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REVIEW

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Fuzzy Logic and Neural Network-based Risk Assessment Model for Import and Export Enterprises: A Review

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Abstract: With the rapid growth in foreign trade business and the continuous expansion of customs functions, the amount of data obtained by customs monitoring systems has drastically increased, and risk management techniques have been widely used in the customs field. Risk assessment, as an important part of risk management, can help departments of customs to understand the possibility and impact of risks in advance. Assessing the risks of import and export enterprises is an important task for customs. However, the assessment is challenging because of the large-scale of data, rapidly changing information, and inherent fuzziness. To address this issue, this survey summarizes the existing risk assessment methods, combines the preliminaries of fuzzy logic and neural networks, and applies the representative risk assessment models in the risk assessment of import and export enterprises. The risk assessment models based on fuzzy logic and neural networks can handle vague and uncertain data and improve the efficiency of risk assessment through adaptive and learning capabilities. The combination of theoretical and simple case suggests that the risk assessment method based on fuzzy logic and neural networks has good feasibility for import and export enterprises and provides valuable references for developing effective risk assessment models of import and export enterprises in the future.

Keywords: customs risk assessment, fuzzy logic, neural network, risk management

1. Introduction

Customs is the national supervision and management agency for import and export which can guarantee the security of international trades. Generally speaking, customs duties are an important source of national fiscal revenue, which can help the government conduct macroeconomic regulation. In recent years, customs has faced various threats, the main threats are illegal trading and tax evasion, which will not only reduce government revenue but also endanger social security. Customs needs to use effective methods to detect financial fraud and other risk objects brought by economic integration, but it is also important to avoid transaction delays and reduce the negative impact of overseas sales (Khojasteh Aliabadi et al., 2022). Due to the rapid development of international trades, the competition in the global market has become increasingly fierce. The uncertainty of the external and internal environment has also led to the increase of the number and level of customs risks (Borysenko et al., 2022).

Because potential risks and threats do exist, appropriate risk management is necessary. A preliminary assessment of the background of risk occurrence can help departments of customs to make actions before risk occurs or in emergency situations. It is essential to understand the consequences after risk occurs and what should be done to avoid or eliminate new threats (Meisel Lanner, 2020). Due to the variety of import and export goods and the lack on customs personnel, introducing risk management can improve supervision efficiency and avoid wasting resources.

A potential strategy for achieving both trade facilitation and revenue maximization is customs risk management. Customs risk assessment is an important component of customs risk management and the basis for customs risk disposal (Al-Shbail, 2020). Customs risk assessment refers to the process in which customs collects and analyzes risk-related information and uses risk assessment methods to determine the level of risks. Customs decision-making departments can take the corresponding risk management strategies according to the results of risk assessment.

With the continuous expansion of international trade, import and export enterprises play an increasingly important role in customs field. However, enterprises have faced with more diverse and complex risks. Risk assessment techniques can classify import and export enterprises by risk level, focus on checking enterprises with potential risks, and simplify the review process for enterprises with lower risks. It is useful to maximize resource utilization and reduce waste.

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Traditional risk control models have a single dimension and limited assessment capabilities. The import and export enterprises involve multiple factors, and traditional risk assessment models may have limitations in handling interrelationships and comprehensive effects among these factors and lead to biased assessment results. Additionally, traditional models are often static and lack adaptive learning capabilities to adjust new data and feedback, resulting in lagging assessment results. In the risk assessment process, some important parameters directly related to the characteristics of enterprise risk may be subjective. In this situation, the proposed assessment models may be ambiguous. In particular, fuzzy logic can handle uncertain and ambiguous information and enhance the evaluation accuracy. The integration of fuzzy theory and neural networks in risk assessment can handle nonlinearity and uncertain problems according to the good adaptability and learning capability of neural networks. In addition, the model parameters can be adaptively adjusted with different assessment requirements and data characteristics, for the purpose of optimizing the model performance (Gevrey et al., 2003).

This paper employs literature review to systematically understand the current status and development trends of risk assessment methods and combines theoretical analysis and simple case to verify the feasibility of using fuzzy logic and neural networks for import and export enterprise risk assessment.

The rest of the paper is organized as follows. Section 2 introduces the methodologies, including literature review, theoretical analysis, and empirical research. Section 3 summarizes the relevant literatures, including the risk management, risk assessment methods, neural networks, fuzzy logic methods, classical data mining-based customs risk assessment methods, and typical risk assessment models based on fuzzy logic and neural networks. Section 4 shows the risk assessment model based on fuzzy logic, and neural networks apply it to the risk assessment of import and export enterprises. Section 5 summarizes this paper and provides the future work on risk assessment technologies for import and export enterprises.

2. Methodology

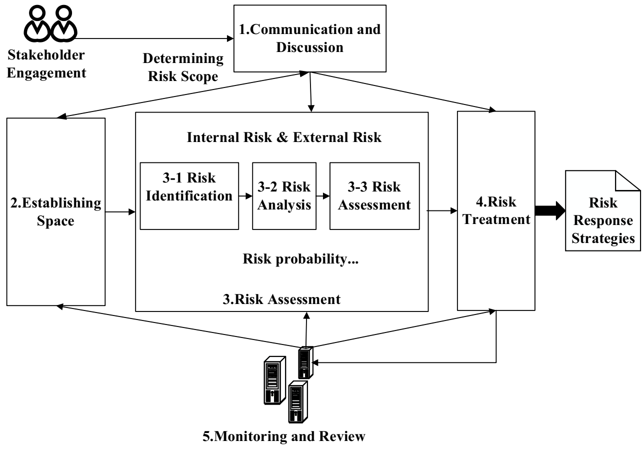
One method used in this study is literature review, which involves summarizing and categorizing a large amount of literature in the field of risk assessment to identify the research themes. This provides a research foundation for exploring this field. The second method used in this study is theoretical analysis, which suggests that fuzzy theory can handle uncertain and vague problems, while neural networks can learn and adapt to complex nonlinear relationships. Through theoretical analysis, it can be argued that the risk assessment method based on fuzzy theory and neural networks has good scientific validity and reliability. On the basis of theory, this paper combines fuzzy rules and neural network theory and selects the typical model ANFIS based on fuzzy rules and neural networks. This model is applied to the risk assessment of import and export enterprises to provide reference for the feasibility of the study.

3. Literature Review

3.1. Risk management

Risk management is a method by identifying, assessing, and disposing potential uncertainties and potential losses. It aims to protect various organizations or individuals to reduce the potential losses (Aven, 2016). Risk management is applied in various fields, for example, finance, public safety, and environment. Organizations or individuals achieve the goal of reducing losses by predicting possible risks and taking preventive measures (Kara et al., 2020) Risk management can support strategic and business planning, provide more effective and efficient resource deployment, and facilitate continuous monitoring and evaluation of risk, promote continuous improvement, and enable efficient and effective response and recovery in the event of risks (Basir et al., 2019).

Figure 1
Risk management process in ISO 31000

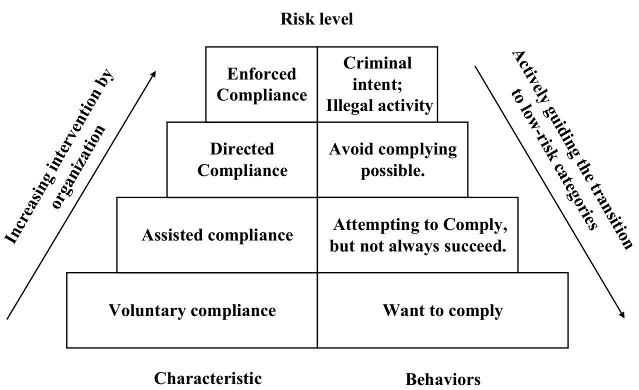


According to the latest ISO 31000 risk management standard proposed by the International Organization for Standardization (ISO), risk management mainly involves establishing space (i.e., identifying the background and the scope of risks), risk assessment (i.e., identifying, analyzing, and evaluating risks), and risk treatment. Adequate communication and coordination should be conducted throughout the entire process, and information exchange should be carried out. In addition, monitoring and controlling should be performed, including routine checks or supervision. The specific process is shown in Figure 1.

3.2. Risk assessment

Risk assessment can eliminate or reduce the consequences of any potential risk by determining the possibility of potential events, the consequences they may bring in, and the degree of tolerance for those consequences (Zio, 2018). ISO 1998 defines risk assessment as a method that can quantify and qualify the risks and evaluates the potential consequences of potential risks on the environment, region, and personnel. In the context of risk management, evaluating risks is very important (Žigienė et al., 2019). The final step in risk assessment is to assign risk levels, which can help organizations identify significant risks and optimize resource allocation. In accordance with ISO 31000, risk levels are presented in Figure 2. The effectiveness of risk management depends on the outcome of risk assessment. The more accurate the results of the risk assessment, the higher reliability of the risk management process (Khojasteh Aliabadi et al., 2022). Customs need to inspect a large number of enterprises and goods every day. By using risk assessment techniques, they can focus on inspecting enterprises with potential risks and simplify the inspection process for enterprises with lower risks. Risk assessment can maximize the utilization of resources and reduce waste of resources.

Figure 2
Risk levels in ISO 31000



3.2.1. Classical methods

The current mainstream methods of risk assessment are primarily quantitative and qualitative. During the phase of decision-making, a quantitative approach is used to quantify risks and safety issues, while qualitative methods supplement with statements that explain the importance and applicability of controlling and safety measures, so as to minimize the losses caused by risks (Evrin, 2021). Quantitative risk assessment methods are used when accurate values are needed for risk assessment, and qualitative risk assessment methods are used when data values are small or risks are difficult to quantify.

(1) Quantitative method. Quantitative risk assessment methods mainly use mathematical models or statistical methods to quantitatively analyze risks and obtain specific risk values. The obtained risk values are then compared and sorted (Gul & Ak, 2018), providing a more objective reference for the formulation of risk control measures. However, the use of quantitative methods requires high data quality, not only requiring a large amount of data to support but also ensuring the correctness and reliability of the data.
(2) Qualitative method. Qualitative risk assessment is almost applicable to all business risks. By evaluating risks through expert judgment, initial conclusions can be quickly drawn. However, because judgments are subjective, when different experts make judgments, there may be significant differences in the results. This leads to less precise results and makes it difficult to compare and rank the risks.

These two methods are suitable for different scenarios, and the comparison between them is shown Table 1.

Table 1
Comparison of quantitative and qualitative methods

Name	Objective	Advantage	Disadvantage	Method
Quantitative method (Abdel-Basset et al., 2019; Hung & Ma 2009; Cellura et al., 2011; Van Duijne et al., 2008)	To assign objective or measurable values.	1. Objective and accurate; 2. It is not easy to cause disagreement.	1. Not enough data to analyze; 2. Evaluation is difficult when there are too many values or related variables; 3. It is difficult to determine the accuracy of the collected data.	Probability analysis: relies on statistical and mathematical methods to estimate the probability and consequences of risk events. Monte Carlo simulations: generate random samples as input to simulations in order to determine the probability and simulations of each kind of risk. Sensitivity analysis: techniques to assess the sensitivity of the output of a model or system to be changed in input parameters. Fault tree analysis (FTA): build a graphical model to analyze the causes and consequences of events and identify key events that need to be resolved. Cost-benefit analysis (CBA): evaluate the costs and benefits of different options to help decision-makers prioritize the risks of options based on economic feasibility and potential impact.
Qualitative method (Han & Weng, 2011; Hagenlocher et al., 2019; Sanni-Anibire et al., 2020; Zalk et al., 2009)	Identify risks that require detailed analysis.	1. Flexible and adaptable to various risk assessments; 2. Easy to understand and implement.	1. Subjective and dependent on experienced technicians; 2. It is difficult to compare risks.	Expert judgment method: it is a qualitative method based on expert experiences and knowledge. It is often used in cases where data are small and cannot be quantified. Event tree analysis: it is a tree structure for users to identify the causes and consequences of adverse events. Failure Mode and Impact Analysis (FMEA): it is used to assess the possibility and impact of failure modes in a system and investigate the impact of this failure mode on the system. Deviation analysis method: it is a method used to compare the differences between actual and expected results and identified the reasons for these differences.

Table 2
Classical data mining-based customs risk assessment methods

Purpose of research	Author	Data set	Arithmetic	Contribution	Limitation
Assisting customs to inspect goods of CBEC	Song et al. (2019)	The 121,506 samples of goods and 333 foods from China Customs food department	Fuzzy rules; Text mining	A CBEC commodity risk assessment framework that combines text mining with fuzzy rule reasoning	The source of risks is not fully considered
Improving the accuracy of customs declaration classification	Zhou (2019)	The 30,000 historical customs declaration records from China Customs	Decision tree; Boosting; C5.0 Algorithm	Taking a cost-sensitive approach with cost matrix in risk detection	Text information extraction is not feasible
Promoting the development of a digital customs system	Kim & Kim (2020)	The case of Korean Customs Service (KCS)	Information and Communications Technology (ICT)	Integrating ICT into the customs risk process	It is only applicable to the KCS at present
Classifying of CBEC goods	Li & Li (2019)	The 10,000 records from Chinese global trade website in September 2018 and six similar HS (Harmonized System) codes about shoes	Convolutional Neural Network (CNN)	Fusion model can recognize text and image information	The limited training scope of the HS codes at one time
Improving the efficiency of customs port inspection	Han et al. (2023)	The 100,000 samples of inspected customs declarations from a customs information center	Can-Tree; Association rules	The Can-Tree algorithm uses a dynamic weighted counting method to sort data items	The result in credibility of customs declaration inspection is not high
Enhancing customs fraud detection capabilities	Vanhoeyveld et al. (2020)	The 9,624,124 records of Belgian Customs administration	EasyEnsemble(EE); SVM	EE is introduced on the basis of linear support vector machine	More advanced feature selection or dimensionality reduction methodologies can be selected
Controlling customs crimes	Zehero et al. (2018)	The 6854 customs offense records from Côte d'Ivoire between 2016 and 2018	Unsupervised Method; Principle of Apriori	To apply the Apriori principle on the basis of frequent grounds	Assessment is applicable only to customs offenses
Classifying risk levels to improve customs clearance efficiency	You (2022)	The index data of Guangzhou port logistics industrial cluster	Back-propagation Neural Network (BPNN)	The additional momentum method and learning rate adaptive method are introduced into BPNN algorithm to improve the convergence speed of the model	Lack of quantitative model

Qualitative and quantitative methods have their own advantages in risk assessment and can provide different types and degrees of information. Different situations require choosing appropriately methods and comprehensively considering the risks in order to make reasonable and feasible decisions.

3.2.2. Risk assessment methods in customs

Risk assessment methods have received extensive attention in the customs field. Data mining-based customs risk assessment methods can analyze large-scale data and help customs to predict and avoid risks. Due to the lack of research work on risk assessment for import and export enterprises, this paper summarizes representative data mining-based customs risk assessment methods in recent years, providing a reference to establish risk assessment models of import and export enterprises. Table 2 shows these methods and summarizes their contributions and limitations.

There are relatively few studies about the research of data mining-based customs risk assessment methods, and most of the literature focuses on solving risk classification problems. Customs data have characteristics such as high dimensionality and imbalance (Zhou, 2019). However, there is significant lack on customs risk classification, because the low quality of customs data and inadequate consideration of factors that could affect the risk. In addition, false or incorrect declarations will lead to imbalanced datasets. Because the proportion of the true data will greatly exceeds the false data, classifiers may overlook the small portions of data during the phase of training, which will decrease of the credibility for data prediction.

3.3. Neural network based methods

Artificial neural networks are inspired by the structure and operation of the human nervous system and can simulate human brain to process information. Neurons are the basic elements of artificial neural networks. A neuron typically has multiple dendrites, which are mainly used to receive information, and only one axon. The axon transmits the signals received by the neuron to the axon terminals, which pass the information to the next set of neurons (Sánchez-Silva & García, 2001). One of the distinguishing features of neurons from other living cells is their ability to communicate with each other. The functions of an artificial neuron include receiving input information from neighboring cells, transforming information through a transfer function, and disseminating the updated information to all other cells. The connection strength between neurons can be adjusted through training and realizing the learning and prediction capabilities of the model (Dongare et al., 2012). The structure of an artificial neural network is shown in Figure 3.

An artificial neuron can be described by the following equation, combining Figure 3 and mathematical knowledge.

In the formula, $x_1, x_2, x_3, \ldots, x_n$ are the input signals;

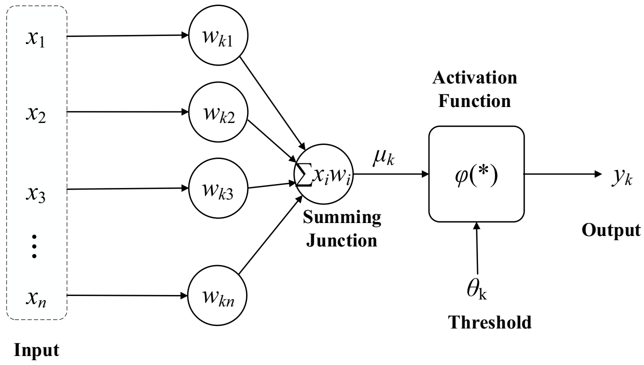
$w_{k1}, w_{k2}, w_{k3}, \ldots, w_{kn}$ are the synaptic weights of a neuron k; μ_k is the sum function; $\phi(*)$ is the activation function; and y_k is the output signal of the neuron.

$$\mu_k = \sum_{j=1}^{n} w_{kj} \times x_j \tag{1}$$

$$y_k = \varphi(\mu_k - \theta_k) \tag{2}$$

Risk assessment methods have been greatly improved, and neural network methods have been widely used in risk assessment. Due to the multiple factors and their complex relationships in the risk

Figure 3
Structure of an artificial neural network



assessment of import and export enterprises, neural networks are capable of automatically learning and extracting nonlinear relationships between input data through extensive training on large amounts of data. As a result, these complex relationships can be recognized, and the model parameters can be continuously adjusted the adaptive capabilities of neural network until an optimal solution is obtained.

(1) Feedforward neural network (FNN): it is composed of multiple layers of neurons, and each layer fully connects to the next layer. The training process typically utilizes backpropagation (BP) algorithm (Yu et al., 2002). FNN iteratively reduces the error associated with its output by adjusting the connection weights in training sample and gradually approaches the expected output value (de Sousa, 2016). FNN can be used in handling classification and regression problems in risk assessment (Angelini et al., 2008; Chen et al., 2000).
(2) Recurrent neural network (RNN): this model incorporates explicit time and memory elements (Schäfer & Zimmermann, 2007). This network has a structure similar to a multilayer perceptron, but it allows connections between hidden units that are related to time delays. In other words, it includes time-delayed feedback connections between hidden units in addition to the feedforward connections found in a typical multilayer perceptron. Through these connections, the model can retain past information and discover time-correlated events from data (Pascanu et al., 2013). RNN can be used for prediction problems in risk assessment (Loy-Benitez et al., 2019; Zhang et al., 2022).
(3) Convolutional neural network (CNN): it is a type of neural network for image recognition and processing (Albawi et al., 2018). CNN combines the biological visual sense organ and can identify various types of objects, including digits, images, and specific actions in any object (Ajit et al., 2020). CNN is widely used in the medical field for feature extraction and recognition in medical images (Usama et al., 2018; Ahn et al., 2021).
(4) Generative adversarial network (GAN): it consists of two neural networks, that is, a generator and a discriminator. The generator aims to learn the distribution of real data, and the discriminator is designed to distinguish real data and generated data. By continually confronting these two networks, GAN can generate new data that is similar to real data (Wang et al., 2017). GAN can be used to generate simulated data to assist in the training of risk assessment models (Dong et al., 2021; Laino et al., 2022).

Different types of neural networks can handle different problems in risk assessment, and appropriate model selection is essential for solving a specific problem.

3.4. Fuzzy logic-based methods

Fuzzy logic (Zadeh, 1965) is a useful technique for dealing with complexity and uncertainty, providing a way to model the systems by simulating human thinking without relying on quantitative and qualitative data in computation (Pislaru et al., 2019). Assessing import and export businesses by using sustainable decision-making process is challenging because the imprecise and multifaceted nature of the parameters are involved. It is difficult to describe the risks by traditional mathematics, because of inadequate understanding and high levels of uncertainty about domain issues (Phillis et al., 2010). Fuzzy logic-based methods enable simple risk assessment, ranking, and prioritization based on the knowledge, experience, and opinions of expert (Meng Tay & Peng Lim, 2006). The key of fuzzy logic is to find appropriate fuzzy rules (Ouenes, 2000). For example, fuzzy IF-THEN rules are IF-THEN statements. Membership functions are used to describe certain linguistic labels in a problem, and the number of rules required varies depending on the specific nature of the problem (Yazdani-Chamzini, 2014).

The fuzziness in the risk assessment of import and export enterprises involves the complexity of the factors or information, the cross-interaction and influence between different factors, and the subjectivity of some factors, making it difficult to quantify and describe accurately. Fuzzy logic does not rely on precise mathematical models, but describes and processes problems by fuzziness, providing a more flexible evaluation method.

Fuzzy logic can handle fuzzy and uncertain situations by introducing membership functions to characterize the relationships between variables and mapping variables to the interval between 0 and 1 (Jain & Sharma, 2020). In the risk assessment process, fuzzy logic is divided into fuzzy inference, fuzzy clustering, and fuzzy decision-making. Fuzzy inference is the process of deducing one or more conclusions from fuzzy rules, and it can solve the problem of uncertainty and vagueness in decision systems (Omair et al., 2021). For instance, when customs officers receive report information most of which are inaccurate linguistic information, fuzzy logic can be used to make the information fuzzy and analyze the risk by fuzzy IF-Then rules. It is useful to assist customs officers in making better decisions (Singh & Sahu, 2004). Fuzzy clustering is used to group data based on similar features and comprehensively conducts risk assessment by modeling each data point to each cluster through membership functions to describe similarity degrees between data and clusters (Mahmoudi et al., 2020; Martin et al., 2022). Fuzzy decision-making is the process to select an optimal decision from multiple possible options, and it can reflect the abruptness and smoothness of variables. It can serve as an effective sensitivity analysis tool for evaluating the interaction of variables and their impact on the output results (Watson et al., 1979).

3.5. Risk assessment models based on fuzzy logic and neural networks

3.5.1. Representative models

Neural networks can automatically learn and extract features from raw data (Kulkarni & Cavanaugh, 2000). Incorporating fuzzy logic into neural networks can enhance the fault tolerance and interpretability of the model (Lin & Lee, 1991). One of the most typical models is Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993).

ANFIS is a self-learning inference system that utilizes neural networks as well as fuzzy logic for adaptive learning and inference, which can solve the weight value problem that artificial neural networks cannot explain. It is capable of handling a wide range of problems, for example, prediction, classification, clustering (Karaboga & Kaya, 2019).

As shown in Figure 4 ANFIS consists of five layers. To make easier to understand, this paper will primarily focus on the ANFIS model structure with two input variables and one output variable. We will also assume that the rule base contains two fuzzy IF-THEN rules.

Rule 1: If x is A_1, and y is B_1, then $f_1 = p_1{*}x + q_1{*}y + r_1$.
Rule 2: If x is A_2, and y is B_2, then $f_2 = p_2{*}x + q_2{*}y + r_2$.

Layer 1 is called fuzzification layer. It can transform the input variables to the corresponding fuzzy sets by using membership functions. The parameters determine the shape of the membership function, and the bell-shaped membership function is often used.

$$\mathrm{O}_\mathrm{i}^1 = \mu_{\mathrm{A_i}}(\mathrm{x}) \tag{3}$$

where i is the node and x is the input value of i. A_i is the linguistic label that describes the characteristics or properties of node functions. O_i^1 is the membership function of A_i, the superscript represents the sequential number of layers.

$$\mu_{\mathrm{A_i}}(\mathrm{x}) = \frac{1}{1+\left[\left(\frac{\mathrm{x}-\mathrm{c_i}}{\mathrm{a_i}}\right)^2\right]^{\mathrm{b_i}}} \tag{4}$$

where $\mu_{\mathrm{A_i}}(\mathrm{x})$ is the bell-shaped function that ranges from 0 to 1, and $\{a_i, b_i, c_i\}$ is the parameter set.

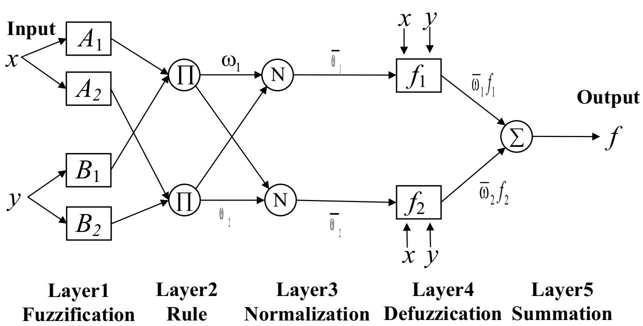
Layer 2 is called rule layer. The firing strength of each rule is calculated by multiplying the membership values of each feature.

$$\mathrm{O}_\mathrm{i}^2 = \omega_\mathrm{i} = \mu_{\mathrm{A_i}}(\mathrm{x}) \times \mu_{\mathrm{B_i}}(\mathrm{y}) \tag{5}$$

where ω_i is the firing strength and $i = 1, 2$.

Layer 3 is normalization layer that is used to obtain the weights corresponding to each rule.

Figure 4
The ANFIS structure that has two inputs and one output



$$\overline{\omega}_i = \frac{\omega_i}{\omega_1+\omega_2} \tag{6}$$

where $i = 1, 2$.

Layer 4 is called defuzzification layer which calculates the results of the rules.

$$O_i^4 = \overline{\omega}_i \times f_i = \overline{\omega}_i \times (p_i \times x + q_i \times y + r_i) \tag{7}$$

where $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5 is called summation layer that calculates the summation of all input signals.

$$O^5 = \sum_i \overline{\omega}_i \times f_i = \frac{\sum_i \omega_i \times f_i}{\sum_i \omega_i} \tag{8}$$

where f_i represents the i-th fuzzy rule.

3.5.2. Optimization of ANFIS

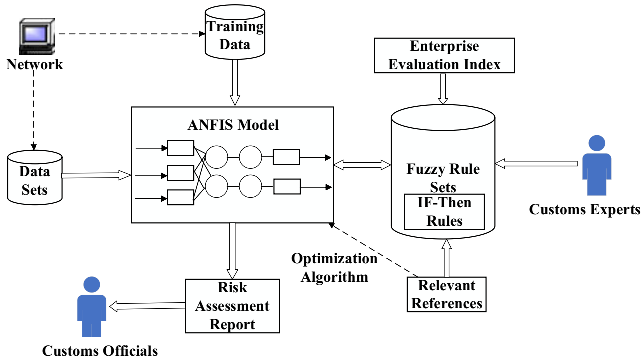
ANFIS reduces the difference between the actual output and the desired output by adjusting its adjustable parameters through learning methods (Mohd Salleh & Hussain, 2016). The parameters are trained by using gradient descent and using BP method in backward propagation. The consequent parameters are trained by using least squares estimator (Rini et al., 2013). However, the parameters are trained by BP method, which is prone to fail in local optimum (AnandaKumar & Punithavalli, 2011).

To improve performance and reduce errors, numerous methods for training ANFIS have been proposed by researchers. Marzi et al. (2017) proposed a hybrid algorithm by integrating the Bees Algorithm and Least Square Estimation to optimizes parameters in ANFIS and find the optimal solution by utilizing iterative updates through both local and global searches. Sarkheyli et al. (2015) proposed a new modified genetic algorithm by using a new type of population to optimize the modeling parameters in membership functions and fuzzy rules in ANFIS. This method reduces the number of evaluations and prediction errors by establishing a fitness function to improve the convergence speed and prediction accuracy. Wang et al. (2012) developed a differential evolution algorithm with ant colony search to identify the parameters, and redundant rules are pruned by applying a threshold which optimizes the strength of rule triggering in the rule base. There are several methods to optimize the parameters and membership functions, such as Simulated Annealing (Haznedar et al., 2021), and Chicken Swarm Optimization (Zarlis et al., 2016).

4. Risk Assessment of Import and Export Enterprises Based on ANFIS

To address the issues of the inability of existing import and export enterprise evaluation models to handle the relationships among multiple factors and provide timely feedback on new data, this paper introduces the classic model ANFIS based on fuzzy logic and neural networks about risk assessment in import and export enterprises for the first time. The theoretical analysis shows that this model has good feasibility. Additionally, the ANFIS can be adjusted by different evaluation conditions to increase its robustness and adaptability by literature research on optimization algorithms.

Figure 5
Risk assessment on import and export enterprises based on ANFIS



The risk assessment process for import and export enterprises using ANFIS is shown in Figure 5.

Firstly, it converts the available import and export enterprise data into the acceptable form of ANFIS by data preprocessing. Secondly, it selects the input and output variables associated with risks. Thirdly, it uses the optimization algorithm to train parameters and membership functions in the ANFIS model. Fourthly, the new import and export enterprises data are input into the trained ANFIS model, and it records risk assessment results. Lastly, the evaluation results are analyzed, and the corresponding risk management and control measures are given.

The purpose of optimizing the parameters and membership functions in the ANFIS model is to optimize the fuzzy rule base. Although it can automatically construct the fuzzy rule base, some parameters and constraints still need to be specified by humans. It is necessary to cultivate professional and technical personnel in risk assessment fields. In addition, it is important to ensure the correctness and quality of data.

Customs personnels play an important role in the collection, analysis, and processing customs data. They can improve and optimize the fuzzy rule base according to the actual situation. Customs authorities should develop their innovation skills to establish a more reasonable and scientific fuzzy rule base and facilitate the development of customs technologies (Kulish et al., 2020).

5. Conclusions and Future Work

There are few risk assessment methods based on import and export enterprises because of the lack of available data on import and export enterprises. Risk assessment models that are based on fuzzy logic and neural networks are capable of handling fuzzy and uncertain information, which can reduce the impact that uncertain and fuzzy data from enterprises has on model training. In this paper, we survey the risk assessment methods and introduce the preliminaries of fuzzy logic and neural networks.

In the future, we can optimize the model parameters and membership functions by combining advanced algorithms and techniques to improve the prediction performance and generalization capability of the model. It is necessary to cultivate professional personnel in the customs field to improve the quality and efficiency of constructing the fuzzy rule library. In addition, this presented model can be extended to other industries, such as finance, transportation, and environment.

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Conflicts of Interest

Shaojie Qiao is the Editor-in-Chief for *Journal of Data Science and Intelligent Systems* and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no conflicts of interest to this work.

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