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Analysis of fault response strategies of Fully Automatic Operation System based on quantitative Resilience Assessment

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The Fully Automatic Operation(FAO) system is the development direction of the current urban rail transit system, but the system changes and manual handling under the failure scenario will have an important impact on the capacity performance of the FAO system. The concept of resilience is introduced to analyse the capacity change of the FAO system after artificial intervention and failure impact. This paper proposes a quantitative assessment method for the resilience of the FAO system. This method is based on the function of the FAO system and combined with the complex network model. The shortest path length of the network model index is used to quantitatively express the resilience of the FAO system. Based on this method, this paper makes a quantitative resilience assessment of the telecommunication failure of the FAO system, and puts forward the improvement direction of the system function and the key links manual disposal that need to be paid attention to according to the verification results.

Keywords: Fully Automatic Operation(FAO), Resilience, Quantitative, Failure Response, Complex Network..

1. Introduction

Fully Automatic Operation (FAO) has become the development trend of rail transportation worldwide (Singh et al., 2021). Studies on the quality of service of FAO lines have shown that FAO systems have obvious advantages in normal operation scenarios. However, once disturbed by faults, they are vulnerable to affect their operational efficiency, which even cause safety accidents. For example, in February of 2023, a signal equipment failure occurred on the Pujiang line in Shanghai, China, which result in a full-line shutdown. The failure was not removed after more than 2 hours of disposal. It can be seen that many FAO system failures require manual intervention to complete the emergency disposal. As such, the formulation of the failure disposal strategy is a decisive factor affecting the operation stability and service reliability of FAO lines.

The analysis and optimization of emergency response strategies has always been a hot topic in safety science. Quite a number of different models and methods have been selected for different analysis purposes by researchers. Some studies focused on the validity of emergency disposal strategies, introduced temporal logic and formal models, and applied model checking methods to check the logical vulnerabilities of emergency disposal strategies (El Koursi & INRETS-CRESTA, 1992; Guo & Yan, 2022; Wang et al., 2011). For example, Li proposed a Petri net-based approach to model and analysed the time and resource issues of the subway fire emergency response process. This method can be effectively used to simulate and train emergency response plans to detect potential conflicts in time, sequence, and resources, which can improve the reliability and effectiveness of emergency response plans (Li et al., 2016). In addition, many studies have focused on the efficiency evaluation and optimization of emergency response strategies. They selected or defined efficiency metrics for specific engineering problems, and comparing the efficiency advantages and disadvantages of different strategies through discrete time simulation models. Hajjarsarae selected the metrics of both patient waiting time and residence time to optimize the fast-track disposal strategy of emergency department in the medical system under different scenarios. In the process of analysis, the discrete event simulation model is used to compare the fast track strategy metrics under different scenarios to achieve the improvement of the strategy (Hajjarsaraei et al., 2018). Rebeeh proposed a response strategy optimization method by evaluating emergency response management system based on the metrics. He integrated the location hazard metrics and response time in the emergency response (Rebeeh et al., 2019). Sun has established an evaluation system of comprehensive capacity of multiple metrics for the four stages of subway emergency management. She used AHP and fuzzy mathematics to evaluate the response strategy to achieve rapid response (Nannan, 2010).

The selection of failure disposal strategy of the FAO system may affect the further propagation and manifestation of the failure, which will affect the degree of traffic backlog and transportation recovery time. If only the results metrics such as punctuality rate or delay time are used, the details of the disposal process will be covered up, which is not conducive to the analysis and optimization of the disposal strategy. This paper introduced the concept of resilience to represent the dynamic change of failure impact in the process of failure disposal. Meanwhile, a complex network model of failure disposal process is established for quantitative calculation of the resilience of the FAO system. Through the analysis of typical signal failure cases, the improvement direction of system function and the key links for manual handling are discussed. The rest of this paper is organized as follows: Section 2 reviews the relevant papers in the field of resilience and rail transit. the differences between this paper and the previous study on resilience are pointed out; In section 3, the complex network framework model and the resilience calculation method based on the complex network model are proposed; Section 4 we illustrate the typical rail transit signal failure cases in the real world with the actual line as the background. The result has been discussed. Section 5 concludes this paper.

2. Literature review

Resilience is system ability that is a both multifaceted and multidimensional concept (Ponomarov & Holcomb, 2009). The study of resilience covers a relatively wide range of fields, from physical properties and organizational management to engineering applications, which has led to the birth of a large resilience literature. The concept of resilience was first proposed by Holling in the field of ecology, whose studies is widely recognized (Holling, 1973).

2.1. *Definition and Application of Engineering System Resilience*

The engineering domain defines engineering resilience as the sum of passive survival rate (reliability) and proactive survival rate (restoration) of a system (Youn et al., 2011), which is the inherent ability of a system to adjust its functionality when changes are generated by perturbations or other unexpected event disturbances. Resilience analysis methods provide a solution for quantitative evaluation of system performance loss (Francis & Bekera, 2014). The concept of engineering resilience provides a new way of thinking for analsis the early stages of management system complexity, extending the system to enhance its adaptive capacity, and quickly disposing of the recovery system (Woods, 2015).

In the study of practical engineering problems, a part of researchers uses resilience to investigate the performance of different complexity systems after a disruption to give recommendations for system management. Baroud introduced cost metrics and used functions to measure the performance of infrastructure network systems under potential disruptions (Baroud et al., 2015). Johnsen qualitatively assessed the resilience of smart grid architectures in urban environments and four topology types were compared. Based on this, the impact of each grid topology on the suitability of ICT components in the communication topology was considered (Eder-Neuhauser et al., 2016).

In addition, a part of researchers studied system adaptive capacity. They use resilience to quantify the change in the ability of a system to overcome a failure event after extending (Tukamuhabwa et al., 2015). For example, in a transportation environment, it is viewed as the variation in the number of routes available between the origin and destination; when a given disruption event occurs, it is viewed as the change in the probability of the system to maintain normal operation (Faturechi & Miller-Hooks, 2014).

Another part of researchers is interested in the system recovery process, where the recovery of engineering systems involves different biological, social and technological dimensions. They use resilience to analyse the conditions under which the system is able to maintain its ability to operate better. Zhang studied the recovery strategies based on resilience for different costs after station outages of subway lines (Zhang et al., 2018). Bruyelle et al. provide a discussion of the resilience changes in the recovery process in a subway terrorist attack from the passenger and vehicle perspective (Bruyelle et al., 2014).

Resilience analysis has gradually become an important tool for in-depth investigation of the system recovery process, especially for system disposal recovery strategy analysis is of irreplaceable significance.

2.2. *Complex Network in Resilience*

Complex network is one of the important ways to measure resilience. Since infrastructure networks have non-regular topological characteristics, elements are neither regular nor completely purely random (Gasser et al., 2021), such as communication networks, power networks, computer networks, and transportation networks. Therefore, complex networks are a possible method used to analyse this type of problem. In power domain research (Bose et al., 2020), the function of power networks is vulnerable to dynamic and diverse disruptions. Resilience is used to evaluate the structure, topology and constructive behaviour of transmission networks. Then vulnerability is assessed by analysing the meshing and network performance in the topology through resilience framework. In the rail transportation domain research, a metro network can be mapped into a topological graph. For this reason, the resilience is expressed by quantitatively evaluating the connectivity efficiency performance of the topology. However, resilience is described only in terms of physical structure, which cannot reflect the internal variation of system equipment. Therefore, this paper provides a solution for studying the internal variation of system functions using complex networks to quantitatively assess the resilience of the failure disposal recovery process.

People use engineering resilience can not only understand the process of system rebounding from a destructive event, but analyse the changes in system performance with different factors as well. In this paper, we use resilience to evaluate the failure disposal strategy of FAO systems. Since the interaction between human and machine is involved in the failure disposal recovery process, this paper unifies the relationship between different objects in the process through complex networks and gives suggestions to enhance the disposal strategy from different perspective to fill the gap in resilience-related research in rail transportation.

3. Methodology

In this study, we first model the system function under normal state (scenario) with complex network model. In order to model the complex network under failure scenario, we analyse the impact of failure and failure disposal process on the system function. Finally, we select the system metrics reflecting the change of passage efficiency to show the system performance loss, which is combine with the complex network model for quantitative calculation of resilience.

3.1. *Complex network models based on system functions*

The rail system achieves its basic function by transporting passengers to different stations through the trains: to undertake urban transportation tasks and to meet the travel needs of the population. While individual trains can only serve the needs of a specific area at a specific time, the multiple trains in the network contributes to overall system's functions to realize.

Scenario-based definition of system functions is a common approach, by which the functions of a single train can be described. A single train achieves its daily operation tasks by sequentially completing a series of prescribed scenarios, which are repetitions and combinations of normal scenarios. On this basis, the system function is realized by the repetitive completion of the above process by multiple trains in the line network within the same time period. The system function is expressed as the sum of the functions of the operating trains in the line.

In the analysis of system performance under failure and failure disposal processes, the use of scenarios as the minimum model unit does not provide a good analysis of system intrinsic device state changes. According to FAO's scenario file definition, the implementation of the scenario function relies on each different device to provide functions that are expressed as different processes. For example, in the inbound stopping scenario, ZC generates the movement authorization to meet the inbound stopping conditions, CI checks the equipment protection position, train outputs the traction brake, and platform doors complete the established opening action. The various functions provided by the FAO ground equipment and the on-board equipment are jointly coupled to complete the scenario function, so the modeling of the system function is completed on the basis of the scenario combined with the equipment function. The whole system function presents network characteristics. Obviously, the complex network modeling method can be used to complete the modeling of FAO system function. The scenario-system relationship is shown in Fig. 1.

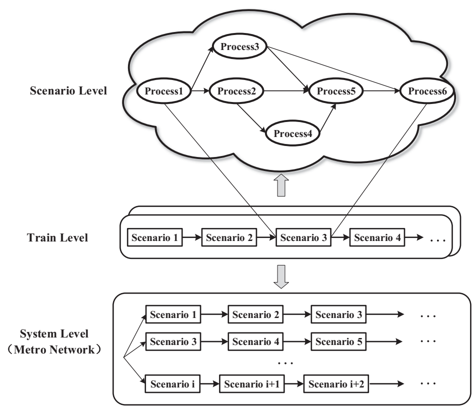


Fig. 1 Scenario and function hierarchy diagram

Due to the fully automatic characteristic, each equipment function implementation has its own fixed time limit as a way to ensure that the train completes the scenario and provides service to passengers at the specified time. Thus the whole system function is realized to guarantee the capacity of the line network. The complex network of the FAO system is defined according to the above relationships as follows.

Definition 1(Functional network). The functions provided by the equipment in the FAO system are abstracted as network nodes. The information flow transmitted between the functions is the network connected edges. There is a certain directionality between the nodes, whose weights represent the time cost of state transfer. So the functional network defined in this study is a complex directed weighted network, which can be expressed by $G(V,E)$. V is the set of nodes, E is the set of directed edges, and the weights are represented by w. The connectivity of nodes in a functional network can be represented by a adjacent matrix A.

Definition 2(Functional path). A functional path is a reachable path between specified nodes in a functional network. According to the definition 1, a functional path represents the functions that a train implemented in the corresponding scenario. The path sequence which can be expressed as $Path_{(O,D)}$ changes with time from the starting node V_O to the end node set V_D.

Definition 3(Functional path length). The reachability m_v of node V_i to V_j in the functional network G is represented by the following Eq.(1).

$$m_{ij} = \begin{cases} 0,\left(v_i \to v_j\right) & unreachable \\ w_{ij},\left(v_i \to v_j\right) & reachable \end{cases} ,v_i,v_j \in V \qquad (1)$$

According to the definition of functional paths, then the functional path length is expressed as the sum of path weights of functional path, which is defined as shown in Eq.(2).

$$d_{Path(O,D)} = W_{(O,D)} = \sum_{v_i,v_j \in Path(O,D)} m_{ij} \qquad (2)$$

$d_{Path(O,D)}$ is called functional path length.

3.2. *Complex network model of system function under failure and failure disposal process*

In a normal scenario, the equipment in the line is in a normal state to provide functional support for line operation. The train completes the specified functions in this scenario. While in a failure scenario, the equipment is in a failure state so that it loses or partially loses the ability to provide functions. The trains cannot complete the specified functions and the system capacity is reduced. Correspondingly, the operation service cannot be fulfilled on time.

To avoid continuous performance degradation, operations personnel manually intervene to dispose of failure. During the failure disposal process, some system functions are replaced by manual, which facilitate rapid recovery of operations. As the failure disposal progresses, the train gradually resumes to complete the prescribed functions, so that the line operation performance recovery. The line returns to the normal scenario.

The complex network of system functions under failure scenarios reflects the process of system performance changes. The impact of failure events in this scenario is often not limited to the failure, but may have an impact on the function and capacity of other equipment in the line, which will manifest in the form of different degrees of late train service. Generally speaking, train delays can be divided into two categories according to the form and source: one is caused directly by external factors, such as on-board equipment failure, ground equipment failure and manual operation adjustment. One category is the late train caused by the previous car. Rail transportation, because of its one-dimensional radial speciality, makes the train can only carry out one-dimensional movement on the track. Once a long time forced stop occurs in the front car, the rear car also cannot pass the failure section, causing the train to be late. Therefore, the system functional complex network model has two kinds of transformation relations in normal scenario and failure scenario.

The first type of delay is caused by external factors. In the process of performance recovery, the system restores the system performance by downgrading or manual intervention. Thus, the original functional path in the system functional complex network is replaced, which lead to that the network structure is changed and a new functional path is formed.

The second type of late caused by the previous train usually does not need to be disposed of. The train function will restore until waiting for the failure of the previous train to be lifted or performance recovery. In such a situation, the node weights in the system functional complex network change.

Signal failures in general do not affect the full operating cycle of the train. The impact is limited to multiple scenarios related to the function of the equipment, while other scenarios are not affected by the failure. For example, a platform door failure affects the inbound and outbound scenarios of a train at that station. In order to facilitate the analysis and research of the system function changes during the failure time and simplify the system function complex network model, the scenes within the impact range of the failure are used to build the system function complex network model. Other unaffected trains and scenes are no longer described as research objects.

As previously mentioned, on the basis of Definition 1, Definition 2 and Definition 3, the functional network as well as the functional paths are further described in detail to facilitate the study of the complex network model under failure, which is defined as follows.

V_O is the network initial node, which is the functional path starting point for all affected trains in the failure scenario as well as in the disposal process.

$V_D = \left\{V_{D1}^t, V_{D2}^t, \ldots, V_{Di}^t\right\}$ is the set of network termination node, which represents the function being completed of the system at time t. It is the end of the functional path of all trains affected by the failure at time t.

V_K^i is the rest of the network node, which represents the function completed of the system by train *i*.

The diagram of the complex network model of the system function in the failure scenario is shown in Fig. 2.

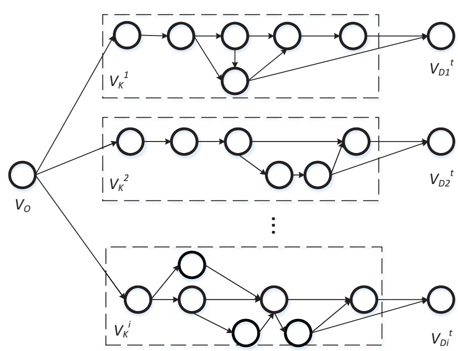


Fig. 2 System function complex network model

3.3. *Resilience calculation*

According to the comparison of the complex network model between normal and failure scenarios in the previous section, it can be found that the decline in system capacity caused by failure is due to the fact that trains in failure scenarios take more time to achieve the corresponding functions than in normal scenarios. When the number of affected trains gradually increases, the deterioration of line network capacity becomes more obvious. This metric which represents time spent during train complete scenario function is a reflection of the system's ability difference to provide service to passengers in fully automatic mode versus failure mode.

In this study, time variables are introduced to describe the network performance at different periods using an event-driven approach. Define the network state at time t as $C(t)$. The network performance of the train i at the state $C(t)$ is denoted as $f(t,s_i)$, and the expression is calculated as shown in Eq.(3).

$$f(t,s_i) = d_{Path^{\,t}_{(O,\,Di)}} \tag{3}$$

After the equipment failure, the train realizes the scenario function in a longer time cost. The system metric is calculated as the sum of the deviation of time to achieve the function in the certain scenario of all trains (Eq.(4) and Eq.(5)). The system resilience is calculated as shown in Eq.(6).

$$\Delta f(t,s_i)=\begin{cases} f(t,s_i)-f_0(s_i) & (f(t,s_i)-f_0(s_i))\geq 0 \\ 0 & (f(t,s_i)-f_0(s_i))<0 \end{cases} \tag{4}$$

$$Q(t) = \sum_{i=1}^{m}\Delta f(t,s_i) \tag{5}$$

$$R = \frac{\int_{t_0}^{t_1} Q(t)dt}{t_1 - t_0} \tag{6}$$

Where, $f_0(s_i)$ is the time to achieve the function in the normal scenario of train i. $Q(t)$ is the sum of all train achieving function time deviations at time t. R is the resilience value. In the calculation process, when the function realization time in failure scenario is less than the realization time in the normal scenario, it is considered that the system has not completed the corresponding function at this time. So, $\Delta f(t,s_i)$ takes the value of 0 at this moment.

4. Case study

In this section, we select the common on-board equipment and platform door failure to analyse the impact of failure on FAO system by quantitative resilience assessment method. We verify the feasibility and applicability of the resilience assessment method for failure and failure disposal process. This study uses Pajek and Matlab to calculate and analyse the complex network model and the resilience results respectively.

The line data in this section comes from Yanfang Line. Yanfang Line includes 9 stations, which are numbered as A, B, C, D, E, F, G, H and I for the convenience of modeling use as shown in Fig. 3.

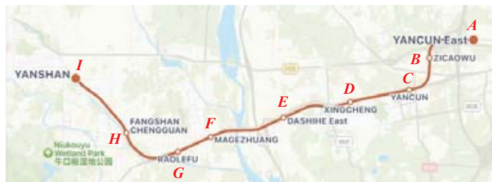


Fig. 3 Diagram of Yanfang Line

The data of the disposal process in the case comes from a drill of the metro operation company. The drill simulates a signal failure during the evening peak period, with a train departure interval of 120s, a train stop time of 30s, and the interval passage time between stations as shown in Table 1.

Table 1 Train passage schedule table

Line interval	Passage time (s)
A-B	120
B-C	120
C-D	180
D-E	180
E-F	180
F-G	120
G-H	180
H-I	120

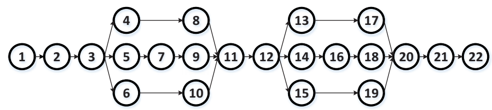
4.1. *case1: On-board equipment failure*

In this case, there was a VOBC both ends ATO failure of train 001. Under the traditional CBTC system, emergency personnel used manual driving to make the failure train run to the end of the line for dropout. For the FAO system, the system can support remote restarting of the equipment and running to the next station for disposal or dropout at a speed limit mode of 25KM/h. Therefore, the emergency personnel restarted the onboard equipment of train 001 after the failure, while train 002, which entered the E-F station interval, was forced to stop the interval because it did not have access conditions. The train at station E was detained and stopped according to the disposal principle. Subsequent train 003, 004 and 005 could not pass the station E forced to stop in the interval. The sequence of events for the process is shown in Table 2.

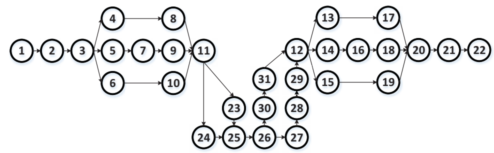
Table 2 On-board failure event sequence table

Time	Event
17:49:00	All trains were operating normally on lines.
17:50:00	Train 001 VOBC both ends ATO were failure and Train 001 EB.
17:50:10	Operation1: Dispatcher noticed alarm and operating status of train 001. Operation2: Dispatcher confirmed failure.
17:50:30	Operation3: Dispatcher remote restarted on-board equipment. Operation4: Dispatcher detained train at station E.
17:53:30	Train 001 signal on-board equipment was successfully restarted and the failure was repaired. Operation5: Dispatcher authorized train to continue operate in RRM mode.
17:54:00	Train 001 entered RRM mode.
17:54:46	Train 001 reached station F. Operation6: Dispatchers resumed train operations at station E.
17:54:56	Train 001 regained position to upgrade to FAM mode.
17:55:06	Trains gradually resumed operation at station E and station F
17:58:00	All trains recovered operate on lines.

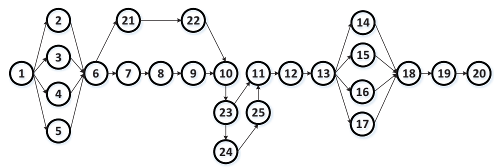
The failure and failure disposal impacts involve the E-F station interval operation scenario as well as the E station inbound scenario and the outbound scenario. In order to establish the scenario complex network model, we reasonably simplified to the scenario. Fig. 4-a shows the system function network diagram under the normal scenario related to on-board VOBC equipment. Fig. 4-b and Fig. 4-c show the system function network diagram under the fault scenario from E station to F station and E station, respectively.



a) Normal complex network model



b) Failure complex network model1



c) Failure complex network model2

Fig. 4 On-board equipment failure complex network model

The resilience assessment results of failure by complex network modeling are shown in Fig. 5.

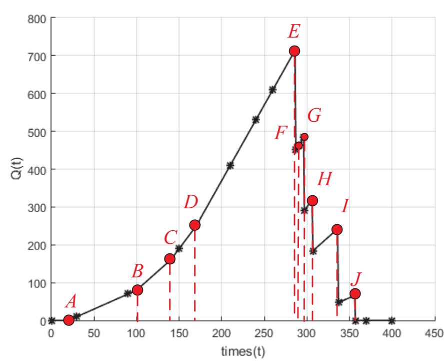


Fig. 5 On-board equipment failure resilience curves

In the figure, A-J represent the key points of the resilience change during the disposal process, where A-D indicate that the perfomance of train 001-004 starts to decline in turn. At point E, train 001 reaches the station F to complete the FAM mode upgrade. The system performance starts to recover so that the resilience curve rebounded significantly. Train 005 starts to experience functional decline at point F because it is far from the failure point. G-J indicate that the performance of train 002- 005 recovers in turn, respectively. According to Eq.(6), the system resilience value is calculated as R=254.91 by using the resilience triangle area. Obviously, the resilience can be seen to recover significantly with manual intervention.

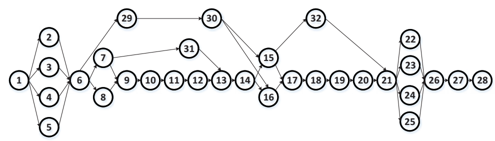
4.2.*case2:Platform door failure*

In this case, there was a platform door failure at station D. Train 001 at station D could not complete the outbound, which forced train 002 entering the interval of station CD to stop in the interval because it did not have access conditions. Emergency personnel detained trains at station C in advance according to the failure disposal principle to avoid deterioration of the failure. Train 003 was therefore detained and stopped, and train 004 entering the interval of station BC was forced to stop in the interval for the reason that it did not have access conditions. As the failure continues to affect, the emergency personnel will detain the train at the upstream station one after another to ensure the emergency personnel's control of the train. The sequence of events for the process is shown in Table 2.

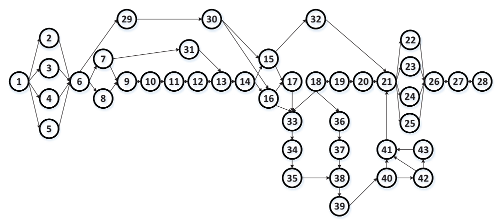
Table 3 Platform failure event sequence table

Time	Event
19:00:00	All trains were operating normally on lines.
19:00:32	Train 001 could not complete the outbound .
19:01:00	Operation1: Dispatcher noticed alarm and operating status of train 001. Operation2: Dispatcher detained train at station B.
19:01:10	Operation3: Dispatcher confirmed failure. Operation4: Dispatcher informed emergency personnel dispose failure.
19:01:20	Operation5: Dispatcher arranged for personnel to board at stations B and C.
19:01:30	Operation6: Emergency personnel disposed failure.
19:02:00	Operation7: Emergency personnel could not close the platform door.
19:02:20	Operation8: Emergency personnel bypassed platform door.
19:02:30	Operation9: Dispatcher resumed train operations at station C.
19:02:40	Trains gradually resume operation at station C and station D.
19:04:30	All trains recover operate on lines.

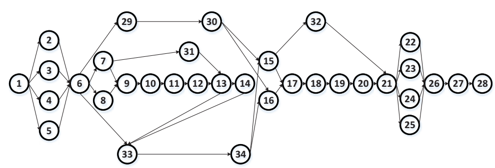
The failure and failure disposal impacts involve the station B, C and D inbound and outbound scenario. In order to establish the scenario complex network model, we reasonably simplified to the scenario. Fig. 6-a shows the system function network diagram under the normal scenario. Fig. 6-b and Fig. 6-c show the system function network diagram under the fault scenario from E station to F station and E station, respectively.



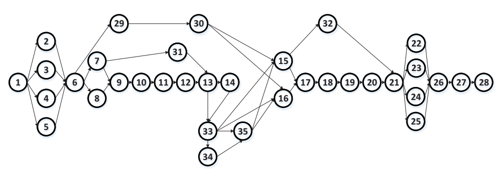
a) Normal complex network model



b) Failure complex network model 1



a) Failure complex network model 2



d) Failure complex network model 3

Fig. 6 Platform door failure complex network model

The resilience assessment results of failure by complex network modeling are shown in Fig. 7.

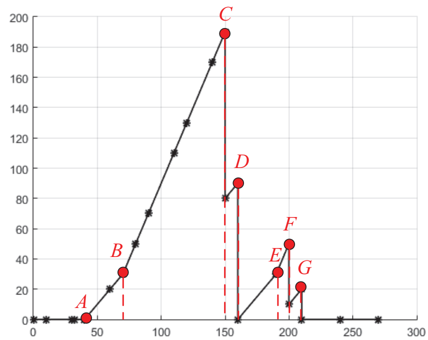


Fig. 7 Platform door failure resilience curves

In the figure, A-G represent the key points of the resilience change during the disposal process, where A-B indicate that the performance of train 001 and 003 starts to decline in turn. At point C, emergency personnel complete the platfom door disposal, then train 001 outbound . The system performance starts to recover so that the resilience curve rebounded significantly. Train 004 starts to experience functional decline at point E because it is far from the failure point. According to Eq.(6), the system resilience value is calculated as R=65.29 by using the resilience triangle area.

5. Discussion

This section takes FAO characteristics as the starting point to discuss the impact of different disposal strategies and different conditions on the disposal effect.

5.1. *Analysis of the effectiveness of the FAO remote function for disposal*

The FAO system provides remote function for emergency personnel to deal with failure, but emergency personnel can also dispose by manual takeover based on traditional processes. Taking case 1 as an example, we analyse and evaluate the resilience under different strategies separately.

- Strategy 1: The dispatcher uses remote function to restart the signal on-board equipment to repair the failure, while the train is detained at the rear station for disposal. After the failure is repaired, the dispatcher authorizes the train to continue operating to the next station in RRM mode. The train is automatically upgraded to FAM mode after it regains its positioning.
- Strategy 2: The dispatcher arranges for emergency personnel to enter the failure section in the form of additional passengers. The emergency personnel make train switch to CM mode and drive away from the section to the next station.

In the original failure case, the failure occurred at a location close to station F. In order to compare the two strategies in depth, we change the failure location in the interval and the train interval respectively. In this case, the failure occurred at the midpoint of EF station, and the train interval was changed to 300 s. The recovery time and system resilience under the two strategies are shown in Fig. 8.

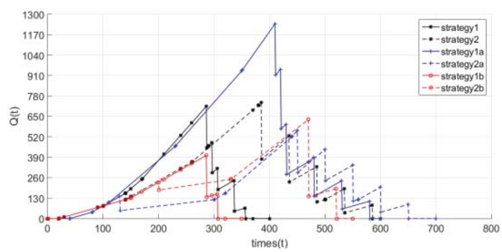


Fig. 8 Strategy 1 and strategy 2 with different conditions resilience curve

Table 4 Strategy 1 and strategy 2 with different conditions resilience values

Case	*R*	*R/R$_{S1}$*
Strategy 1	254.91	100%
Strategy 2	268.36	105.3%
Strategy 1a	429.88	100%
Strategy 2a	185	43%
Strategy 1b	240.42	100%
Strategy 2b	222.30	92.4%

Where R_{S1} is Strategy 1 with different conditions resilience values. Strategy1a and Strategy2a represent Strategy 1 and Strategy 2 after changing the failure occurrence point, while Strategy1b and Strategy2b represent Strategy 1 and Strategy 2 for changing the train departure interval.

Moreover, considering the failure occurred close to station E, the failure train under strategy 1 spends more than 600s in passing interval of station EF because the equipment is in RRM mode for a long time in the interval after remote restart. As thus, resilience in this case is no longer calculated for comparison.

Comparing the two strategies resilience, it can be seen that the impact of strategy 1 and strategy 2 on the system resilience performance in the original case is close to, but the recovery time under strategy 1 is faster. So, in this case it is recommended to choose strategy 1. After changing the failure occurrence point between EF stations, the disposal time of strategy 1 and strategy 2 are comparable, however, the resilience is much worse than that of strategy 2. Additionally, after changing the train departure interval to 300s, the resilience of strategy 1 and strategy 2 are comparable, but the disposal time of strategy 1 is much less than that of strategy 2. In this case, it is recommended to choose strategy 1.

Based on the above discussion we can find an interesting conclusion that the effect of FAO remote disposal function is not better than the traditional manual takeover strategy in all cases. Furthermore, resilience of the two strategies can be significantly different with comparable disposal time. Therefore, a suitable disposal strategy should be selected according to the line specifics in the actual disposal. The proposed quantitative evaluation method of resilience can do this job well.

5.2. *Analysis of the effectiveness of the personnel ability for disposal*

People have a variety of operational behaviours during failure disposal. The CEMS model, which is commonly used in human factors engineering domain, classifies human behaviour into three levels (Reason, 1987): skill-based behaviour, rule-based behaviour, and knowledge-based behaviour. In this paper, we classify the operational behaviours in the case with the three types mentioned above. For the failure disposal process, the proficiency of skill-based behaviours affects the execution time of individual operations, and the familiarity with the rule-based behaviours affects the interface time between operations. It is with little difference in time for well-trained metro employees to do those. The accuracy of knowledge-based behaviour can lead to redundant disposal steps or lack of necessary operation steps in emergency disposal, which is the biggest uncertainty of failure disposal effect. In this paper, the standard data provided by operating units are used for skill-based behaviour and rule-based behaviour, and the impact of knowledge-based behaviour on emergency disposal resilience index is focused on.

Operation 4 in Case 1 and Operation 5 in Case 2 are both knowledge-based behaviours. In Case 1, the dispatcher needs to judge the scope and duration of detaining train based on experience. Inexperienced dispatchers tend to be more conservative in their disposition, possibly detaining multiple upstream stations and setting longer detaining times (as shown by the blue line in Fig. 9). Relatively, experienced dispatchers can more accurately judge the impact of failures and the effect of disposal, effectively narrowing the scope of stopping and reducing the stopping time (as shown by the yellow line in Fig. 9). In Case 2, the dispatcher needs to decide the timing of boarding preparation and whether to execute boarding. Similarly, it also depends on the dispatcher's prediction of the failure impact, which may lead to changes in the resilience curve. (as shown by the blue and yellow lines in Fig. 10).

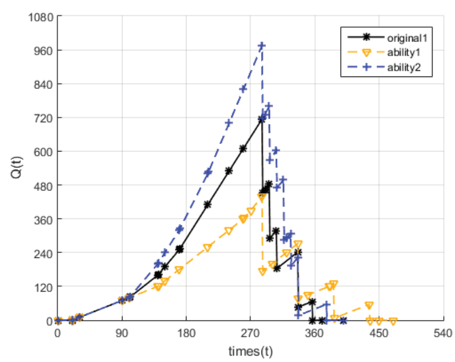


Fig. 9 Case 1 with different personnel ability resilience curve

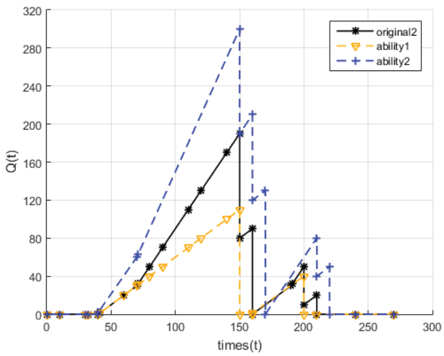


Fig. 10 Case 2 with different personnel ability resilience curve

Table 5 Case 1 with different personnel ability resilience values

Case	R	$R/R_{Original}$
Original 1	254.91	100%
Ability 1	154.84	60.7%
Ability 2	323.90	127.0%

Table 6 Case 2 with different personnel ability resilience values

Case	R	$R/R_{Original}$
Original 2	65.29	100%
Ability 1	42.81	63.6%
Ability 2	114.61	175.5%

It is known from the Table 5 and Table 6 that the sensitivity of emergency disposal resilience index is influenced by knowledge-based behaviour, which has a significant impact on the disposal effect. Due to the fact that it is an active adjustment to the disposal process after improving the personnel ability.

Compared with the traditional CBTC system, the FAO system reduces the staffing and increases the monitoring equipment. The dispatchers can view the status information through remote equipment. For this reason, the percentage of knowledge-based behaviours of dispatchers in the disposal process would be increased significantly. As a result, different types of abilities of personnel should be improved for different positions.

6. Conclusion

The dynamic changes in the number of train backlogs and transport recovery times on the line network will be caused by faults and disposal process in the FAO system. Such changes cannot be reflected by the result-oriented operation assessment metric. Therefore, this paper introduces the concept of resilience and proposes a quantitative resilience assessment method for the emergency disposal strategy of FAO system. Firstly, the hierarchical relationship of scenario, vehicle and system is topologized in network structure to obtain the system function network under normal scenario. Secondly, the impact under failure and failure disposal is considered to get the system functional network structure under failure scenario. Then, the resilience value of the resilience triangle curve is calculated by the time deviation that the train achieves the corresponding scenario function between the normal scenario and the failure scenario. Finally, this paper uses the method to evaluate two cases of Yanfang Line and discusses them in terms of both equipment and personnel with the characteristics of FAO system.

According to the traditional concept of UTO fault disposal: when a train is forced to stop in the interval, try to keep the train running automatically to the next station so that personnel can board the train for disposal. Under this concept, the emergency disposal method is based on automatic emergency disposal by the equipment and remote disposal by the dispatcher. In the case study, we analysed the resilience variation of remote and manual disposal strategies, however, the results showed that the failure disposal assistance provided by the FAO system is not always the optimal disposal strategy. For example, for the on-board equipment failure in Case 1, Strategy1a is inferior to the disposal results under Strategy1b. Meanwhile, the emergency disposal results are more sensitive to personnel capabilities. For example, in Case 1 and Case 2, after changing the knowledge-based behaviour of personnel in failure disposal, the resilience value of the disposal results obtained fluctuates up and down that is more obvious.

According to the validation results, we suggest to pay more attention to several aspects in emergency management and system design for FAO system: from the aspect of emergency management, in the process of failure disposal and recovery, the disposal personnel should not rely too much on remote disposal or automatic disposal of equipment and blindly use a single disposal strategy. They should select the appropriate disposal strategy according to different situations. On the other hand, more attention should be paid to the personnel's own experience and ability in key positions. The ability of personnel for different positions to be improved to match the position. In terms of system design, the accuracy of the system failure reminder display and alarm information should be improved, while the failure judgment mechanism should be established with the aid of information fusion to reduce the percentage of knowledge-based behaviour in the disposal process.

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