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*Research Article*

# Aviation and Airspace Management under Rough Set Theory

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With the development of aviation industry, a series of problems have appeared in aviation and airspace, among which the most prominent problem is the congestion of aviation and airspace. Airspace congestion has become a major problem in the development of civil aviation in China. Especially in the central and eastern regions of China, airspace congestion is becoming more and more serious. To better solve the problem of airspace congestion, rough set theory and the Fuzzy C-means (FCM) model are first analyzed. By analyzing the temporal and spatial characteristics of traffic congestion in the control sector, a multisector traffic congestion identification model is established based on radar track data. Four multisector congestion characteristics including equivalent traffic volume, proximity, saturation, and traffic density are established. FCM and rough set theory are used to classify and identify sector congestion. Finally, the model based on FCM-rough set theory is compared with other methods based on the data of the regional control sector in northwest China. The experimental results show that the congestion recognition rate of the model is 92.6%, 93.5%, and 94.2%, and the congestion misjudgment rate is 1.5%, 1.2%, and 1.3%, respectively. Hence, the multisector congestion recognition model has a high recognition rate and a low misjudgment rate, and the overall discrimination result is relatively stable. By comparing the proposed method with other methods, it is concluded that the recognition accuracy of the model based on FCM theory is superior to other methods. In summary, the congestion situation of the sector is affected by a variety of macro- and micro-characteristics of the sector, and the congestion identification model is feasible and efficient. Multisector traffic congestion identification has certain application value for airspace planning, air traffic control-assisted decision making, and air traffic flow management. This work can optimize the aviation and airspace management system and provide relevant suggestions for the study of aviation and airspace congestion.

## 1. Introduction

In recent years, relevant departments of China have gradually realized the great value of the general aviation industry in promoting national economic development and industrial structure transformation and have issued a series of policies to support its development. With the booming development of China's general aviation industry, the demand for airspace resources has been increasing, and the effectiveness of airspace utilization and the safety of general aviation flight have been affected, bringing enormous pressure to airspace management. Promoting the reform of airspace management has become a hot topic of concern [1]. Affected by historical factors, the reform process of airspace management in China is slow, but relevant national departments have been trying to promote the reform process [2]. In October 2018, the Civil Aviation Administration of China (CAAC) issued the overall plan for the construction of low-altitude flight service guarantee system. The plan provides solutions to problems in the implementation of such guidelines issued in 2010. According to several aviation experts, this move is an important measure of CAAC to accelerate the reform of decentralization, regulation, and service, which will help accelerate the reform of low-altitude air traffic control and drive the development of the general aviation industry [3]. At present, there is some research foundation about airspace congestion nationally and internationally. Fanice compared the traffic demand of sectors, anchor points, and crossing routes with capacity thresholds to monitor and warn the air traffic congestion situation [4]. Bo and Jesper studied measures to alleviate congestion in European airspace from the perspective of flight plans and operational networks of airlines [5]. Daniel analyzed airspace congestion from the perspective of air traffic complexity and extracted the traffic complexity characteristics of airspace congestion [6]. The above studies focus on the congestion theory of a single traffic unit, but they have not carried out the study of multisector traffic congestion, and have not analyzed the congestion situation of multisector and large-area airspace from the macro-level. It is difficult to recognize traffic congestion in real time because the research index is too heavy on the consequence index.

The key to an intelligent information system is knowledge expression. From a large amount of existing data information, the analysis of valuable rule information is called knowledge acquisition, which helps to transform knowledge from original representations (raw data representations) into new ideal expressions. Knowledge acquisition of rough set theory usually obtains system knowledge through data table knowledge such as an information table [7]. First, the concept of knowledge utilization classification is briefly introduced. Then, a knowledge representation system is introduced to describe the function of the information table. A formal description is given, and the decision table is discussed in detail. Finally, the decision weights and decision rules corresponding to the decision table are discussed [8]. The logical model, framework, semantic network, state space, and generation rule are commonly used knowledge representation methods at present. These are the research directions and contents of knowledge expression [9]. Information table knowledge representation based on rough set theory is a scientific tool for knowledge representation and processing. To deal with practical problems in daily life, the research object is usually limited to a specific area or corresponding numerical value. The set of all individuals in this region is the problem domain [10]. In 1982, Polish mathematician Professor Palak announced the birth of rough set theory. The first international symposium on rough set theory was held in Poland in 1992, and an international symposium on rough set theory has been held every year since then. The International Rough Set Society was formally established in 2005 and published the latest research progress papers on rough set theory and its applications in some journals and magazines. Since the first China Rough Set and Soft Computing Symposium was successfully held in Chongqing University of Posts and Telecommunications in 2001, the research and communication of rough set theory started. Since then, the conference has been held annually, involving mathematics, management science, information science, computer science, control science, and systems science. In 2003, China Artificial Intelligence Society Rough Set and Soft Computing Special Committee was established in Guangzhou.

Literature showed that many scholars have conducted research studies on air and airspace management at present. At present, air and airspace traffic is complex, and most research studies focus on the analysis of the complexity of single air traffic, but there is a lack of research studies on multisector traffic congestion [11]. To this end, research on multisector congestion identification method is carried out to analyze the spatio-temporal characteristics of aviation and airspace sector congestion and traffic congestion law of multisector in detail. The congestion indexes of equivalent traffic volume, proximity, saturation, and traffic density are established. Fuzzy C-means (FCM)-rough set theory is used to establish the multisector traffic congestion identification model, which can identify the multisector congestion problem from the level of regional control center. It has certain application value for airspace planning, control operation, and air traffic flow management. The innovation of the study is different from the traditional aviation and airspace management research. By focusing on the problem of airspace congestion and combining FCM theory with rough set theory, the problem of airspace congestion is analyzed more comprehensively and the experimental results are more reliable [12].

The research framework of this work is as follows: First, rough set theory is analyzed so as to lay a foundation for further analysis of FCM-rough set theory. Second, according to the radar track data, the congestion characteristics of the airspace are analyzed, and the congestion index of the airspace sector is selected. Then, based on the FCM-rough set theory and the selected crowding index, the FCM-rough set aviation sector congestion identification model is established, and the identification model is tested. Furthermore, the FCM-rough set model designed in this work is compared with other models to judge the effect of the model.

## 2. Methods

### *2.1. Rough Set Theory Analysis*

*2.1.1. Basic Theoretical Analysis.* Rough set theory is another mathematical tool to deal with uncertainty after probability theory, fuzzy set, and evidence theory. In 1982, a set of theories was proposed to study incomplete data and inaccurate knowledge expression, learning, and induction [13]. The main idea is deriving the decision or classification rules of the problem through knowledge reduction on the premise of keeping the classification ability unchanged. From a mathematical point of view, rough sets are the study of sets. From a programming point of view, rough sets are studied by matrices, just some special matrices. From the perspective of artificial intelligence, rough sets study decision tables [14]. The main feature of a rough set is that it does not need to provide subjective evaluation of knowledge or data but can achieve the purpose of deleting redundant information, comparing the degree and roughness of incomplete knowledge, and defining the dependence and importance of attributes based on only observation data [15].

Both rough sets and fuzzy sets can deal with incomplete data, but their processing methods are different. The fuzzy set pays attention to the vagueness of describing information, while the rough set emphasizes the indiscernability, imprecision, and vagueness of data [16]. Using the language of image processing as an analogy, when discussing the

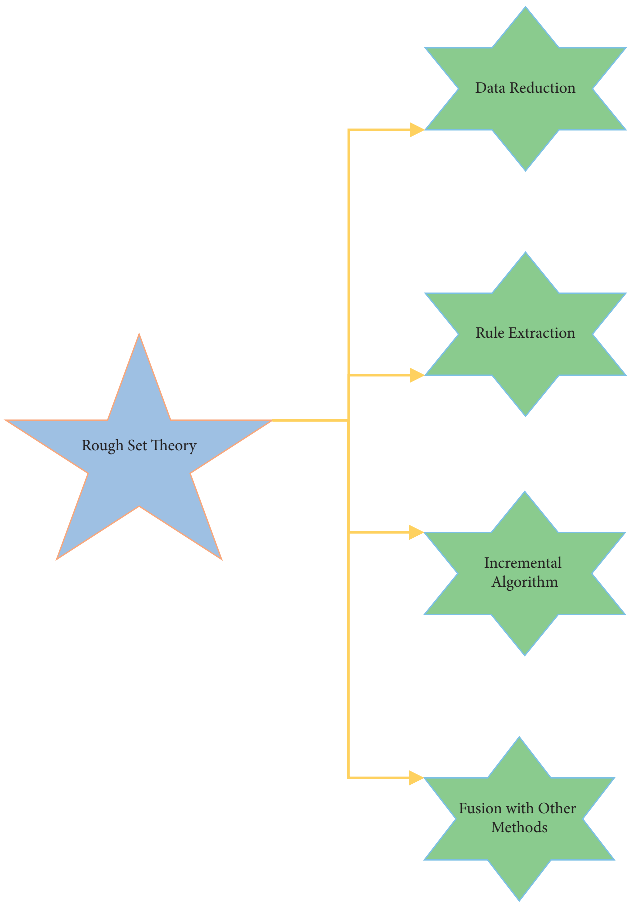


Figure 1: Rough set theory in action.

clarity of an image, a rough set emphasizes the size of the image pixels, while a fuzzy set emphasizes the existence of different gray levels of pixels. Rough set studies the relationship between sets of objects in different classes, focusing on classification. Fuzzy set studies the membership of different objects belonging to the same class, especially the degree of membership. Therefore, rough set and fuzzy set are two different theories, but they are not opposite to each other. They can complement each other in dealing with imperfect data [17]. Rough set theory is widely applied in data mining, involving fields such as medical research, market analysis, business risk prediction, meteorology, speech recognition, and engineering design [18]. In numerous data mining systems, the role of rough set theory is shown in Figure 1.

In Figure 1, the role of rough set theory mainly focuses on the following aspects: I. Data reduction. Rough set theory can provide effective methods for data reduction in information systems. In the preprocessing stage of the data mining system, the redundant information (attribute, object, attribute value, etc.) can be deleted by rough set theory, which can greatly improve the operation speed of system. II. Rule extraction. Compared with other methods (such as neural networks), using rough set theory to generate rules is relatively simple and direct. Each object in the information system corresponds to a rule. The general steps of generating rules in rough set theory are as follows. Step 1: A reduction of conditional attributes is harvested, and redundant attributes are deleted. Step 2: The redundant attribute values of each rule are deleted. Step 3: The remaining rules are merged [19]. III. Incremental algorithm. In the face of large-scale and high-dimensional data in data mining, finding an effective incremental algorithm is a research hotspot. IV. Integration with other methods. The combination of rough set theory and other methods, such as neural networks, genetic algorithms, fuzzy mathematics, and decision trees, can give play to their respective advantages and greatly enhance the efficiency of data mining [20].

*2.1.2. Fuzzy C-Means Rough Set Theory Analysis.* Fuzzy control is a classical method in the field of automatic control. Its principle is fuzzy mathematics and fuzzy logic. Fuzzy clustering is a kind of clustering algorithm in which each object can partly belong to a certain class, that is, the value of membership degree is not limited to 0 and 1 but in the interval of [0,1] [21]. Objects no longer have either/or characteristics for classes but can belong to multiple classes at the same time, and the specific degree of belonging to classes can be expressed by a membership function [22]. Among various fuzzy clustering algorithms, the fuzzy C-means algorithm is the most important and widely used. This algorithm first extended the clustering criterion function of hard clustering to fuzzy clustering, proposed the error square sum function with membership weighting, and then performed further expansion work [23]. The standard FCM algorithm is an iterative method in clustering methods, clustering a group of objects into the best C class by minimizing the weighted sum of error squares [24]. This algorithm allows overlapping parts between classes, allowing objects to be included in multiple classes [25]. The algorithm needs to minimize the following objective function:

$$
\begin{aligned}
J_m &= \sum_{k=1}^{c} \sum_{i-1}^{n} u_{ki}^{m} \|x_i - u_{k2}\|, \\
S.t. \sum_{k=1,}^{c} u_{ki} &\in [0,1], 0 \le \sum_{i-1}^{n} u_{ki} \le n,
\end{aligned} \tag{1}
$$

where $n$ is the number of data objects, $c(2 \le c \le n)$ is the number of clusters, the operator || is the Euclidean norm, and $x_i$ is the $i$th data object in $d$-dimensional vector space. Parameter $m$ $(m \ge 1)$ is the weight factor of the membership function of FCM, which can control the fuzzy degree of partition data. The larger the value of $m$, the greater the fuzziness of the function. $u_k$ $(1 \le k \le c)$ represents the center of the class, and $u_{ki}$ $(1 \le k \le c, 1 \le i \le n)$ represents the degree to which $x_i$ belongs to the $k$th class [26–37]. The algorithm framework of FCM is shown in Figure 2.

In Figure 2, the fuzzy C-means algorithm consists of six steps:

(1) Step 1: initialization. The iteration termination threshold $\varepsilon$, cluster number $C$, and fuzzy factor $M$ are set.

(2) Step 2: the iteration counter $q = 0$ is set.

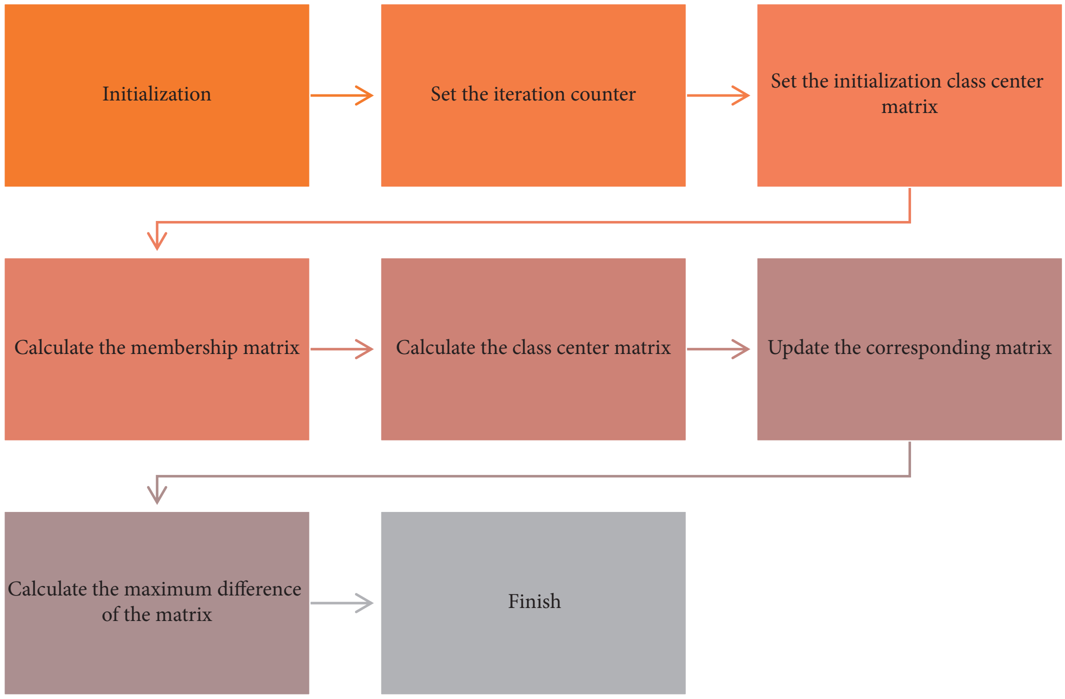


FIGURE 2: FCM algorithm block diagram.

(3) Step 3: the class center matrix is randomly initialized [27], and the calculation method is shown in

$$C^{(q)} = C_k \, (k = 1, 2, \ldots, c). \tag{2}$$

(4) Step 4: the membership matrix $U^{(q)}$ is calculated according to $C^{(q)}$, as shown in

$$U_q = \frac{1}{\sum_{k=1}^{c} \left( d_{ji}/d_{ki} \right)^{2/m-1}}. \tag{3}$$

(5) Step 5: the class center matrix $C^{(q+1)}$ is calculated according to $U^{(q)}$, as shown in

$$C^{(q+1)} = \frac{\sum_{i=1}^{N} u_{ji}^{m} X_i}{\sum_{i=1}^{N} u_{ji}^{m}}. \tag{4}$$

(6) Step 6: the membership matrix $U^{(q+1)}$ is updated according to $C^{(q+1)}$ and (3); Step 7: if max $\{U^{(q+1)} - U^{(q)}\} \leq \varepsilon$, the algorithm stops. Otherwise, $q = q + 1$, it will return to Step 4 [28].

FCM is an extension of the traditional K-means algorithm, which continuously updates the membership degree by minimizing the intra-class spacing. When the membership degree of all objects to all classes is determined, the class with the largest membership degree is selected as the class to which the object belongs [26–37].

*2.2. Analysis of Airspace Congestion Characteristics Based on Radar Track Data.* Congestion identification in the airspace sector based on radar track data is studied. At present, studies on airspace congestion mainly use simulation data, statistical prediction data, controller workload data, etc., but few studies are based on radar track data. Radar track data have been used for traffic flow and inbound and outbound program identification, airspace operation status monitoring, and airspace complexity analysis. Based on radar track data research, it has the advantages of real time, accuracy, and practicability. Using the radar track data of a certain area control sector and based on the geographic information tool, the radar track data are processed to construct the airspace congestion evaluation indicator. To meet the modeling requirements, it is necessary to discretize the radar track data. The original radar track data are discretized at an interval of 5 min, and the isolated and abnormal data as well as the repeated track point data within the time slice are eliminated to generate track sample data. Based on the characteristics of radar track data, the traffic congestion situation is analyzed from macro- and micro-dimensions. The built metrics are detailed in Figure 3.

In Figure 3, traffic congestion characteristic indicators of equivalent traffic volume, proximity rate, saturation, and traffic density in four sectors are constructed. I. Equivalent traffic volume indicator. It is defined as the total equivalent sorties of aircraft in the sector within a unit time interval. When the traffic volume is greater, the sector is more prone to congestion. Different types of aircraft vary in size, flight performance, flight speed, and control workload. For this reason, equivalent traffic volume is selected to describe the quantitative characteristics of aircraft in the sector. The equivalent traffic volume is obtained by summing the number of different types of aircraft by weighting, and the weighting calculation is shown as follows:

$$q = k_1 a_1 + k_2 a_2 + k_3 a_3, \tag{5}$$

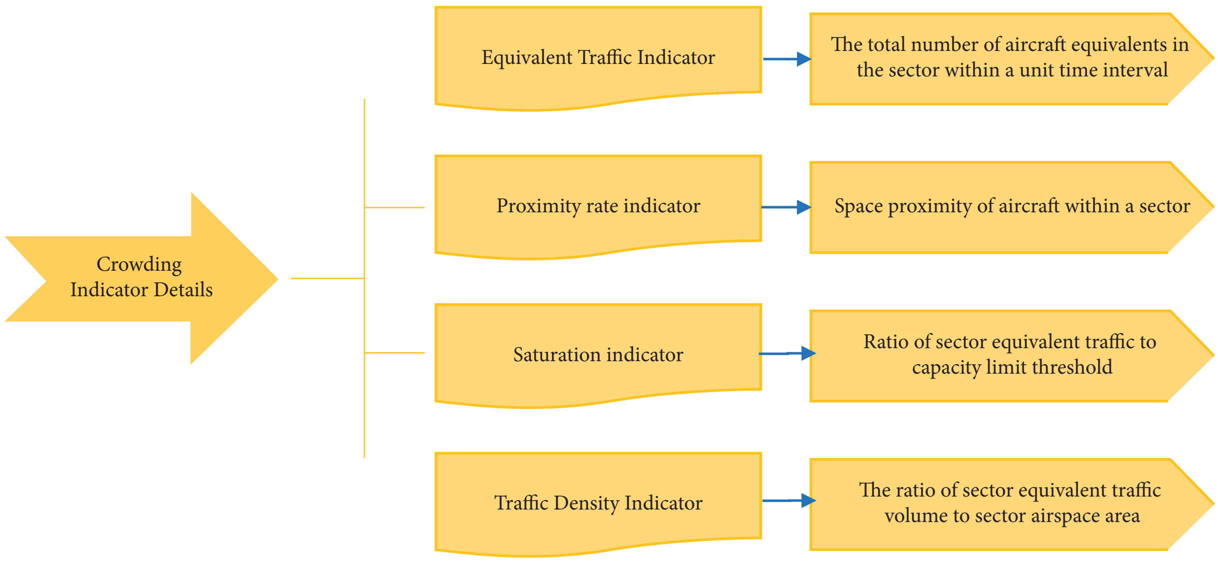


FIGURE 3: Build metrics detail diagram.

where $q$ is the equivalent traffic volume of the sector; $a_1$, $a_2$, and $a_3$ are the times of the heavy machine, medium machine, and light machine, respectively; and $k_1$, $k_2$, and $k_3$ are the corresponding weights of heavy, medium, and light machines, respectively. Taking the light machine as the equivalent standard, the coefficients of the heavy machine, medium machine, and light machine are $k_1 = 1.3$, $k_2 = 1.1$, and $k_3 = 1.0$, respectively.

*Proximity Indicator*. The proximity rate describes the spatial proximity of aircraft in a sector and reflects the characteristics of traffic distribution. The space distribution of aircraft affects the degree of sector congestion. The traffic proximity rate of the sector reflects the congestion degree of the sector from the micro-level. In the radar control environment, aircraft in the sector must meet the horizontal minimum interval of more than 10 km or the vertical minimum interval of 300 m; either of the two must meet; otherwise, it will constitute a dangerous approach and violate the control operation rules. Therefore, the Euclidean distance is not simply used to determine the approach degree of the aircraft. The ellipsoid is used to define the relative distance of the aircraft and calculate the approach rate of the sector. The calculation is as follows:

$$
\begin{aligned}
d_{ji} &= \left\| \underset{po_i}{\longrightarrow} - \underset{po_j}{\longrightarrow} \right\|_{a,h} = \sqrt{\frac{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}{a^2} + \frac{\left(z_i - z_j\right)^2}{h^2}},\\
p &= \sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} e^{-d_{ij}},\\
p_{\text{sector}} &= \frac{p}{N},
\end{aligned}
\tag{6}
$$

where $d_{ij}$ is the relative distance between aircraft $i$ and $j$ in the sector; $\underset{po_i}{\longrightarrow}$, $\underset{po_j}{\longrightarrow}$ is the position vector of aircraft $i$ and $j$; $a$ and $h$ are the horizontal minimum safety interval and vertical minimum safety interval, respectively; $(x_i, y_i)$ and $(x_j, y_j)$ are the coordinate positions of aircraft $i$ and $j$, respectively; $(z_i, z_j)$ is the flight altitude of aircraft $i$ and $j$; $p$ is the proximity of aircraft in the sector; $N$ is the number of aircraft in the sector; and $P_{\text{sector}}$ is the sector proximity rate.

According to the above equations, the sector proximity rate is the ratio of the sector proximity to the sector traffic volume, reflecting the proximity of aircraft in the sector. When the aircraft is denser, the relative distance is smaller, the sector proximity rate is larger, and the sector is more crowded. Taking the measured radar track data of a certain day in northwest China as an example, the airspace proximity and proximity rate are calculated, and the results are shown in Figure 4.

In Figure 4, after comparison of the traffic volume, the proximity curve and the proximity rate curve are relatively close to the traffic volume curve. Therefore, both the proximity and proximity rate can reflect the intensity of aircraft distribution in the sector.

III. Saturation indicator. It is defined as the ratio of sector equivalent traffic volume to the capacity limit threshold in a certain period of time. Saturation can well measure the degree of traffic load in sectors and facilitate the comparison of congestion degree among different sectors. The calculation method is as follows:

$$
s_i = \frac{q_i}{c}, \tag{7}
$$

where $s_i$ is the traffic saturation of the $i$th interval sector, $q_i$ is the equivalent traffic volume of the space unit in time interval $i$, and $c$ is the capacity limit threshold of the sector. The sector capacity limit threshold $c$ adopts the data obtained from the capacity assessment results of the controlled sectors of Air Traffic Management Bureau of Civil Aviation Administration of China. To realize the fine management of air traffic control operations, the civil aviation air traffic control authority has basically

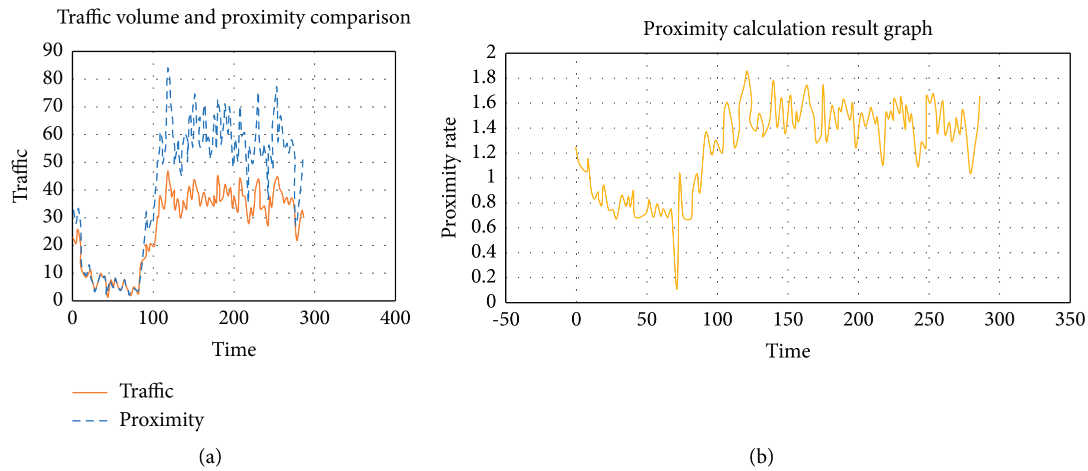


Figure 4: Spatial proximity and proximity result diagram. (a) Traffic volume and proximity comparison diagram of a certain sector and (b) calculation results of the proximity rate.

completed the capacity evaluation of the control sector, and the corresponding capacity limits of the control sector have accurate data.

IV. Traffic density indicator. It is defined as the ratio of sector equivalent traffic volume to sector airspace area, represented by $k$. Under the same traffic volume, the smaller the sector space is, the smaller the maneuvering space of the aircraft will be, and the more crowded the airspace will be. The traffic density of a sector can reflect the congestion degree of the sector and facilitate the comparison of congestion degree among different sectors.

### 2.3. FCM-Rough Set Sector Congestion Identification Model in Aviation Airspace

*2.3.1. Crowding Degree Division of Multiple Sectors Based on FCM.* The radar track data are collected for preprocessing, and the equivalent traffic volume, proximity rate, saturation, and traffic density of the sector are calculated at a statistical interval of 5 min so that the sector traffic congestion characteristic matrix $X$ is constructed. The FCM clustering method is used for $X$ clustering analysis, and the congestion degree of the airspace sector is divided. The FCM algorithm divides $n$ groups of crowding feature vectors into $m$ fuzzy groups, where $1 \leq i \leq n$, calculates the clustering center of each group, and calculates the membership value of each group of feature vectors belonging to each group of clustering centers to determine the crowding degree corresponding to each group of feature vectors. Due to the selection of continuous radar track data, the traffic volume in some intervals is zero. Therefore, the traffic congestion degree is classified into six levels, namely, zero traffic volume, little traffic volume, smooth, stable, crowded, and seriously crowded. The corresponding clustering centers are also six. FCM clustering can only classify the degree of sector congestion, so rough set theory is used to identify the degree of airspace sector congestion.

*2.3.2. Congestion Identification of Airspace Multisector Based on Rough Set.* Rough set theory is used to identify sector congestion. Rough set theory is an effective way to deal with imprecise, uncertain, and incomplete data and extract the required knowledge. The knowledge representation system for discriminating sector traffic congestion is a quad $S = (U, A, V, f)$, where $U$ is the domain of sector congestion characteristics. $A$ is the set of sector congestion attributes, which is composed of conditional attribute $C$ and decision attribute $D$, $C = \{$equivalent traffic volume, proximity rate, saturation, traffic density$\}$ and $D = \{$category description: unblocked state, crowded state$\}$. $V$ is the corresponding range of the attribute. $F$ is a traffic congestion information function that assigns an information value to the traffic congestion object attribute of each sector. The value of the sector congestion attribute is discretized to facilitate attribute reduction. The purpose of attribute reduction is to remove unnecessary attributes from the attribute set. By reducing the congestion attribute, the identification rules of sector traffic congestion can be generated.

Figure 5 shows the computational flow of the FCM-rough set aviation airspace sector congestion identification model.

In Figure 5, the calculation process of the FCM-rough set aviation airspace sector congestion identification model is shown as follows: (I) Data preparation: multisector radar track data are collected, sector congestion characteristic indicator values are calculated, and multisector traffic congestion characteristic matrix $X$ is constructed in chronological order. (II) Classification of traffic congestion degree: the FCM algorithm is adopted to cluster the sector traffic congestion feature matrix $X$. The number of cluster centers is $m = 6$, and the iteration

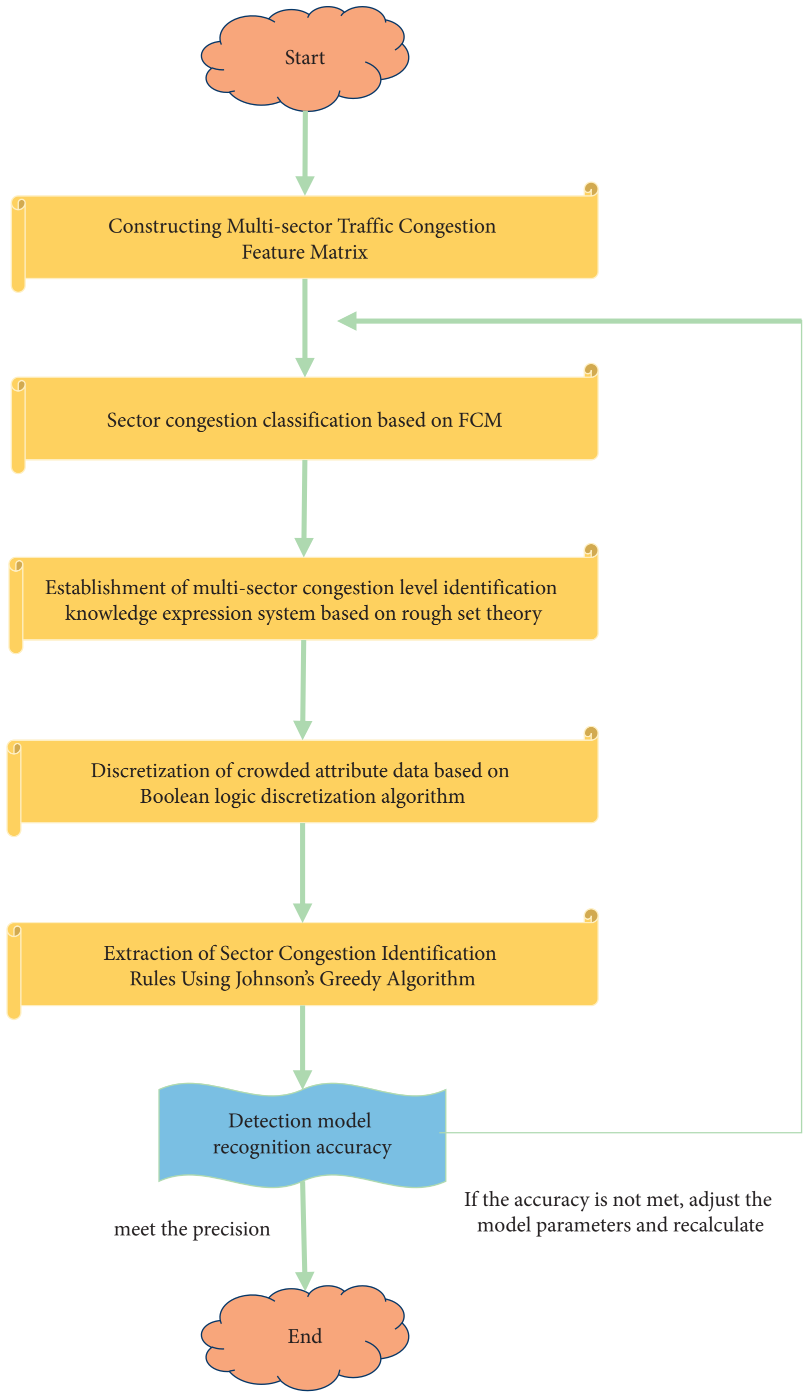


FIGURE 5: Flow chart of model calculation.

stop threshold is $E = 1 \times 10^{-6}$. The clustering center of each crowded category is obtained to minimize the sum of squares of weighted errors within the class. The fuzzy division method, namely, membership matrix, is adopted to determine the crowding degree of each time slice of multiple sectors. Sector congestion can be classified into zero traffic volume, little traffic volume, smooth, stable, crowded, and seriously crowded. (III) A sector congestion recognition knowledge representation system is established. A sector congestion recognition knowledge representation system is constructed by selecting the sector congestion characteristics and corresponding congestion levels. The conditional attributes are equivalent traffic volume, proximity, saturation, and traffic density, and the decision attributes are unblocked state and congestion state, in which congestion degree zero traffic volume, little traffic volume, smooth, and stable are the unblocked state, and congestion degree crowded and severe crowded are the congestion state. (IV) Discretization of crowding attribute data: a Boolean logic

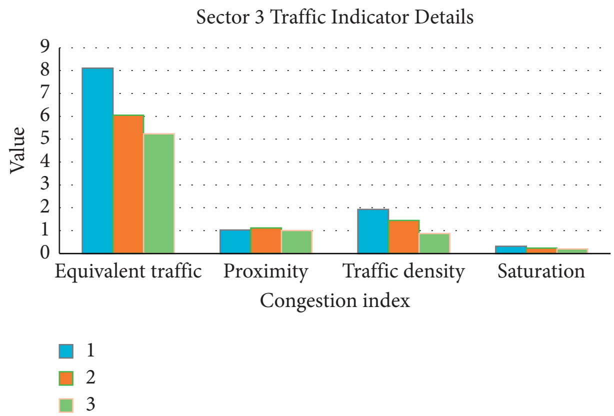


Figure 6: Detail diagram of the traffic congestion indicator in sector.

discretization algorithm is used to find the minimum possible set of segmentation points according to the initial segmentation points while maintaining the indiscernible relation of the information system. (V) The crowding attribute is reduced, and the decision rules are extracted. The Johnson greedy algorithm is used to reduce the discrete traffic congestion attributes, delete the unimportant, redundant, and interfering attributes, and screen out the key attributes that can reflect the essential relationship between data under the condition that the classification ability of the knowledge base remains unchanged. (VI) The identification accuracy of the detection model. If the accuracy requirements are not met, return to Step II, adjust the model parameters, recalculate, and meet the accuracy requirements until the end of the model calculation.

*2.4. FCM-Rough Set Identification Model Verification of Airspace Sector Congestion.* In the experiment, the radar traffic data of three sectors in a controlled airspace in northwest China are selected as the research object to study the traffic congestion problem in the airspace multisector and verify the effectiveness of the research model. The traffic congestion indicator of the sector is shown in Figure 6.

In Figure 6, the current traffic volume of sector 1 is 8.11, the proximity is 1.029, the traffic density is $1.925 \times 10^{-4}$, and the saturation is 0.32. The current traffic volume of sector 2 is 6.05, the proximity is 1.118, the traffic density is $1.444 \times 10^{-4}$, and the saturation is 0.24. The current traffic volume of sector 3 is 5.23, the proximity is 1.055, the traffic density is $0.875 \times 10^{-4}$, and the saturation is 0.2. The model output is compared with the actual situation, and the congestion discriminant rate $I$ and congestion misjudgment rate $R$ are used to measure the validity of the model. The calculations of the indicators are as follows:

$$I = \frac{\mathrm{NIR}}{\mathrm{IT}},\qquad R = \frac{\mathrm{FNIR}}{\mathrm{NIR}}. \tag{8}$$

Table 1: Multisector congestion identification rule table.

| No. | Saturation | Proximity | Equivalent traffic | Crowding decision value |
|---|---|---|---|---|
| 1 | $[0.71 + \infty)$ | $[1.25 + \infty)$ | $[15 + \infty)$ | Crowded |
| 2 | $[0.71 + \infty)$ | $[0, 0.125)$ | $[15 + \infty)$ | Crowded |
| 3 | $[0.71 + \infty)$ | $[0, 0.125)$ | $[10, 15)$ | Crowded |
| 4 | $[0, 0.71)$ | $[1.25 + \infty)$ | $[15 + \infty)$ | Crowded |
| 5 | $[0.71 + \infty)$ | $[1.25 + \infty)$ | $[10, 15)$ | Crowded |
| 6 | $[0, 0.71)$ | $[0, 0.125)$ | $[10, 15)$ | Unblocked |
| 7 | $[0, 0.71)$ | $[0, 0.125)$ | $[15 + \infty)$ | Unblocked |
| 8 | $[0, 0.71)$ | $[0, 0.125)$ | $[0, 10)$ | Unblocked |
| 9 | $[0.71 + \infty)$ | $[0, 0.125)$ | $[0, 10)$ | Unblocked |

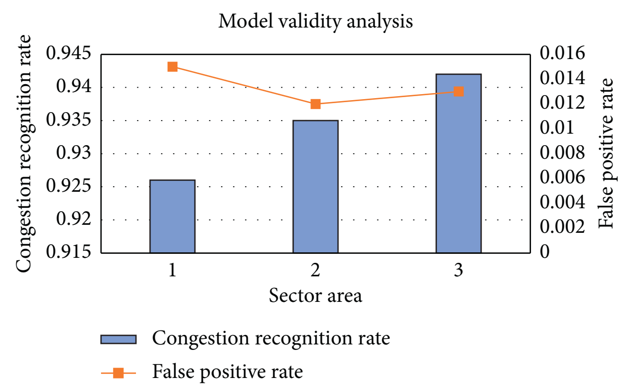


Figure 7: Analysis results of model validity.

NIR is the congestion number detected at time $t$. IT is the actual number of crowding events at time $t$. FNIR is the crowded number of false positives at time $t$.

## 3. Results

*3.1. Model Recognition Rate Analysis.* The congestion recognition rate of the aviation and airspace multisector based on FCM-rough set theory is analyzed, and the recognition rules are shown in Table 1.

In Table 1, according to saturation, proximity, and the actual value range of the current traffic volume, the current aviation and airspace sector congestion degree can be obtained corresponding to different categories in Table 1. Two indicators, congestion discriminant rate $I$ and congestion misjudgment rate $R$, are calculated to evaluate the validity of the model. The result is shown in Figure 7.

In Figure 7, after sampling detection of recognition results, the congestion recognition rate and misjudgment rate of the model for sector 1 are 92.6% and 1.5%, respectively. The congestion recognition rate of sector 2 is 93.5%, and the congestion misjudgment rate is 1.2%. The congestion recognition rate of sector 3 is 94.2%, and the congestion misjudgment rate is 1.3%. Notably, the multisector congestion recognition model has a high recognition rate and a low misjudgment rate, and the overall discrimination result is relatively stable, which can accurately identify the congestion degree of the multisector.

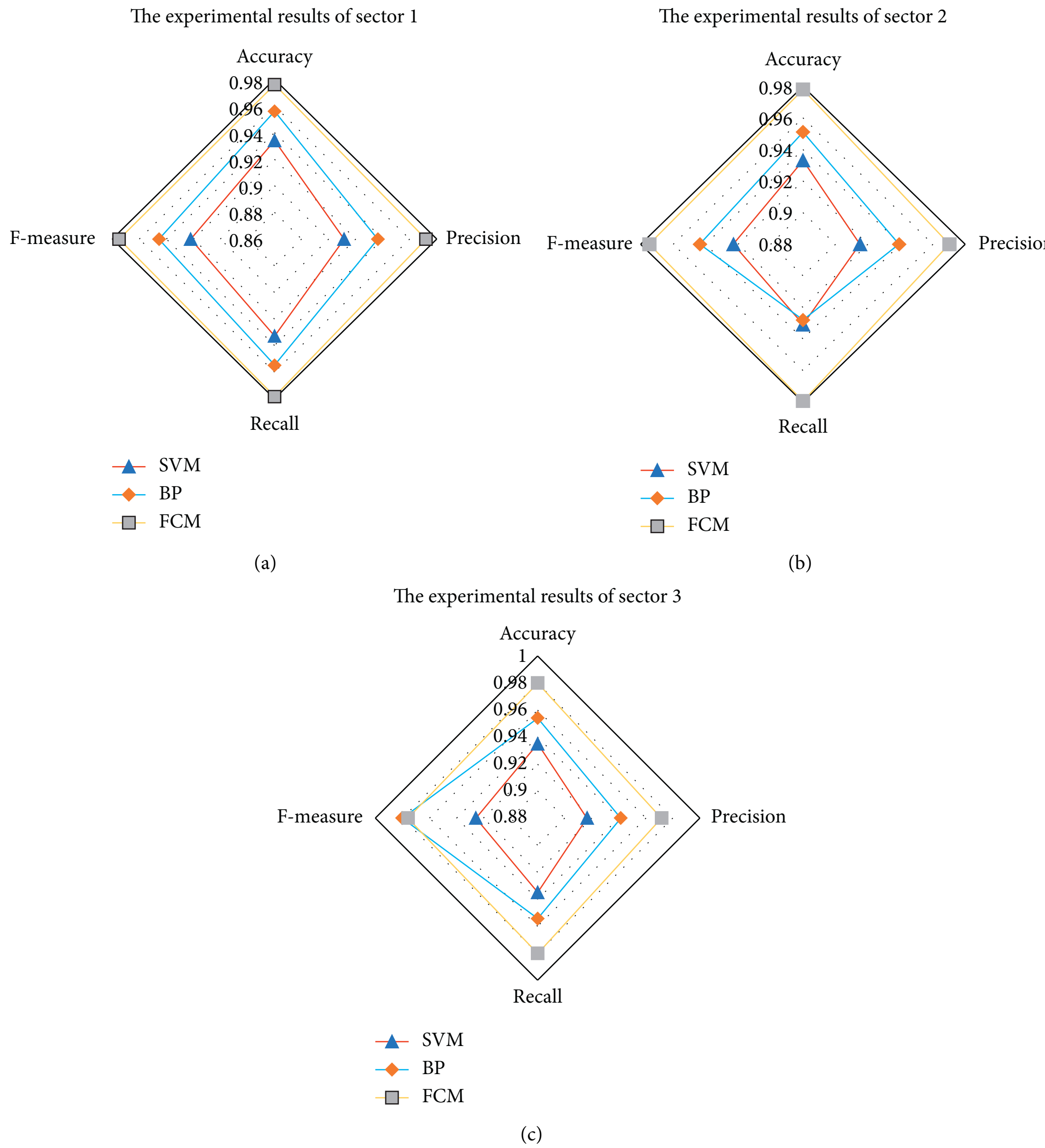


FIGURE 8: Comparison of the experimental results of different methods. (a) Comparison diagram of sector 1, (b) comparison diagram of sector 2, and (c) comparison diagram of sector 3.

*3.2. Crowding Judgment Model Analysis Based on FCM-Rough Set Theory.* To verify the superiority of the proposed method, the proposed method is compared with the Back Propagation (BP) neural network structure and Support Vector Machine (SVM) method. The basic idea of the BP neural network algorithm is that the input signal is input through the input layer, and output from the output layer through the hidden layer calculation. The output value is compared with the marked value. If there is error, the error is propagated reversely from the output layer to the input layer. In this process, the gradient descent algorithm is used to adjust the weight of neurons. The SVM algorithm is a supervised learning model to analyze data in classification and regression. Given a set of training instances, each training instance is marked as belonging to one or the other of two categories. The SVM training algorithm creates a model that assigns new instances to one of two categories, making it an improbability binary linear classifier. The SVM model represents instances as points in space so that instances of separate categories are separated as clearly as possible. The new instances are then mapped to the same space, and the category is predicted based on which side of the interval they fall on. The comparative experimental results of the three models are shown in Figure 8.

In Figure 8, in the experimental results of sector 1, the accuracy of the SVM-based method is 93%, the precision is 91.2%, the recall rate is 93.5%, and the F measure is 92.4%. The accuracy of the method based on the BP neural network is 95.8%, the precision is 93.9%, the recall rate is 95.6%, and the F measure is 94.6%. The method based on FCM-rough

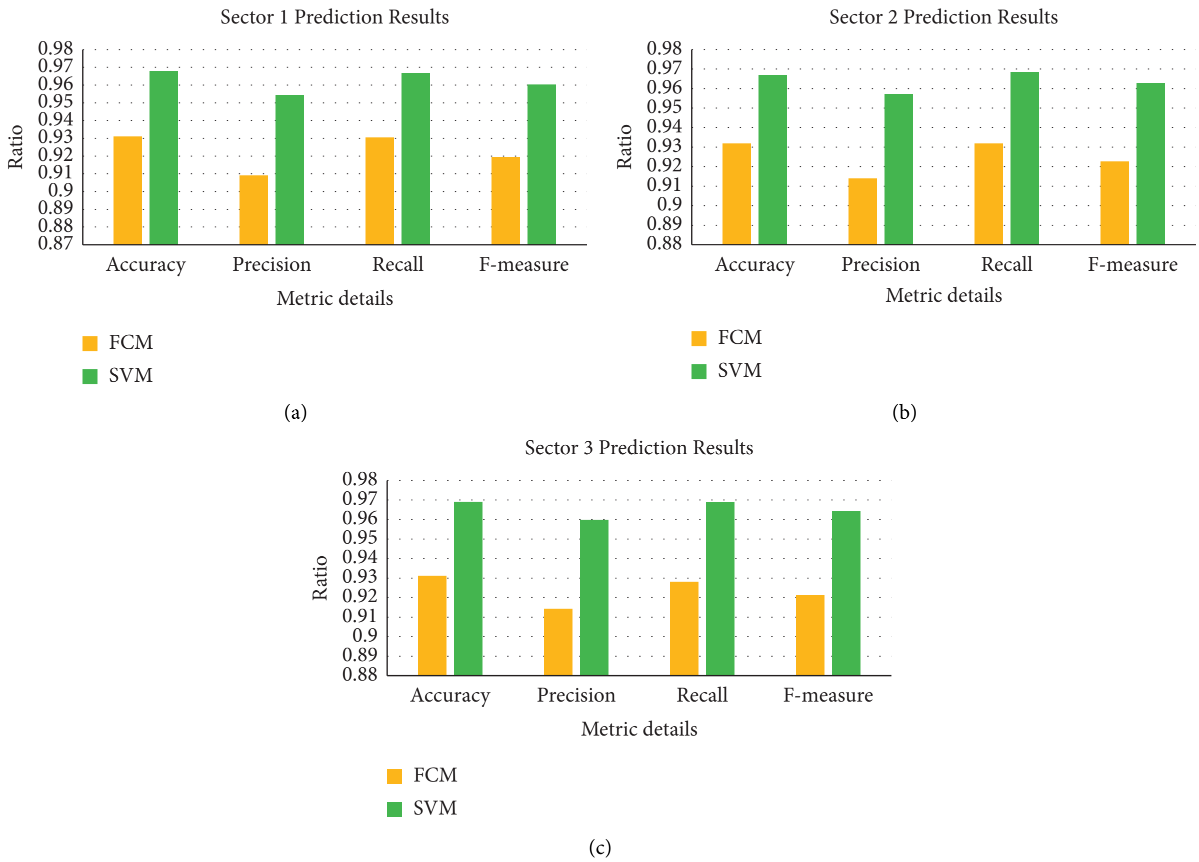


Figure 9: Prediction accuracy results. (a) Sector 1 (b) sector 2 and (c) sector 3.

set theory designed in this work has 97.7% accuracy, 97.2% precision, 97.7% recall rate, and 97.6% F measure.

In the experimental results of sector 2, the accuracy of the SVM-based method is 93.4%, the precision is 91.5%, the recall rate is 93%, and the F measure is 92.3%. The accuracy of the method based on the BP neural network is 95.1%, the precision is 93.9%, the recall rate is 93%, and the F measure is 94.4%. The method based on FCM-rough set theory designed in this work has 97.8% accuracy, 97% precision, 97.9% recall rate, and 97.5% F measure.

In the experimental results of sector 3, the accuracy of the SVM-based method is 93.5%, the precision is 91.7%, the recall rate is 93.5%, and the F measure is 92.6%. The accuracy of the method based on the BP neural network is 95.4%, the precision is 93.1%, the recall rate is 95.4%, and the F measure is 98%. The method based on FCM-rough set theory designed in this work has 98% accuracy, 97.1% precision, 98% recall rate, and 97.6% F measure.

Comprehensive analysis shows that the method based on FCM-rough set theory designed in this work has higher accuracy and a better model effect.

The prediction accuracy of the model for the congestion degree of the aviation and airspace sector is analyzed, and the design model is compared with the SVM method. The results are shown in Figure 9.

In Figure 9, after comprehensive analysis of the prediction indicator results of the three sectors, it is found that the prediction accuracy of the model based on FCM-rough set theory designed in this study is higher than that of the SVM-based algorithm, so the model designed in this study has a high accuracy in predicting the traffic congestion degree of aviation and airspace.

## 4. Conclusion

First, rough set theory and the FCM model are analyzed. Second, the two research theories are combined for analysis. Then, FCM-rough set theory is applied to the identification of traffic congestion in aviation and airspace in multiple sectors, and appropriate indicators of aviation and airspace sector congestion are selected. Then, the actual radar track data of the regional control sector in northwest China are used to verify the case. The results show that FCM can quickly classify the congestion degree of sectors and analyze the spatial and temporal evolution of traffic congestion degree from the macro-perspective and the dimensions of multiple sectors. The recognition model can discretize attributes quickly and remove redundant information, and the congestion recognition rate can reach 92.6%. The congestion attribute of multisectors can be predicted in real time by identifying the congestion degree of sectors based on the radar track data, which can be used to assist the decision-making of aviation and airspace management and air traffic flow management. The deficiency of this work lies in the small number of selected variables and survey samples. The next research focus is collecting more experimental data for in-depth analysis. The innovation of this work lies in focusing on the problem of airspace congestion and combining FCM theory with rough set theory, which analyzes the problem of airspace congestion in a more comprehensive way, and the experimental results are more reliable. This work can optimize the aviation and airspace management system and provide relevant suggestions for the study of aviation and airspace congestion.

## Data Availability

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

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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