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INTELLIGENT ANALYSIS OF IMPORT AND EXPORT IN GREEN TRADE BARRIER BASED ON BIG DATA ANALYSIS

Abstract: With the rapid development of economic globalisation, global economic and trade activities are escalating. However, environmental problems and the emergence of green economy, a response to these problems, has led to the widespread introduction of green trade barriers. These barriers implicitly limit the development of trade activities. This paper focuses on the export difficulties caused by green trade barriers and proposes a method to quantify discrete product characteristics, explore the internal characteristics of commodities and decide optimally on intended export regions. Firstly, the discrete feature of products is quantified by quantitative transformation method. Secondly, the quantitative data are used to derive the best decision for export regions through support vector regression (SVR) method. Particle swarm optimisation is used in optimising SVR parameters to achieve high-precision decision making. Comparison with historical data from the industry park shows the identification accuracy of the optimised SVR model to be better than that of the traditional regression model. This finding presents a novel perspective for developing import and export under the background of green trade barriers.

Keywords: green trade barrier, intelligent decision, big data analysis

Introduction

Given the evolution of economic globalisation and the liberalisation of global trade, the traditional methods of trade barrier protection have been changed accordingly. Countries around the globe have been actively adjusting and improving their trade strategies to boost exports, strengthen the protection of their domestic industries and leverage a range of innovative trade barriers to develop their own industries [1-4]. One of those protection regulations is the green trade barrier, otherwise referred to as the environmental trade barrier. This measure manifests as a strategic approach undertaken by countries involved in import and export practices. It aims to safeguard the health of humans, animals and plants by implementing legal constraints, setting environmental technical standards and using methods such as inspection and quarantine. These measures are designed to restrict and penalise the import of goods or services that do not adhere to the stated regulations, thereby creating a healthy, sustainable trade environment.

Green trade barriers have become a critical concern in response to escalating global awareness of environmental issues. As the urgency around climate change mitigation,

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biodiversity conservation, resource efficiency enhancement and pollution combatting mounts, nations are implementing measures that promote sustainable practices through trade. These barriers are crafted to discourage the trade of goods associated with environmentally harmful processes or resource-intensive production methods while incentivising the adoption of eco-friendly technologies and practices. By integrating environmental considerations into their trade policies, countries aim to foster a transition towards a green economy. This approach helps mitigate the adverse effects of industrialisation, thereby promoting a sustainable and resilient global economic system. Green trade barriers not only require imported goods to meet certain standards but also necessitates that environmental protection should be applied to all aspects of product design, manufacturing, packaging and consumption. Green trade barriers have formed a noticeable effect on China's international trade activities [5-8]. Most countries, especially those in developed regions, protect their domestic products and restrict the entry of foreign products by employing stringent environmental protection standards or imposing relevant environmental sanctions. Therefore, how to face green trade barriers and accurately identify their environmental protection components is the key to deal with such barriers. Companies with low added value products, such as clothing, agriculture and food industries, are particularly affected by green trade barriers. However, such small companies often lack the capacity to manage legal and financial risks effectively, making the need for smart solutions to overcome product restrictions in green trade barriers a pressing issue [9-13]. Green trade barriers incorporate measures such as stringent product standards, eco-labelling, carbon border adjustment mechanisms and renewable energy subsidies, which all pose significant challenges to international trade. These constraints can amplify exporters' compliance costs, impose burdensome certification procedures and distort fair competition. Specifically, small and medium-sized enterprises encounter difficulties in satisfying diverse and often complex environmental requirements across different markets. Addressing these barriers is imperative to facilitate global trade, as it enhances market access, ensures fair competition, promotes innovation and technology transfer and prevents trade disputes.

Traditional agricultural products and small commodities often face challenges in directly identifying the corresponding chemical components that are present during the manufacturing process or within the materials themselves. However, determine these components is essential as they frequently play a crucial role in permitting the export of such commodities. To overcome existing green trade barriers, relevant product characteristics must be used to assess their export restrictions in specific regions. Environmental protection policies and green trade barrier-related features in import and export products are usually discrete variables, which require quantitative data transformation through quantitative methods. Through this process, export region characteristics can then be identified, and intelligent decision making can be implemented using artificial intelligence and machine learning technologies [14-16]. The optimal decision of export destination can be abstracted as a multiobjective regression problem through multidimension characteristics of products. Such problems can be solved through statistical learning methods. These methods are used to study the theory of statistical laws when the sample data volume is limited, which is applicable to the regression prediction learning of small samples [17-20]. For commodities produced by companies in the industrial park, this method can achieve the optimal matching of export destination. Common statistical learning regression methods include linear regression, logistic

regression and polynomial regression, which are generally applied to predict linear data. These methods rely on least squares and convex optimisation to calculate the regression decision and predict relevant data. Although they have a good mathematical foundation and are easily interpretable, they may not be suitable for addressing the regional matching problem of green trade exports using discrete variables. In recent years, neural network methods and their corresponding improvements [21-24] have been used for regression, especially with the advancement of computer computing capabilities. By employing supervised learning, neural networks can adjust the neuron weights according to input and output data to achieve the minimum loss function and derive the optimal model simultaneously. Despite achieving high-precision recognition and regression, neural networks lack interpretability, and their training times can be excessively long due to extensive parameters being set. As a result, their applicability is greatly reduced. In view of the characteristics of products in green trade, this paper proposes using the support vector regression (SVR) method to determine the ideal export destination. SVR has a substantial advantage in handling nonlinear and small sample problems. This method maps nonlinear samples in a low-dimensional space to a high-dimensional space, constructing linear functions that describe the regular pattern of data. Consequently, SVR can overcome dimension disaster problem effectively and avoid falling into local extremum. It has certain advantages in multi objective optimal decision making of discrete characteristic variables.

In view of the difficulties in export caused by green trade barriers and insufficient information flow from some small-scale manufacturers, products must be analysed in detail. Examining the internal attribute characteristics of products prior to export and comparing these to the corresponding export standards can help prevent the incidents where products become unsellable due to green trade barriers. Therefore, according to the characteristics of the commodities' own attributes, utilising intelligent decision making for selecting export regions is essential for overcoming green trade barriers.

In this paper, we initially quantify the product attributes based on the specific characteristics of the products found in the industrial park. Then, these attributes are used as input to the SVR model for intelligent decision making concerning the product export region. To further enhance model accuracy and efficiency, particle swarm optimisation (PSO) is used during the model development process to optimise model parameters. Following these steps allows us to make optimal green trade decisions based on the SVR method.

Method

To realise the final decision of export regions in the process of green trade, this paper establishes a model based on historical data, namely, the supervised learning method. Firstly, the discrete variables in the attributes are quantised by qualitative sorting and quantitative transformation methods. Then, regional intelligent decision making based on SVR is realised by using quantitative features. Finally, the model is optimised by PSO. The detailed steps of the algorithm are as follows.

Data preprocessing and quantisation

Green trade data usually involve qualitative indicators. To quantify these qualitative indicators, this paper uses the methods of qualitative sorting and quantitative transformation to convert qualitative data into quantitative data. This method is applicable to variables with

ordered discrete variables. The data used in this paper completely conform to this standard, and the scale is calculated as follows:

$$S_i = \frac{\ln(m-i)}{\ln(m+i)} \tag{1}$$

where S_i is the scale score of category i, and m is calculated as

$$m = (MAX) + 2 \tag{2}$$

MAX represents the largest classification number. According to the qualitative sorting and quantitative transformation method, variables with different classification numbers can be listed into a quantitative transformation table, and scale standards can be formed according to the classification numbers. Therefore, the qualitative data in the process of green trade export can be quantified according to the methods described above.

SVR-based export region decision

The ultimate goal of green trade is to export or import to the destination, which belongs to the final decision-making model [25-27]. The basis of classification and regression is to find the best hyperplane. For the regression prediction problem, there exist training samples, $T = \{(X_i, Y_i), \cdots, (X_n, Y_n)\}$, $i \in n$. By searching for the optimal hyperplane, the distance between Y and the hyperplane in the sample data is as small as possible to obtain the regression plan. SVR creates a space on both sides of the linear function with the distance ε, which is also called zero-tolerance deviation. No loss is calculated for all samples falling into the interval band. Finally, the optimal model can be acquired by minimising the total loss and maximising the interval. In comparison with the traditional well-known SVM method, SVM aims to maximise the distance of the closest sample to the hyperplane, whereas SVR aims to minimise it, hoping to include as many samples as possible.

SVR optimised by PSO

In the decision-making process using the SVR method, its related parameters (mainly penalty parameters) need to be constantly adjusted to obtain better prediction accuracy. In this paper, PSO is used to find the optimal parameters, which can effectively avoid the occurrence of underfitting and overfitting, and finally obtain the ideal prediction results. Particle performance can be evaluated by adaptation [27-29].

The features selected in this paper are processed by Gaussian kernel function. The choice of parameters significantly influences the result, so the scope and penalty function of the Gaussian kernel function in the SVR method also requires optimisation. We use the PSO method for this purpose. After the initial numerical value is established, the PSO calculates the fitness, and the particle position is updated. If the max iteration is reached, the optimisation will end; otherwise, the position and velocity of particles will be updated and the prediction results of the SVR are recalculated.

After thorough parameter optimisation, the SVR model exhibits noteworthy enhancements across various aspects. The optimised model demonstrates increased accuracy and precision in predicting the target variable, facilitated by a fine-tuned sensitivity to underlying patterns in the data. Improved generalisation capabilities enable the model to perform effectively on diverse datasets, mitigating overfitting and ensuring

reliable performance on unseen data. Moreover, the model's resilience to noise and outliers is reinforced, thereby enhancing its robustness. Fast convergence speeds during training reduce computational resources and training time. The optimal kernel function selection and fine-tuned regularisation parameters contribute to the model's ability to capture complex relationships and strike a balance between underfitting and overfitting. The optimised SVR model displays increased predictive power, scalability and effectiveness in handling nonlinear relationships, making it a potent tool for regression tasks.

Experiment and results analysis

Data preprocessing

This study gathers and analyses historical data related to green trade products exported by numerous companies within a local industrial park. The export regions are categorised using text analysis techniques, with expert classification of the data. Given the vast quantity of exporting countries, these are systematically grouped into four region-based labels based on geographical location and regional characteristics: Europe, America, Asia and Africa. A statistical analysis of the gathered samples reveals the number of products originating from various regions in the company's export zones: Europe (65), America (80), Asia (42) and Africa (89). The primary export destinations for green products from the park are Africa and the Americas. The reason can be attributed to the fact that trade in these regions is more mature compared with the EU and developed Asian countries. Moreover, the existence of mainly underdeveloped areas in these regions indicates a wider range of products available for export.

The highest number of dimensions in the features set is 15. For products with feature sets of less than 15 dimensions, supplementary features are added. Conversely, for products with 15 feature sets exceeding dimensions, the excess features are removed based on their data forms. In this paper, three features are randomly selected for observation.

Recognition results

The specific recognition rates of different export regions under different feature dimensions are shown in Figure 1. The analysis reveals that the optimal feature dimension varies for each region: Europe and Africa exhibit peak recognition rates with 10-dimensional features, whereas a 7-dimensional feature set works best for America and Asia. Given the balance between the model's computational speed and recognition accuracy, we have decided to employ a 7-dimensional feature set.

Differences in national standards and green export product projects lead to Africa having the most export data and the highest identification rate of related products. This finding is attributed to the lower product standards in the related regions; although a vast array of green products exported, they possess highly differentiated characteristics. In addition, the overall product requirements are lower, leading to a higher differentiation compared with other regions.

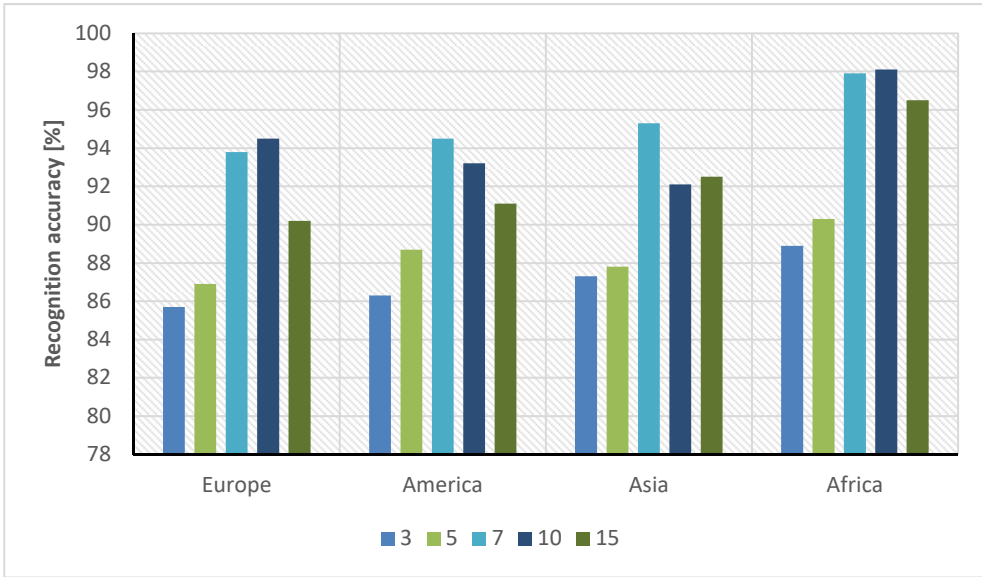


Fig. 1. Accuracy with different numbers of feature

Comparison of different methods

To verify the recognition accuracy of the methods proposed in this paper, we compare the proposed methods with some traditional classification decision methods. The recognition accuracy of each method is shown in Table 1.

Table 1

Comparison result amongst different methods

Model	Linear regression	Neural network	Tree regression	SVR	PSO optimised SVR
Accuracy [%]	91.2	93.5	89.2	93.2	95.4

Amongst the models evaluated, the accuracy results showcase distinct performances. Linear regression yields a respectable accuracy of 91.2 %, whereas neural network surpasses it with 93.5 %. The tree regression model lags slightly behind with an accuracy of 89.2 %. The SVR model achieves a commendable accuracy of 93.2%, highlighting its efficacy. The performance is further elevated when applying PSO to SVR, resulting in an impressive accuracy of 95.4 %. This result demonstrates the value of optimisation techniques in enhancing predictive models, as the PSO-optimised SVR outperforms all other models in terms of accuracy in this evaluation.

The evaluation reveals that the PSO-optimised SVR model attains the highest recognition rate compared with traditional tree regression, linear regression and other foundational methods. Notably, even the SVR method without PSO optimisation exhibits excellent recognition rates, surpassing many basic methods. This result suggests the inherent strength of the SVR approach. Furthermore, the performance of the single SVR

model is commendable on its own, and with the incorporation of PSO optimisation, it experiences a notable enhancement, underlining the efficacy of this optimisation technique in refining the model's predictive capabilities.

Discussion

Enterprises within the industrial park typically engage in export trade via intermediary companies, which leverage their experience to facilitate the matching of products with the target export regions. However, in the context of current green trade barriers, small intermediaries often struggle with discernment, posing risks for the advancement of small to medium-sized enterprises [25]. According to the characteristics of different export regions, we search the historical data in recent years to extract the features of the key components of interest and compare the optimal decision recognition effects under different dimension features. The comparison of the algorithms shows that in comparison with traditional methods such as linear and tree regression, the recognition rate of the proposed method is also higher when parameters are not optimised, and the recognition rate will be further improved after the PSO parameter optimisation. In addition to using the PSO method, genetic algorithms [29], ant colony [30] and other methods can be used to gradually optimise the parameters in future research. The principle is similar to that of using the maximum Bayesian probability to achieve the optimal estimation of parameters, which further improves the overall algorithm accuracy.

China is currently experiencing mid- to high-speed economic development, with green trade serving as an integral component of its economy. To address the issues posed by green trade barriers, intelligent methods must be complemented with a robust policy framework [31-33]. Firstly, environmental protection legislation must be advanced. The government should establish and improve the legal norms for environmental protection, upgrade green standards scientifically, strengthen the regulation of corporate behaviours, improve public environmental awareness and ensure the implementation of environmental protection [34]. Secondly, technological innovation is key. Products need to be manufactured and marketed in line with green environmental standards to penetrate international markets. Support for green technology should also be increased within enterprises, providing an accommodating environment for the development of green technology enterprises [35-37]. Formulating a green agenda, attracting advanced technical expertise, and intensifying research into clean production technologies can lead to systematic green enhancements and innovations. This, in turn, can consistently raise enterprises' level of pollution control and amplify the practical value of green technologies [38-40]. Finally, enhancing the early warning mechanism is also critical. Assisting enterprises in monitoring international trade barriers, strengthening the gathering of relevant data and performing comprehensive evaluations and analyses of this information can guide companies in making informed production and operation decisions. A dedicated database platform for green trade barriers should be established, with specialised personnel assigned to collect, sort and analyse information about international market green trade barriers. This approach is essential in overcoming green trade barriers, ensuring the sustained growth and success of the foreign trade economy.

In the current global context of increasing environmental awareness, some countries have implemented green trade barriers to promote sustainable development. Taking the example of an electronics manufacturing company, it is directly affected by the

implementation of green trade barriers in a certain country, which requires imported electronic products to comply with a series of environmental standards, including the use of renewable energy and reduction of electronic waste. This condition poses significant challenges for the company, necessitating efforts in supply chain adjustments, technological upgrades and cost increases to meet the new environmental requirements, lest it faces import restrictions and high tariffs.

Amongst the methods to mitigate these challenges, the intelligent optimisation algorithm PSO-SVR shows potential applications. The PSO-SVR can be applied to optimise a company's supply chain, assisting in the selection of environmentally friendly materials and components to meet the requirements of green trade barriers. By considering multiple variables such as material sources, production processes and transportation methods, the PSO-SVR seeks the optimal solution to minimise environmental effects. Furthermore, the PSO-SVR can be used to optimise energy usage, support the transition to renewable energy, conduct cost-benefit analyses and identify the most economical solutions under environmental standards. The algorithm also plays a role in planning technological upgrades, aiding companies in selecting appropriate environmental technologies and equipment to enhance production efficiency. Through the comprehensive application of the PSO-SVR method, companies can effectively adapt to green trade barriers, improve environmental standards and minimise the adverse effects on costs and production efficiency. This intelligent optimisation method provides scientifically sound decision support for companies facing complex environmental requirements, potentially facilitating their improved integration into the green trends of international trade.

Acknowledging the proposed method's limitations is crucial for a comprehensive understanding of its applicability. Firstly, the PSO-SVR's performance is dependent on the quality and representativeness of the input data. In scenarios where data are scarce or unrepresentative of the actual operational complexities, the algorithm may provide suboptimal solutions. Moreover, the algorithm's efficiency may be affected by the dimensionality of the optimisation problem, potentially leading to increased computational demands for large-scale applications. Another limitation lies in the assumption that the environmental standards and regulations remain static over time. If these standards evolve or new regulations are introduced, then the model may require frequent updates to maintain relevance and accuracy. Moreover, the method assumes a linear relationship between environmental factors and business operations, potentially overlooking nonlinear dependencies that can affect the effectiveness of the proposed optimisation approach.

Conclusion

Focused on addressing green trade barriers in the development of the green economy, this paper proposes an intelligent method of optimal decision making for export destinations, grounded in commodity characteristics. The process involves leveraging the inherent attributes of a commodity, combined with the relevant laws and regulations of different regions. The indicators are quantified using a quantitative transformation method, shaping the feature vector from these quantised indicators and employing SVR for optimal export region decision making. The PSO is used to optimise the model parameters for improved recognition accuracy. The results show that the optimised model has a high recognition rate. This paper, originating from the commodity viewpoint, digs deep into the intrinsic attribute characteristics of commodities before export. This approach proves

effective in mitigating instances where products are unsellable due to green trade barriers, thereby providing technical support for the green trade initiatives of small to medium-sized enterprises. Future research will refine the various chemical components of products and refine the green information in the process of product export from a molecular and reaction standpoint, enhancing their competitiveness in green trade and promoting further economic development.

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