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Adaptive Scheduling Method for Passenger Service Resources in a Terminal

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Abstract: To alleviate the tense situation of limited passenger service resources in the terminal and to achieve the matching of resource scheduling with the flight support process, the process–resource interdependent network is constructed according to its mapping relationship and the time-varying characteristics of the empirical network and network evolution conditions are analyzed. Then, node capacity, node load, and the cascading failure process are investigated, the impact of average service rate and service quality standard on queue length is considered, the node capacity model is constructed under the condition of resource capacity constraints, and the load-redistribution resource adaptive scheduling method based on cascading failure is proposed. Finally, the method's effectiveness is verified by empirical analysis, the service efficiency is assessed using the total average service time and variance, and the network robustness is assessed using the proportion of maximum connected subgraph. The results indicate that the resource adaptive scheduling method is effective in improving service efficiency, and the average value of its measurement is smaller than that of the resource average allocation method by 0.069; in terms of the robustness improvement of the interdependent network, the phenomenon of re-failure after the load redistribution is significantly reduced.

Keywords: resource allocation; adaptive scheduling; interdependent network; cascading failure; robustness

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1. Introduction

With the rapid development of the civil aviation industry, the contradiction between the ever-increasing demand for air transport and the insufficient supply capacity of resources has become increasingly prominent. Within the terminal, constraints in passenger service resources and suboptimal resource efficiency can result in issues like passenger congestion and resource overload during peak departure hours, significantly impacting flight operations. Under specific resource limitations, finding reasonable resource-scheduling methods to shorten service time and improve the resource-utilization rate is an important challenge for flight safety operation assurance work. Hence, conducting a thorough investigation into resource-scheduling methods is significant in enhancing the efficiency of airport operation guarantees and minimizing flight delays.

The focus of terminal resource scheduling primarily involves check-in counters, security check channels, and boarding gates, with scholars having attained specific research outcomes. Yang et al. proposed an extended social force model to describe each passenger's movement at an airport terminal, designed a route-guidance strategy and a greedy algorithm to search for the optimal route for passengers, verified the reasonableness of the model, and improved the efficiency of passenger check-in [1]. Zhang et al. constructed a terminal queuing-simulation model to simulate the passenger security check queuing service process, and the results show that the optimization model is in line with the actual operation of the security check area [2]. Li et al. calibrated a mixed logistic model using sample passenger data, which showed that distance, queue length, age and baggage significantly affected the choice of safe passage and that decision-making was influenced by a high degree of passenger heterogeneity [3]. Yu et al. established a multi-objective nonlinear 0–1 integer planning model for flight-gate assignment, designed a genetic algorithm based on improved gene coding to solve the model, and verified the algorithm's effectiveness by comparison [4]. Liu et al. summarized the common configuration optimization strategies at home and abroad for the three main service resources of check-in, security check, and boarding, including the check-in resource-allocation method based on the static configuration model and dynamic configuration model, and the security inspection optimization method considering passenger movement characteristics and the security inspection process, and the gate assignment method based on mathematical induction methods and computer simulation technology [5]. Current resource-scheduling methods encounter issues, including insufficient rationality and balance in resource allocation, challenges in promptly adjusting plans for emergencies, and the inability to schedule resources promptly as they approach maximum capacity.

Due to the close connection between support processes and service resources, the support process network and the service resource network interact with each other and are interdependent; the dependency enables faults to propagate across the network, resulting in a cascading failure process within the interdependent network. Cascading failures of interdependent networks are involved in many fields. Wang et al. introduced a dynamic factor and proposed a dynamic cascading failure model against cascading failure; the simulation results show that the controllability robustness and economy after cascading failure based on the dynamic cascading failure model is feasible and effective [6]. Chen et al. proposed a novel nonlinear model of cascade failure in weighted complex networks considering overloaded edges to describe the redundant capacity for edges and capture the interaction strength of nodes. The results show that the model can significantly improve the destructiveness of complex networks against cascade failure [7]. Xu Xiaohan et al. proposed a modelling method for multilayer interdependent multimodal public transit networks that represent the coupling relationship of multiple modes of transport. They then designed the metrics and the cascading failure model and verified its feasibility and validity [8]. Li Meixuan Jade et al. studied cascading failure propagation in power systems and presented methods for quantifying important failure-propagation properties [9]. Based on the theory of interdependent networks, Bai et al. proposed a new cascading failure model for air traffic-control networks based on air traffic-management regulations; the model established a dual-layer dependency relationship between the control coordination network and the air route facility network [10]. Cascading failure load-redistribution strategies mainly include average allocation strategy, degree-allocation strategy, remaining capacity-allocation strategy [11], load local priority redistribution rule [12], neighbouring load-redistribution strategy [13], and dynamic load redistribution based on metrics updated after each round of cascading failure [14]. Wang et al. proposed a load-reallocation strategy based on the maximum residual capacity of neighbour nodes and simulations. They analyzed the influence of tolerance parameters, load distribution parameters and path length on the load distribution effect [15]. Zhang et al. established an interdependent network model of maintenance, storage and supply support. They proposed a dynamic load-redistribution strategy based on node-local load rate, and the simulation results show that the dynamic allocation strategy can improve the equipment support network's anti-attack ability and recovery ability to a certain extent [16,17]. Wang et al. established an air traffic cyber–physical system model and adopted different flow-allocation strategies, including degree allocation, betweenness centrality allocation, and remaining capacity allocation to alleviate the cascading failure of the air route network and air traffic-control network [18]. Yu et al. proposed a cascading failure model of interdependent networks considering dependent side loads. They analyzed the impact of different allocation strategies on the robustness of the network. The results show that the residual capacity-allocation strategy can effectively alleviate the overload failure of dependent edges [19]. Xie Yiran et al. argued that most passengers will evacuate to nearby stations when a station fails. Therefore, a load-capacity cascading failure model with power law load redistribution was investigated [20]. Song Bo et al. proposed a new cascading failure model with a heterogeneous redistribution strategy to describe and analyze node fault propagation in community networks [21]. Zhang JR et al. proposed a cascading failure model with adjustable parameters, designed a load delay judgment mechanism, and constructed a load-allocation strategy, which improved the network's robustness and efficiency [22].

In summary, interdependent networks offer notable advantages in addressing relationship issues of multiple complex networks, and their application in the field of civil aviation mainly focuses on the construction and optimization problems of air transport networks, with limited applications in describing the resource-allocation and -scheduling process. Consequently, this paper transforms the resource-scheduling problem into a passenger flow diversion-control and -optimization process implemented to enhance the efficiency of passenger service in the terminal building by studying the cascading failure transfer process and load-redistribution mechanism of the interdependent network. This paper provides a reference basis for the rational allocation of flight support resources.

This study is organized as follows: Section 2 builds the process–resource interdependent network. Section 3 defines the node's load and capacity and proposes a load-redistribution resource adaptive scheduling method based on cascading failure. Section 4 validates the method's feasibility and evaluates the service efficiency and interdependent network's robustness. The conclusions are given in Section 5.

2. The Process–Resource Interdependent Network

2.1. Network Topology

Flight support tasks/services are interrelated and synergistic, forming complex spatial and temporal network relationships. The allocation of service resources is meticulously planned to align with the requirements of the regular operation of the support process. There is a dependency between the support process network and the service resource network, and these two networks are coupled to form a process–resource interdependent network.

The support process network is a complex network formed by the abstraction of passenger departure guarantee process-oriented services. The network has a linear structure and sets up virtual start and termination nodes. G_A is the support process network and is denoted as

$$G_A = (V_A, E_A) \tag{1}$$

where N_A is the total number of nodes in the support process network, $V_A = \{v_{Ai} | i = 1, 2, \cdots, N_A\}$ is the set of nodes of the network G_A. Node v_{Ai} represents the i-th task or service provided to the passenger. $E_A = \{e_{Aij} | e_{Aij} = (v_{Ai}, v_{Aj}), i = 1, 2, \cdots, N_A; j = 1, 2, \cdots, N_A; i \neq j\}$ is the set of edges of the network G_A. The edge e_{Aij} represents that the start of the latter task depends on completing the former task.

The service resource network is obtained by a high degree of abstraction of the real resource system, which has a complex structure and characteristics. The network has a modular structure with interconnected nodes within modules and sparse inter-module node connections with ∞ edge weights, which do not pass the load. G_B is the service resource network and is denoted as

$$G_B = (V_B, E_B) \tag{2}$$

where N_B is the total number of nodes in the service resource network, $V_B = \{v_{Bi} | i = 1, 2, \cdots, N_B\}$ is the set of nodes of the network G_B. Node v_{Bi} represents the i-th resource used to provide a particular service type. $E_B = \{e_{Bij} | e_{Bij} = (v_{Bi}, v_{Bj}), i = 1, 2, \cdots, N_B; j = 1, 2, \cdots, N_B; i \neq j\}$ is the set of edges of the network G_B. The edge e_{Bij} represents the existence of cooperation or substitution between resources.

The process–resource interdependent network is denoted

$$G = (G_A, G_B, E_{AB}) \tag{3}$$

The support process network and the service resource network are connected by dependent edges and are expressed as

$$e_{AiBj} = \begin{cases} 0, & v_{Ai} \in V_A, v_{Bj} \in V_B, \text{ There is no dependent edge between node } v_{Ai} \text{ and node } v_{Bj} \\ 1, & v_{Ai} \in V_A, v_{Bj} \in V_B, \text{ There is a dependent edge between node } v_{Ai} \text{ and node } v_{Bj} \end{cases} \tag{4}$$

$E_{AB} = \{ e_{AiBj} | e_{AiBj} = (v_{Ai}, v_{Bj}), i = 1, 2, \cdots, N_A; j = 1, 2, \cdots, N_B \}$ is the set of dependent edges of the network G. Dependent edge e_{AiBj} represents the use of a resource v_{Bi} to provide an operation or service v_{Ai} to a passenger. The number of support process network nodes is much larger than the number of service resource network nodes, and the coupling mode between two networks is in the form of one-to-many connections [23].

The process–resource interdependent network is visualized using Gephi, as shown in Figure 1. The upper network is the support process network and the lower network is the service resource network.

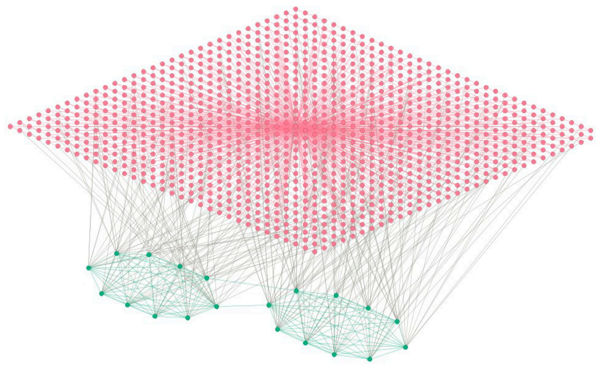


Figure 1. The process–resource interdependent network.

2.2. Time-Varying Characteristics of Network Topology

The operation support of flights is a dynamic process, and changes in passengers and resources will cause changes in the network topology. During the support process, a change in the service time will lead to a change in the node's weight; the number of nodes will increase when new passengers arrive at the terminal to start the services; according to the process, the dependent edges will change when passengers complete the former service and start the latter service; and the resource failure will make the nodes and the edges connected to the nodes all change. As a result, the process–resource interdependent network is constantly changing over time, and the network evolution conditions are as follows:

(1) The state of any node changes, such as the weight of nodes v_{Ai} or v_{Bi} changes;
(2) Network G_A or G_B adds new object node v_{Ak} or v_{Bk};
(3) The relationship between nodes changes, such as e_{Aij}, e_{Bij}, or e_{AiBi}.

The network topology is constantly changing, resources and processes are matched in real-time, and the network time-varying process is shown in Figure 2.

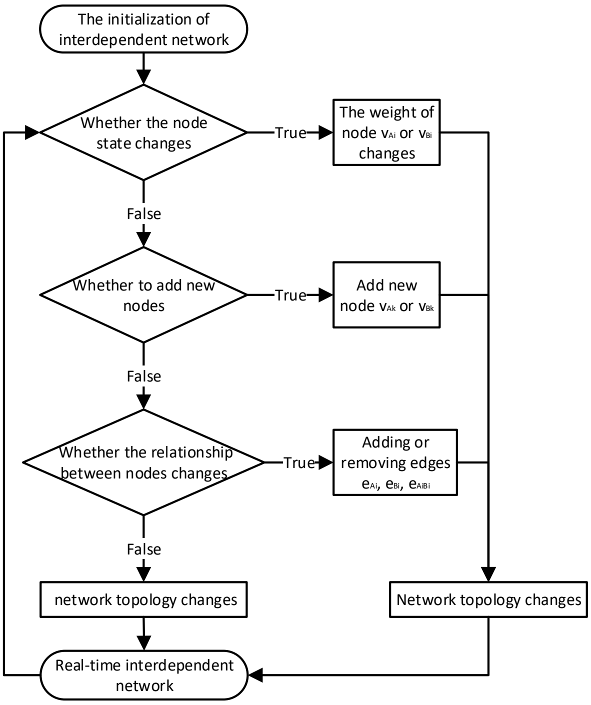


Figure 2. Interdependent network time-varying process.

3. Resource Adaptive Scheduling Method for Load Redistribution Based on Cascading Failure

3.1. Capacity, Load, Cascading Failure Process

In this paper, a cascading failure load-reallocation method is used for resources adaptive scheduling for arriving passengers.

Traditional cascading failure models are mainly based on single-layer complex networks, defining the initial load of node v_j as

$$L_o(v_j) = \alpha k_j^{\beta} \tag{5}$$

where α and β are adjustable parameters, v_j is a node of the single-layer network, and k_j is the degree of node v_j, "degree" typically refers to the number of edges connected to a node.

Loads in interdependent networks can be expressed through dependent edges, and the cascading failure load capacity model applies not only to single-layer networks but also to interdependent networks. Since process–resource interdependent network needs to consider interlayer edges, the interlayer degree of a resource node to express its load. The initial load $L_0(v_j)$ of a service resource network node is defined as

$$k_j = \sum_{i=1,2,\cdots,N_A} e_{AiBj} \tag{6}$$

$$L_0(v_j) = k_j \tag{7}$$

where v_i is a node of the support process network G_A, v_j is a node of the service resource network G_B, e_{AiBj} is a dependent edge of the two networks, and k_j is the interlayer degree of node v_j, i.e., the number of passengers queuing for service.

Resource service capabilities vary; combined with the M/M/1 queuing theory model and passenger service quality standards of civil airports, service intensity ρ_j can be calculated through the following formula:

$$\mu_j = \frac{60}{T_j} \tag{8}$$

$$\lambda_j = \mu_j - \frac{60}{W} \tag{9}$$

$$\rho_j = \frac{\lambda_j}{\mu_j} \tag{10}$$

where T_j is the weight of node v_j, representing the average service time of resource v_j; μ_j is the average service rate of check-in counters; λ_j is the average arrival rate of passengers; W is the maximum waiting time for 95% of passengers to check-in. According to the airport service quality standards, 95% of domestic economy class passengers should have a queuing and check-in time of no more than 10 min, and W = 10. ρ_j is the service intensity, representing the utilization factor of service resources.

Based on the service intensity, the queue length l_j of service resource node v_j is denoted as

$$l_j = \frac{\rho_j}{1-\rho_j} \tag{11}$$

The queue length l_j is the maximum number of passengers to be served by the resource node v_j. The node capacity $C_0(v_j)$ is denoted as [24,25]

$$C_0(v_j) = (1+\alpha)l_j \tag{12}$$

where α is adjustable parameter [26].

In the cascade failure process, if the service resource node load is less than its capacity, the node is in a normal state, and the node can continue to receive additional load $\Delta L_0(v_j)$, adding the corresponding dependent edge; if the total load of the node after receiving the load is greater than its capacity, the node is in a failure state, and the node load needs to be allocated to the adjacent nodes in a new round of load allocation, and the corresponding dependent edge is reconnected. The mathematical expression for node state identification is given below [27]

$$\begin{cases} L_0(v_j) + \Delta L_0(v_j) \le C_0(v_j), & \text{the normal state} \\ L_0(v_j) + \Delta L_0(v_j) > C_0(v_j), & \text{the failed state} \end{cases} \tag{13}$$

3.2. Load Distribution Model under Cascading Failure Condition

The residual capacity load-reallocation strategy was selected in the study to enhance the control of the network. The residual capacity of a service resource node is proportional to its residual tolerable load. The load distribution ratio of the new load L allocated to each node in a certain time frame or phase is [28]:

$$P_j = \frac{C_0(v_j) - L_0(v_j)}{\sum\limits_{v_a \in V_B} (C_0(v_a) - L_0(v_a))} \tag{14}$$

where v_j is service resource network node, P_j is the ratio of load; $C_0(v_j) - L_0(v_j)$ is the remaining capacity of service resource node v_j; v_a is any node in the service resource network that can receive the load [29].

Therefore, the load $\Delta L_0(v_j)$ allocated to the resource node v_j by the new load L in a certain time frame or phase is:

$$\Delta L_0(v_j) = P_j \times L = \frac{C_0(v_j) - L_0(v_j)}{\sum\limits_{v_a \in V_B} (C_0(v_a) - L_0(v_a))} \times L \tag{15}$$

where L is the new load, and the corresponding dependent edge is added after load distribution.

After service resource node v_j receives additional load $\Delta L_0(v_j)$, the total load is

$$L_1(v_j) = L_0(v_j) + \Delta L_0(v_j) \tag{16}$$

If the sum of the load received by the service resource node v_j and its load exceeds its capacity, i.e., $L_0(v_j) + \Delta L_0(v_j) > C_0(v_j)$, it will fail node v_j. The load on node v_j will be redistributed proportionally to its neighboring service resource nodes. The process is repeated until all resource nodes do not exceed the capacity limit.

4. Empirical Analysis

4.1. Example

For instance, in the case of check-in counter allocation, the allocation scheme is obtained using a load-redistribution resource adaptive scheduling method based on cascading failure. Assume there are ten check-in counters in the terminal building, one hundred passengers are already in the check-in queue, and the existing twenty additional passengers are diverted to the ten counters. There is a need to ensure load balancing of service resources.

The interdependent network topology is shown in Figure 3 (the service resource network only contains check-in counter resources, and other resources are not considered now). Based on Formulas (8)–(12), α = 0.3, the calculation results of the average service rate and capacity are shown in Table 1. According to the load-allocation Formulas (14)–(16), 20 unit loads are allocated to 10 resource nodes, and considering its practical meaning, rounding is taken to the nearest whole, and the allocation scheme is shown in Table 1. After the adaptive scheduling of resources, none of the loads exceeds the node capacity limit, and the dependent edges are added according to the load-scheduling results. At this time, the interdependent network is shown in Figure 4.

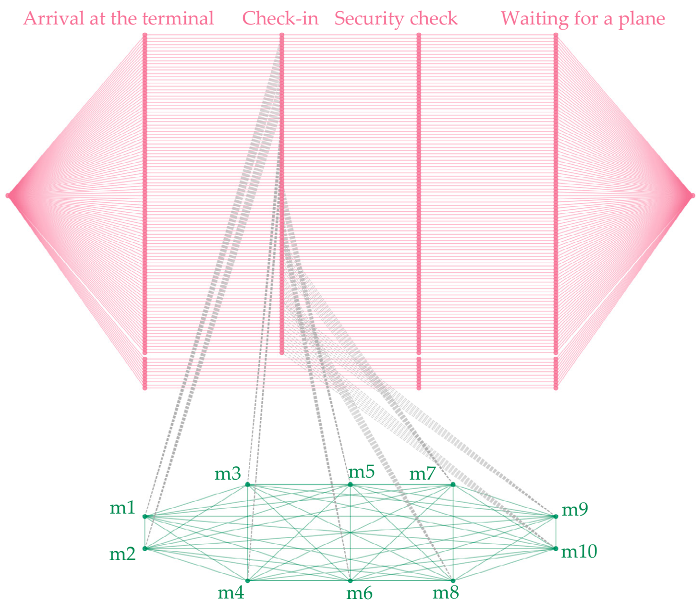


Figure 3. Interdependent network topology.

The relationship between resource capacity, average service rate μ and the number of queuing passengers is plotted according to Table 1. The relationship graph is shown in Figure 5: the resource capacity is proportional to μ; the remaining capacity of the resource is proportional to its remaining tolerable load; the number of passengers after resource adaptive scheduling has an apparent positive correlation with the resource capacity and μ. Therefore, the method has a certain degree of adaptability, and the number of passengers after resource adaptive scheduling within the capacity limit.

Table 1. Comparison of data before and after adaptive scheduling of check-in resources.

Check-In Counter	Weights	Average Service Rate	Capacity	Load before Scheduling	Distribution of Loads	Load after Scheduling
m1	0.55	109	22.33	12	2	14
m2	0.50	120	24.70	12	3	15
m3	0.60	100	20.37	11	2	13
m4	0.65	92	18.70	10	2	12
m5	0.70	86	17.27	9	2	11
m6	0.60	100	20.37	10	2	12
m7	0.65	92	18.70	10	2	12
m8	0.75	80	16.03	9	2	10
m9	0.80	75	14.95	8	1	10
m10	0.70	85	17.27	9	2	11
total				100	20	120

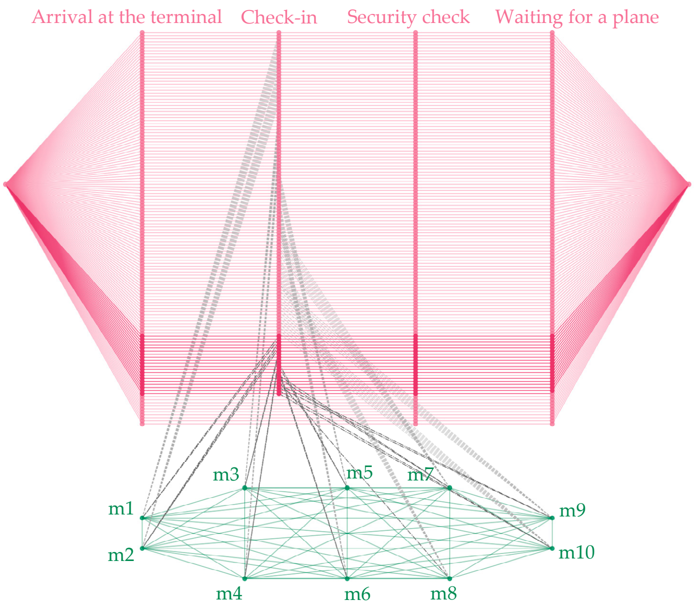


Figure 4. Interdependent network topology after resource adaptive scheduling.

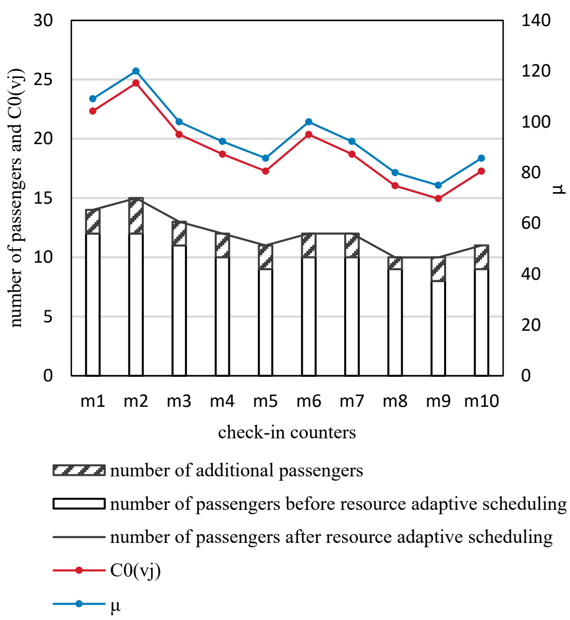


Figure 5. Relationship between $C_0(v_j)$, μ, and number of passengers.

Figure 6 shows the curves of the relationship between the number of queuing passengers and time before resource allocation, after resource adaptive scheduling, and after the average allocation of resources. After the adaptive scheduling of resources, the ten check-in counters complete the services within 7.2–8 min, with a relatively concentrated completion time, reflecting the balanced resource load. If the average allocation of resources strategy is used, i.e., $\Delta L_0(v_j) = L/N$, the earliest completion time of the check-in work is 7 min, and the latest is 8.25 min. Obviously, the resource adaptive scheduling method based on the cascade failure model is more efficient and has more evident advantages in improving the overall effectiveness of resources. From the passengers' perspective, resource adaptive scheduling reduces the overall waiting time and improves passengers' travelling experience.

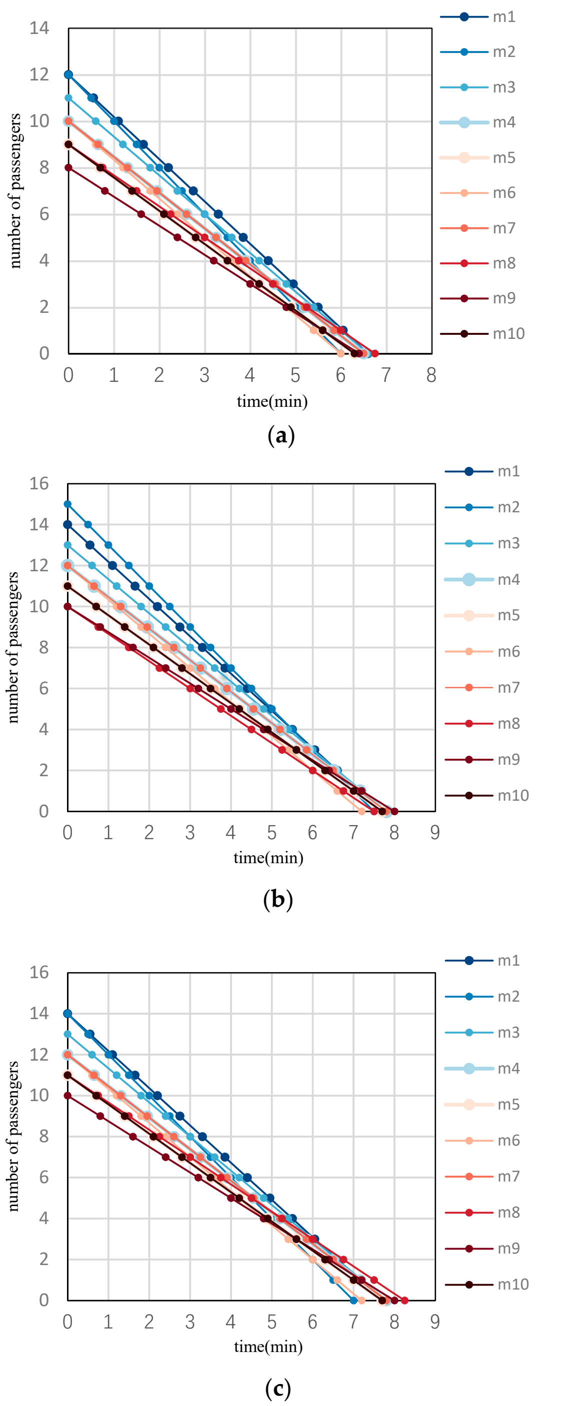


Figure 6. Changes in the number of queuing passengers over time: (**a**) before resource allocation; (**b**) after resource adaptive scheduling; (**c**) after the average allocation of resource.

In summary, the algorithm achieves resource adaptive scheduling, and the load-redistribution resource adaptive scheduling method based on cascading failure can be applied to passenger service resource allocation.

4.2. Simulation Analysis

4.2.1. Service Efficiency Analysis

The efficiency of the interdependent network after resource adaptive scheduling is analyzed based on the rationality and effectiveness of resource adaptive scheduling method. The measurement is a function Z of the total average service time and variance of the resources.

The average service time is the main indicator of the overall service level of the resource, and the total average service time T of the resource is defined as

$$T = \frac{\sum_{j=1}^{m} (k_j \times T_j)}{\sum_{j=1}^{m} k_j} \tag{17}$$

where m is the total number of resources, k_j is the interlayer degree of node v_j, and T is the node's weight, representing the average service time.

To ensure a balanced allocation of resources, the variance D is defined as

$$D = \frac{\sum_{j=1}^{m} \left(k_j \times T_j - \frac{\sum_{j=1}^{m} (k_j \times T_j)}{m} \right)^2}{m} \tag{18}$$

Considering both total average service time T and resource load balancing, a weighted summation method is used to define the measurement Z.

$$Z = \beta \times \frac{\sum_{j=1}^{m} (k_j \times T_j)}{\sum_{j=1}^{m} k_j} + (1-\beta) \frac{\sum_{j=1}^{m} \left(k_j \times T_j - \frac{\sum_{j=1}^{m} (k_j \times T_j)}{m} \right)^2}{m} \tag{19}$$

where β = 0.5, the smaller the value of Z, the less the total average service time and the more balanced resource allocation.

Figure 7 shows the ten sets of Z-values for the resource adaptive scheduling method and the average allocation of resource method for different numbers of additional people.

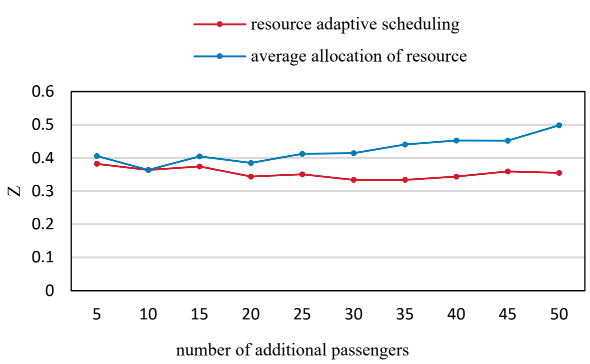


Figure 7. Comparison of the efficiency of the two allocation methods.

Figure 7 shows that the Z value obtained by the resource adaptive scheduling method based on the cascading failure model is significantly smaller than the Z value of the average allocation. Z is equal only once when the number of additional passengers is ten because the two methods have the same calculation result. The more additional passengers there are, the more obvious the gap between the two is, with the average Z value of the former at 0.354 and that of the latter at 0.423, which is a difference of 0.069. This indicates that the resource adaptive scheduling method obtains a smaller total average service time and a more balanced resource load.

4.2.2. Robustness Analysis

When attacking a certain proportion of resource nodes, the interdependent network will undergo a cascading failure. When the failure reaches stability, the ratio of the number of valid nodes in the remaining maximum connected subgraph to the total number of initial nodes is a robustness indicator, i.e., the proportion of maximum connected subgraph of the interdependent network [30], s:

$$s = \frac{X_A + X_B}{N_A + N_B} \tag{20}$$

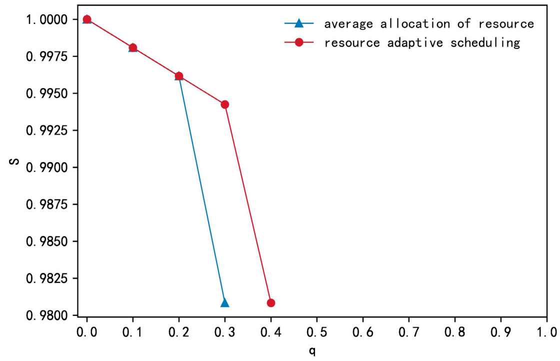
where X_a and X_b are the effective nodes in the maximum connected subgraph in the support process network G_A and the service resource network G_B, respectively, N_a and N_b are the total number of nodes in the initial state of the networks G_A and G_B; the larger the value of s, the more effective nodes in the interdependent network and the better the network robustness.

Assuming that equipment failure or operator absence will lead to resource node failure, the results of resource adaptive scheduling in Section 4.1 are used as a simulation use case to attack the service resource network nodes and distribute the load of the nodes. The impact of the load-allocation method of the interdependent network on the network robustness is explored under two attack methods, namely random attack and deliberate attack with node weights ranging from small to large, and the simulation results are shown in the following figure.

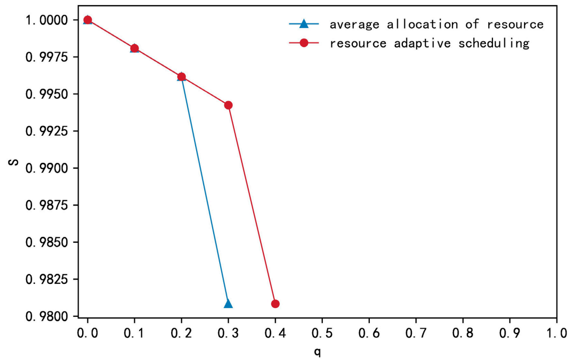
The horizontal coordinate in the figure is the proportion of maximum connected subgraph s, and the vertical coordinate is the node destruction ratio q. When s = 0.981, the capacity of nodes of the service resource network exceeds the limit, and the passenger cannot complete the service within the specified time, failing the support process network nodes and thus, the whole interdependent network is paralyzed. Figure 8 shows that the interdependent network with the average resource-allocation method fails at q = 0.3, and the interdependent network with the resource adaptive scheduling method fails at q = 0.4. Resource adaptive scheduling can reduce the phenomenon of re-failure after the load allocation to a certain extent. However, due to the small number of nodes in the service resource network, the network fails very quickly after an attack. Comparing Figure 8a,b, the effects of the two allocation methods on the network robustness under different attack strategies are roughly the same. In summary, the resource adaptive scheduling method can achieve better results than the average resource-allocation method, and resource adaptive scheduling reduces the cascade failure rate and improves the network's robustness.

Considering the small number of nodes in the service resource network, this paper introduces security check resources, including ten security check channels and 105 passengers waiting to perform security check services. Resource adaptive scheduling will be performed for the additional 25 new passengers. The results of resource adaptive scheduling are shown in the following Table 2.

The resource nodes of the check-in counters and security check channels constitute the service resource network. There are edges between the two resources with edge weights ∞, and the edges cannot pass the load. The process nodes of 250 passengers together constitute the support process network. Under the random attack and the deliberate attack based on the weight of the check-in and security check nodes, the impact of the load-distribution method of the interdependent network on the robustness is explored. The simulation results are shown below [29,31].



(**a**)



(**b**)

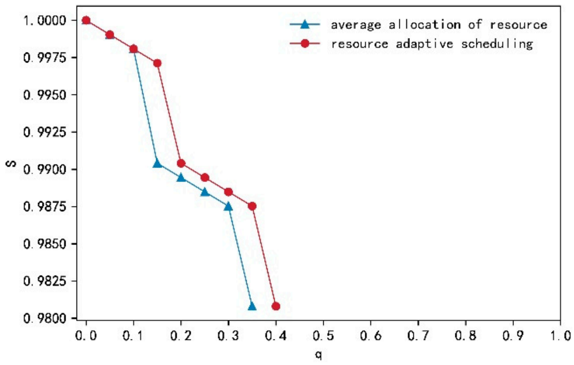
Figure 8. Comparison of the robustness of interdependent networks at check-in counters resource. (**a**) Deliberate attacks. (**b**) Random attack.

Table 2. Comparison of data before and after adaptive scheduling of security check resources.

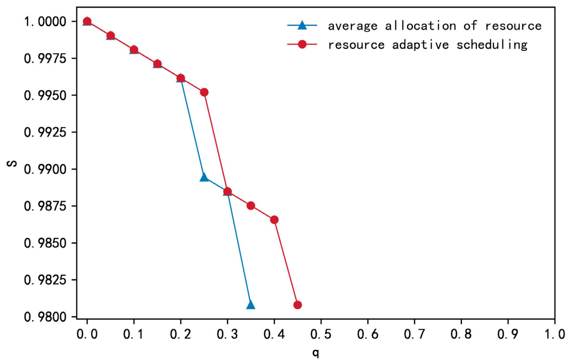
Security Check Channel	Weights	Capacity	Load before Scheduling	Distribution of Loads	Load after Scheduling
m11	1	22.4	13	2	15
m12	0.9	25.1	14	2	16
m13	0.95	23.7	14	2	16
m14	1.05	21.3	12	2	14
m15	1.05	21.3	11	2	13
m16	1	22.4	10	3	13
m17	1	22.4	9	3	12
m18	1.1	20.2	8	3	11
m19	1.15	19.3	7	3	10
m20	1.2	18.4	7	3	10
total			105	25	130

The vertical coordinate in the figure is the proportion of maximum connected subgraph s, and the horizontal coordinate is the ratio of node destruction q. Figure 9 shows that the effect of resource adaptive scheduling method is better than that of the method of average allocation of resources. Resource adaptive scheduling can improve the robustness of the network, and it has an obvious advantage in mitigating cascading failure.

After the number of nodes in the service resource network increases, different attack methods have significantly different impacts on the robustness of the interdependent network. Compared with random attacks, deliberate attacks have a more significant impact on the robustness of the interdependent network; the proportion of the maximum connected subgraph of the dependent network decreases faster during deliberate attacks, and the interdependent network is more sensitive to deliberate attacks based on node weights.



(**a**)



(**b**)

Figure 9. Comparison of the robustness of interdependent networks at check-in counters and security check channels resource. (**a**) Deliberate attacks. (**b**) Random attack.

5. Conclusions

(1) Based on the matching relationship between the support process and service resource, this paper constructed a process–resource interdependent network and a load-capacity model for interdependent networks based on the traditional single-layer network model, and the load-redistribution model based on cascading failure is still well-suited for process–resource interdependent networks.

(2) The example shows that the number of passengers after resource adaptive scheduling has an apparent positive correlation with the capacity and average service rate, and the number of passengers is within the capacity limit; the check-in counters after resource adaptive scheduling serve all the passengers within 7.2 min to 8 min, which is relatively concentrated in one time period. Therefore, the load-redistribution resource adaptive scheduling method based on cascading failure has certain adaptability and balance and can be applied to allocating passenger service resources in the terminal building.

(3) This study used a function of the total average service time and variance of the resources as a measurement and analyzed the service efficiency of the interdependent network. The mean of the function after resource adaptive scheduling is 0.069 smaller than after performing average resource allocation. The resource adaptive scheduling method effectively improves service efficiency.

(4) This study used the maximum connected subgraph of the network as a measurement and explored the effect of load-allocation methods of interdependent networks on network robustness under different attack strategies. Resource adaptive scheduling can

reduce the re-failure phenomenon after load allocation to some extent and improve the network robustness. The interdependent network is more sensitive to deliberate attacks based on node weights than random attacks.

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