S and standard error σ in the evaluation column should be recalculated until $|v_{nijk}| < 3\sigma$, whereafter the arithmetic mean $r'_{\mu ij}$ of the evaluation column at this time is taken as the evaluation value r_{ijk} of the i-th level and j-th item index grade (Table 2).

The i-th level evaluation matrix $\boldsymbol{R_i}$ of the key indicators of the new competitive advantages of China's export can be expressed as:

$$
\boldsymbol{R_i} = \begin{bmatrix} r_{i11} & r_{i12} & r_{i13} & r_{i14} & r_{i15} \\ r_{i21} & r_{i22} & r_{i23} & r_{i24} & r_{i25} \\ r_{i31} & r_{i32} & r_{i33} & r_{i34} & r_{i35} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{iJ1} & r_{iJ2} & r_{iJ3} & r_{iJ4} & r_{iJ5} \end{bmatrix} \tag{1}
$$

Step 3 Construction of the entropy weight matrix of the key indicators evaluation value of the new competitive advantages of China's export.

Step 3.1 The fuzzy judgement matrix of the credibility of the key indicator evaluation values of the new competitive advantages of China's export.

Step 3.1.1 Fifty experts are asked to freely score the credibility of the key indicator evaluation values of the new competitive advantages of China's export between [0, 1]. The n-th expert gave the maximum u_{nijk} and the minimum l_{nijk} for the credibility of the k-th evaluation value of the i-th level and j-th item indicator of the new competitive advantages of China's export. Thereafter, the n-th expert can represent the variable

Table 2 Key indicator evaluation table of new competitive advantages of China's export

Judge factors	Evaluation grade of the key indicators of competitiveness of new competitive advantages of China's export					W_{ij}	W_i
	Excellent	Good	Medium	Less inferior	Inferior		
x_1							W_1
x_{11}	r_{111}	r_{112}	r_{113}	r_{114}	r_{115}	W_{11}	
x_{12}	r_{121}	r_{122}	r_{123}	r_{124}	r_{125}	W_{12}	
x_{13}	r_{131}	r_{132}	r_{133}	r_{134}	r_{135}	W_{13}	
x_2							W_2
x_{21}	r_{211}	r_{212}	r_{213}	r_{214}	r_{215}	W_{21}	
x_{22}	r_{221}	r_{222}	r_{223}	r_{224}	r_{225}	W_{22}	
x_{23}	r_{231}	r_{232}	r_{233}	r_{234}	r_{235}	W_{23}	
x_{24}	r_{241}	r_{242}	r_{243}	r_{244}	r_{245}	W_{24}	
x_3							W_3
x_{31}	r_{311}	r_{312}	r_{313}	r_{314}	r_{315}	W_{31}	
x_{32}	r_{321}	r_{322}	r_{323}	r_{324}	r_{325}	W_{32}	
x_{33}	r_{331}	r_{332}	r_{333}	r_{334}	r_{335}	W_{33}	
x_4							W_4
x_{41}	r_{411}	r_{412}	r_{413}	r_{414}	r_{415}	W_{41}	
x_{42}	r_{421}	r_{422}	r_{423}	r_{424}	r_{425}	W_{42}	
x_{43}	r_{431}	r_{432}	r_{433}	r_{434}	r_{435}	W_{43}	

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interval of credibility of the k-th evaluation value of the i-th level and j-th item indicator of the new competitive advantages of China's export as: $e_{nijk} = u_{nijk} - l_{nijk}$.

Step 3.1.2 Apparently, this credibility interval reflects the change of the credibility of the k-th evaluation value of the i-th level and j-th item indicator of the new competitive advantages of China's export given by the n-th expert. The smaller the e_{nijk}, the higher the credibility of the k-th evaluation value of the i-th level and j-th item indicator of the new competitive advantages of China's export given by the n-th expert.

Step 3.1.3 The k-th credibility value w_{ijk} of the j-th indicator in the i-th grade initial credibility weight matrix W_0 of the key indicators of the new competitive advantages of China's export can be defined as:

$$w_{ijk} = \left[l_{ijk}, m_{ijk}, u_{ijk} \right] \tag{2}$$

where $l_{ijk} \leq m_{ijk} \leq u_{ijk}$, l_{ijk}, m_{ijk}, and u_{ijk} are the lower, median, and upper limits, respectively, of the k-th credibility of the i-th grade j-th indicator.

Step 3.1.4 The lower limit l_{ijk}, median m_{ijk}, and upper limit u_{ijk} of the k-th credibility of the i-th grade j-th indicator are determined using formulas (3)–(5), respectively.

$$l_{ijk} = \frac{1}{50} \sum_{n=1}^{50} l_{nijk} \tag{3}$$

$$m_{ijk} = \frac{1}{50} \sum_{n=1}^{50} \left(l_{nijk} + u_{nijk} \right) / 2 \tag{4}$$

$$u_{ijk} = \frac{1}{50} \sum_{n=1}^{50} u_{nijk} \tag{5}$$

Step 3.1.5 According to the characteristics of the research data on the evaluation of the key indicators of the new competitive advantages of China's export, the bell-shaped membership function is used as a variable fuzzification function to fuzzify the credibility and fuzzy weight of the k-th evaluation value of the i-th grade j-th indicator, expressed as:

$$\mu_{ijk} = \left(\frac{1}{1 + \left(\frac{r_{ijk} - u_{ijk}}{l_{ijk}} \right)^{2m_{ijk}}} \right) \tag{6}$$

Step 3.2 Determination of the credibility entropy weight of the evaluation value of the key indicators of the new competitive advantages of China's export.

Step 3.2.1 The evaluation value of the key indicators of the new competitive advantages of China's export is mainly obtained via qualitative evaluation by 50 experts, while the credibility is also subjective. Therefore, the credibility of the evaluation value of the different key indicators of the new competitive advantages of China's export obtained will vary with the attributes and characteristics of the various key indicators.

Step 3.2.2 The credibility entropy weight method of the key indicators evaluation value of the new competitive advantages of China's export shown in the formula (7) is introduced to adjust the fuzzy weight of the *k*-th evaluation value of the *i*-th grade *j*-th indicator.

Step 3.2.3 The entropy of the *k*-th evaluation value of the *i*-th grade *j*-th indicator of the new competitive advantages of China's export.

$$
H_{ijk} = -k(\alpha)\left[\alpha\mu_{ijk} + (1-\alpha)\left(1-\mu_{ijk}\right)\right]e_{ijk}\ln e_{ijk}
$$
$$
s.t.\begin{cases} 0 \le \alpha \le 1 \\ k(\alpha) = \begin{cases} 1 & \alpha \ne 0.5 \\ 2 & \alpha = 0.5 \end{cases} \end{cases} \tag{7}
$$

where e_{ijk} is comprehensive credibility variable interval of the *k*-th evaluation value of the *i*-th grade *j*-th indicator of the new competitive advantages of China's export.

Step 3.2.4 When $\alpha = 1$, 0.5, and 0, the generalized entropy of the *k*-th evaluation value of the *i*-th grade *j*-th indicator of the new competitive advantages of China's export, respectively, becomes the entropy definition of the *k*-th evaluation value, credibility variable interval, and indeterminate fuzzy of the *i*-th grade *j*-th indicator of the new competitive advantages of China's export.

Step 3.2.5 The entropy of the *i*-th grade *j*-th indicator of the new competitive advantages of China's export is:

$$
H_{ij} = -\frac{1}{3\ln n}\sum_{k=1}^{5} H_{ijk} \tag{8}
$$

Step 3.2.6 Therefore, the entropy weight of the *i*-th grade *j*-th indicator of the new competitive advantages of Cha's export is:

$$
w_i = \left(\frac{H_i}{\sum_{i=1}^{I} H_i}\right) \tag{9}
$$

Step 3.2.7 Thus, the entropy weight set of the key indicators of the new competitive advantages of China's export can be obtained:

$$
W = \left[\, w_1,\ w_2,\ w_3,\ w_4 \,\right] \tag{10}
$$

Step 4 Fuzzy hierarchy comprehensive evaluation of the key indicators of the new competitive advantages of China's export.

Step 4.1 The evaluation matrix B_i of the key index parameter of the *i*-th grade of the new competitive advantages of China's export can be obtained, and after normalization, it can be derived as follows:

$$
\boldsymbol{B}_i = \boldsymbol{R}_i \cdot X^{\mathrm{T}} \tag{11}
$$

where $0 \le i \le I$ and T represent the transposition, While X is the corresponding score vector in the evaluation set. The evaluation score table is shown in Table 3.

Step 4.2 The key index parameter evaluation matrix $Y_i = [y_1, y_2, y_3, y_4]$ of the new competitive advantages of China's export can be expressed as follows:

$$Y_i = B_i \cdot W_i^{\mathrm{T}} \tag{12}$$

Step 4.3 The fuzzy comprehensive evaluation is carried out for the key indicators of the new advantages of China's competition, and the result set of fuzzy comprehensive evaluation is obtained, i.e., the integration of the weight vector W and the evaluation matrix Y_i of the key index parameters of the new competitive advantages of China's export can be used to obtain the soft measurement value Y_{c1}:

$$Y_{c1} = Y_i \cdot W^T \tag{13}$$

Soft measurement model of the key index parameters of the new competitive advantages of China's export based on the fuzzy least squares support vector machine

Fuzzy least squares support vector machine

Based on Table 1, for the k-th evaluation value of the i-th grade j-th indicator given by the n-th expert, let $z_{n1} = x_{n11}$, $z_{n2} = x_{n12}$, $z_{n3} = x_{n13}$, $z_{n4} = x_{n21}$, $z_{n5} = x_{n22}$, $z_{n6} = x_{n23}$, $z_{n7} = x_{n24}$, $z_{n8} = x_{n31}$, $z_{n9} = x_{n32}$, $z_{n10} = x_{n33}$, $z_{n11} = x_{n41}$, $z_{n12} = x_{n42}$ and $z_{n13} = x_{n43}$, $\mu(z_{n1}) = [r_{n111}, r_{n112}, r_{n113}, r_{n114}, r_{n115}]$, $\mu(z_{n2}) = [r_{n121}, r_{n122}, r_{n123}, r_{n124}, r_{n125}]$, $\mu(z_{n3}) = [r_{n131}, r_{n132}, r_{n133}, r_{n134}, r_{n135}]$, $\mu(z_{n4}) = [r_{n211}, r_{n212}, r_{n213}, r_{n214}, r_{n215}]$, $\mu(z_{n5}) = [r_{n221}, r_{n222}, r_{n223}, r_{n224}, r_{n225}]$, $\mu(z_{n6}) = [r_{n231}, r_{n232}, r_{n233}, r_{n234}, r_{n235}]$, $\mu(z_{n7}) = [r_{n241}, r_{n242}, r_{n243}, r_{n244}, r_{n245}]$, $\mu(z_{n8}) = [r_{n311}, r_{n312}, r_{n313}, r_{n314}, r_{n315}]$, $\mu(z_{n9}) = [r_{n321}, r_{n322}, r_{n323}, r_{n324}, r_{n325}]$, $\mu(z_{n10}) = [r_{n331}, r_{n332}, r_{n333}, r_{n334}, r_{n335}]$, $\mu(z_{n11}) = [r_{n411}, r_{n412}, r_{n413}, r_{n414}, r_{n415}]$, $\mu(z_{n12}) = [r_{n421}, r_{n422}, r_{n423}, r_{n424}, r_{n425}]$ and $\mu(z_{n13}) = [r_{n431}, r_{n432}, r_{n433}, r_{n434}, r_{n435}]$, then let the input fuzzy samples of the FLS-SVM shown in Fig. 2 be:

$$(z_1, y_1, \mu(z_1)), \ (z_2, y_2, \mu(z_2)), \ (z_3, y_3, \mu(z_3)), \ldots, (z_k, y_k, \mu(z_k)), \quad k = 1, 2, \ldots, 13 \tag{14}$$

where $\mu(z_k)$ is the membership function value, $\mu(z_k) = \sum \mu(z_{nk})/n$, $0 < \mu(z_k) \le 1$, $n = 1, 2, \ldots, 50$; $z_k = [z_{1k}, z_{2k}, \ldots, z_{nk}]$, $n = 1, 2, \ldots, 50$, $k = 1, 2, \ldots, 13$; $y_k = Y_{c1}$, $k = 1, 2, \ldots, 13$.

For the given FLS-SVM, a nonlinear mapping $\varphi(z_k)$ is introduced to transform the input variable to a high-dimensional space, wherein linear regression is carried out and the objective function can be expressed as:

$$R(\omega, \xi)_{\min} = \frac{1}{2} \|\omega\|^2 + \frac{C}{2} \sum_{i=1}^{N} \mu(z_k) \varepsilon_k^2$$
$$s.t. \ y_k = \omega \cdot \varphi(z_k) + b + \varepsilon_k \tag{15}$$

where ε_i is the slack variable, b is threshold, c is the penalty factor, and $\mu(x_i)$ is the membership of x_i.

Table 3 Rating table of the key indicators of competitiveness of new competitive advantages of China's export

Score X	0.95	0.80	0.65	0.50	0.35
Indicator grade	Excellent	Good	Medium	Less inferior	Inferior

Fig. 2 Soft measurement model of the key index parameters of the new competitive advantages of China's export based on the FLS-SVM
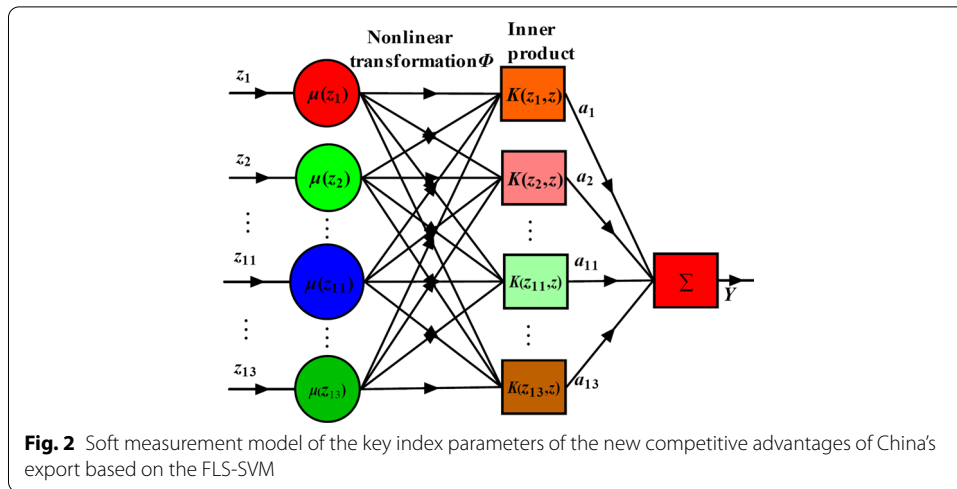
The Lagrange operator a_i ($i = 1, 2, ..., 13$) is introduced to construct a Lagrange equation to solve this optimization problem, and the FLS-SVM optimization problem is converted to the problem of solving linear Eq. (15):

$$\begin{bmatrix} 0 & y_1 & \cdots & y_1 \\ y_1 & y_1 y_1 K(z_1, z_1) + 1/C & \cdots & y_1 y_1 K(z_1, z_k) \\ \vdots & \vdots & \ddots & \vdots \\ y_k & y_k y_1 K(z_k, z_1) & \cdots & y_k y_k K(z_k, z_k) + 1/C \end{bmatrix} \times \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \quad (16)$$

Thus, the soft measurement model of the key index parameters of the new competitive advantages of China's export based on FLS-SVM can be expressed as follows:

$$Y_{c2}(z) = \sum_{l=1}^{L} a_i K(z_l, z) + b \quad (17)$$

where $K(z_l, z) = \exp\{-|z_k - z|^2/\sigma^2\}$, σ is the nuclear parameter, while for the Lagrange operator a_i, $0 < a_i < C$, C is a regularization parameter and b is the threshold value.

Parameter optimization of the soft measurement model of the key index parameters of the new competitive advantages of China's export based on the FLS-SVM

When carrying out the soft measurement with the soft measurement model of the key index parameters of the new competitive advantages of China's export based on the FLS-SVM, the generalization ability and accuracy of the FLS-SVM depend mainly on the effective selection of the regularization parameter C and nuclear parameter σ (Hong et al. 2011, 2019). Therefore, when optimizing the regularization parameter C and nuclear parameter σ of the FLS-SVM via the adaptive chaotic immune algorithm with mutative scale, the fitness function can be determined using formula (18).

$$F(C, \sigma) = \frac{1}{\sum_{l=1}^{13} [Y(z_l) - y_l]^2 + e} \quad (18)$$

where y_l is the desired output, $Y(z_l)$ is the actual output, and e is a small real number, which prevents the denominator from being zero; here, it is 10^{-3}.

The error function, i.e., mean squared error (MSE) (Kundra and Sadawarti 2015), is defined as the evaluation index of the generalization performance of the FLS-SVM:

$$\text{MSE} = \frac{1}{13} \sum_{l=1}^{13} \left\{ \frac{1}{50} \sum_{n=1}^{50} [Y(z_{nl}) - y_{nl}]^2 \right\} \tag{19}$$

The specific steps of the adaptive chaotic immune algorithm with mutative scale to optimize FLS-SVM parameters are shown in the research results (Wang and Zuo 2014). If the cut-off criterion $\text{MSE} < 10^{-5}$ is satisfied, the search is cut off and the optimal output solution z_l is the output.

Combined soft measurement model of the key index parameters of the new competitive advantages of China's export

The geometric mean value of the soft measurement results Y_{c1} and Y_{c2} of the key indicators of the new competitive advantages of China's export based on the fuzzy entropy weight analytic hierarchy process and FLS-SVM, respectively, is taken as the combined soft measurement result Y_c, and it can be expressed as:

$$Y_c = \sqrt{Y_{c1} \cdot Y_{c2}} \tag{20}$$

Simulation experiment of the soft measurement model

To validate the prediction accuracy of the soft measurement model based on the adaptive chaotic immune algorithm with mutative scale herein, the input parameters of the soft measurement model are set to 3, and taking the three-dimensional nonlinear function $y = [1.0 - (z_1)^{1/2} + (z_2)^{-1} + (z_3)^{-1.5}]^2$ as an example, the soft measurement model in this paper is used to simulate and analyze it. Upon making the value ranges of z_1, z_2, and z_3 be [1, 5], 100 data pairs are generated, as shown in Fig. 3, whereof 50 data pairs each are used as training and test data pairs. Taking z_1, z_2, and z_3 as the input parameters and the nonlinear function value y as the output parameter of the prediction methods in the research results of Yan et al. (2008) and Nieto et al. (2015), as well as those of the soft measurement model in this study, the prediction accuracies of the three above-mentioned prediction models are compared and studied.

The first 50 test data pairs are trained, respectively, using the prediction method in the research results of Yan et al. (2008) and Nieto et al. (2015), as well as the soft measurement model herein. The relative error η between the calculated and actual values after the completion of the training is shown in Fig. 4.

Figure 4 reveals that the relative error values η of the prediction method in the research results of Yan et al. (2008) and Nieto et al. (2015) fluctuate between -5.234% and 5.315% and -3.298% and 3.485%, respectively, while that of the soft measurement model herein fluctuates in the range of -1.913% to 1.972%. Evidently, compared with the other two prediction methods, the soft measurement model herein has a higher training accuracy for the first 50 training data.

Fig. 3 Simulation analysis data
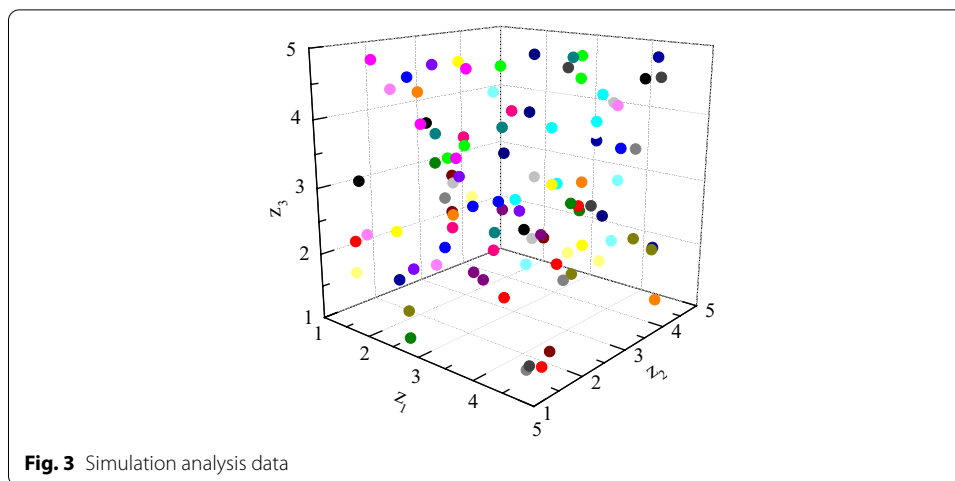
The last 50 test data pairs are respectively tested by the prediction methods in the research results of Yan et al. (2008) and Nieto et al. (2015), as well as the soft measurement model in this study. The relative error η between the calculated and actual values is shown in Fig. 5.

Figure 5 shows that the relative error values η of the prediction methods in the research results of Yan et al. (2008) and Nieto et al. (2015) fluctuate between -5.464% and 5.756% and -3.325% and 3.534%, respectively, whereas that of the soft measurement model in this study fluctuates in the range of -1.926% and 1.948%. Apparently, compared with the other two prediction methods, the soft measurement model in this study has a higher test accuracy for the last 50 test data pairs and a stronger generalization ability.

The prediction errors of the three models based on the statistical test are presented in Table 4.

Based on the statistical test, as shown in Table 4, the superiority of the soft measurement model in this study is more evident than the other two prediction methods.

In conclusion, the soft measurement model in this study has significant advantages in both accuracy and generalization ability.

Empirical analysis of the soft measurement model of the key index parameters of the new competitive advantages of China's export
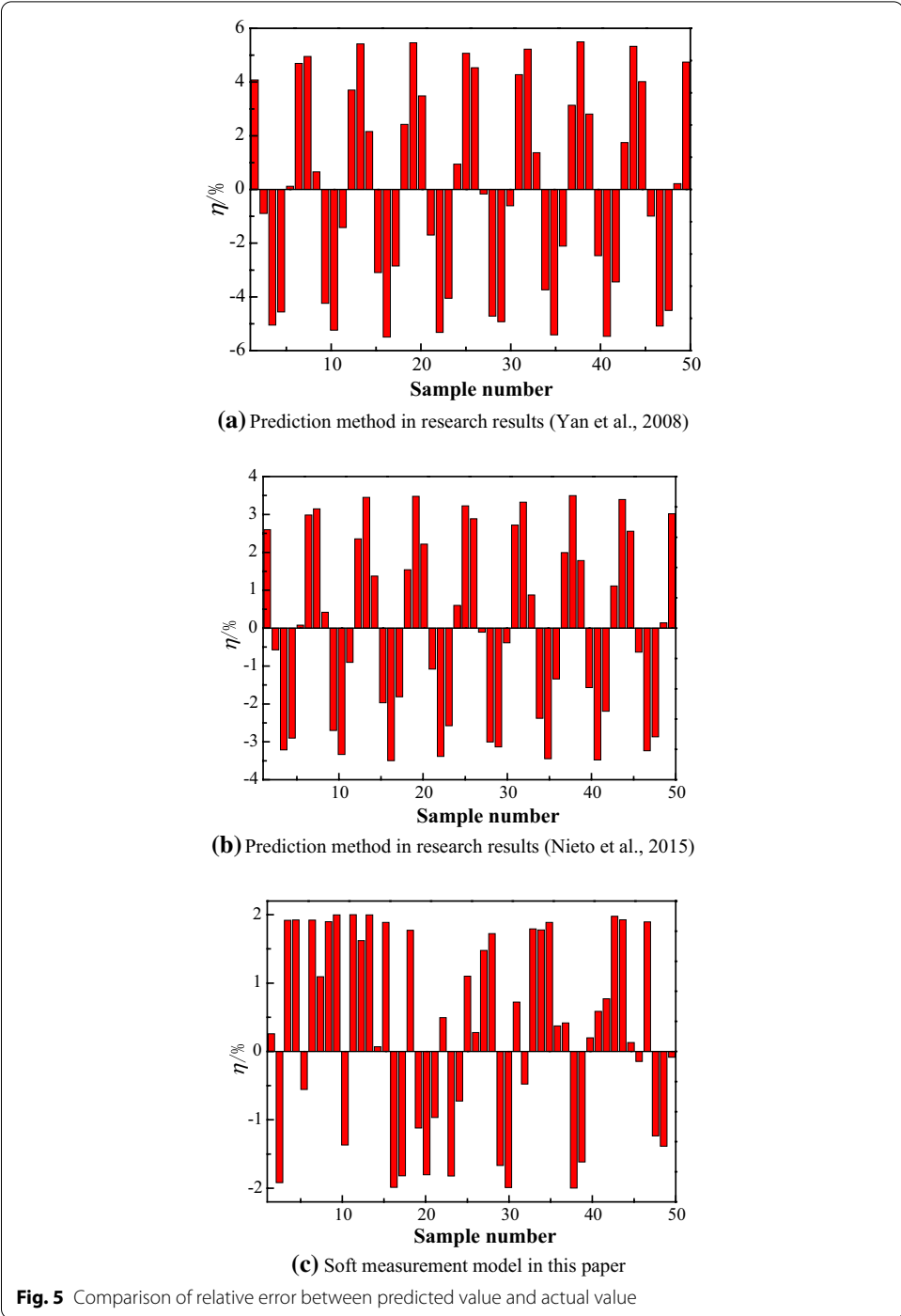
In this section, the key indicators of the new competitive advantages of China's export which satisfy the requirements given by a group of experts are discussed.

Empirical analysis of the soft measurement model of the key indicators of new competitive advantages of China's export based on fuzzy entropy weight analytic hierarchy process

The data validity is processed for the key indicator evaluation values that satisfy the requirements of the new competitive advantages of China's export given by 50 experts. The arithmetic mean value of the key indicator evaluation values of the new competitive advantages of China's export (including the technical complexity of export products x_{11}, intermediate input ratio x_{12}, high-tech products export share x_{13}, classified brand products export flow structure x_{21}, brand products profitability x_{22},

(a) Prediction method in research results (Yan et al., 2008).

(b) Prediction method in research results (Nieto et al., 2015).

(c) Soft measurement model in this study.

Fig. 4 Comparison of relative error between the calculated and actual values
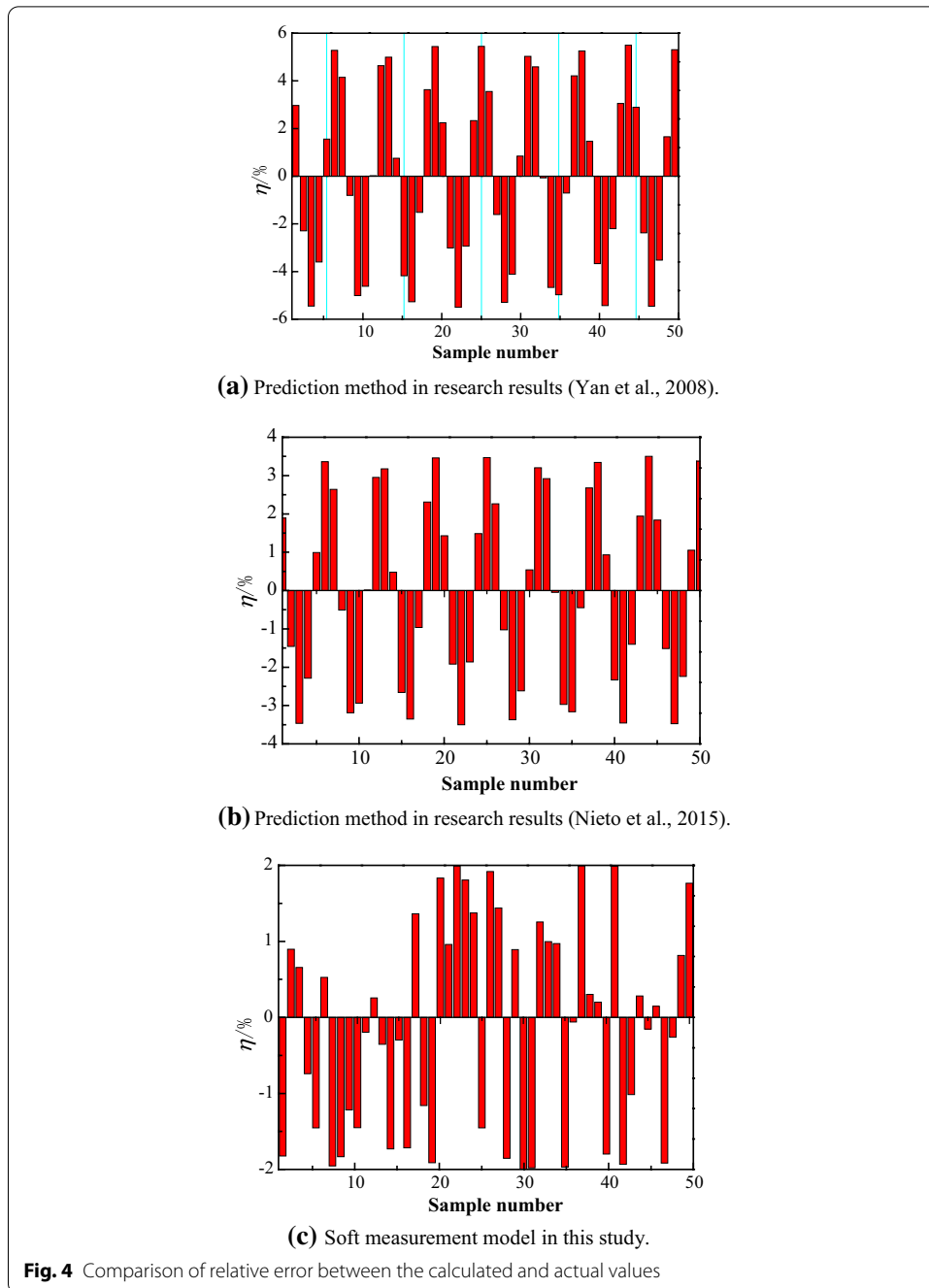
brand products market share x_{23}, demand intensity and evaluation for the brand products by the consumers in importing country x_{24}, export price index x_{31} after excluding the influence of non-quality factors, the added value ratio of export products x_{32}, the quality reputation x_{33}, the proportion of service income of export products to the total sales of export products x_{41}, the proportion of service income of manufacturing products to the total service income of similar products in the world x_{42}, and the satisfaction of service quality x_{43}) are shown in Table 5 (Taking 2016 as an example).

(a) Prediction method in research results (Yan et al., 2008)

(b) Prediction method in research results (Nieto et al., 2015)

(c) Soft measurement model in this paper

Fig. 5 Comparison of relative error between predicted value and actual value

According to the arithmetic average of the evaluation values of the key indicators of the new competitive advantages of China's export, the entropy weight set of the key indicators of new competitive advantages of China's export can be obtained by calculation: $W = (W_1, W_2, W_3, W_4) = (0.23, 0.30, 0.26, 0.21)$, $W_1 = (W_{11}, W_{12}, W_{13}) = (0.36, 0.30, 0.34)$; $W_2 = (W_{21}, W_{22}, W_{23}, W_{24}) = (0.25, 0.22, 0.28, 0.25)$; $W_3 = (W_{31}, W_{32}, W_{33}) = (0.38, 0.22, 0.40)$, $W_4 = (W_{41}, W_{42}, W_{43}) = (0.35, 0.25, 0.40)$.

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Table 4 Prediction errors of the three models based on the statistical test

Error type	Prediction method in the research (Yan et al. 2008)	Prediction method in the research (Nieto et al. 2015)	Soft measurement model in this paper
Average relative error	2.8974%	2.3217%	2.2642%
Relative root mean square error	3.3846%	2.9942%	2.8462%
Posterior error ratio C	0.0084	0.0069	0.0059
Small error probability P	0.9876	0.9913	1.0000

The smaller C is, the better the prediction effect is; the higher P is, the better the prediction effect is

Table 5 Key indicator evaluation table of new competitive advantages of China's export in 2016

Judge factors	Evaluation grade of the key indicators of competitiveness of new competitive advantages of China's export					W_{ij}	W_i
	Excellent	Good	Medium	Less inferior	Inferior		
x_1							0.23
x_{11}	0.4	0.3	0.2	0.1	0.0	0.36	
x_{12}	0.2	0.5	0.2	0.1	0.0	0.30	
x_{13}	0.4	0.5	0.1	0.0	0.0	0.34	
x_2							0.30
x_{21}	0.1	0.5	0.3	0.1	0.0	0.25	
x_{22}	0.2	0.5	0.3	0.0	0.0	0.22	
x_{23}	0.1	0.5	0.2	0.1	0.1	0.28	
x_{24}	0.3	0.3	0.1	0.2	0.1	0.25	
x_3							0.26
x_{31}	0.4	0.3	0.2	0.1	0.0	0.38	
x_{32}	0.2	0.3	0.3	0.2	0.0	0.22	
x_{33}	0.3	0.5	0.2	0.0	0.0	0.40	
x_4							0.21
x_{41}	0.2	0.2	0.2	0.3	0.1	0.35	
x_{42}	0.3	0.4	0.2	0.1	0.0	0.25	
x_{43}	0.2	0.2	0.2	0.3	0.1	0.40	

From Table 5, it is evident that the key indicator fuzzy evaluation matrix R_i of the new competitive advantages of China's export is:

$$R_1 = \begin{bmatrix} 0.4 & 0.3 & 0.2 & 0.1 & 0.0 \\ 0.2 & 0.5 & 0.2 & 0.1 & 0.0 \\ 0.4 & 0.5 & 0.1 & 0.0 & 0.0 \end{bmatrix} \quad R_2 = \begin{bmatrix} 0.1 & 0.5 & 0.3 & 0.1 & 0.0 \\ 0.2 & 0.5 & 0.3 & 0.0 & 0.0 \\ 0.1 & 0.5 & 0.2 & 0.1 & 0.1 \\ 0.3 & 0.3 & 0.1 & 0.2 & 0.1 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 0.4 & 0.3 & 0.2 & 0.1 & 0.0 \\ 0.2 & 0.3 & 0.3 & 0.2 & 0.0 \\ 0.3 & 0.5 & 0.2 & 0.0 & 0.0 \end{bmatrix} \quad R_4 = \begin{bmatrix} 0.2 & 0.2 & 0.2 & 0.3 & 0.1 \\ 0.3 & 0.4 & 0.2 & 0.1 & 0.0 \\ 0.2 & 0.2 & 0.2 & 0.3 & 0.1 \end{bmatrix}$$

The key indicator evaluation matrix B_i of the new competitive advantages of China's export after normalization is as follows:

1. The export product technology competitiveness indicator evaluation matrix $B_1 = (0.8000, 0.7700, 0.8450)$, representing the soft measurement values $B_{11} = 0.8000$,

$B_{12} = 0.7700$, and $B_{13} = 0.8450$ of the export technology complexity indicator, ratio indicator of intermediate input products, and export share indicator of high-tech products, respectively. Evidently, the indicator of the export share of high-tech products has the highest contribution to the technological competitiveness indicator of export products.

2. The export product brand competitiveness indicator evaluation matrix $B_2 = (0.7400, 0.7850, 0.7100, 0.7250)$, representing the soft measurement values $B_{21} = 0.7400$, $B_{22} = 0.7850$, $B_{23} = 0.7100$, and $B_{24} = 0.7250$ of the classified brand products export flow structure indicator, profitability indicator of brand products, market share indicators of brand products, and consumers' demand strength and evaluation indicator for the brand products of importing countries, respectively. Apparently, the profitability indicator of brand products has the highest contribution to the brand competitiveness indicator of export products.

3. The export products quality competitiveness indicator evaluation matrix $B_3 = (0.8000, 0.7250, 0.8150)$, representing the soft measurement values $B_{31} = 0.8000$, $B_{32} = 0.7250$, $B_{33} = 0.8150$ of the export price indicator excluding the influence of non-quality factors, ratio indicator of the added value of exports, and quality reputation indicator, respectively. Evidently, the ratio indicator of added value of export products contributes less to the quality competitiveness indicator of export products.

4. The export products service competitiveness indicator evaluation matrix $B_4 = (0.6650, 0.7850, 0.6650)$, representing the soft measurement values $B_{41} = 0.6650$, $B_{42} = 0.7850$, $B_{43} = 0.6650$ of the proportion indicator of export product service income in total export product sales, proportion indicator of manufactured products service income to the total income of similar product service worldwide, and service quality satisfaction indicator, respectively. Evidently, the proportion indicator of manufactured products service income to the total income of similar product service worldwide has a significant contribution to the service competitiveness indicator of export products.

The result set of the fuzzy comprehensive evaluation of the key parameter indicators of the new competitive advantages of China's export: $Y_i = B_i \cdot W_i^T = (0.8063, 0.7378, 0.7895, 0.6950)$, which implies that the soft measurement values of the technical, brand, quality, and product service competitiveness indicators are 0.8063, 0.7378, 0.7895, and 0.6950 respectively. It is evident that the technical and brand competitiveness indicators of export products have a significant contribution to the new competitive advantages of China's export, while the service competitiveness indicator of export products contributes the least to the new competitive advantages of China's export.

From the soft measurement value $Y_{c1} = Y_i \cdot W^T = 0.7580$ of the key indicator of the new competitive advantages of China's export, it is evident that the new competitive advantages of China's export in 2016 is discouraging, and further improvements of the technological and brand competitiveness of export products through high-tech, institutional, and management innovation are needed to ultimately enhance the new competitive advantages of China's export.

Table 6 Comparison of soft measurement values for key index parameters of new competitive advantages of China's export

Index parameters	Y_{c1}	Y_{c2}	η/%	Y_c
B_1	0.8063	0.8142	0.9798	0.8102
B_2	0.7378	0.7435	0.7726	0.7406
B_3	0.7895	0.7974	1.0006	0.7934
B_4	0.6950	0.7059	1.5683	0.7004

$\eta = 100 \times (Y_{c2} - Y_{c1})/Y_{c1}$
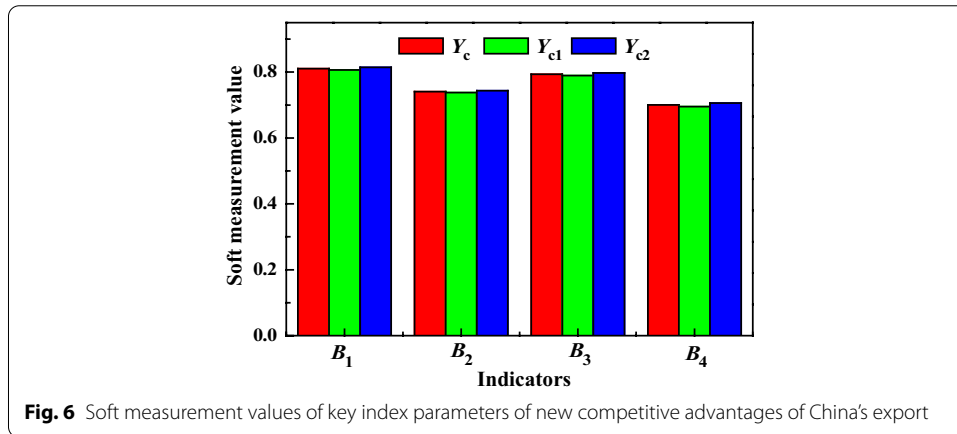
Fig. 6 Soft measurement values of key index parameters of new competitive advantages of China's export

Empirical analysis of the soft measurement model for the key index parameters of the new competitive advantages of China's export based on the fuzzy least squares support vector machine

The evaluation values of the key indicators of the new competitive advantages of China's export which satisfy the requirements given by 50 experts are incorporated into the soft measurement model based on the FLS-SVM for soft measurement. The comparison between the obtained soft measurement value Y_{c2} of the key index parameter of the new competitive advantages of China's export and that based on the fuzzy entropy weight analytic hierarchy process, Y_{c1}, is shown in Table 6.

According to Table 6, the maximum relative error between the soft measurement value Y_{c2} of the key index parameter of the new competitive advantages of China's export based on the FLS-SVM and that based on the fuzzy entropy weight analytic hierarchy process, Y_{c1}, is 1.5683, indicating that the two soft measurement models can truly reflect the intrinsic measurement mechanism of the key indicators of the new competitive advantages of China's export. Moreover, the combined soft measurement value of the key index parameter of the new competitive advantages of China's export $Y_c = (0.8102, 0.7406, 0.7934, 0.7004)$. Evidently, the combined soft measurement value Y_c is between the corresponding soft measurement values Y_{c2} based on the FLS-SVM and Y_{c1} based on the fuzzy entropy weight analytic hierarchy process (see Fig. 6), which can better eliminate subjectivity in the scoring of the key index parameters of the new competitive advantages of China's export.

The partial derivative a_i of the output of the FLS-SVM for input components is adopted as the criterion for the influence of index parameters on the soft measurement
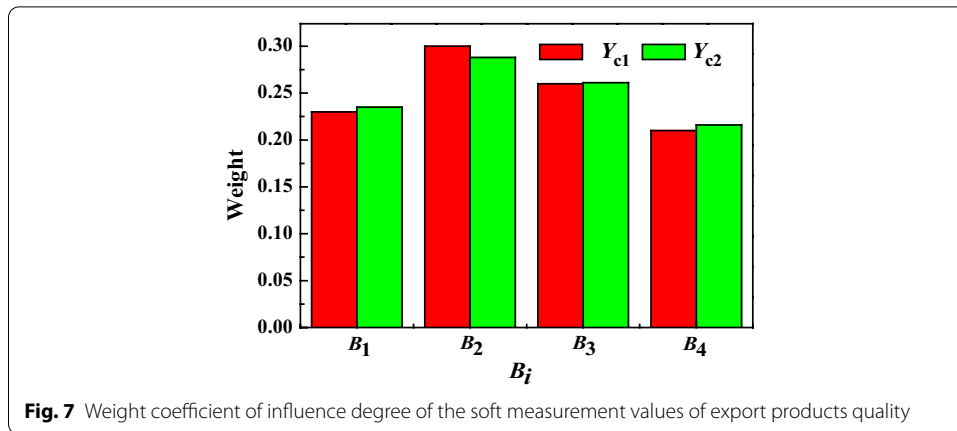
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Fig. 7 Weight coefficient of influence degree of the soft measurement values of export products quality

Table 7 Relative errors comparison with different soft measurement values

Soft measurement model	Average relative error (%)	Maximum relative error (%)
Zhang et al. (2019)	1.36	4.06
Leung et al. (2019)	1.15	3.45
In this paper	0.98	3.13

value of key index parameters of new competitive advantages of China's export. The larger the partial derivative, the more significant the effect of this factor on the key index parameters of the new competitive advantages of China's export. The comparative result of the degree of influence of each index parameter and the obtained weight coefficient W_i based on the fuzzy entropy weight analytic hierarchy process of the soft measurement value of the key index parameter of the new competitive advantages of China's export is shown in Fig. 7. Therefore, it is evident that the partial derivative a_i of the output of the FLS-SVM for input components maintains the same influencing trend with the obtained weight coefficient W_i of the soft measurement of the key index parameter of the new competitive advantages of China's export based on the fuzzy entropy weight analytic hierarchy process.

As shown in Fig. 7, $a2 > a_3 > a_1 > a_4$ and $W_2 > W_3 > W_1 > W_4$ simultaneously. It is evident that the soft measurement values of the brand, quality, technical, and service competitiveness indicators of export products consequently have a more significant impact on the soft measurement values of the new competitive advantages of China's export.

Comparison of results with other soft measurement models

Some soft measurement models in the research by Zhang et al. (2019) and Leung et al. (2019), as well as the soft measurement model presented in the present study are used to compare the relative errors from different soft measurement values, as expressed in Table 7.

As shown in Table 7, compared with other soft measurement models, the soft measurement model, whose parameters is optimized by the self-adaptive variable metric chaos immune algorithm in the present study, is highly precise. This can be mainly expressed as follows: after the self-adaptive variable metric chaos immune algorithm

is used to the optimize the parameters of the FLS-SVM, the complexity and overfitting phenomenon of the soft measurement model considerably diminish; therefore, its generalization ability is enhanced and relative errors are reduced accordingly.

Summary

In this work, a comprehensive evaluation index system for new export competitive advantages is initially developed. Thereafter, a combined soft-sensing model for the new export competitive advantages of China based on the fuzzy entropy weight analytic hierarchy process is established. The soft-sensing values of the key indexes are finally obtained. The major contributions can be expressed as follows:

1. The combined soft-sensing model of China's new export competitive advantage proposed in this work can overcome the limitation of the traditional export competitiveness evaluation index and method. It can serve as an effective measurement tool to evaluate and analyze new export competitive advantages, thereby efficiently solving the measurement problem of new export competitive advantages.
2. The measurement methods and results reported in this work can provide a reference basis for governments and policymakers at all levels, as well as decision makers in relevant departments. Consequently, they can appraise the current situation of the new export competitive advantages of the manufacturing industry and the gap between China's manufacturing industry and those of other countries. Furthermore, it may involve multiple decision makers and stakeholders, and the complexity of such a decision-making group will be high; thus, group decision-making models (Li et al. 2016, 2021) could be useful.

Conclusions

1. Owing to the fuzzy characteristics of the key index parameters of the new competitive advantages of China's export, a soft measurement model of the new advantages of export competition based on the FLS-SVM and fuzzy entropy weight analytic hierarchy process is established, respectively, and the combination of these two soft measurement models is constructed, which will provide a theoretical basis for the realization of the combined soft measurement of the key index parameters of the new competitive advantages of China's export.
2. The empirical analysis results of the combined soft measurement of the key index parameters of the new competitive advantages of China's export show that the technical and brand competitiveness indicators of export products have a more significant contribution to the new competitive advantages of China's export, while the service competitiveness indicator of export products has the least contribution to the new competitive advantages of China's export.
3. In future studies, more original sample data and more excellent expert evaluation values will be used to further enhance the accuracy and generalization ability of the combined soft measurement of the key indicators parameters of the new competitive advantages of China's export.

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Declarations

Competing interests
The authors declare that they have no competing interests.

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