A Hybrid Forewarning Algorithm for Train Operation under Adverse Weather Conditions

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Abstract
This paper presents a combined method of fuzzy theory and rough sets theory for the early warning of high-speed railway (HSR) under adverse weather conditions. Based on the monitoring data of meteorological indicators along the railway, a fuzzy c-means (FCM) clustering is first applied in order to figure out the fuzzy distribution of sample data and to fit the corresponding membership function of every indicator. According to the clustering results, every original sample is transformed into its cluster level as string data for the subsequent application of rough sets theory. Then a series of effective rough rules between conditional indicators and the decision indicator is extracted after attribute reduction by the Rosetta toolkit, where the decision indicator is represented by the train deceleration rate. Since the value of an indicator may correspond to several fuzzy levels, the multiple combinations of different conditional indicators will activate multiple rough rules. In order to forecast a clear value of the decision indicator, a centroid-based Max-Min compound arithmetic is applied to clarify relevant rules and determine the warning level. Using the designed algorithm, a case analysis of an HSR line section is conducted to verify the feasibility of the combined method, all meteorological data and operation records are provided by the Shanghai Railway Bureau in China. The results prove that the hybrid algorithm can be applied in the real-time forewarning of HSR train operation, with a global accuracy over 86%.

Keywords
High-speed railway, Forewarning algorithm, Adverse weather, Fuzzy theory, Rough sets

1 Introduction

High-speed railway (HSR) has recently become an important share of the transport market in China, with advantages of comfort, convenience and punctuality. Currently, in view of the high service frequency and high management demand, developing the forewarning system has become an essential way to proactively secure the train operation and guarantee the transport efficiency. The early warning of HSR operation has been extensively explored in the literature. Risk factors of HSR accidents usually come from railway infrastructure, train equipment, operation management and external environmental conditions (Goverde and Meng, 2011; Li et al., 2018). The infrastructure failure, train equipment malfunction and operation error are usually unexpected and are uncertain with emergency responses (Fan et al., 2015; Ouyang et al., 2010), while the escalation of environmental conditions can be predictable under the real-time monitoring. Meanwhile, adverse weather conditions such as wind gust and heavy rainfall have strong effects on high-speed train operation according to the aerodynamic analysis (Baker, 2010; Shao et al., 2011; Du and Ni, 2016), and relevant possibility of derailment is higher. Xia et al. (2013) also found that the train arrival punctuality and cancellation rate become worse under bad weather conditions. Therefore, it is necessary to establish an effective forewarning method to guide the HSR operation under bad weather.

Forewarning methods such as the decision tree algorithm, Bayesian training network and support vector machine (SVM) algorithm are frequently used in training datasets and predicting the impacts of occurring event, based on the data of high nonlinearity and dynamicity (Castillo et al., 2016; Jiang et al., 2017; Annelies et al., 2018; Yan et al., 2018). In addition, An et al. (2016) applied fuzzy analytical hierarchy process (AHP) approaches in the railway risk decision making process. Hu et al. (2018) constructed a rough measurement model to describe the safety of high-speed train operation. However, when faced with the forewarning of train operation under adverse weather conditions, some algorithms will have limitations. To our best knowledge, the decision tree algorithm is unable to distinguish the noisy datasets from valid datasets (Oates and Jensen, 1997). The SVM is a learning method for small sample data (Yang et al., 2018), and it is hard to deal with complex multi-dimensional data of weather conditions. Meanwhile, the Bayesian network model requires that the data obey a Gaussian distribution (Xie et al., 2017), which doesn't meet the abrupt changes of meteorological indicators such as rain intensity and wind speed, meanwhile prediction failure occurs when a real-time data is outside of the original training set.

On the basis of above mentioned limitations, this study presents a hybrid algorithm of fuzzy theory and rough sets theory, composed of fuzzy c-means (FCM) clustering, fuzzy distribution fitting, attribute reduction, rough rules extraction and Max-Min compound arithmetic. This combined method was designed with advantages of mitigating the influence of noisy data for efficient forecasting, due to the correlation between indicators. This algorithm has been applied to an HSR section (shown in Figure 1) of Shanghai Railway Bureau in China, based on the historical monitoring data of meteorological conditions and operation records.

Figure 1: The railroad section of Beijing-Shanghai HSR

The remainder of this paper is structured as follows. Section 2 first outlines the algorithm framework; Section 3 describes the details of models in fuzzy theory and rough sets theory. Following this, Section 4 performs a case analysis using real monitoring data under adverse weather, where the results are fully discussed. Eventually, Section 5 reaches some conclusions and makes suggestions for future work and research aspects.

2 Algorithm design

In China, current forewarning system for train operation under adverse weather is designed according to the *Regulations on Railway Technical Management* and the *Detailed Rules on Organization of Train Operation*, where speed limits have been regulated for train operation under windy weather and rainy weather seperately, as shown in Table 1. Since the speed limits for wind speed are inconsistent with the hourly rainfall, we found difficulties in train dispatching when faced with complex weather conditions, especially the wind-driven rain.

Table 1: Speed-limit standards under windy weather and rainy weather

Wind Speed (m/s)	Top Speed (km/h)	Rainfall (mm/h)	Top Speed (km/h)
[0, 20]	300	[0, 30]	300
(20, 25]	200	(30, 45]	250
(25, 30]	120	(45, 60]	120
> 30	Stop	> 60	45

Therefore, it is essential to propose a forewarning algorithm to support the decision making of train operation under complex weather conditions. For this purpose, a hybrid algorithm of fuzzy theory and rough sets is then developed, shown in Figure 2.

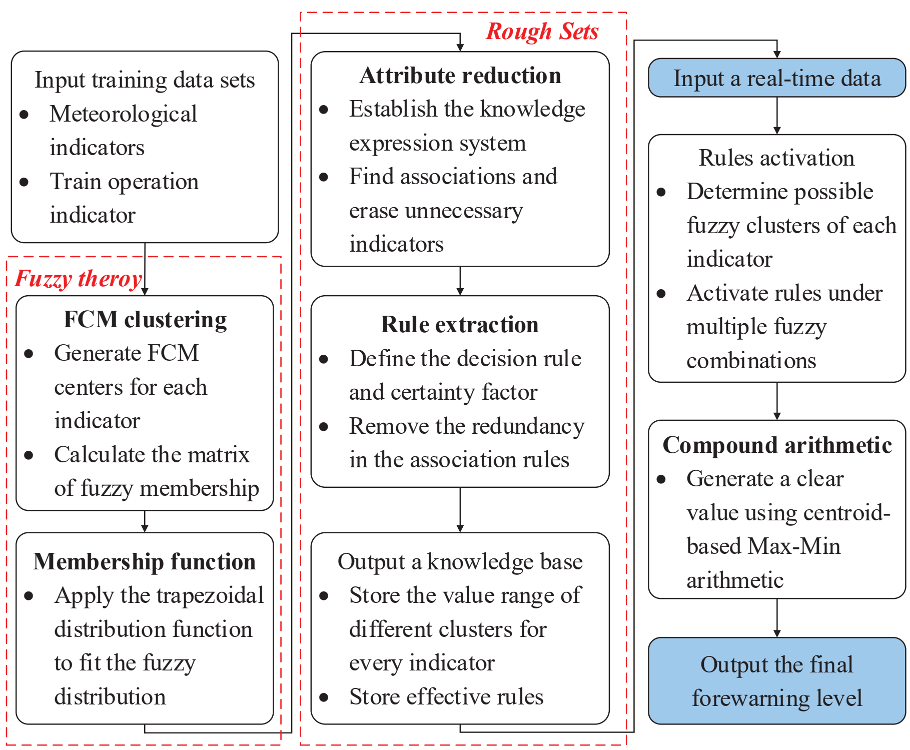


Figure 2: The algorithm process

Five major steps in the algorithm procedure are listed below.

Setp1. FCM clustering. For each indicator (including conditional indicators and decision indicator), several cluster centers and fuzzy membership grades are generated from corresponding original data.

Step2. Membership function fitting. The membership function of each conditional indicator is fitted to the fuzzy membership grades. To simplify the calculation, the trapezoidal distribution function is applied to each cluster level of indicators.

Step3. Attribute reduction. The FCM is an independent fuzzy classification of each indicator, while the attribute reduction can efficiently find out associations and erase unnecessary indicators according to the rough sets theory.

Step4. Rule extraction. This step is a further analysis to remove the redundancy in the association rules, and to reduce the impact of noisy data. Upon introduced certainty factor, effective rules between conditional indicators and the decision indicator are figured out.

Step5. Compound arithmetic. Given a real-time monitoring data of conditional indicators, an intersection set is naturally output from the multiple combinations of fuzzy levels. The centroid-based Max-min compound arithmetic is applied in order to defuzzy the calculation and to get a clear value for judging the forewarning level.

3 The combination of fuzzy theory and rough sets

3.1 Fuzzy theory

Fuzzy c-means clustering

As compared to traditional clustering models like k-means method and density-based methods, the FCM can better accommodate the rough sets theory in discretizing the original datasets and in performing a comprehensive arithmetic based on the value of fuzzy membership. For each indicator, the FCM clustering is performed based on the original data set, which is a column vector. Assuming that n is the number of samples in the original data set, and $P = \{p_1, p_2, \cdots, p_n\}$ is the values set, the problem of FCM clustering can be formulated as:

$$T = \min\{\sum_{j=1}^{K}\sum_{i=1}^{n} v_{ij}^{\alpha} \left\| p_i - m_j \right\|^2\}, \quad \alpha \geq 1 \tag{1}$$

$$s.t. \quad \begin{cases} \sum_{j=1}^{K} v_{ij} = 1 \\ 0 \leq v_{ij} \leq 1 \end{cases}, \quad i = 1, 2, \cdots, n \tag{2}$$

where v_{ij} denotes the probability when the i^{th} sample belongs to the j^{th} clustering center, namely the fuzzy membership, m_j represents the value of the j^{th} clustering center, K is the number of clustering centers, and α is the fuzzy parameter with a positive relation to the fuzziness (Gong et al., 2005). It is important to note that initial centers are random selected from P, and the value of K should consider practical significance.

Fuzzy membership function

According to the coverage of clustering centers, the distribution patterns of membership function include left type, right type and center type, where the triangular function and trapezoidal function are included in the center type distribution, shown in Figure 3. Since the left type and right type distribution are two special cases of the trapezoidal distribution (Botzheim et al., 2001), the center type is selected to fit the fuzzy distribution.

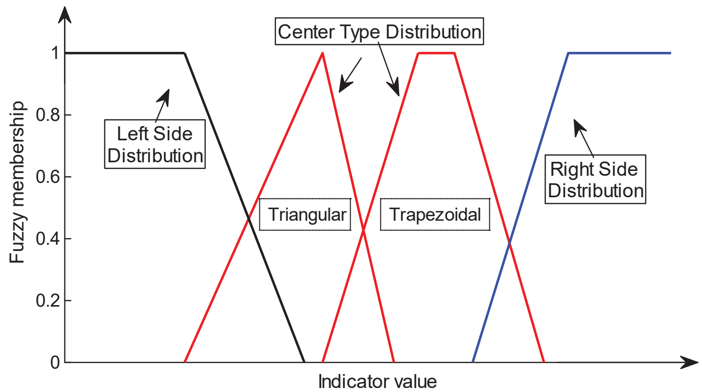


Figure 3: Three typical distribution patterns of membership function

3.2 Rough sets theory

Attribute reduction

The rough sets theory was first proposed by Pawlak (1982), which can be applied in fields of machine learning, knowledge acquisition, decision analysis and process control (Pawlak, 2002). Before attribute reduction, a knowledge expression system (KES) of the rough sets should be established, which is defined as:

$$S = (U, A, V, f) \tag{3}$$

In this equation, U is the set of samples defined as $U = \{x_1, x_2, \cdots, x_n\}$, where x_i is a row vector representing the i^{th} individual sample. A is the set of attributes including conditional indicators (denoted by C) and the decision indicator (denoted by D). V is the set of value ranges of all attribute indicators. f represents the information function. It is noted that every indicator's value of x_i is uniquely determined in V.

Based on the discernible matrix from original decision table, attributes should get reducted to erase the linearity between conditional indicators as much as possible. The decision table is defined by $T = (U, A, C, D)$, and the corresponding discernible matrix is denoted as an $n \times n$ matrix $M(T)$. Any element in $M(T)$ is determined by:

$$c_{ij} = \begin{cases} \left\{ a \,\middle|\, a \in C \;\&\, f(a, x_i) \neq f(a, x_j) \right\}, & (x_i, x_j) \notin ind(D) \\ \phi, & (x_i, x_j) \in ind(D) \end{cases} \tag{4}$$

where c_{ij} represents the set of attributes which can distinguish sample x_i from sample x_j, and ind (D) is the indiscernible set of samples with the same attributes values of D. Obviously, c_{ij} is an empty set when samples x_i and x_j belong to the same indiscernible set.

Rough rules extraction

Rough rules extraction is in a critical position between the attribute reduction and compound arithmetic, aiming to output decision rules from conditional indicators to the decision indicator (Maji and Garai, 2013). For example, if a decision table contains 2 conditional indicators and 1 decision indicator, assuming every indicator has 3 clustering levels, then there are 27 decision rules in an exhaustive way, while the number of rules will get significantly reduced by the rules extraction considering the certainty of each rule.

During rules extraction, the decision rule is defined as:

$$r_{ij}: des(C_i) \rightarrow des(D_j), C_i \cap D_j \neq \phi \tag{5}$$

$$des(C_i) = \{(a, V_a) | f(x,a) = v_a, \forall a \in C\} \tag{6}$$

$$des(D_j) = \{(a, V_a) | f(x,a) = v_a, \forall a \in D\} \tag{7}$$

Also, the corresponding certainty factor of rule r_{ij} is therefore determined by:

$$\mu_{ij} = \frac{card\{D_j \cap C_i\}}{card\{C_i\}}, \quad C_i \cap D_j \neq \phi \tag{8}$$

where μ_{ij} denotes the certainty factor, ranging from 0 to 1. Rule r_{ij} is a certain decision rule when μ_{ij} is 1, otherwise it is uncertain. Decision rules with high certainty are output into a knowledge base to improve the calculation efficiency of subsequent work.

3.3 Compound arithmetic

Given a real time monitoring data, values of conditional indicators correspond to different levels and will activate different rough rules in the knowledge base. The compound arithmetic is a centroid-based Max-Min arithmetic (Wang, 2009) used to forecast a clear value of decision indicator under different rough rules activated by the same sample data of conditional indicators. The basic function centroid-based Max-Min arithmetic is:

$$x^* = \frac{\sum_{i=1}^{P} \int_{U_x^i} x \cdot v_D(x) \mathrm{d}x}{\sum_{i=1}^{P} \int_{U_x^i} v_D(x) \mathrm{d}x} \tag{9}$$

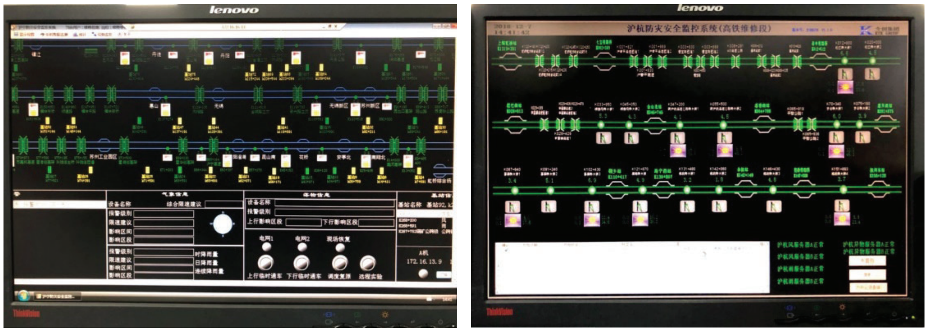
$$\{U_x^i\} = \max\{\min[v_{C1}(x), v_{C2}(x), \cdots, v_{Ck}(x), v_D(x)]\} \tag{10}$$

where x^* denotes the clear value of the decision indicator, $v_D(x)$ is the fuzzy distribution function of the decision indicator, $v_{Ci}(x)$ is the fuzzy distribution function of the i^{th} conditional indicator, U_x^i represents the domain set activated by the i^{th} rough rule, and P is the number of activated rough rules under current sample data.

4 The Case Analysis

4.1 Data collection

The original monitoring data of weather conditions and train operation under adverse weather conditions of an HSR section (see Figure 1) are provided by the Shanghai Railway Bureau in China. As shown in Figure 4, rainfall indicators and wind indicators are two key targets in current safety monitoring system of HSR. With the help of this system, continuous monitoring data of meteorological indicators are easily associated with train operation records under adverse weather conditions. The date of collected data is 10$^{\text{th}}$ June, 2017, a day during stormy weather.



(a) Monitoring rainfall indicators (b) Monitoring wind indicators

Figure 4: The disaster prevention and safety monitoring system of HSR

The meteorological indicators function as the conditional indicators, including wind speed (WS), wind direction (WD), rainfall intensity (RI), hourly rainfall (HR), daily rainfall (DR) and continuous rainfall (CR). The actual deceleration rate (AD) functions as the decision indicator to determine the level of early warning. The training data of 297 valid samples under bad weather have been studied, as shown in Table 2.

Table 2: Original sample data of HSR operation under adverse weather conditions

A	**Conditional indicators**						**Decision indicator**
	C_1	C_2	C_3	C_4	C_5	C_6	D_1
n	WS (m/s)	WD [0,180°]	RI (mm)	HR (mm/h)	DR (mm/day)	CR (mm)	AD (m/s^2)
1	12.1	46.4	0.0	0.0	0.3	0.3	0.11
2	12.8	39.4	0.0	0.0	0.3	0.3	0.14
3	13.6	40.7	0.0	0.0	0.3	0.3	0.17
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
175	15.3	88.1	25.5	53.0	44.1	150.9	0.97
176	15.6	88.0	25.4	52.4	44.3	151.2	1.17
177	15.8	87.0	22.5	51.9	44.5	151.4	0.94
178	16.0	93.5	14.5	51.4	44.8	151.6	1.03
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
295	9.7	60.6	0.0	1.0	27.8	155.6	0.08
296	9.6	65.4	0.0	1.0	27.8	155.6	0.00
297	9.4	60.4	0.0	0.9	27.8	155.6	0.03

4.2 Algorithm application

Based on the sample data, FCM is first performed to obtain the fuzzy membership distribution of each indicator, shown in Figure 5. Using the indicator of wind speed as an example, data of wind speed have been classified into level I, II, III and IV, and the corresponding function curves are plotted by different colors. Similarly, indicators of wind direction, rainfall intensity, hourly rainfall, daily rainfall and continuous rainfall are classified into 3, 4, 5, 3 and 3 levels respectively, where the number of levels are carefully determined to satisfy relevant HSR technical regulations.

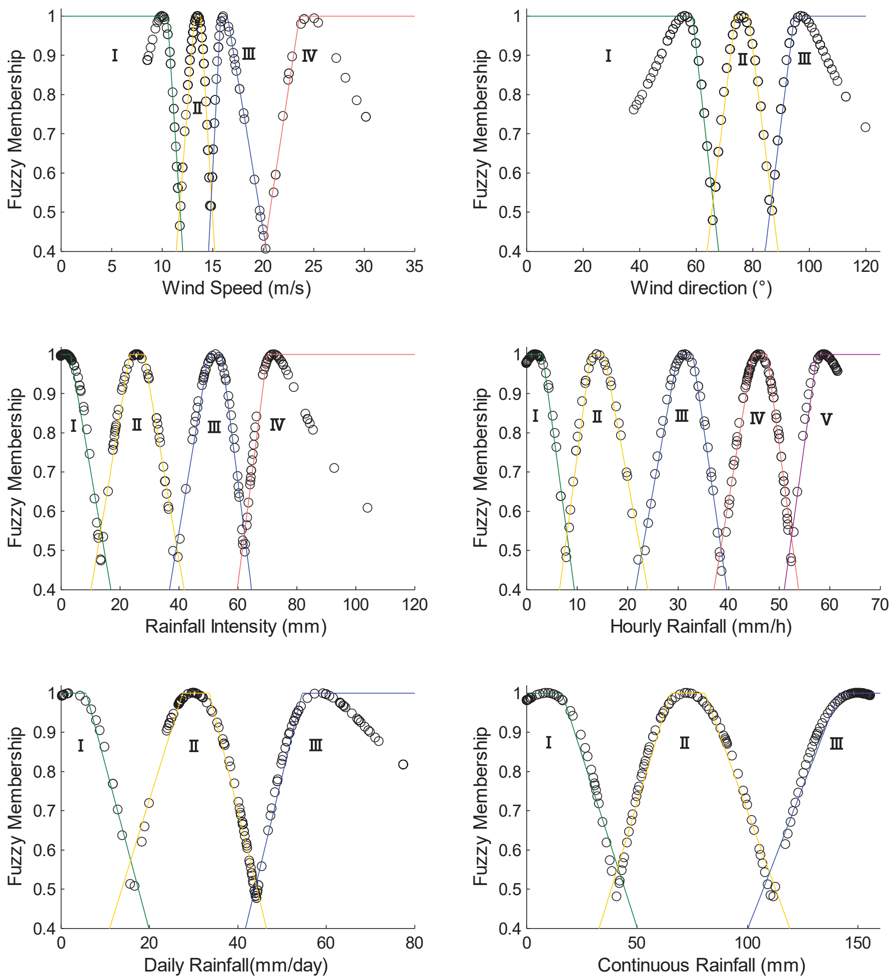


Figure 5: The fuzzy membership distribution of 6 conditional indicators

Based on the results of fuzzy clustering of each indicator, original numeric data of attributes are converted into string type data for the analysis in Rosetta toolkit. Through attribute reduction, the indicator C_6 (CR) is removed from the original data set, and 66 rough rules have been generated. Given a sample data set {21.2, 67.9, 47.5, 52.3, 86.7}, six rough rules are activated, shown in Table 3.

Table 3: Activated rough rules

Activated rules (Inputs → Output)	Fuzzy Membership Grade WS	WD	RI	HR	DR	Min value
III, I, II, IV, III → V	0.271	0.401	0.148	0.548	0.718	0.148
III, II, II, IV, III → I	0.271	0.645	0.148	0.548	0.718	0.148
III, II, III, V, III → V	0.271	0.645	0.883	0.519	0.718	0.271
IV, I, II, V, III → IV	0.591	0.401	0.148	0.519	0.718	0.148
IV, II, II, IV, III → V	0.591	0.645	0.148	0.548	0.718	0.148
IV, II, III, V, III → V	0.591	0.645	0.883	0.519	0.718	0.519

Then the max-min compound arithmetic is applied based on the 6 activated rules. In combination with the fuzzy membership function of deceleration rate, the max-min area is designated by the shaded area, as shown in Figure 6. The clear value of decision indicator DR is 0.994 m/s^2 according to the centroid arithmetic in Equations (9) and (10); the corresponding forewarning level is IV.

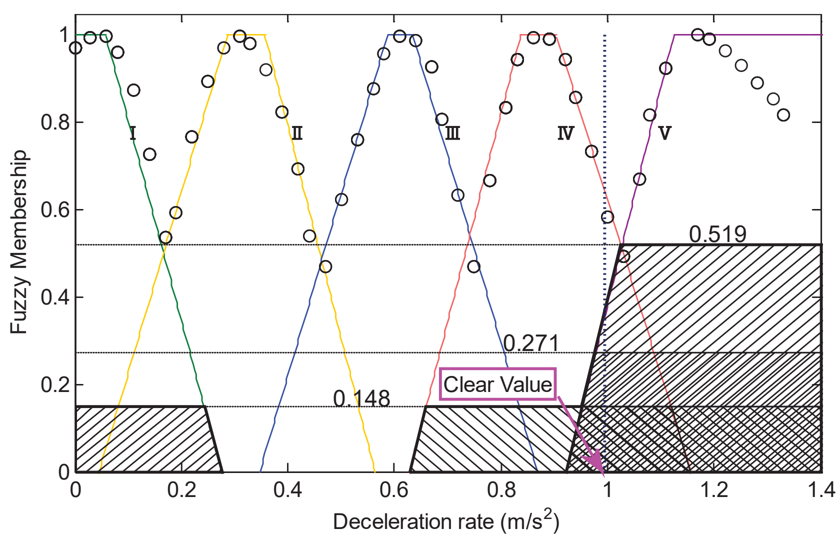


Figure 6: The max-min area of decision indicator DR under 6 activated rough rules

4.3 Discussion

Before evaluating the accuracy of this hybrid algorithm, samples are divided into 2 groups (Group 1 and Group 2) according to the actual deceleration rate. Under current early warning system, the service braking curve is frequently applied to HSR train operation. Based on the braking curves of CRH2 series train (Shangguan et al., 2011) at an initial velocity 300 km/h (see Figure 7), the average deceleration rate under service braking is approximately 0.83 m/s^2. Based on this, Group 1 contains sample data with actual deceleration rates below this average value, and Group 2 contains sample data with deceleration rates above the average value.

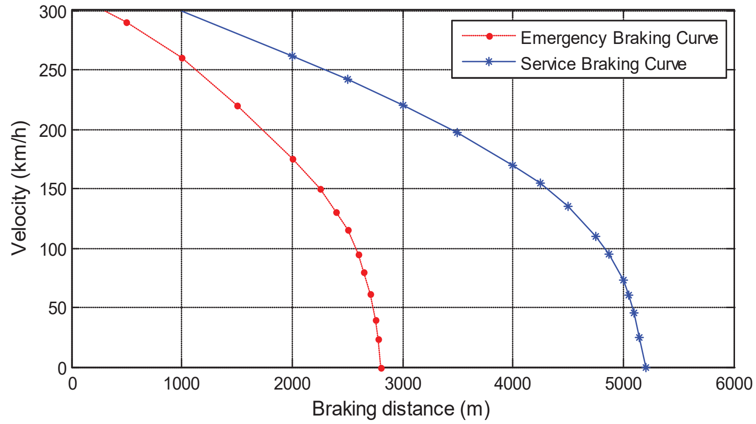


Figure 7: Braking curves of CRH2 series train

The accuracy is defined as the proportion of samples whose forecasting levels are consistent with practical levels. To acquire the accuracy rate, the hybrid forewarning algorithm is applied to all 297 samples, and the results are shown in Table 4.

Table 4: Forewarning accuracy of samples in Group 1 and Group 2

Group	**Number of samples**	**Forewarning accuracy**	**Global accuracy**
Group 1 (AD<0.83)	174	83.33%	86.53%
Group 2 (AD≥0.83)	123	91.06%	

As indicated in Table 4, we have 174 samples in Group 1 with a forewarning accuracy of 83.33%, and 123 samples in Group 2 with a forewarning accuracy 91.06%. Meanwhile, it is obvious that Group 2 has a higher forewarning accuracy as compared to Group1. As we know, the actual deceleration rate is correlated with weather conditions, and the deceleration rate increases with weather conditions getting worse. Since the actual deceleration rates of Group 2 are bigger than Group 1, the weather conditions of samples in Group 2 are worse than Group 1.

Based on the above analysis, the hybrid model seems better suited to data under extremely adverse weather conditions. The phenomenon may be explained the indicator level is sensitive under extremely adverse weather, which is easy to identify by the hybrid algorithm. In general, the global accuracy of all 297 samples is approximately 86.53%.

Meanwhile, the suggested top speed can be obtained by combining the threshold intervals of forewarning levels with the characteristics of the service braking curve, shown in Table 5. In the case study, the final forewarning level is IV, meaning that the corresponding top speed for train operation is suggested to be 200 km/h.

Table 5: Suggested top speed under each forewarning level of DR

Level	**I**	**II**	**III**	**IV**	**V**
Threshold Interval (m/s^2)	[0,0.17)	[0.17,0.46)	[0.46,0.74)	[0.74,1.03)	[1.03, 1.4]
Top Speed (km/h)	300	300	250	200	100

The algorithm is logically divided into parts of offline computation and real-time computation. Basic decision rules get extracted or updated by training and analyzing historical datasets in the offline computation, while the compound arithmetic is operated efficiently in the real-time computation with a little computational load.

5 Conclusions

In this paper, authors contribute to the forewarning method for train operation under adverse weather conditions. It is a combined algorithm of fuzzy clustering and rough sets, where monitoring data of meteorological indicators like wind speed and rain intensity are used for the data training and analysis. Main novelties introduced by this paper are the adoption of combining the fuzzy theory with rough sets theory, characterized by: (a) a fuzzy distribution of original conditional indicators and the decision indicator; (b) a set of reducted indicators after attributes reduction; (c) effective rough rules represented by the level of conditional indicators and the decision indicator; (d) a clear value output by the compound arithmetic under activated rough rules.

The application of this early warning method has indicated the feasibility of decision rules. The global forewarning accuracy is approximately 86.53%, where the accuracy is higher for 123 samples under extremely adverse weather conditions. Nonetheless, due to the difficulty in data collection considering some confidentiality and privacy, the number of valid samples is below our expectation. Given more sample data, the conditional attributes will get fully reducted, and the rough rules will describe the relationship between conditional attributes and decision attributes more precisely, thus the algorithm can guarantee the accuracy of the forewarning level.

Further developments will be focused on the expansion of conditional indicators such as atmospheric pressure and ambient temperature, and additional efforts has to be spent in the modification of reduction algorithm to guarantee the nonlinearity among conditional indicators. Nevertheless, the authors believe that the proposed method can be applied in the revision of corresponding rules and regulations, and the hybrid algorithm can provide basic support for HSR train operation under complex adverse weather conditions.

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