Risk management prediction for overcrowding in railway stations utilising Adaptive Nero Fuzzy Inference System (ANFIS)

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Abstract. In this research, an intelligent system for managing risks is developed with a framework to aid in managing the risks in the railway stations. A method to advance risk management in the railway stations is needed in order to minimize risk through an automated process taking into consideration all the factors in the system and how they work together to provide an acceptable level of safety and security. Thus, the Adaptive Nero Fuzzy Inference System (ANFIS) is proposed to improve risk management as an intelligently selected model which is powerful in dealing with uncertainties in risk variables. The methods of artificial neural network (ANN) and Fuzzy interface system (FIS) have been proven as tools for measuring risks in many fields. In this case study, the railway is selected as a place for managing the risks of overcrowding in the railway stations taking two parameters as input for risk value output using a hybrid model, which has the potency to deal with risk uncertainties and to learn by ANN training processes. The results show that the ANFIS method is more promising in the management of station risks. The framework can be applied for other risks in the station and more for a wide range of other systems. Also, ANFIS has the ability to learn from past risk records for future prediction. Clearly, the risk indexes are essential to reflect the actual condition of the station and they can indicate a high level of risks at the early stage, such as with overcrowding. The dynamic model of risk management can define risk levels and aid the decision makers by convenient and reliable results based on recorded data. Finally, the model can be generalised for other risks.

1. Introduction

In recent years, there has been an increase in demand and usage of railway transportation and therefore the utilisation of railway stations, and this is expected to continue to increase worldwide [1].

The vital mass of traveller flows through stations has become important in terms of both of passenger satisfaction and passenger safety and thus have become major concerns for railway station operators. Managing such passenger flows and overcrowding risks is not an easy task and that is due to the complexity of some station designs and unexpected passenger behaviours.

The effect of this high demand and intensive usage on the old systems will raise the risks of the railway and keep business under pressure from the society and government. Stations are an essential part of the railway system as a point where the passenger starts and ends their journey [2].

Moreover, uncertainty will have an impact on the risk management process. Risk management has many applications in different areas such as financial management, project engineering, military and many business systems, and an operator on the railway stations has to monitor, scan, manage and investigate the factors and to update their plans based on the level of expected hazard to select appropriate plans and strategies for reducing the risks to achieve accepted levels [3].

In this paper, a study of predicting the risk level is performed using China's station data from the literature [4].The suggested prediction model uses (ANFIS) as the method of risk prediction for overcrowding, which affects the quality of the service, perceptions of the risk to personal safety and security for the travellers and might extend to damaging the business image in the worst case scenario. This may subsequently interrupt operation continuity because of the growth of the dwell time [5-9].

2. The ANFIS Model and the framework

Owing to the effective learning and reasoning capabilities of the ANFIS model, it has become more and more attractive and interest of scholars in engineering fields and in numerous scientific fields has been increasing. This model is combined with the power of ANN and explicit knowledge representation of FIS. The ANFIS is able to construct a network realization of IF / THEN rules and one of the earliest projects in ANN in the identification risk literature was carried out by McKim (1993) [10-13]. This was a multilayer feed-forward network that employs an ANN and fuzzy logic system FLS to map inputs into an output (see Figure 1). The model is a FLS integrated into the structure of adaptive ANN [10]. The output is predicted through an adaptive network which is fed forward multi-layers of ANN with adaptive nodes, and learning rules specify the parameters of the adaptive node and the adjustment of the parameter due to error value [14-17].

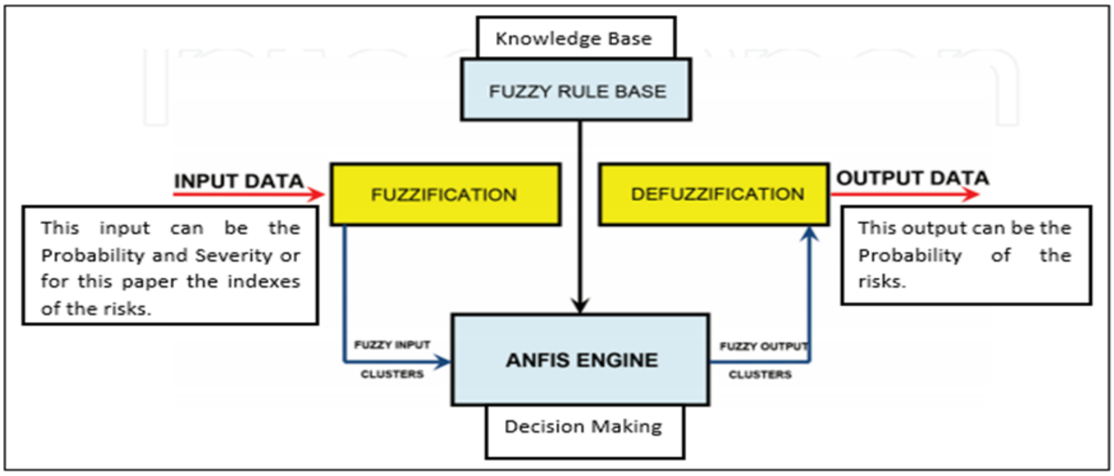

Figure 1. Proposed Fuzzy logic inference system for risk management in railway stations.

3. Data of Overcrowding and Risk Management Methodology

The suggested intelligent prediction model is designed based on on-hand data from digital sources which can gather the data in real time. The selected actual data from the literature has been collected from GuoMao station of Beijing metro in China during the peak hours. It proposed a risk scale which has been used in stating the level of probability of risks in the form of a 4-choice scale of (very unlikely, unlikely, likely, very likely). The case of risk selected is congestion in the station and that will be evaluated utilizing the indexes. It is suggested here that the risk of congestion be divided into many different levels, that will fluctuate between levels of the index effect. If the number of the warning levels is not clearly high or low, each group may cover a wide range, leading to an unreliable level of managing risks and an inaccurate response for the real conditions. Due to its importance, the level of risk should be classified into four levels with diverse colours for an active mention, assuming that the probability of risks is in the form of a 4-choice scale of (very unlikely, unlikely, likely, very likely). As well as data related to ratios (stranded) and transfers of efficiency in the station, the feature dimensions of the inputs need to be converted to be based on the probability of risks level in the form that been suggested. The correlation matrix and the patterns and colours of the risk level are noted in Table 1 and 2. Some scale has been done to keep the same range of values for each of the inputs to the model.

Table 1. The scale of the level of risk probability.

Result	Description (Retention rate of the platform)	Description (Transfer efficiency)	Risk Levels Indexes
very unlikely	Full capacity and have chance to ride without being stranded	Passengers can move easily	D
Unlikely	A few stand and wait for the next train	A few lines before the lift and stairs	C
likely	Some are waiting for the next train	Some lines before the lift and stairs	B
very likely	Highly crowded and no chance to ride	Very slow movement	A

Table 2. The risk matrix for two indexes.

		Index 1				Index 2			
		A	B	C	D	A	B	C	D
Index 1	A								
	B								
	C								
	D								
Index 2	A								
	B								
	C								
	D								

The data has been extracted from Beijing's GuoMao metro station which has a limited amount of data but selected two input parameters [4], namely retention rate index, transfer efficiency index η_T as input for predicting overcrowding risk levels in the station (see Table 3).

Table 3. The data from the station with the risk value.

Stranded ratio % η_R	Risk level 1	Transfer efficiency η_T	Transfer efficiency %	Risk level 2	Overall risk	MAX (Risk) %	Risk value %
11	C	1.45	36	C	CC	36	22.96
13	C	1.28	32	C	CC	32	24.47
7	C	1.28	32	C	CC	32	13.89
0	D	1.28	32	C	DC	32	0.00
19	B	1.55	39	C	BC	39	44.39
7	C	1.55	39	C	CC	39	16.64
12	C	1.55	39	C	CC	39	27.21
10	C	1.67	42	B	CB	42	25.81
14	C	1.67	42	B	CB	42	34.62
20	B	1.67	42	B	BB	42	50.00
13	C	1.22	31	D	CD	31	22.97
14	C	1.22	31	D	CD	31	25.32
11	C	1.22	31	D	CD	31	20.44
17	B	1.47	37	C	BC	37	37.53
17	B	1.47	37	C	BC	37	38.12
0	D	1.47	37	C	DC	37	0.00
18	B	1.61	40	C	BC	40	43.93
16	B	1.61	40	C	BC	40	39.04
5	C	1.61	40	C	CC	40	11.61
9	C	1.26	32	D	CD	32	16.59
9	C	1.26	32	D	CD	32	16.02
0	D	1.26	32	D	DD	32	0.00
3	C	1.21	30	D	CD	30	5.33
4	C	1.21	30	D	CD	30	7.04
4	C	1.21	30	D	CD	30	6.36

To use the ANIFS for managing the risk in the station, existing data from the China metro relating to the risk of overcrowding are used for training the model which sets the parameters of the system. A section of these data for training the system will be used and the remaining will be used for testing the model. The retention rate index η_R aims at capturing the number of passengers who are stranded on the platform for the next train because they did not have space on the arriving train. The transfer efficiency index in the station is essential to the index to present the station statistics, and this index depends on time and distance transfer. It can be concluded from the literature that computing the index in the station channel location is affected by the amount of equipment in the channel, such as stairs and escalators, walking velocity between the equipment and the distance between different equipment. The area size of platforms leads to computing the number of passengers who are able to wait and then sets up the level of risk. Some factors such as human factors, standards and passenger belongings are factors that must also be considered [18-22].

4. The result

The ANFIS output which is the risk level of the overcrowding can be predicted. In addition, the graph of training error has been presented in Figure 2. The model has been set up to train the steps in 300 epochs and with the addition of a number of epochs, errors diminish, and error fluctuations reach a steady state. Clearly, the small amount of training data is a significant performance variable but the benefit is that the intended ANFIS example does not require time-consuming iterative training and testing.

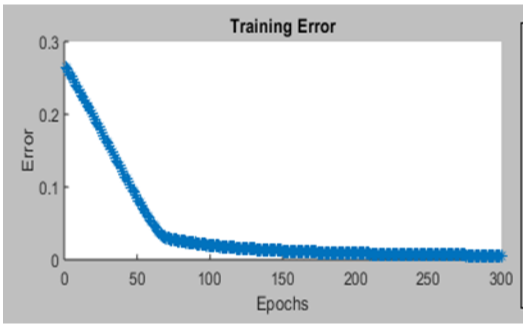

Figure 2. Trend of errors of trained fuzzy system

Moreover, the surface plot shows that the 3-D surface is hard to evaluate and the two indexes have a significant impact on the expected overcrowding (see Figure 3). In general, it can be inferred that with the 3-D diagram there is an increase in index probability, and the risk level increases, which is a logical conclusion. For other risk indexes of the railway station, this procedure could be used.

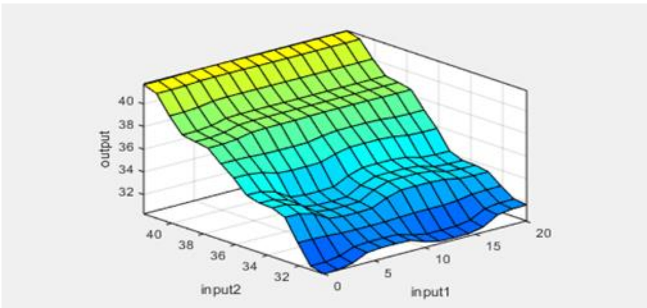

Figure 3. The 3-D surface of the rule based system adapted for the data with MFs = 16 mf Type = gaussmf epoch_n = 300.

5. Conclusions

In this paper, the selected model seems to be powerful for predicting the risks and aiding the decision-making for risk management in the case of overcrowding in railway stations. The proposed new method of railway station risk management model using ANIFS can deal with risk data index and information in real-time. It is shown that the ANFIS appears to be more reasonable and appropriate because of its smoothness in calculating the risk levels. This dynamic model of risk management can define risk levels and aid the decision makers by producing convenient and reliable results based on real time data. In practice, the prediction ANFIS model can be a decision smart support system for managing risks which that can be captured through indicators or indexes to create rules depending on the inputs. The model has the flexibility to create a greater amount of input for future research and this is considered to be not such an easy task.

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